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POWER SPECTRAL ANALYSIS OF CONTINUOUS TEXT STRINGS

5/87

Arne Graff, 1984
Stirling University

To my little daughter Sofie
who had to be silent while
her dad was studying language.

SUMMARY.

The present study aims at evaluating structures and information transfer in text strings. 42 text strings written by children (younger and older) and 22 text strings written by adults (scientists, newspapers and childrens books) were analysed in three ways. Firstly by simple statistical means, secondly by a time-series analysis based on Fourier analysis and thirdly by a pattern evaluation analysis based on the Fast Fourier Transform, all three methods having been developed for this analysis.

The analysis involving simple statistical means was based on my discovery that the distribution of 'new' words along any natural text string is one of exponential 'decay'. In a double-logarithmic coordinate system each text string can be represented by a straight line determined by the two parameters: intercept A and gradient B, both a function of how fast the vocabulary becomes exhausted as the string is extended. The numerical values of A and B were established for all the text strings, before and after permutation of the words in each text string, and it was shown that the permutation of the strings caused intercept A to increase and gradient B to decrease significantly thus indicating that A is invertedly, B directly related to sequential structure. The analyses established that adult text strings have a higher level of sequential structure than do childrens strings and that amongst adults, popular newspapers have the highest level of structure as well as the highest vocabulary.

A computer model (the 'model of best fit') of language perception was created in which the sememe evaluation and information transfer of the human 'linguistic device' - two features which are not easily simulated by a computer - is instead represented by one procedure which lends itself to computer processing and numerical analysis. In this model each incoming word is checked against a 'reference field' and sememe evaluation and information transfer are seen in terms of length of text string between reappearances of words. Before the text strings of this study were subjected to power spectral analysis, they were processed by this 'model of best fit'.

The two different methods of Fourier analysis gave virtually identical power spectra when applied to the same text strings. The Mean Power Density (MPD) and the Variance (CHI2) were measured from the power spectra of 25 of the childrens text strings and all 22 adult text strings. Although only by a small amount, MPD's were consistently higher for adults than for children, confirming earlier findings that adult strings have a higher seqential structure than childrens strings, although the significance level did not quite make it to the 5% level. CHI2 of the spectra turned out to be much more significantly correlated with age and language development than was vocabulary and gradient B earlier. The 'reference field', defined in the study, was the parameter with the highest correlation with language development. The popular press had the highest MPD, CHI2 and 'reference field' of all text strings. Both MPD and CHI2 decreased with permutation although only the difference with regard to CHI2 was significant. Both emission and absorbtion features were present in all the power spectra. It was suggested that these features represent generative and filter (lexical) functions of the 'linguistic device'. The position of two of the peaks in the power spectra were shown to be common to most of the spectra. These were F=0.484 in the childrens spectra and F=0.375 in the adults' spectra. Finally it was shown that when a grammatical category (eg. nouns) were weighted in different text strings, the same peak(s) appeared at about the same frequency in the different spectra, suggesting that identical, grammar specific, generator and filter functions were involved in the generation of the different text strings.

CONTENTS.

ADULT TEXT SAMPLES USED IN ANALYSES:

(All samples are printed in chapter 4, index on page 91)

SCIENTISTS.

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DREC2:
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pp 40-43.

PAD4:
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Macmillan, 1865,
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Pan Books Ltd, 1973,
pp 13-15.

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All in the golden afternoon
Full leisurely we glide;
For both our oars, with little skill,
By little arms are plied,
While little hands make vain pretence
Our wanderings to guide.
C.L. Dodgson.

PREFACE.

This present work is an attempt to evaluate structure in text strings. 'Structure' is here taken to mean structure in the information theoretical sense as opposed to the concept of structure in the grammar-based structuralism usually associated with structural analysis of text strings. For this reason, this thesis begins with an examination of Information Theory with particular emphasis on the concept of structure within this theory.

The meaning of 'textstring' is the one usually accepted in linguistics i.e. not restricted to written communication. The text strings written by adults and used in this study have been picked from a number of books, while the text strings written by children have been written specifically for this study. However, even if the database of this study has been written text strings, it could in principle have been transcripts of spoken text strings. The main reason for my not using spoken strings has been the great number of repetitive and irrelevant? features such strings exhibit.

My preliminary research into structures in text strings was based on the established concept of vocabulary combined with some relatively simple statistical methods. This research is presented in chapters 5 and 6.

The severe limitations of the established concepts of words and vocabulary - and therefore of the outcome of this analysis based on simple statistical methods - however, compelled me to develop a more dynamic model of cognitive processing of text strings. This dynamic model is presented in chapter 8 as the model of 'best fit'.

The ultimate aim of my research has been to gain access to the so called 'linguistic device' i.e. to find particular features, amongst the general structures in text strings, which are telltales of the sub-controls in this 'device' rather than just the output from the 'device'. In this study, the 'linguistic device' is seen very much as a 'black box' with the text strings forming the output from the box. Because of the successful application of Fourier analysis to 'black box' problems in other fields, this particular kind of analysis was chosen to evaluate the structures in the text strings used in this study.

The explanation, modification and application of Fourier analysis to our particular signal base - the text strings - is presented in chapters 7, 8, 9 and 10, while the analyses themselves are presented in chapters 11 and 12.

Due to the vast number of words analysed in this research and the complexity of the mathematical analysis involved, the reading of the text strings and the analysis have had to be done automatically with a computer and consequently with no 'human touch'. This in turn has meant that even if some of my considerations regarding the way in which the 'linguistic device' functions may have some relevance, my analysis can at best be seen as a very crude attempt to simulate cognitive language processing. However, it is a beginning, and even if this simulation of cognitive language processing has obvious limitations, the results presented in this thesis do indeed suggest that the Fourier analyses have picked up some of the underlying structures of the text strings.

In spite of the present research not being based on any particular linguistic school of thought, some of the results of this study can be seen as graphic representations of the 'generative' and 'lexical' capacities of some of the more recent transformational grammars. However, it is worth keeping in mind, that the method of analysis, presented in this paper, has not to my knowledge been attempted before and the results should therefore be treated with caution.

This thesis can be read on several levels. The theory and the methods behind the analyses in this thesis are complex at times - so far from the 'Full leisurely we glide' of the poem by Lewis Carroll (top of page). If you feel this to be the case, you are taking it too seriously. The understanding of the intricacies of Fourier analysis and the statistics involved in the evaluation of the results is not a condition to the understanding of this study.

The spirit of most of the research in this study was that of solving an exciting puzzle; a succession of 'what if....'s alternating with 'what then....'s. Indeed, this research was never intended to be more than an exploratory trip along the banks of substance and form on that 'golden afternoon'.

A.G.

CHAPTER 1.

INFORMATION THEORY.

The mathematical discipline, which is now called information theory, was founded by the American engineer C.E. Shannon in 1948 in 2 articles "A mathematical theory of communication" in Bell System Technical Journal. The term "information theory", which was not coined by Shannon himself, is an unfortunate choice, since it tends - due to the common sense meaning of "information" - to give raise to expectations, which the theory cannot satisfy.

The theory deals with the transmission and reception of signals and the statistical considerations of error and success in this process. Information in this sense has nothing to do with meaning and says nothing about the value of the information in itself. Information in these terms is an absolute quantity which has the same numerical value for any observer. The human value of information, which the theory takes no account of, would necessarily be a relative quantity and would have different values for different observers.

The theory is based on statistics and applies to the following problem: After an experiment with a given number of possible outcomes has been fully explored, we will have gained some information. Can we measure this information?

As this information can not arise from nothing we will regard it as having been present in some form in the system before our influence transformed this form into information.

What is this substance then that information is made from. What do I mean when I say that it is transformed into information. Let us try and compare the situation before an experiment is carried out with a well known situation. You are setting up the new TV-set and everybody is gathered around you in admiration of your anticipated skills. You switch the set on and try to find the proper channels. The screen is but a big grey frame of black and white dots jumping about in the millions; a picturesque example of what a mathematician would call randomness and an electronic engineer would call noise. As you turn the channel selector, the random pattern here and there along the line of search changes into lumpy conglomerations of black and white. The whole thing looks like a jigsaw puzzle put together by a monkey. By this time the grateful audience will boost your ego by telling you that the picture is there and some amicable discussion will arise as to what the picture is a picture of. One and each of your little herd will analyse this near-random pattern and suggest a solution and eventually one suggestion will change everybody's perception of the screen as being a puzzle and everybody will aggree and say "oh" and "of course", and so a reference has been found by which the whole random pattern suddenly reveals itself as a picture of something.

What happened in this example - if we strip it of its homely atmosphere - was, that we decreased the level of randomness in a system by applying a structure to it, thereby transforming some of the randomness into information.

The potential for information or the form which can be transformed into information is called entropy with a term borrowed from the field of thermodynamics. Entropy is a measure of the lack of structure and if we take a common thing like water as an example and look at what happens on a molecular level when we change the temperature of the water, we can get an idea of what entropy is a measure of. Let us imagine, that we could magnify a lump of ice so much that we could see the very molecules; we would then see them quite stationary. Although the molecules would themselves writher about a little, they would still stay within a confined space and fixed distance to other molecules all giving the impression of a structure, which is of course the crystalline structure of ice. As we heat the ice - as we increase the entropy of the "subsystem" ice-water - the increasing entropy will eventually - when this subsystem has reached a level of entropy which we in our human "system" call zero centigrade - break the bindings between the water molecules giving them freedom to move about in a less structured - more random way. We say in the system which represents the human reality and which is overlaying the subsystem ice-water,that the ice has melted. As we increase the temperature of the water, or: increase the entropy of the subsystem water, the water molecules move about more and more at random until the entropy has reached a level, where any additional input of entropy will give the water molecules enough energy to escape the subsystem and move into our "system". In the human "system" the temperature of the water is now hundred centigrade, and the escaped molecules are called "steam". We say that the water boils. The boiling point of water represents this subsystems highest degree of randomness, temperature, entropy or lack of structure. It is clear enough now, that there is a link between temperature, entropy and randomness on one side and information and structure on the other side. They are merely different ways of expressing the same concepts in different systems. It is equally clear now, that as we increased the temperature in our system, we increased the entropy and the randomness in the subsystem.

As a simple experiment let us take the throw of a dice. If the dice is unbiased we know that each of the six faces has an equal chance of 1/6 th of coming up.

Before we throw the dice we are UNCERTAIN about which face will come up. Instead of the concept of 'uncertainty' we shall use the concept from the theory of thermodynamics of 'ENTROPY' and we shall define the entropy H of the experiment before the throwing of the dice as

$$H\ (T) = \log(6)$$

We now know, that before the dice had come to rest we had an uncertainty, or entropy as we have chosen to call it, of log(6). After the dice has come to rest the uncertainty no longer exists - the entropy has become zero - and we have gained some information. The entropy, which was log(6), has become zero and it seems reasonable to equal the amount of information gained with the amount of entropy lost. If we look at what has taken place during the experiment, we could clarify the transfer of entropy into information like this:

	ENTROPY	INFORMATION
Before the experiment	log(6)	0
Experiment fully explored	0	log(6)

As we can see, entropy and information are reciprocal, and for this reason information is sometimes termed "negentropy". This is not a very helpful concept however, and is mentioned here only as a curiosity.

More generally we have that the information gained from the experiment with N equally possible outcomes is

$$I\ (E) = \log(N) \tag{2.1}$$

Looking at equation (2.1) we can see, that the higher the number of possible outcomes of the experiment, the higher is the transfer of entropy into information taking place during the experiment, and there is theoretically no limit to the positive size of I. It is easy to see too, that if there is only one possible outcome then the entropy is zero ($\log 1 = 0$) and as there in this case can not be any transfer of entropy into information, we get the perfectly reasonable result that there is no information gained from an experiment with only one outcome.

In the field of thermodynamics, from where the concept of entropy comes, the logarithm used is the so called natural logarithm, the base of which is e = 2.71828.. We could choose what ever base we wanted, but dealing with signals and electronic communication hardware the obvious choice would be a logarithm with the base 2, since so many situations in communication can be described in terms of 2 states: "low level - high level" or "0 - 1". When we write log in the future we will therefore understand the logarithm with base 2.

For all logarithmic functions - whatever the base of the logarithm - we have that

$$\log(N) = 0 \quad \text{for } N = 1$$

so, recalling the experiment with only one outcome, it does not depend on which base we have chosen - the information gained from an experiment with only one possible outcome is always zero.

Let us consider a pack of 32 different cards of which we will select one at a time - and put it back - until we are shure that we have been through them all. As 32 equals 2 in power 5 the logarithm of 32 is 5 and the information gained is 5. It has become customary in information theory to say that the unit of information is "bit" (short for "binary digit"), so we would say that the information gained is 5 bit.

Let us now consider two separate packs of cards each containing 32 different cards and let us keep picking 2 cards, one from each pack, until we find no new combinations of the two cards we pick each time. The number of possible ways in which this can be done is 32*32 and the information derived from this experiment would therefore be log(32*32) = log 1024 = 10 bit. This seems perfectly reasonable since we would have expected to gain twice as much information from this experiment as we had from the above mentioned experiment. It is easy to see now, that the reason for using a logarithmic function in (2.1) is the additive property of such functions.

We have - in our imaginary experiments - so far dealt with number of outcomes. As it is often more practical to use probabilities we will change (2.1) to accommodate probabilities rather than number of outcomes. To return to the throw of a dice, we know, that each of the 6 faces has an equal chance of coming up and we say that the probability of any single face coming up is 1/6th. More generally we have that the probability p that one particular outcome out of N possible outcomes will occur is equal to 1/N where N is the number of possible outcomes, and if we want to substitute number of outcomes with probability in (2.1) we get

$$I\ (E) = -\log(p) \qquad (2.2)$$

Since the logarithm to a number between 0 and 1 is itself negative, the information derived from (2.2) is of course still positive.

Similar to our considerations regarding (2.1) we realise, by looking at (2.2), that the smaller the probability is, the higher is the information gained when the experiment is fully explored.

It is important at this stage to emphasize, that the amount of entropy retained in such an experiment is not released by any single action, e.g. a single throw of a dice. As mentioned above, information theory is a statistical theory and you do not make judgements on single cases in statistics. Statistical assessments are retrospective by nature, and when we make statistical judgements like: the probability that one particular face of a dice comes up is 1/6, we are really not saying anything about the single outcome of a throw of a dice. What is hidden in the statement is the assumption that if we were to throw a dice many times - and that means: more times than there are different outcomes - then this particular face in question would come up (ideally) 1/6 of the times.

It is important to understand that if it was not for reasons of simplification we should not be talking about single action experiments at all. Many introductions to information theory fail to emphasize this and often state that the information gained from the throw of a dice would be I=-log(1/6), and that the higher the number of different possible outcomes of an experiment, the higher is the information gained when one outcome is picked or confirmed. This is not the case. I shall later explain this more thoroughly. At this point I will just stress that the information I=-log(1/N) is the amount of information which can (ideally) be gained from the FULL exploration of the experiment with N equally possible outcomes, NOT the pick of a single outcome. If we do want to look at single actions like the single throw of a dice, we will then have to talk about the average information per outcome, which in the case of a dice would be

$$\begin{aligned} I(\text{each face}) &= 1/6 * I(\text{dice})\ \text{bit} \\ &= -1/6(\log 1/6)\ \text{bit} \end{aligned}$$

which more generally, for the experiment with N equally possible outcomes can be written

$$I(average) = -1/N * \log(1/N) \text{ bit}$$
$$= -p\log(p) \text{ bit} \qquad (2.3)$$

Now let us consider what would happen if the dice was biased. The probability of each face coming up would no more be exactly 1/6. When we counted the number of times each face had come up after a great number of throws we would find that some faces had turned up more than 1/6 of the total number of throws and some had turned up less than 1/6, but the sum of the fractions would of course still be 1.

If we were to sum up these different amounts of information we could of course write that

$$\begin{aligned} I(dice) = \quad & I(face\ 1) = -p_1 \log(p_1) \text{ bit} \\ + \ & I(face\ 2) = -p_2 \log(p_2) \text{ bit} \\ + \ & I(face\ 3) = -p_3 \log(p_3) \text{ bit} \\ & \vdots \\ + \ & I(face\ 6) = -p_6 \log(p_6) \text{ bit} \end{aligned}$$

(where p +p +p...+p again equals 1), but the established way of expressing this summation would be

$$I(dice) = -\sum_{n=1}^{n=6} p_n \log(p_n) \text{ bit}$$

or more generally where the case is not a dice but an experiment with j outcomes

$$I(exp\ ) = -\sum_{n=1}^{n=j} p_n \log(p_n) \text{ bit} \qquad (2.4)$$

This is in fact the main theorem - sometimes called the first equation - of the information theory. Again the sum of all the different probabilities equals 1 or put another way

$$\sum_{n=1}^{n=j} p_n = 1$$

and we can see now, that (2.2) is just that special case of (2.4) where all outcomes are equally probable and we therefore immediately can set p = 1 without special concideration to differing probabilities of single outcomes.

A couple of practical examples:

If we substitute in (2.4) with the relevant values for an unbiased coin we get that the information gained after several throws is

$$I(coin) = -\sum_1^2 0.5 * \log(0.5) \text{ bit}$$
$$= 1 \text{ bit}$$

and likewise, the substitution in (2.4) with the values for an unbiased dice would give

$$I(dice) = -\sum_1^6 0.167 * \log(0.167) \text{ bit}$$
$$= 2.6 \text{ bit}$$

which again is the information gained after experiment "dice" is fully exhausted.

REFLECTIONS ON INFORMATION THEORY.

The relevance of information theory to the research presented in this thesis arises from the idea that a natural text string in some respects can be compared to a successions of dice throwings. At every encounter with a word in the string our linguistic device selects one meaning of a word from a number of possible meanings.

As explained much more thoroughly in chapter 8, most of the words we use have a number of uses, each with smaller or greater variation in meaning. The particular meaning of a word in a text string depends on the context in which the word is embedded. When one particular use of a word, out of a number of possible uses, has been established, we have established the meaning of the word in its particular context. From the introduction to information theory above, we know that when we, out of a number of possible outcomes, establish one single outcome, there is a transfer of information. The greater the number of possible outcomes, the greater is the transfer of information, once the single outcome has been established. Roughly speaking, the number of possible outcomes is given by the number of possible uses of a word. When we have established which use of the word makes most sense in the given context, we have the result of the "experiment" - the meaning of the word in this particular comtext - and the information transfer has taken place as a result. This is obviously a very crude attempt to apply the principles of Information Theory to language perception, but I think that the similarities shall become more striking in later chapters.

More generally, one of the problems arising from trying to explain a statistical model like information theory, let alone attempting to apply it to human reasoning, is that as soon as we move into human perception and language, we are dealing with many-valued, often concealed quantities, all highly non-mathematical ground.

Take for example the word 'dice' used in the beginning of this chapter in a describtion of a simplistic experiment. Ideally, to start the experiment 'throw of a dice' without any information at all, we should not have used the word dice since in the concept of 'dice' is already the knowledge of six faces numbered consequtively with the numbers one to six; three important features of information. We should have used a word like 'polyhedron' instead of 'dice'. However, in most of real-life experiments we do not start out with zero information. We start out with both knowledge about initial conditions and expectations about outcome.

This leads us to a very important point. Contrary to the impression one gets from most introductions to information theory, information is NOT hanging around in big balloons waiting to be pierced by inquisitory minds. To gain information about a system you have to put as much IN to the system as you want to get out - in theory. In practice however, you will always have to put MORE into the system than you want out because of inevitable losses.

Let us go back to the dice. Because of the information inherent in our idea of what a dice is, we have, already before we start tossing the dice, an expectation as to how the output will be structured and we use this structure to retrieve the rest of the information - which of the six number of eyes came up. This is very typical of the way we retrieve information in real life. We use structures - or information - from some systems to retrieve information from other systems, always moving forwards and backwards between randomness and structure, sometimes increasing randomness in one system to retrieve information from another system. Because of this duality, this balance between input and output, the equations for the measure of information arrived at earlier in this paper are not only measures of the information we can get out of a system, they are as well measures of the minimum amount of information needed to put into a system to "map" or understand this system.

To illustrate this point let us return to the tossing of a coin. As you remember, we calculated the information gained from this 'experiment' (several tosses of the coin) as being 1 bit, but this is at the same time the (minimum) information needed to "map" the system "coin".

The fact, that we by inputting only one bit into a system can map this system is used in the very efficient way of information retrieval called binary search. This is basically done by dividing the masses of information, that have to be searched, into two subgroups and establishing which of the two contains the wanted information. When this subgroup has been found, this group is itself divided into two groups and so on by dichotomy until in the end one of the two groups is the wanted element of information.

It is often difficult, if not impossible, to assess the bi-directional flow of entropy and information in a system or between a system and any number of subsystems. This is because the degree of structure in one system depends on which other system we compare it to, and although we are able to give an exact measure of the entropy of one system, it still depends on the entropy of another system whether the flow of information would go one way or another. It is entirely like two jars of warm water. If I hold them in my hands, they may both seem warm to me, that is, the entropy is decreasing in both jars and increasing in my hands, but interconnected by a hose and otherwise isolated from the environment the entropy will flow from the relatively warmer jar to the other jar until the entropy has reached an equilibrium in the two jars. This demonstrates how degree of structure and flow of information or entropy depend entirely upon which system we decide to use as our frame of reference.

It is our fate as humans that we are the creatures most able to direct and increase the flow of entropy and information at will. We are like little creatures hungering for structure. From the first genetically inherited structures make it possible for us to structure an otherwise random flow of information, it is a tragic and incomprehensible fact that we move, during our life, through ever increasing structures always using formerly acquired structures to create new more complex ones until ultimately our structures - you and I - dissolve.

From the second law of thermodynamics we know that the overall amount of entropy of all the systems involved in an exchange of entropy or information can never decrease. It can remain constant or increase. Because of this fact, all our harnessing of the entropy around us, all our wrenching structures from randomness is in some respects futile. We are merely redistributing structures. We may have been creating structures in one system where there were randomness before, but this has only been possible at the expence of structures in one or more other system/s.

I shall not dwell with the extent of this chinese box of subsystems-systems-supersystems, only state that the intrinsic losses in all heat transfer from any system to its surrounding systems always entails that the total amount of entropy - all systems taken into consideration - will increase, and consequently the total amount of entropy/heat/randomness is ever increasing and leading us slowly, but surely, to the grand structureless finale. Whether your temperament considers our chinese box monitored or not, the fact is that its surface is getting hotter all the time.

2. INFORMATION THEORY IN LINGUISTICS.

There is some scope for applying information theory to linguistics. Shannon was the first one to point this out. It is a common feature of all attempts so far though, that they reveal very little from a linguistic point of view. They can however be quite entertaining.

To understand the limitations of information theory from the linguistic point of view we will have to dwell for a while at what can be termed different depths of language.

The building blocks of our language are the words which in turn are made up of sounds or graphic representations of these like the alphabet. This is termed the surface sructure of the language. It is on the surface that a language shows its greatest variation, and it is on the surface that we find the greatest differences between languages of different speech communities.

Exactly how you consider words to transfer the kind of mental action which we term "meaning" depends on which school of thought you chose to venture. The development of linguistics over the past couple of generations - or in some aspects over the past century - has not been unlike a childs own development of language. Initially total pre-occupation with single words, then a spell of absorbtion into syntactics and grammar later followed by the exploration of the meaning of "meaning". At present, structural linguistics is exploring the very generating of meaning-structures.

It is obvious, that words in some sense evoke meaning. We can not say however, that the words themselves mean anything. Words are only lumpy conglomerations on a background of randomness which we may be able to structure if we have the proper frame of reference as the case was with the TV-screen. We can put together words to form utterances and sentences, but the words, utterances or sentences are only what they are because we recognize them as such. Although the problem, of how our communication elements evoke meaning, is itself a fascinating one, we must not get lost in the mist of the intellectually no man's land of epistomology. It is sufficient for our present purpose to point out, that there are at least four disciplines in our study of language which we need to consider: two - phonology and morphology - dealing with the surface structures of language and another two - syntax and semantics dealing with the "deeper" levels like the grammatical analysis or synthesis of sentences and, for semantics, dealing with meaning and connotation.

There is some confusion as to the terminology within the linguistic disciplines mentioned above. We have stated four "levels": phonology, morphology, syntax and semantics. Some linguists do not see morphology as a special subject, but consider the matter dealt with partly by phonology, partly by syntax. Another course for confusion is the use of the term "grammar". Some linguists tend to see the two middle levels, morphology and syntax, as the one termed "grammar" and leave phonology and semantics out. Others put the three upper levels, phonology, morphology and syntax, under the one heading "grammar", but leave semantics out. Most recently "grammar" has been taken to mean semantics as well. This is mainly due to Chomsky considering his transformational grammar dealing with semantics as well as syntax.

The reason that we need at least two dicliplines to cover the research into the surface level of language is of course, that we perceive language in at least two different ways: through the eyes and through the ears. We say, that we perceive language through a visual and through an auditory channel.

PHONOLOGY is the discipline which deals with the reception of the sounds through the auditory channel; the single sounds which we join together and perceive as words. These sounds, which are the smallest units we are able to distinguish from each other, are called phonemes and most languages operate with 30 - 40 of these. Examples of these are the different sound qualities which consonants and wovels acquire in their different combinations. Although we are able to distinguish these different phonemes, this is not due to the acoustic stream of sounds actually consisting of discrete units. It is easy to show electronically that on the acoustic signal level there exist no such discrete units or segments and that at any given instant of time, information about several phonemes coexists in the sound wave. This means, that on the acoustic level the signal is not segmented. However, since we perceive it as being segmented, somewhere along the auditory channel our perceptual system must impose segmentation upon the signal. Recent research (1) indicates that this ability is not acquired after birth, but that we are indeed born with the ability to segment the incomming signal continuity.

The MORPHOLOGY -the classification and conjugation of the words - is the more readily accessible entrance into the human language behaviour and the more objective. There is little room for discussion in matters concerning the spelling or conjugation of words and a wide scope for attempts to create formal systems which simulate the grammatical constructions of our language function on the surface level.

In morphology we classify words primarily according to their function, but as the function of a word is intrinsically connected to its meaning, the meaning too comes into the classification. The smallest measuring unit in morhology is the "morphem" which is the smallest carrier of meaning. If we take a word like "dogs" we have a word wich is made up of two morphems. The first, "dog" signalling a well known creature and the second,"s" signalling: plural. In European liguistics it has been customary to distinguish between semantic morphems like "dog" and grammatical morphems like "s", but the move is towards the American practice where morphem is used in the wider sense.

Whereas morphology deals with the analysis of single words, SYNTAX is the discipline dealing with the analysis and

1) Lasky et al.(1975).

theoretical synthesis of whole sentences from the basic units, morphemes and sememes. It is in the attempt to find out what constitutes the transformation, from the basic units of the language function to a meaningful sentence in either its phonetical or graphic representation, that the generative grammar has seen its most recent development into the so called transformational grammar, which in spite of being a major step towards a model of the human language function is, as I see it, a descriptive rather than explanatory model in the sense that it details the routes between the different levels of our language function, but not the vehicles of the transformations.

In SEMANTICS we move into a far more difficult and subjective area of language behaviour in as much as we are concerned with the meaning of the words we use and try to classify words according to common areas of meaning e.g. Child, colt and calf are all classified as "offspring" thereby attributing child, colt and calf the same "semem": offspring.

In semantics the issues become very complex because the connotations created in human minds, even for the same word, to a high degree depends on the background and experiences of each human mind concerned. But even so, it is in the varied field of semems that the human mind picks its information. It is by pinpointing thee connotation from a number of possible connotations that the receiving mind extracts the information from a statement.

APPLYING INFORMATION THEORY TO THE SURFACE LEVEL.

Let us imagine that $x_1 x_2 x_3 \ldots . x_n$ is a text string n letters long. For this purpose we will regard space as a letter. Since there are 26 letters in the English alphabet and we add the space we operate with a total of 27 symbols. If these symbols were equally probable we would have from (2.1) that the information contained in this textstring would be

$$\begin{aligned} I &= n*\log(27) \text{ bit} \\ &= n* 4.76 \text{ bit} \\ &\text{or} \\ i &= 4.76 \text{ bit pr letter} \end{aligned}$$

This is of course not the real value since each letter does not occur with the same frequency in the language.

letter	probability	letter	probability
space	0.1859	N	0.0574
A	0.0642	O	0.0632
B	0.0127	P	0.0152
C	0.0218	Q	0.0008
D	0.0317	R	0.0484
E	0.1031	S	0.0514
F	0.0208	T	0.0796
G	0.0152	U	0.0228
H	0.0467	V	0.0083
I	0.0575	W	0.0175
J	0.0008	X	0.0013
K	0.0049	Y	0.0164
L	0.0321	Z	0.0005
M	0.0198		

TABLE 1. The probability of occurence of different letters.

There are several different accounts of the frequencies of the different letters in English litterature, the problem being of course that the results depend on which kind of litterature you choose to base your statistics on. Table 1 gives the different probabilities of letters and space according to Reza (1).

Given the different probabilities from table 1. and the equation (2.4) which we arrived at earlier, we are now able to give a more realistic value for the average information per letter.

Let p_j be the probability of the j'th letter in table 1, (j=1,2,3...,27). According to (2.4) the average information can now be written

$$I = -\sum_{j=1}^{j=27} p_j * \log(p_j) \text{ bit}$$
$$= 4.03 \text{ bit per letter}$$

More refined considerations regarding the structure of English (e.g. how great is the probability that the letter e follows the letters th ~~ p(e|th)) further reduced the information pr letter to 3.1 bit. Other considerations regarding the bindings within the English language allowed Shannon to calculate that

$$I(x_8 | x_1, x_2, x_3, x_4, x_5, x_6, x_7) \sim\sim 2.0 \text{ bit}$$

Involving more than 7 letters in his calculations over the bindings and structures in English, Shannon found, did not decrease the average information per letter significantly and so set the average information per letter = 2 bit. If we compare this value to the theoretically possible of around 4.7 bit per letter arrived at above, we realise, that because of the structures already present in the language we can only transfer about half of the theoretically possible information per letter.

This leads us to another important concept: REDUNDANCY. This is a measure of the degree of certainty in the transfer of the information and was introduced by Shannon in 1948.

The relative redundancy is defined as 1 minus the ratio between the actual information gained and the information it would have been theoretically possible to transfer

$$\text{relative redundancy} = 1 - \frac{\text{actual information}}{\text{maximum information}} \qquad (3.1)$$

According to what we have stated above, the relative redundancy of English is

$$\text{relative redundancy} = 1 - \frac{2 \text{ bit}}{4.7 \text{ bit}} = 57\%$$

Studies of other European languages show, that the relative redundancy in these languages too is 50 - 60%, but like the case is in English - depends on a variety of factors, degree of difficulty of the text being the most obvious one.

1) F.M. Reza(1961).

It is a mistake to judge redundancy on its name. Redundancy is very far from being redundant in language. It is because of the redundancy that we are able to understand a message even when some of the information is missing. If you have tried to wrench meaning from the loudspeakers on a railway platform, you wil know what I am talking about. Not to mention some peoples handwriting which depends entirely on the redundancy in language for decoding of the message. But apart from these extremes, we rely - to a lesser degree - on redundancy even in everyday conversation to check that we understand what is being communicated to us.

We can see from (3.1) that the relative redundancy and the information are reciprocal. If we try to increase the certainty that the information is transferred correctly, we can only do this on the expense of the information itself. If we try on the other hand to increase the transfer of information to the theoretically possible, we will be left with no redundancy and no chance of knowing whether the received message was correct. A popular way of putting this is: If we get 100% certainty that the information is transferred correctly there will be no information left, and if we want 100% information transferred, we will not be able to understand it!

As I have explained, the redundancy in the language is mainly due to the structures and bindings within the language. It is not the other way round. The bindings or the structures of a language are NOT a result of the redundancy of a language and we can NOT judge the internal structures of a language by assessing the redundancy of the language. I am emphasising this because quite a few attempts have been made in the past to evaluate structural qualities of a text by measuring the redundancy. The futility of this will be evident from the following approximations to English, all constructed by Shannon.

Here is a first order approximation:

AI NGAE ITF NNR ASAEV OIE BAINTHA HYR
OO POER SETRYGAIETRWCO EHDUARU EU C F
T NSREM DIY EESE F O SRIS R UNNASHOR

The letters and space appear with the right frequencies, but are otherwise independent of each other.

Here is second order approximation to English:

URTESHETHING AD E AT FOULE ITHALIORT W
ACT D STE MINTSAN OLINS TWID OULY TE T
HIGHE CO YS TH HR UPAVIDE PAD CTAVED

In this approximation the letters and space appear with the right frequencies AND each letter appear with the right probability to the letter preceding it.

And finally a third order approximation by Shannon:

TANKS CAN OU ANG RECON THATTED OF TO S
HOR OF TO HAVEMEM A I MAND AND BUT
WHISSITABLY THERVEREER EIGHTS TAKILLIS TA

In this approximation the conditions are like above, but each letter appears with the right probability to the TWO letters preceding it.

Approximations of still higher orders can be constructed, but the complexity of the mathematics involved soon outweighs the usefullness of the exercise. I think you will agree, that it is a feature of the third order approximation that it is possible to recognize it as an attempt to reconstruct English. I will shortly show you some third order approximations of French and German and you will see, that these too are recognizable as being approximations of a particular language. It is obvious though, that nothing like real language can be constructed in this way.

Apart from the entertainment of getting closer and closer to something that looks like language, there is the important point I mentioned before, that we can not judge the structures of the language by measuring the redundancy. Just try and measure the redundancy of the textsamples above! Your ability of predicting a letter - let alone a "word" - will not exceed chance, and yet - the text is highly structured.

Here are some third order approximations of German and French:

BET FREINER SOMMEIT SINACH GAN TURHATT
ER AUM WIE BEST ALLIENDER TAUSSICHELLE
LAUFURCHT ER BLEINDESEIT UBER KONN

JOU MOUPLAS DE MONNERNAISSAINS DEME U
S VREH BRE TU DE TOUCHEUR DIMMERE LL
ES MAR ELAME RE A VER IL DOUVENTS SO

I think you will agree, that there is little doubt which is which!

Although I do not want to enlarge further on the attempts to synthesize language, I have to mention that attempts similar in nature to the above approximations have been made on a WORD level. Words have been labelled according to their grammatical function (e.g. adverb, noun) and possible order in a sentence. The game in this case consists of letting a computer program pick members of different word categories and try to construct a sentence. Needless to say the value of this has so far not exceeded the entertainment value.

Parallel to the attempts to synthesize language on a morphological level has of course gone the attempts to analyse it. The first and most obvious have been within the "diachronic"(1) field of research (diachronic = through time): The history of language, the origin of words, the change of words over generations etc. This field of research goes back literally hundreds of years (e.g. Plato's Kratylos) and is still a very important part of modern language science.

The area which we shall deal with is termed the "synchronic" field of research (synchronic = same time) and is as the name implies the area where those elements of language behaviour,

1) The terms "syncronic" and "diacronic" are both due to one of the founders of modern structurel linguistic, Ferdinand de Saussure.

which are more or less independent of time, are the object of the research. Most of the present language science lies within this field.

REFLECTIONS ON LANGUAGE SCIENCE VS. LANGUAGE BEHAVIOUR

Before we venture into the realms of language science, it is important that we do not loose the perspective. When we talk about a text, analyse a piece of literature or enjoy a poem, we tend to regard it as if we are dealing with the language "substance" itself, to such an extent, that while I am making this very statement, I am painfully aware, that you probably do not understand what I am trying to put over to you. What I mean is, that while we enjoy one of the above activities we do not consider ourselves in any way attending a kind of shadow performance. We do not even wonder whether we are dealing with the "real" thing! I will try and make myself a little clearer.

We take reading and writing for granted. Although we have to learn to read and write and although we take it for equally granted that some unfortunate people will remain illiterate, we still consider literacy the necessary path to an inter-human language universe.

To keep your perspective, I must remind you, that the space of time in wich humans have tried to communicate in writing is but a minute fraction of hundreds of thousands of years saturated with spoken human language. There is nothing in our present knowledge about language which indicates, that the quality of a language, its beauty or its ability to express the human condition is in any way depending on it having a graphic representation. We know many societies which do not communicate in writing, but we do not know of any primitive human languages.

A man mumbles a word; scratches a little with his knife in a stick and sends the stick with his messenger miles away to another man who looks at it and says exactly the same word without fail. This is magic. But it is a magic that we can not see anymore. This is OUR problem. A problem of literacy. We are so used to reading and writing, that we do not pay it a thought, that reading and writing are only symbolic representations for the genuine language behaviour, and whereas language behaviour is an intrinsic part of human behaviour, literacy is not.

Quite a portion of research in linguistics still seems to be based on the assumption that language behaviour and written language is one and the same, or indeed, that humans did not really have a language till they developed writing.

If we look at the morphological level again, it is obvious, that meaning is extracted not only from the words used, but - among many other things - from the strict succession of these words. A blind Venetian is not the same as a Venetian blind. There is no need to give further evidence of how a change in the succession of words can change the meaning of a sentence, and indeed the meaning of the words themselves - the connotations. And yet, under the assumption that words are words whatever way you look at them, an obsession with word statistics grew up in the thirties. An obsession with the number of different words the individual could produce, and a lot of work went into counting words in the litterature and labelling authors - the great and the not so great - according to their vocabulary.

The rapid changes of the social structures in the thirties created a real or an imagined need to isolate the sheep from the goats and so the age of the word counting began. A tedious task indeed as it all had to be done "by hand" until the development of the electronic computer had reached a stage in the fifties, where it was almost crying out for the kind of crude sorting and counting involved in measuring vocabulary and so the whole thing took off in an unchallenged pandemonium. Words and computers are powerful magic indeed. More powerful than just words.

To concentrate on single words, rather than sentences, for whatever reason, was, I think, the greatest pitfall of linguistics so far. The importance of dealing with the continuum of speech, rather than the single units, whether it be in its phonological or its graphic representation can not be emphasized enough. But the obsession with wordcounting is still with us. Not only does it thrive well in the so called "type token ratio"(1), but the concept of a vocabulary still occupy peoples mind as if it was something real, something aggreed upon in linguistics. The concept of a vocabulary - whether internal in a human brain - or external in a text, is a fallacy. The concept of a vocabulary is intrinsically linked to words detached from their context. But words detached from their context are no longer part of a language behaviour. They are just lumpy conglomerations on a background of randomness.

I shall in a later chapter show how little the concept of vocabulary has to do with language quality. This has indeed been pointed out several times in the past, most strikingly by the American linguist Labov in his anlysis of the language behaviour of different social strata in New York (2). It still remains to be picked up by the media though, who in this respect are devant-garde beyond belief, probably pre-occupied from being in the trade of wordselling as they are, with the attempts of conforming to the other gigantic fallacy: the language norm.

We must not forget, that the reality of being a human is not very different from individual to individual, nor has it changed very much through the hundreds of thousands of years we have detached ourselves as the ultimate in refined language behaviour. The difference between being a Shakespeare and not being able to spell properly is microscopic compared to the dramatic difference between human language behaviour and the spontaneous language behaviour of other primates.

Although the commonly held view untill very recently: "The ability to acquire and use human language does not depend on being intel-

1) Type token ratio: The ratio between the number of different words and the total number of words in a textstring. A method still widely used, especially in USA, to judge the vocabulary and difficulty of a text. The method becomes particularly farcical, when the text samples are of different length, since the number of different words in a textstring can be shown to fall exponentially with the length of the textstring.

2) Labov(1966),(1970).

ligent or having a large brain. It depends on being human.."(1) still holds regarding spontaneous language behaviour, research into the language acquisition of chimpanzees and gorillas suggests that the difference between the language behaviour of humans and that of other primates is one of degree rather than of nature.

1)Lenneberg(1967).

3. LINGUISTIC MODELS RELEVANT TO THIS COURSE.

We have seen, that information theory evaluates information according to probability of occurrence, e.g. the information carried by a sentence depends alone on how rare this sentence is within a chosen sample of sentences. As stated in chapter 1, information theory does not deal with the problems of meaning or the human value of information.

In this chapter I shall begin by introducing you to the first attempts to simulate human language by means of formal logic. The approach comprised some simplistic aspects of grammar and meaning. The model was developed by Y.Bar-Hillel and Rudolf Carnap in the early fifties - a few years after Shannon had published his information theory and bears the hallmark of that last great period of confidence: Logical Positivism.

The next decade, the late fifties and the beginning of the sixties, saw the move within linguistics away from the "clear-and-cut" rather unrealistic optimism of the above theories and towards a more embracing common-sense approach searching for structures which were reaching INTO the language rather than moulding the surface of it. The clearest example of one such theory was the IMMEDIATE CONSTITUENTS analysis.

Again the demands for computability influenced the trend in linguistics. The logistic models of the positivistic era on one hand and the downward structuring models of the following decade on the other were eventually united in one form of generative grammar, TRANSFORMATIONAL GRAMMAR which has been most influenced by the American linguist Noam Chomsky. I shall later in this chapter introduce you to both "immediate constituents analysis" and "transformational grammar", but before I enlarge upon any of the recent trends within the linguistic field, I would like to correct a misapprehension about generative grammar.

Generative grammar is not, as the sudden attention paid to it in recent years might suggest, a new theory. Any grammar consisting of a set of rules which makes it possible to describe the structure of an infinitely large number of sentences may be called "generative". Traditional grammar was generative in that sense. What is a recent development within generative grammar though, is the attempt to formalize explicitly the rules of the grammar, in an attempt to make it possible to specify which rules and which basic elements (phonemes, morphemes and sememes) have gone into the generating of any correct meaningful sentence. This move within he generative grammar was mainly due to Y.Bar-Hillel and Rudolf Carnap's attempts to formalize human language (1).

1) Y.Bar-Hillel and R.Carnap (1950). R.Carnap (1953).

BAR-HILLEL AND RUDOLF CARNAP's MODEL.

The work of Bar-Hillel and Rudolf Carnap is based on the axioms and signs of the propositional logic. Rudolf Carnap was himself a member of the so called "Vienna Circle", known for its influence - "Logical Positivism" - during the twenties and thirties on science and a remarkable exponent for that confidence in empirical scientific methodology which has now become the "accepted" scientific method. As scientific methodology is intrinsically linked to the problems concerning the capacity of human language for describing scientific observations, the Vienna circle put great emphasis on the study of language and the possibility of expressing factual knowledge in a logistic-symbolic language.

In their work Bar-Hillel and Carnap restrict their considerations to sentences of a very simple grammatical construction. They exclude considerations of whether the receiver interprets the sentence in the way it was intended, but give room for some aspects of "meaning".

The model is based on the methods and symbolism of symbolic logic. Both receiver and transmitter are visualised as in possession of all the possible logical deductions from the structure of the given language system, so that a sentence like "17 * 19 = 323" is redundant, because this would already be implied by the known structures. Only sentences, whose content is not implied by the structure of the language, carry information.

The language consists of a number "n" of nouns (called "individuals" in their papers) and a number "p" of adjectives (called "predicates" in the papers) and the single verb "has" or "is". So, if "a" is a noun (or individual) and "P" is an adjective (or predicate), then (Pa) is read as "a has the property P" or, more simply: "a is P". To build up longer sentences, the language has the following connectives well known to anybody with some knowledge of propositional logic:

~ not: negation; (~Pa) means "a is not P".
v or: disjunction; (Pa v Qb) means "a is P or b is Q".
^ and: conjunction; (Pa ^ Qb) means "a is P and b is Q".
-> if..then implication; (P -> Q) means "if P then Q".
=> if and only if: equivalence; (P=>Q) means"Q if, and only if P"

The choice of the p adjectives is restricted in as much as they are not to overlap in meaning in any way, nor may any adjective imply the use or non-use of any other adjective. The vocabulary can now be extended by adding to it the opposite - or negation - of each of the already existing adjectives P either by denotion (~P) or by adding a new adjective which is equal to (~P). (1)

There are three classes of sentences in this language:

1) A false sentence (selfcontradictory): (Pa ^ ~Pa) meaning "a is P and a is not P".

1) Obviously the authors assume, that their model, as indeed natural language, are "open" systems (in the logical sense), and so (Pa) does not exclude the use of (~Pa), even though a conjunction of the two naturally produces a false statement.

2) A factual sentence (logically indeterminate): (Pa) meaning "a is P".

3) A true sentence (tautological): (Pa v ~Pa) meaning "a is P or a is not P".

Carnap and Bar-Hillel maintain Shannon's evaluation of information according to probability of occurrence. The way they see this applied to their language model is as follows: Given the number of adjectives and nouns in our "vocabulary", there is a finite number of sentences which could be constructed using these adjectives and nouns. However, some of these sentences would be logically related. If we want to measure the information of a sentence S, we would first have to evaluate how many sentences we could construct using the nouns and adjectives in our vocabulary. Let us say that this number of possible sentences is N. However, a number M of the possible sentences would be logically related to our sentence S. These related sentences would have to be deducted from N. So, the number of sentences not related to S would be N - M. The probability of our sentence occurring from the N - M sentences logically unrelated to our sentence would be a measure of the information contained in this sentence.

I shall enlarge further on this. Let us imagine, that we want to describe the observation of an experiment to a fellow researcher. A number of very basic factual statements could be made and a number of these would be needed to make up the full description of the experiment. Carnap and Bar-Hillel introduce such a kind of description, the STATE DESCRIPTION denoted by Z. A state description is a sentence consisting of a number of simple (in the papers called "atomic") factual statements made up of the nouns and adjectives or their negation (but not both) relevant to the description. If there are p adjectives and n nouns relevant to the description of our observation, then the number of possible combinations of the p adjectives and n nouns in the state description Z is p*n, and since each combination of a noun and an adjective can occur in two ways - either with the adjective itself or with its negation - there are altogether 2 in power p*n possible atomic statements in the state description Z.

Let us say that we have a vocabulary consisting of 3 nouns: a,b,c and 3 adjectives: P,Q,R. These can be combined in 3*3 different ways, but because we are allowed to use the negation of each adjective as well as the adjective itself (but not at the same time) in our statements, the number of possible atomic statements increase to 2 in power (3*3) = 512. Let us further imagine, that we want to make a state description consistiong of two atomic statements i.e. Z=(Pa^Qb). By the same combinatoric rules we arrive at a possible 512 in power 2 (well over 260.000) state descriptions consisting of just 6 variables in their different combinations. Now, some of these state descriptions will be inherently true (tautological statements) and some will be logically related to Z. Since we want to measure the probability of Z with regard to the number of FACTUAL sentences NOT related to it, we must subtract a): the number of tautologically true statements and b): the number of state descriptions related to Z from the total number of state descriptions. Let us say, that after this we are left with 8192 factual state descriptions unrelated to Z. The model then follows information theory and states, that the numerical information value of Z=(Pa^Qb) is

$$I(Z) = \log(8192) = 13 \text{ bit}$$

Already at this point Carnap and Bar-Hillel's language model has become so complex, that it is impossible to assign any realistic probability of occurrence to any, but the most basic state descriptions. This does not matter for our purpose, since what is relevant to us - and the genuine development - is that at this point Carnap and Bar-Hillel introduce "set theory" to accommodate some rudimentary form of meaning. Let us imagine, for instance, that we discuss temperatures and designate those above 20 centigrades by "high" and those below 20 centigrades by "low". Now, a number of atomic statements can be made associating the noun "temperature" with the adjective "high" or its opposite "low", and it is obvious, that the probability of an atomic statement like "temperature is high" occurring in the Sahara Desert is higher than the same statement occurring on the North Pole and the numerical information value of the statement in the Sahara Desert therefore less than the value of the same statement on the North Pole. The model now states, that the RANGE of such an atomic statement is the SET of those state descriptions in which the statement holds, or to put it another way: whereas the atomic statement can occur meaningfully in some state descriptions and not meaningfully in other state descriptions, the number of state descriptions, for which "temperature is high" holds, is bigger in the Sahara Desert than on the North Pole, thereby giving "temperature is high" a greater range of meaningful state descriptions in the desert than on the pole. From this it follows, that whereas the numerical value of the information has decreased, the set of meaningful state descriptions has increased in size. Although this is an interesting parallel to the redundancy function mentioned in chapter 2, the important contribution of this model is without doubt the introduction of set theory into linguistics. A part of a sentence or a statement is here seen as a SET of meaningful functions or applications, and it was along this path that subsequent structural theories in linguistics ventured.

CONSTITUENT STRUCTURE.

The complexity of deterministic models like the one by Carnap and Bar-Hillel forced the logical positivists to rethink the function of language. Wittgenstein, one of the most influential of the positivists, regarded in his first major work "Tractatus Logico-Philosophicus" (1922) language as a picture of facts. In his later work "Philosophishe Untersuchungen" published after his death in 1951 he had completely given up this idea. Rudolf Carnap too expressed this new attitude in his "Meaning and necessity" (1956) where he, as the title implies, gave further considerations to the problems of "meaning". In this work, which is based on the ideas and the formal logic from his and Bar-Hillel's earlier papers (see page 20), he formally introduced the term "meaning postulate". The meaning postulates or semantic rules, were a further development of the application of propositional logic to the problems of semantics and became part of the inventory of generative grammar right up to the present. A couple of examples will illustrate meaning postulates:

1) boy -> male ^ ~adult
2) girl -> female ^ ~adult

3) human -> man v boy v woman v girl
4) adult -> man v woman

Applying the rules explained on page 20, 1) reads "boy implies male and not adult"; 2) reads "girl implies female and not adult"; 3) reads "human implies man or boy or woman or girl"; 4) reads "adult implies man or woman".

We shall return to meaning postulates later, when we deal with generative grammar and semantics. At this point I just want to emphasize the importance of Bar-Hillel and Rudolf Carnap's contribution to those developments which followed in linguistics. It was out of the ashes of Bar-Hillel and Rudolf Carnap's attempt to apply information theory to language that modern structuralistic linguistics rose as the bird Phoenix. Their model is now largely forgotten, partly because it was written in a language, formal logic, which then (this was 7 years before Chomsky's "Syntactic Structures") was still strange to most linguists, and partly because the common interest for liguistics did not "take off" for another ten years when a reaction against the phenomenological and psychoanalytical linguistic theories of Western Europe (Predominantly those of French linguists like Merlau-Ponty and Paul Riceur) demanded stringency in thought and expression and so made the linguistic theories of English and American positivistic descent (Predominantly those of Chomsky) with their mathematical notation seem more palatable.

Two clear lines of development have lead to present structuralistic theories like that of Richard Montague. One is a naturalistic - as opposed to positivistic - one which began with the theories developed by Ferdinand de Saussure and Louis Hjelmslev. The other line of development - the positivistic - began with the theories of the Vienna Circle, was taken up by Wittgenstein and Russell, was further developed by Carnap and Bar-Hillel with their information theoretical approach and did eventually with Chomsky's version of generative grammar become a challenging conglomerate of naturalistic and positivistic ideas. It is worth noting, that some of Chomsky's earliest ideas were published in "Transactions on Information Theory" (1) and both here and in "Aspects of the Theory of Syntax" he makes several references to the works of Bar-Hillel.

Stuart Hampshire wrote in his influential "Thought and Action" (1960): "After the early experiments of Russell and Wittgenstein, most contemporary philosophers are probably convinced that the idea of 'the facts', which are already individuated in reality independently of our forms of reference to them, is an illusion that cannot be given a sense. We divide and redivide reality into its segments and subsegments along the lines of our practical interests, which are reflected in our conventions of reference" (p.216).

This "division and redivision into segments and subsegments" was a reference to the CONSTITUENT STRUCTURE model and the influence which Carnap's meaning postulates had on it. The theory behind the constituent structure model is, that the words in a sentence are not (always) just individual parts linearly adding up to a whole. Some of the words in the sentence are more closely related

1)Chomsky (1956).

than others and form blocks or segments within the sentence. A sentence is then seen as made up of a number of segments each consisting of one or more words. But as well as being part of segments within the sentence, the words are themselves part of subsegments implied by the structure and the meaning of the sentence. This language model was a major step forward from the initial rather crude logistic-deterministic models of the positivist school and an attempt to look at the ways the mind might synthesise a sentence. It was an attempt too, to follow, backwards, the path which the mind presumably had used in its synthesis of the sentence. To explain this I shall give you an example of the way an analysis of a sentence would be carried out according to this model.

If we take a simple sentence like "The old man eats the green apple", we recognise intuitively that "The old man" constitutes a group of words wich are somehow bound together. The same can be said about the last three words "the green apple". We could symbolize this relationship by putting brackets around the groups like this: (The old man) eats (the green apple). There is room for some discussion as to where "eats" belongs. Does it go with "The old man" since this segment is the agent or does it belong to "the green apple" since this is the goal of the action (the patient)? The most common way of analysing this sentence according to constituent structure would be like this:

```
  The         old       man    eats    the         green      apple
determiner  adjective  noun         determiner  adjective  noun
                                                    NOUN PHRASE
                               verb
      NOUN PHRASE                          VERB PHRASE
                        SENTENCE
```

We notice, that the verb is considered more closely related to the patient than to the agent, but this is by no means the only way the analysis could have been carried out. Some linguists would divide the sentence into three segments rather than two and so leave the verb on a par with the two noun phrases. However, whether we consider the binary or the ternary division as the one which most closely mirror the syntactic function of our linguistic device is not a matter of great importance. May be the mechanism which this linguistic device uses sometimes works binary, sometimes ternary, sometimes linearly. Or something entirely different. We are in search of patterns, not of another deterministic model, but as the case often is in the speculative areas of science - and linguistics is no exception - we tend to develop mental tunnel vision. The research presented later in this paper - once we get through the preliminary fencings - makes it plausible, that the faculty, which generates grammatically correct sentences, does not make use of any single, through life, static mechanism, but develops during the acqusition of language from a function, which initially is linear or serial, later, whith increasing acqisition of grammar, becomes predominantly binary and eventually, when the "grammar function" is fully developed, can combine anything up to 20 - 30 units in parallel.

The IMMEDIATE CONSTITUENTS (IC) analysis is a strictly binary way of analysing a sentence. Let us choose the same sentence as above and look at how IC analysis would proceed. At each step of the procedure we divide the whole - or part of the whole - into TWO segments, each of which is again divided into two subsegments and so on, until each word has been isolated. Before the analysis our sentence is envisaged, like before, as having a natural weak binding after "man", and the first step of the analysis would therefore be a division of the sentence into its two IMMEDIATE CONSTITUENTS: "The old man" and "eats the green apple". These constituents would again be divided into each their two immediate constituents and so on like the diagram shows in figure 1.

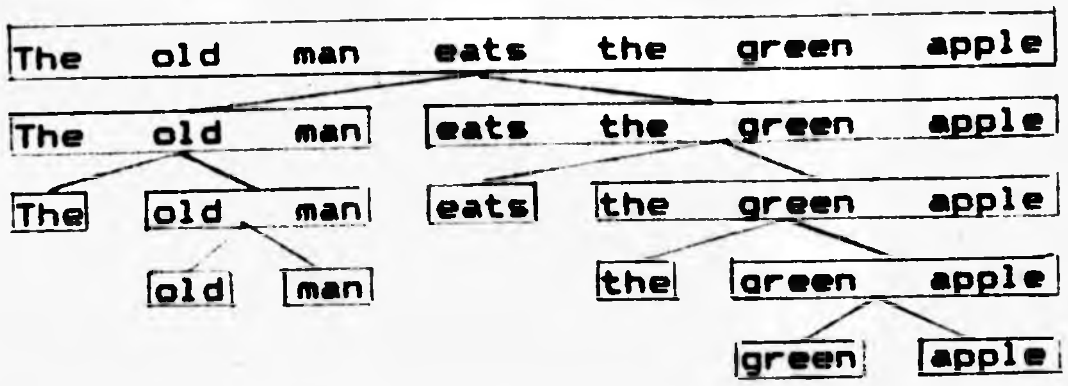

Figure 1. Diagram of binary IC analysis.

This is the analysis by immediate constituents. But we can go the opposite way. Instead of dissection of the sentence into its smallest units, we can by TRANSFORMATION or substitution show, how it is possible to reduce a sentence to a few comprehensive concepts in backward moves. To demonstrate this we will take a rather more complex sentence like

The old man who lives here has gone to his son's house (4.1)

By substituting "old man" with "man" and "lives here" with "survives", "has gone" with "went", " his son's house" with "the house", (4.1) has been reduced to "The man who survives went to the house". By taking the substitution further we get: "who survives" -> "surviving", "the house" -> "town", reducing (4.1) to "The man surviving went to town". Next step: "man surviving" -> "survivor" and "to town" -> "there". The final step, "The "survivor" -> "he" and "went there" -> "went" has thus reduced (4.1) to "he went", which is said to be the BASIC PATTERN of (4.1).

Figure 2 is a diagram of this transformation, and we recognise the use of meaning postulates; each level is a meaning postulate/substitute/transformation of the former level. Admittedly, the direction of the implications is ambiguous. "he" -> "survivor" and "survivor" -> "he" is equally feasable depending on how one wants to define what constitutes a transformation, but the idea is, that each word is substituted with a word which in its concept contains the first word: Remember how Carnap's meaning postulates above had it that "boy -> male ^ ~adult" meaning "boy -> male and not adult". The set of qualities constituting "man" could be: human ^ ~female ^ young v old, meaning human and not female and young or old. In this way "man" can be said to contain the special case of "old man" in (4.1) and thus be regarded as a "higher" concept than "old man". The same goes for "house" in (4.1) versus the substitution "town", since "house" (albeit with some optimism) can be regarded as a special case of "town" (assuming that the house is situated in a town).

```
The old man who lives here has gone to his son's house
The     man     who  survives          went    to    the  house
The     man       surviving            went    to        town
The        survivor                    went           there
            He                                went
```

Figure 2. Transformation of a sentence.

It is important to understand, that whereas the analysis depicted in figure 1 is an analysis of the SYNTAX of a sentence, the diagram in figure 2 is based on the SEMANTICAL aspect. These two aspects - the syntactical and the semantical - co-existing in IC grammar were eventually combined and further developed in the so called TRANSFORMATIONAL GRAMMAR, which we are going to have a closer look at in the following.

TRANSFORMATIONAL GRAMMAR.

Transformational grammar and the name of the American linguist Noam Chomsky have almost become synonymous, but without refuting the impact which Noam Chomsky has had on linguistics in general and on transformational grammar in particular, I would like to make it clear, that there are a number of grammars, which all merit the prefix "transformational" in the sense that they envisage the human language function as a device, which, by imposing transformations on several levels, is able to transform our speech-intention into the actual phonological output. The difference between the various transformational grammars is mainly one of nomenclature, clarity and deterministic approach. What I refer to by tying together "clarity" and "deterministic approach" almost synonymously in this last statement is the well known phenomenon in science that a theory, which is well developed in the sense that its theoremes are put in very clear terms, not only is an easy target for general critisism, but often also suffers the fate of being labeled "deterministic", because its clarity leaves little room for ambiguity. I think it is important to keep this in mind when we in the following deal with one particular model of the transformational grammars.

The greatest influence on modern linguistic theory has undoubtedly been the American linguist Noam Chomsky, whose theories have aroused a common interest not normally shared by scientific thinking of any kind. The popularity of Chomsky's theory in wider circles is without doubt due to the fact, that a superficial interpretation of its deep structure <-> surface structure distinction in some ways echoes the isolation and lack of understanding which we - the captives of technical societies - seem likely to experience. We shall later see however, that Chomsky's concept of "deep structure" is rather less emotional than many of his followers would like to believe.

There are two parallel lines of thought, which I would like to pursue in this present exploration of Noam Chomsky's work. The first one is Chomsky's emphasis on the syntactical aspect of our language function. The second is his emphasis on the semantical substance of our speech intention and the uniqueness which this substance attributes to most of our linguistic output.

Chomsky's work is an attempt to establish common rules for the formal description of all meaningful sentences. Although he in this continues the positivistic tradition instituted by the "Vienna Circle" and applied to language by Wittgenstein, Shannon, Carnap and Bar-Hillel, Chomsky differs fundamentally in many aspects, the most important being, that whereas the positivistic linguistic theories evaluated a sentence according to the probability of its occurrence, Chomsky sees each utterance or sentence as in some sense unique.

Chomsky returns to this idea again and again in his writings. From his "Language and Mind" I quote: "....the normal use of language is innovative, in the sense that much of what we say in the course of normal language is entirely new, not a repetition of anything that we have heard before"(1). This is achieved because language "makes infinite use of finite means" as Chomsky writes in the preface of his very influential "Aspects of the Theory of Syntax" in a quotation from the writings of the 19th Century German philosopher Wilhelm von Humboldt (2).

Earlier in the present paper (p.10) I mentioned, that sentences or utterances are only what they are, because we perceive them as such. It is one of the hallmarks of transformational grammars, that the graphic or phonological representation - the signs or the sounds - of our intention to inform are only the superficial forms which evoke meaning through the receiver's ability to interpret them according to inter-human rules. The forms themselves do not contain any primary information however, they are, according to their specific construction, the triggers of specific trains of processes in the receivers mind; e.g. a statement about the "real world" does not in itself link it to the "real world". It is the number of processes which the statement triggers in our mind, our UNDERSTANDING of the statement, which links it to any particular matter. It is the ability of our "linguistic device" to anticipate, which processes will be triggered in the receivers mind, that puts this "device" and our language behaviour way ahead of that of other primates.

Obviously the present state of linguistic research does not make it possible to describe exactly what happens in this "linguistic device", and Chomsky stresses emphatically that his theory is NOT a perceptual model or a model of speech, a so called theory of performance. Comsky's theory is a theory of competence, the speaker-hearers knowledge of his language.The attempt to describe how a hearer or a speaker proceeds to construct or perceive a sentence is a matter for the theory of language use, the theory of performance. So, for what it is worth, we have to work with suggestions of certain transformations without any real knowledge about what such a transformation represents. Clearly, the linguistic field of research suffers the same uncertainty regarding interpretation as do other fields of research except for the additional problem, that linguistic research has its own method as its research object, or to put it another way, is trying to describe the subject of its research by means of the subject itself. The problems, which this impose, are again not a matter for generative grammar, but belong to epistomology and I shall

1) Chomsky (1968). 2) Chomsky (1965).

not enlarge further on this. Let us just for the sake of the continuation of this introduction assume that we have agreed, that a speakers speech-intention has to go through a number of transformations in his "linguistic device" before it materialises in the form of an utterance, and that the very same utterance has to go through a number of transformations in the listeners "linguistic device" before it evokes the intended meaning in his mind.

With Chomsky the distance between the form and the substance of language becomes wider than ever and the complexity of our language function greater. Although Saussure - the founder of modern structuralism - implied these differences decades before with his distinction between "langue", "langage" and "parole" (1), his view of our linguistic ability or our competence to transform the substance into the superficial form is very much that of a linear translation word for word, or concept for concept, whereas Chomsky sees the transformation from the semantical to the phonological level, as a much more context sensitive process. Chomsky writes: "The distinction I am noting here is related to the langue-parole distinction of Saussure; but it is necessary to reject his concept of langue as merely a systematic inventory of items and to return rather to the Humboldtian conception of underlying competence as a system of generative processes".(2).

The more traditional view of grammar, "a systematic inventory of items" as Chomsky calls it above, sees the morphological level as a direct representation of the semantical level. According to this view, the creation of language on the semantical level takes place by means of morphemes. We think in words according to this view, and linguistic development, the acquisition of language, is the acquisition of the vocabulary and the application of the accepted grammatical rules on the semantical level. From the semantical level to the phonological level it is more or less a question of employing motor skill verbally or graphically.

It caused quite some commotion, when Chomsky in 1957 in his "Syntactic Structures" rejected this view and stated, that the morphological level of language is of an entirely different nature from that of the semantical level. The sentences in a language do not represent or refer to the semantical level in the traditional way. According to Chomsky a sentence (called a phrase marker) is only a surface structure. But this structure represents a code (a deep structure) which is able to evoke meaning. The meaning is not present in the sentence as such, or even in the deep structure. The meaning arises in the listener's mind, because the deep structure, the code, present in the sentence, is inter-human and therefore able to evoke the same semantical processes in the receivers mind, as the processes which encoded the surface structure according to the speech-intention of the speaker. The ability to encode the speech-intention onto the surface structure according to rules accepted within a language community is seen by Chomsky as not only singularly human, but also innate.

In science we often achieve knowledge about normal processes by examining the cases where the normal processes have gone wrong. If we want insight into how our linguistic device works we can do

1) F.de Saussure (1916). 2) N. Chomsky (1965).

the same by deliberately constructing sentences which are on the borderline of the acceptable, and then try to find out what created the anomaly.

Take a perfectly normal sentence like:"Teachers may admire the boy" and substitute "teachers" with "sincerity". We have now got a sentence

sincerity may admire the boy (4.2)

which grammatically is perfectly acceptable, yet it is meaningless. Let us take another example: "Mother opened the door", and substitute "mother" with "sincerity"

sincerity opened the door (4.3)

which again is grammatically correct, but meaningful only on a very abstract level. Problems of this kind led Chomsky to reconsider the labelling of the constituents of a sentence as it had been carried out in traditional grammatical analysis. Chomsky emphasised the importance of analysing a sentence in functional terms i.e. how the constituents functioned in a sentence ("subject", "object", etc.) rather than which category they belonged to (verb, noun, adjective, etc.). To explain this let us look at a sentence like

sincerity may frighten the boy (4.4)

which is another "borderline" sentence, less abstract than (4.3), but still demanding special attention to make it comprehensible. Traditional grammar would analyse it thus:

(4.4) is a sentence (S); "frighten the boy" is a verb phrase (VP) consisting of the verb (V) "frighten" and the noun phrase (NP) "the boy"; "sincerity" is also a NP; the NP "the boy" consists of the determiner (Det) "the", followed by a noun (N); the NP "sincerity" consists of just one N; "the" is, furthermore, an article (Art); "may" is a verbal auxiliary (Aux) and, furthermore, a modal (M).

The "functional" way of analysing (4.4) would according to Chomsky be:

The NP "sincerity" functions as the subject of the sentence (4.4), whereas the VP "frighten the boy" functions as the predicate of this sentence; the NP "the boy" functions as the object of the VP, and the V "frighten" as its main verb; the grammatical relation subject-verb holds of the pair ("sincerity", "frighten"), and the grammatical relation verb-object holds of the pair ("frighten", "the boy"). (1)

There are two ways of describing these differences more clearly. One is by using a stem diagram and the other is by expressing the transformations in "rewrite rules". The traditional analysis of (4.4) expressed in rewrite rules would look like the diagram in figure 3 (next page).

This may look like a way of confusing the issue, rather than clarifying it, but if we make a stem diagram like the one in

1) Chomsky (1965).

figure 4 of the same analysis, and compare the transformations of the rewrite rules in figure three whith those of the stem diagram in figure 4 step by step, it becomes rather straight forward what Chomsky is trying to express:

S -> NP + Aux + VP
VP -> V + NP
NP -> Det + N
NP -> N
Det -> "the"
Aux -> M

Figure 3. Rewrite rules for (4.4)

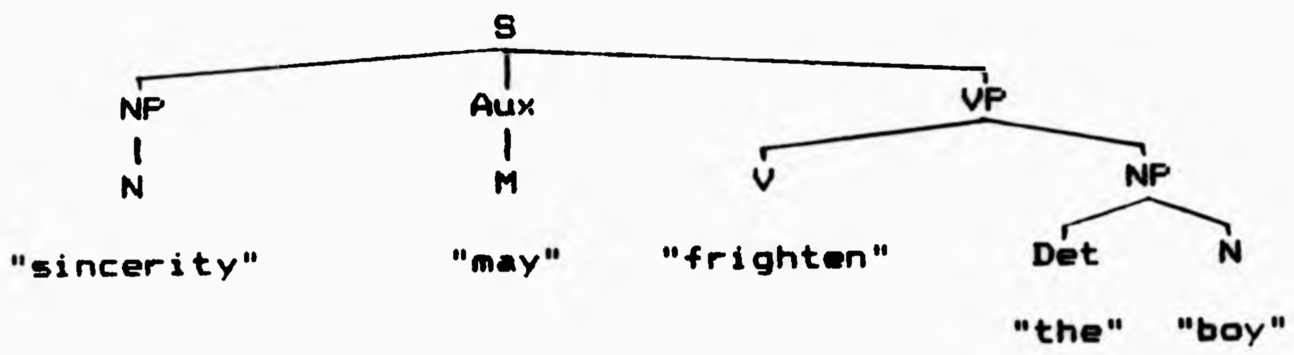

Figure 4. Stem diagram of traditional analysis of (4.4).

We can see, that the first rule of the rewrite rules in figure 3 represents the first branching of the stem diagram in figure 4. The second rewrite rule goes on to describe that the verb phrase (VP) rewrites as a verb (V) and a noun phrase (NP) as described on the stem digram in figure 4, and so on.

If we compare the stem diagram in figure 4 with the one in figure 5, the differences between the traditional and the functional analysis become much clearer: What has happened in the functional analysis is obviously, that we have pushed an extra level of functional description in between the sentence and the traditio- nal categorial description. This is very important since it allows us to analyse the sentence structure according to the semantical-grammatical function of the constituents rather than

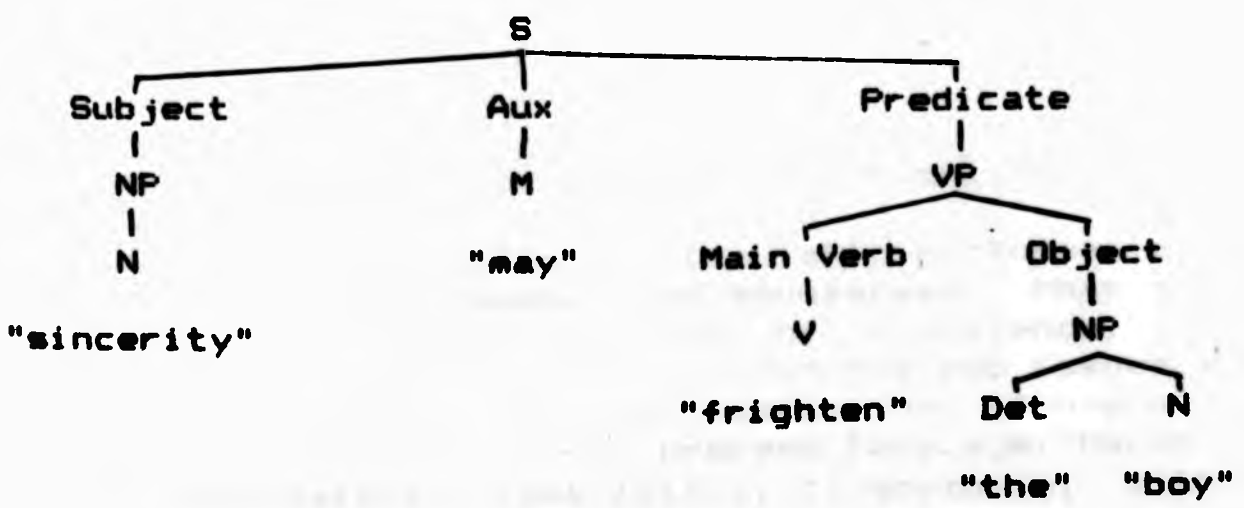

Figure 5. Stem diagram of functional analysis of (4.4).

only the grammatical function. Or, to put it another way, it gives room for the idea that the grammatical construction of a sentence reflects an underlying semantical theme.

In mathematical proof theory we talk about "necessary" and "sufficient" demands, where "necessary" means "necessary as part of a whole in the description of a certain condition", whereas "sufficient" means the total sum of necessary demands which goes in to the description of a certain condition.

Are the rewrite rules in figure 3 sufficient to create a sentence like (4.4)? No, they are not. They may be the NECESSARY rules, but they are not SUFFICIENT, since they could also create deviant sentences like "boy may frighten the sincerity". So, apart from the rules of labelling, whether categorial or functional, we need rules which prevent the creation of meaningless sentences. If we analyse "boy may frighten the sincerity" or the sentence (4.2) above, we realise that the reason for the lack of meaning in these sentences are of a semantic nature: in (4.2) "admire" must take a human agent, "frighten" in the last sentence must take an animate patient. So we must build into our rewrite rules the semantic content of the smaller units (morphemes) as well as the semantic content of the context (called the environment by Chomsky). In this way our transformations would become context sensitive and we would rule out incompatibility between the segments and between the segments and the environment of the segments. The semantic content is according to Chomsky covered by each morpheme having a lexical unit attached to it, governing what is allowed or not allowed in the use of this morpheme. These lexical attributes are, as I see them, part of the positivistic heritage (Carnap's meaning postulates). The problem of accepting the idea of predetermined lexical units attached to each morpheme clashes though with Chomsky's own - and I think appropriate - principle of the uniqueness of most language use, and he falls into the trap - albeit on a "higher" level - of "a systematic inventory of items".

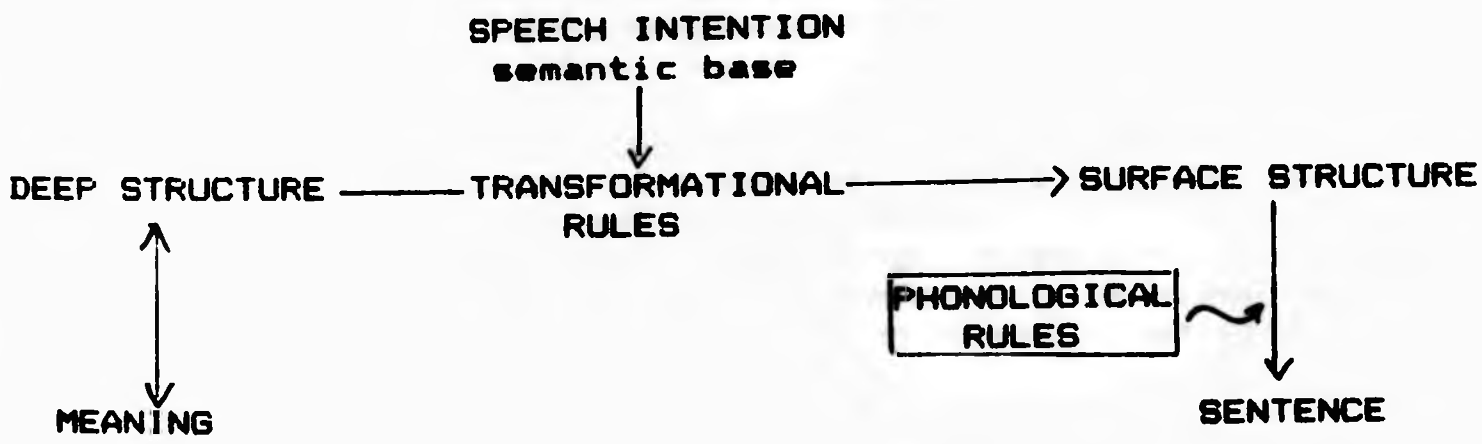

Figure 6. Graphic illustration of Chomsky's model

Figure 6 is an illustration of linguistic performance according to Chomsky. Although Chomsky has emphasised, that his model is not one of performance, but one of competence, it is not possible, not even for Chomsky, to keep the two issues apart. The most fascinating problem remains, namely that of how we in actual fact in psycho-biological terms process language. Recent research has merely emphasized, that little, if anything, is known about this.

REFLECTIONS ON LINGUISTIC MODELS.

We have here touched only briefly on Chomsky's theory and importance to linguistics and those fields of research which are connected to linguistics e.g. psychology. The problems, which Chomsky's transformational grammar (nowadays called TRADITIONAL transformational grammar) ran into, arose, as I have expressed it earlier, as much from its clarity and lack of ambiguity as from its positivistic heritage. When a theory is expressed clearly, it becomes vulnerable. It can be amended. And the amendment can be proved insufficient and it can be re-amended and so on. This is exactly what happened to the traditional transformational grammar. A continuous spiral of development, defeat and amendments made most rewrite rules and transformations so cumbersome that this alone could cast doubt on the validity of the basic principles.

This is a well known phenomenon in science. One of the best examples of this state of affairs is that of astronomy at the time, when the geocentric system was the only system of celestial bodies imaginable: To explain the apparently spiral movements of the planets as seen from the earth, these were envisaged as moving along epicycles. As the accuracy of observation improved, it became clear, that there was a difference between the observed and the predicted data. So it was assumed that the planets were moving along epicycles, which themselves moved along epicycles and so on; with improving accuracy of observation it became necessary to adopt higher and higher orders of epicycles, until eventually as we know, the heliocentric system was accepted, and it became a simple matter to explain the planets apparent movement.

As mentioned before, Chomsky has emphasised that his model is not one of performance, but one of competence. In doing so I think he defeats one of the major achievements of his theories, namely that language should be regarded as functional. But functional in analysis as well as in usage. In syntax as well as in semantics. A valid formal syntactical description of any language - if this is at all possible - would be a fascinating academic conversation piece, BUT it would only account for part of - may be even a minor part of - what language behaviour is about. Language behaviour is inherently social. Language is the vehicle for our emotions and convictions. It is used for social purposes such as posturing, demanding, questioning, blaming, denying and the like and must always be seen in a wider context. Referring to Chomsky's own emphasis on context sensitivity we must widen this context and sensitivity to the full social-pragmatic aspect of language. Chomsky's greatest service to linguistics, as I see it, is his emphasis on the importance of the linguistic environment of the segment of a sentence. The research in linguistics began by focusing on words totally detached from their environment. With Chomsky the words or morphemes were allowed to remain in the micro environment of a sentence, while being analysed. But we must try to take the full environment into account when we analyse the segments. The syntactical analysis, which it is possible to carry out in a micro environment, can easily distract our attention from the fact, that a sentence is normally a severed part of a conceptual "univers", whether that of a continuum of textstrings in a book or the kaleidoscopic patterns of human interaction.

The research during the past decade has indeed followed this trend with the emphasis less on syntax and more on semantics and language in a social context.

In the beginning of the Seventies Richard Montague put forward his general theory of language (R. Montague, 1970) which has become to recent linguistic research, what Chomsky's "Syntactic Structures" was to the linguistic research of the Sixties. In his philosophy Montague puts a much greater emphasis on the semantic aspects of the generative transformational grammar than Chomsky did. while still adhering to the use of formal (propositional) logic as the vehicle for his argumentation. The present trend in the theoretical field is the attempt - on the basis of Montague's language philosophy - to dissolve th difference between the formal truth concept introduced in semantics by the positivist school of thought, and the pragmatic truth concept "meaning" held by many workers in cognitive research like Artificial Intelligence.

MINSKY'S FRAME THEORY.

Some research into artificial intelligence centers around computer simulations of cognitive processes. All theorems must of necessity be expressed explicitly and unambiguously in software or firmware form. This demand for exactness and clarity makes the artificial intelligence approach appear laborious when compared to the more traditional and accommodating approaches to linguistics based on the use of natural or semi-natural language.

Marvin Minsky has over the past three decades approached the description of (human) perception with the conceptual framework of the research into artificial intelligence. One of the valuable concepts in the simulation of perception was that of 'perceptrons': imaginary - but well defined - functions of basic visual perception (Minsky et Papert, 1972). All theorems in this theory are based on computer simulations and representation in software form. On the basis of the possibilities and impossibilities encountered during the formulation of these theoremes in software form he has assembled and defined a considerable armamentorium with which to approach the problems relating to perception in general and to the meaning of 'meaning' in particular. Perceptrons - in their software form - are procedures or algorithms which define a mathematical, probability weighted, strategy for the sorting of, or switching between, incoming (visual) data. The feature of probability weighting is important because it opens up the possibility of changing by 'learning', thus making perceptrons heuristic rather than determined procedures. Minsky and Papert envisage perceptrons working together in parallel in circuits wich would - by way of a decision making or strategy - reduce the number of incoming channels to single channels. Perceptrons may be programmable or preprogrammed. 'Programmable' means that there is some scope for learning; 'preprogrammed' means that the strategy of the perceptron is genetically based with little scope for learning.

Minsky and Papert, in their 1972 work, are mainly concerned with perceptrons in visual channels. An example of a visual perceptron is the functioning of the retina of the cat. It has been shown that in the retina of the cat there are rods which 'fire' only in response to horizontal movements while other rods 'fire' only in response to vertical movements. In Minsky and Papert's terminology such direction specific perceptors are one example of perceptrons. The many rods in the cat's retina constitute as many initial perception channels processing in parallel. A (pre)programmed decision making process picks up the data from similar channels i.e. channels which have processed data from movements in one direction only. Each perceptron selects, from a great number of data appearing in a great number of channels, those data that are most significant (according to the programmed strategy of that particular perceptron) and directs those data into a single channel. If we use familiar terms from the field of neuro-dynamics we would say that a number of action potentials in a number of nerve fibres wil be subjected to a (basic) decision making process before being passed on as a single action potential along a single nerve fibre.

However, we have to be careful not to get too stuck in the similarity between neural cells and perceptrons. The concept of perceptrons cover a much wider field. A perceptron is above all a strategy determined or determining structure with a degree of programmability.

Two features of the concept of perceptrons are important for the course of this thesis. The first has to do with the properties of the particular signal wich a perceptron is programmed to process. Even a relatively simple signal like that triggering the direction sensitive rods in the cat's retina would be made up of a number of components with simple properties. Because of the probabilistic-heuristic nature of the perceptron, each of these simple properties are seen as probability weighted in an n-dimensional probability field (n may be 1, in which case we are not talking about vector calculatin, but about simple summing up of probabilities), and the probability of the perceptron reaching its reaction threshold is the sum of the probabilities of the individual properties present in the signal. The sum of the probability vectors is always less than or equal to 1. The idea, that the component's place in a probability field determines the threshold of the perceptron, I have exploited later in this thesis when a program will simulate information transfer from a text string to the human linguistic device.

Minsky and Papert use the term 'word' instead of 'signal'. The computational term 'word' is wider than, but not vastly different from, that of normal language use. A 'word' in computational terms is a string of ones and/or zeros (as a special case it might be empty). The length of the 'word' depends on the hardware used. A word, in the common sense of the term, can easily be translated to a 'word' in computational terms (but not necessarily the other way).

The second feature of Minsky and Papert's work, important to the research of this thesis, is their reflections on how much identity is necessary between a 'word' A and a 'word' B before a perceptron will respond to 'word' B as if it was 'word' A. They demonstrate that we do not need total identity between 'words', and even if we did, we would not be able to achieve it. 'Words' are compared and selected on a 'best match' basis.

The theory about perceptrons is limited to the processing of sensory inputs on the perception level. To account for the processing on a cognitive level, Minsky suggested 'A Framework for Representing Knowledge' (M. Minsky, 1975). In this theory 'frames' are seen as the cognitive representation of the subjects of the real world. I shall briefly define the most important terms used in this theory of frames.

A FRAME is a data-structure for representing a stereotyped situation like being in a certain kind of living room or going to a child's birthday party. Attached to each frame are several kinds of information. Some of this information is about how to use the frame. Some is about what one can ecpect to happen next. Some is about what to do if these expectations are not confirmed. We can think of a frame as a network of nodes and relations. The top levels of a frame are fixed, and represent things that are always true about the supposed situation. The lower levels have many TERMINALS or SLOTS that must be filled by specific instances or data. Each slot can specify conditions its assignments must meet. (The assignments themselves are usually smaller subframes). Simple conditions are specified by MARKERS that might require an assignment to be a person, an object of a specified character, or a POINTER to a subframe of a certain type. Collections of related frames are linked together in FRAME-SYSTEMS. As the mind assimilates a situation in accordance with a relevant frame-system the action is mirrored by TRANSFORMATIONS betwen the individual frames of the system. Different frames of the same frame-system share the same slots.

Originally the theory of frames was a model of the cognitive processing of the visual 'real world'. Later Minsky expanded the theory to the wider field of cognitive processing, including semantics. The application of the theory of frames to semantics I shall leave until chapter 8 where we deal more thoroughly with the concept of 'meaning'. Here I shall explain the theory of frames and introduce the terminology in the simplest way, namely as it started: as a theory of the cognitive processing of the visual world.

Let us imagine that we enter a room. We see in front of us all those objects which make us recognise the image as being that of a 'room'. What is it that makes it possible for us to deduct that what we see is a room. First of all we have in our cognitive make-up a number of frames: wall frames, ceiling frames, window frames and door frames. These frames together constitute a frame-system assigned to the association 'room'. Each of the frames: door, window, wall etc. in the frame-system 'room' consist of subframes. Let us take a frame like 'window'. The top level of the frame 'window' is fixed and represent things that are normally true about the frame. Here we could assign 'placed in wall' as a necessary condition while 'glass' would not be a necessary quality of the frame 'window' since a number of translucent materials could be used. So 'glass' would be assigned to a slot on a lower level of the frame. Since most of the windows we experience are indeed made of glass it would not be a slot on the lowest level. On the lowest level of the frame 'window' such qualities as colour or size would be slotted in. If the slot 'glass' is filled, a marker will point to a subframe common to all frame-systems with 'glass' slots, namely the special qualities of 'glass' like the ability to shatter on impact. When we move about in the room, the frames: wall, ceiling, window etc will change shape and size due to the change in the perspective. The slots, however, the different conditions which make up each frame, will not change. Nor will those slots that are common to different frames in the frame-system like left-wall-meets-middle-wall or walls-meet-ceiling. For this reason we are still able to recognise the frame 'room' even if we change our viewpoint of the room.

A frame's slots are normally filled with 'default' assignments or conditions. Thus, a frame may contain a great many details whose supposition is not specifically warranted by the situation. They may represent general knowledge, most likely cases, ways to make useful new generalisations, even expectations. The default assignments are attached loosely to their slots so that they can be easily displaced by new items that better fit the current situation.

The frame-systems are linked, in turn, by an INFORMATION-RETRIEVAL NETWORK. When a proposed frame cannot be made to fit reality - when we cannot find conditions that suitably match the slots or markers of that frame, the information-retrieval network provides replacement frames until a 'best match' is achieved.

Because 'frame' is applied in a relative sense - a slot in a frame may itself be a (sub)frame. and a marker of a frame may refer to another frame - it gives rise to some confusion as to on which level the information-retrieval network works. Minsky talks about retrieving frames ad libitum until a 'best match' is found.

Let us imagine that we find ourselves in front of an object wwhich may or may not be a tree. It may be a real live tree; on the other hand the grey dusty surface and the lack of green leaves make us wonder whether it is the real thing or, say, a look alike made of concrete. Our information-retrieval network will. based on the clues of the situation, 'pull in' a number of frames and compare them with the clues of the object in front of us to find a 'best match' i.e. a frame which match the greatest number of clues (weighted accoding to perceived importance of each clue). The comparator which assesses how well a frame compares to reality may have established that the frame 'real tree') gives the best match to the object in front of us.

However, the function of the information-retrieval network is not to passively present a multitude of static frames. As each frame is retrieved and presented by the information-retrieval network, slots and markers on the lower levels of each frame are being assessed and, where necessary, emptied and refilled by other subframes. Thus, on the slot and marker level in the frame 'real tree' another number of choices are being made between slots to find a 'best match' to match the more subtle clues like colour or age, shape or number of leaves. Whether we want to imagine that this is done by the same information-retrieval network or by a perceptron-like function is not important. What is important - and in line with the overall theme of this thesis - is that whenever we have established a 'best match' a choice has been made, and, according to information theory, some entropy has been transformed into information. Whether the choice is made by a perceptron-like structure selecting data according to a strategy on a local level, or whether the choice is made by a more complex comparator between a number of frames presented by the information-retrieval network, does not make any difference to the basic fact that when the choice has been made, some entropy has been transformed into information.

JOHNSON-LAIRD'S MENTAL MODELS.

A number of criticisms could be raised against Minsky's theorv of frames. The most obvious is that it is over-simplistic. Johnson-Laird (P.N. Johnson-Laird. 1983) points out that it is inconceivable that the mental representation of the real world should take onlv one form. First of all. Johnson-Laird points out. even if there is no precise line between perception and conception, it is necessarv to distinguish between 'physical' (perceptual) and 'conceptual' mental models. Physical models represent the physical world: conceptual models represent more abstract matters. Within the group of phvsical models Johnson-Laird distinguishes between at least six major tvpes:

Relational models are static 'frames' consisting of a finite set of tokens representing a finite set of physical entities.

Spatial models consist of a relational model in which the onlv relations between the entities are spatial, and the models represent these relations bv locating tokens within a dimensional space (tvpicallv of two or three dimensions).

Temporal models consist of sequences of spatial 'frames' that occur in a temporal order corresponding to the temporal order of events.

Kinematic models consist of a temporal model that is psvchologicallv continuous. The models represent changes and movements of depicted entities with no temporal discontinuities.

Dvnamic models are kinematic models in which there are relations between certain frames representing the causal relations between the events depicted.

Images which consist of viewer-centred representations of the visible characteristics of underlving three-dimensional spatial or kinematic models.

Johnson-Laird's 'phvsical' models are basicallv static or algorithmic of nature. Thev can be made to change i.e. thev are reproorammable, but without a 'control' or 'supervisorv' function to change the program, they won't. A physical model will thus give identical responses to the same specific input. This is clearlv a feature which the phvsical models have in common with Minskv's perceptrons. Both concepts - the physical models and the perceptrons - are lexicon functions in the sense that a 'higher' function, Minsky's information-retrieval network or Johnson-Laird's conceptual models, has access to these functions and can modifv them when the need arises. Even on the conceptual level there is some similaritv between Minskv's and Johnson-Laird's models. Both have access to a number of frames and in both theories the conceptual model (in Minsky's theorv: the information-retrieval network) is able to select a frame by recursive inference or modifv an existing frame by recursive revision if no suitable frame can be found. However, whereas Minskv sees his information-retrieval network as a single function, Johnson-Laird distinguishes between at least four different tvpes of conceptual models with the 'machinerv' (sic) for their own recursive revision and the revision of the physical models:

Monadic models, which represent assertions about individuals, their properties, and identities between them. Such models consist of three components: 1) A number of tokens representing individual entities and properties. 2) A binary function which is able to establish whether two tokens are identical or not. 3) A device which is able to indicate that the existence of a particular entity is unlikely.

Relational models, which introduce a number of relations, possibly abstract, between the tokens in a monadic model.

Meta-linguistic models, which contain tokens corresponding to linguistic expressions, and certain abstract relations between them and elements in a mental model of any type. The abstract relations include key semantic ones such as 'refers to' and 'means'.

Set-theoretic models, which contain a number of tokens directly representing sets. They may also contain a set of associated tokens designating the abstract properties of a set, and a set of relations (including identity and non-identity) between the tokens designating sets.

As stated above, Johnson-Lairds conceptual models are able to revise themselves and the physical models by recursion. They are thus heuristic in contrast to the physical (perceptual) models which are algorithmic. In response to an incoming signal the conceptual models search through a number of physical models, compare, identify or discard and revise as the case may be, and select the physical model which gives the highest level of identity - or as Minsky would say: gives the 'best match'.

Minsky's theory of frames is simple (may be even seductively so) and 'rich' in the epistomological sense in which he and Papert use the word (page 34) in their strive towards a 'rich enough theory'. Johnson-Laird's theory of mental models is more sophisticated. However, in practical research one has to strike a balance between the ideal and the possible, and for the research presented later in this thesis Minsky's theory of frames has provided a workable model. Johnson-Laird's 'Mental Models', in my view by far the most thorough and sophisticated examination of mental representations of the real world presented so far, has served as a reassuring frame of reference: In spite of their differences, Minsky's theory of frames and Johnson-Laird's mental models have in common the procedure which, when presented with a physical representation of the real world, mobilises a finite number of 'frames' (Johnson-Laird too uses this term) and selects the frame which best matches the representation of the real world. This is the key feature of both theories if we want to apply information theory to the conceptual level, because, when a choice is made from a number of possibilities, as when one particular frame is selected, entropy is transformed into information.

Consequently, in this thesis I shall concentrate on the information transfer which takes place when a choice is made on what Minsky would call the slot and marker level, and Johnson-Laird would see as the level of conceptual models. In chapter 8 of this thesis, when we shall deal more thoroughly with the interaction between frames and context, we shall take heart in the fact that, for the research presented in this thesis, it is not essential to establish at which cognitive level the selection between frames or mental representations takes place or where the procedures of strategy are to be found. The main point is that selections are made and therefore entropy is transformed into information.

CHAPTER 4.

TEXT SAMPLES USED IN THIS RESEARCH.

The research presented in this paper concerns itself with structures in text strings. As the title of the paper suggests, we will try to uncover these structures by applying power spectral analysis to the text strings. This is not immediately possible. A text string - or any other medium used by our linguistic device - does not easily lend itself to this kind of analysis. The full explanation for this I shall leave till a later chapter, suffice to state here, that the particular power spectrum analysis which we shall use - the Fourier analysis - is very sensitive to variations in the medium - in our case: text strings - that carry the structures.

It would have been ideal to base an analysis of this kind on a huge variety of text samples ranging from the bold unreflected phraseology of younger children to the seductive pandering by some gentlemen of the press. However, for reasons of manageability, In between these extremes I have had to pick a relatively small number of samples.

In my choise of text samples I have focused on the complexity of the information which the author wants to convey to the reader. Some authors are able to convey very complex information in a smooth and readable manner. Other authors are so caught up in linguistic mannerism, that the information becomes secondary - or lost all together. Finally I thought it could be interesting to see how text strings written for children by adults compare with those written by the children themselves.

The text strings as a data base serve different purposes. In Chapter 5 the samples are used to find those structures in the text strings which are SPECIFIC to each string. In Chapters 11 and 12, the samples are used to find GENERAL structures; structures which are common to all the strings.

The text strings are analysed, as they are printed on the following pages i.e. without punctuation. There are at least two reasons for this.

The first one is my wish to analyse a wide range of text-material. Many people, particularly children, do not use punctuation. As a matter of fact, you often see, that children persistently use "and" instead of full stop, and the presence of full stops in some text strings and not in others, would make it impossible to compare the results.

The second reason has been the difficulty in deciding how to handle this punctuation, particularly the full stops. Two functions of punctuation become obvious from the reading aloud of text strings.

One is to allow time for a deep intake of air. This is not to say, that we only breathe in at punctuation marks, but to some extent this seems to be the case, especially for professionally trained readers or actors.

Another function of full stops is that of delaying the arrival of the following word to add importance i.e. to add information. The first problem along this line of reasoning is the difficulty of assessing just how long such a delay is meant to be since the pause after a full stop can be lengthened or shortened with different effect. The second problem is that of the information value of each full stop i.e. should each full stop be counted as a new word or as a repeat?

I have therefore chosen to omit punctuation all together. This is a safety precaution which may or may not add to the crudeness of my analysis. However, somewhere we will have to strike a balance between the amount of speculation which is necessary for the development of an idea, and further speculation which may turn the whole idea into mere ornaments.

TEXT STRINGS WRITTEN BY CHILDREN.

The 42 text samples on the following pages (pp. 41 to 88) have been produced by kind co-operation of children in two schools in Central Region in Scotland. The stories were written by the children with no assistance from adults as to the making up of the story. However, as is clearly evident, somebody has on occasions helped with the spelling of 'difficult' words (in spite of instructions to the contrary) whereas the more common words have been left for the children to spell in their own way. This does not matter. The spelling of a word - or any word - is irrelevant for our purpose, as long as the spelling is consistent throughout the same text string. For this reason, I have had to change spelling in cases where the same word was spelled in different ways in the same text string. In these cases, I have always chosen a spelling suggested by the child, instead of adhering to 'correct' spelling. As stated, the correctness of the spelling is irrelevant, the computer will compare words in the strings, and as long as the same words are spelled the same way, they will be recognised. In one case, 64C (p. 44), I have felt it necessary to 'translate' the story, merely so that the reader does not miss the very charming contents. The 'translation' is printed after the original version.

The children were in all cases told that they could write whatever they liked, but that fiction was preferable to facts. Some stories were useless, because they merely enumerated geographical facts or - in two cases of apparently deprived children - masses and masses of different dishes and recipes, which, albeit very charming and mouth watering, were not representative of the kind of natural language I wanted to analyse.

The authors range in age from 6 years to 14 years. The text strings are indexed according to the age of the author and the serial number of the text sample. All labels consist of a capital

'C' and a two or three figure number. In the case of the index being a two figure number like '61C', the number to the left indicates the age of the author and the number to the right indicates the serial number of the sample within this age category, ie age: 6, serial number within this age category: 1. In the case of the index being a three figure number like '134C', the two numbers to the left indicate the age of the author and the number to the right is still the serial number within the age category, ie age: 13, serial number: 4. There is really no need to try to memorise this method of indexing; it does not give rise to mis-interpretation. If you read the index '114C' as the serial number 14 in the category of text strings written by one year olds, you will probably realise, that you have separated the index in the wrong place. Although the 'C' stands for 'child' it is not a necessary part of the indexing, only a reminder, and it will indeed appear sometimes first in the index, sometimes last. On the graphs resulting from the analysis of a particular text string, the label of the graph will be made up of the index of the text sample followed by a number of parameters, eg., the label on a graph resulting from an analysis of text sample 65C may look like this: '65C48B91RF47SOF1'. In this case, the 'C' serves as a separator between the index and the parameters. Sometimes, when the text sample is referred to as a text file (for memory disk use) and is not followed by a string of parameters, the file may be referred to as C65 instead of 65C, simply because my computer does not accept file names which begin with numbers. The 'C' could for that matter have been any other character, like an asterix, but I have tried through out this research to make the labels meaningful, and whether the 'C' appears first or last in an index, it serves as a clear reminder that the text string is written by a child.

Generally, the younger children have been brief. In the group of 6 year olds, the text strings are typically around 60 words long. At the other end of the age spectrum, the 14 year olds, the text strings can be up to 700 words long. The story 95C is untypically long (n=867) for a child of this age. It was written by my daughter, who was, on that occasion, paid per word and thus heavily motivated to exceed normal 'production targets'.

As a data base, the brevity of the young age group did not cause any problem for the analysis carried out in the preliminary research (chapter 5), and all the strings could indeed be analysed in this part of the research. With regard to the later research (chapters 10 to 12), which is based on Fourier Analysis of the text strings, 12 of the strings had to be abandoned because they were too short to be analysed by means of this kind of analysis.

I shall assume that in normal children, the level of linguistic competence depends on the children's general development. I shall further assume, that this development is significantly correlated to the children's age. The contribution of this category of children's text strings is therefore, that it represents a number of strings which presumably are arranged according to a gradually increased level of linguistic competence. As the age of the children is thus the most important parameter, and as this parameter is part of the index of each text string, I shall not go into further detail regarding each text string, but refer the reader to the strings themselves on the following pages.

TEXT STRINGS WRITTEN BY CHILDREN

INDEX:

TEXT STRINGS WRITTEN BY CHILDREN

INDEX:

61C
ONE MORNING I WOKE UP IN BED I HEARD A
NOISE OUT SIDE AND I LOOKED I SAW A SPACESHIP
OUT CAME A RABBIT AND SAID COULD I STAY FOR
THE NIGHT YES I SAID IN THE MORNING THE RABBIT
GAVE ME ONE WISH I WISHED FOR SOME SILVER AND
I GOT THE SILVER AND I WENT TO MURRAYS AND
BOUGHT TWENTY SWEETS AND I STILL HAD SILVER LEFT

62C
ONE DAY I FELL OFF MY BIKE AND KNOCKED A TOOTH OUT AND IT WAS ONE OF MY LITTLE TEETH MUMMY SENT ME BACK TO THE ROAD TO LOOK FOR IT AND I SOON FOUND IT IT WAS LONG AND WHITE AND SHINY AND I PUT IT UNDER MY PILLOW SUNDAY NIGHT BECAUSE I FORGOT TO PUT IT UNDER MY PILLOW ON SATURDAY NIGHT THEN ON SUNDAY I PUT IT UNDER MY PILLOW AND ON MONDAY MORNING I FOUND A TEN PENCE AND I SPENT IT ALL ON A PACKET OF SALT AND VINEGAR CRISPS AND I ATE THEM ALL

630
I WAS A HEAD FEATHER FROM A PHEASANT AND THERE
WERE SOME CHILDREN PLAYING AND ONE OF THEM PICKED ME
UP AND STUCK ME ON A STUFFED DUMMY BIRD THE
NAME OF THE PERSON WAS STUART WILSON AND HE HAD
MADE QUITE A LOT OF THEM HE HAD SET UP
A ROOM OF WILD LIFE LIKE WOOD AND FOREST AND
LAKES AND PONDS WITH STUFFED ANIMALS HE INVITED ALL HIS
FRIENDS TO COME AND SEE US

64C
ON FRIDAY FIONA IN PE 1 BROT HUR LAMB TO
SCHOLL IT BLETED AND BLETED AND THE CULIR OF ITS
MARKINGS IS BLUE ITS DADDAY IS FRENSH AN DITS MUMMY
HAD HORINS AND YESTDAY KAET BROT HERS WE SAY BOB
A BLACK SHEP IT WAS CYOOT LAST YEAR THE LAMB
CEPT DOWING THE TOLET ON THE FLOR

ON FRIDAY FIONA IN P ONE BROUGHT HER LAMB TO
SCHOOL IT BLEETED AND BLEETED AND THE COLOUR OF ITS
MARKINGS IS BLUE ITS DADDY IS FRENCH AND ITS MUMMY
HAD HORNS AND YESTERDAY KATE BROUGHT HERS WE SANG BAH
BAH BLACK SHEEP IT WAS CUTE LAST YEAR THE LAMB
KEPT DOING THE TOILET ON THE FLOOR

650
ONCE THERE WAS A RABBIT WHO WAS CHASING MY FRIEND
SQUIRREL AND ONE DAY I MADE A NUT LINE FOR
THE BIRDS AND ESPECIALLY FOR THE BLUETITS AND MY BROTHER
MADE ONE TOO AND WHEN HE PUT IT UP THE
SQUIRREL PULLED IT DOWN OFF THE BIRD TABLE AND TOOK
THEM AND HID THEM AND THEN I THOUGHT THAT I
WOULD PUT MY NUT LINE ON THE WASHING LINE BUT
THE RABBIT STILL CHASES THE SQUIRREL RABBITS ARE VERY ANNOYING
YOU KNOW AND THAT EVEN EAT OUR CARROTS LETTUCE AND
CAULIFLOWER

66C
I HAVE A LITTLE HOUSE IN KILLEARN IT IS A
LOVELY COUNTRY VILLAGE I HAVE SEEN MANY BIRDS THERE ARE
DRAGON FLIES AND BLACK BIRDS AND A ROBIN I LIKE
KILLEARN BETTER THAN BISHOPBRIGGS BECAUSE THERE ARE MORE FRIENDS THAN
IN BISHOPBRIGGS BISHOPBRIGGS IS MESSY BUT KILLEARN IS NOT MESSY
AND I LIKE KILLEARN BECAUSE THE TEACHERS ARE NICER

670
MY DADDY HAS BLACK HAIR AND GREEN EYES HE LOVES
TO SING SONGS IN THE BATH HE TELLS ME TO
SING IN THE BATH AS WELL TO MAKE SURE THAT
I AM ALL RIGHT IN THE BATH HE WORKS IN
GLASGOW AT GORDON MOTORS AT A GARAGE I SOMETIMES GO
TO SEE HIM IN HIS OFFICE WHEN HE IS VERY
BUSY DADDY IS FAT HIS HOBBY IS LYING ON THE
COUCH WATCHING THE FOOTBALL ON SATURDAYS

70C
I LIKE MUSIC BECAUSE IT GIVES ME A HAPPY FEELING
I LIKE MUSIC THAT IS FAST BECAUSE MY MUM CAN
PLAY THE PIANO FAST PEOPLE HAVE INSTRUMENTS TO MAKE MUSIC
POP MUSIC IS MY FAVOURITE MY MUM SAID SHE DANCES
WITH THE MUSIC WHEN SHE IS IN THE MOOD FOR
DANCING I LIKE THE SOUND OF DANCING BECAUSE I DANCE
WITH THE MUSIC AND MY MUM COMES TO DANCE WITH
ME TOO TOMORROW I AM GOING TO A PARTY AND
I AM GOING TO GET THE RADIO AND I WILL
LISTEN TO IT UNTIL I AM AT THE PARTY I
LIKE THE POP MUSIC THE BIRDS LIKE TO SING ALL
DAY THE RADIO IS THE BEST TO GET MUSIC TO
DANCE WITH THE SOUND OF MUSIC IS GOOD I CAN
PLAY THE PIANO WHEN I PLAY THE PIANO MY MUM
COMES IN MY ROOM AND DANCES TO IT SOME PEOPLE
LIKE POP MUSIC MY MUM SAID TO ME MUSIC IS
INTERESTING MY GRAN LIKES TO HEAR MUSIC ON TELEVISION KEVIN
HATES MUSIC

71C
OUR VILLAGE IS A PRETTY LITTLE VILLAGE I HAVE LIVED IN KILLEARN ALL MY LIFE I WAS BORN IN KILLEARN WHEN I LEFT NURSERY SCHOOL I CAME TO KILLEARN SCHOOL AT KILLEARN SCHOOL WE GET PLENTY OF WORK WE HAVE A KILLEARN CHURCH THAT WE SING IN WE HAVE SOME SHOPS IN OUR VILLAGE LIKE THE COOP AND MURRAYS WE HAVE A HOTEL CALLED THE BLACK BULL MY VILLAGE KILLEARN IS NEAT AND TIDY WE HAVE A SWING PARK IN OUR VILLAGE WE HAVE A SHOOT AT THE SWING PARK AND SOME SWINGS WE HAVE LOTS OF MOUNTINS IN KILLEARN WE HAVE GOT A MONUMENT IN MEMORY OF GEORGE BUCHANAN

72C
ONE DAY AT HALF PAST THREE WE WENT HOME FROM
SCHOOL AND THE TEACHERS TOO IN MRS FLEMINGS DESK HER
DRAWING PINS WERE BANGING ON TOP OF THE BOX THEY
WERE MAKING SUCH A NOISE AT LAST THEY GOT OUT
OF THE BOX THEY JUMPED ON TO THE FLOOR AND
GOT OUT OF THE DOOR OFF THEY WENT DOWN THE
STEPS AND THEY WENT IN TO THE GYM HALL BECAUSE
THEY HEARD MUSIC THERE WAS A MAN TEACHING LADIES TO
DANCE THE PINS STARTED TO DANCE AFTER THAT THEY WENT
BACK TO THE CLASS ROOM TO EXPLORE BUT SOON THEY
HEARD THE CLEANERS COMMING AND THEY DIVED BACK ON THEIR
POINTED TIPS BACK IN TO THE BOX

73C
YUCK A VISIT TO THE DENTIST WHEN THE NURSE SAID COME GIRLS I THOUGHT IT WAS THE DENTIST AND IT WAS I WAS SCARED BECAUSE I DO NOT LIKE FILLINGS AND BECAUSE I DID NOT WANT ANY TREATMENT WHEN THE DENTIST SAID THAT MY TEETH WERE FINE I WAS GLAD GLAD THAT I DID NOT HAVE ANY TREATMENT THEN WHEN MARGARET CAME OUT I TOLD HER THAT I DID NOT HAVE ANY TREATMENT AND SHE SAID THAT SHE DID NOT HAVE ANY FROM THE DENTIST ONCE WHEN I WAS AT MY OWN DENTIST I BIT HIS FINGER BECAUSE I DID NOT LIKE IT

74C
WHEN I SHUT MY EYES IT MAKES ME THINK OF
MRS SMITH AT SINGING I HAVE A RADIO AT HOME
I PLAY IT A LOT I LOVE MUSIC BECAUSE IT
MAKES ME FEEL VERY HAPPY MRS YOUNGS CLASS WENT TO
SINGING TO DAY SOME MUSIC TELLS A STORY YOU CAN
MAKE MUSIC WITH INSTRUMENTS IT MAKES A LOVELY TUNE I
LIKE POP MUSIC BEST I LIKE LISTENING TO RECORDS ON
THE RECORD PLAYER SOMETIMES I DANCE AND DANCE TO MUSIC
TILL I AM OUT OF BREATH WHEN YOU ARE AT
A PARTY WE HEAR MUSIC A LOT I LIKE MUSIC
AT PARTIES WHEN YOU PLAY MUSICAL BUMPS I LOVE IT

75C
AN ORANGE IS A FRUIT ITS COLOUR IS ORANGE THEY GROW IN COUNTRIES LIKE FRANCE AND SPAIN AND SOME PARTS OF AMERICA AN ORANGE IS A FRUIT CALLED CITRUS IT IS A VERY JUICY FRUIT I LIKE THEM ALOT I HAVE ONE CUT IN QUARTERS I SUCK EVERY DROP OF JUICE OUT WHEN YOU HAVE EATEN AN ORANGE YOUR HAND GET VERY STICKY INDEED I HAVE LOTS OF ORANGES IN MY FRUIT BOWL IF YOU SQUIRT THE JUICE IN SOMEONES EYES THEY STING ALOT THE SKIN OF AN ORANGE IS THICK AND SOFT

75C
AN ORANGE IS A FRUIT ITS COLOUR IS ORANGE THEY
GROW IN COUNTRIES LIKE FRANCE AND SPAIN AND SOME PARTS
OF AMERICA AN ORANGE IS A FRUIT CALLED CITRUS IT
IS A VERY JUICY FRUIT I LIKE THEM ALOT I
HAVE ONE CUT IN QUARTERS I SUCK EVERY DROP OF
JUICE OUT WHEN YOU HAVE EATEN AN ORANGE YOUR HAND
GET VERY STICKY INDEED I HAVE LOTS OF ORANGES IN
MY FRUIT BOWL IF YOU SQUIRT THE JUICE IN SOMEONES
EYES THEY STING ALOT THE SKIN OF AN ORANGE IS
THICK AND SOFT

76C
DARKNESS IS FUN YOU CAN PLAY HIDE AND SEEK AND RUN UP TO THE DEN BEFORE ANYONE CAN SEE YOU DARK IS NECESSARY OUR TEACHER READ US A STORY ABOUT AN OWL WHO WAS AFRAID OF THE DARK IT WAS UNUSUAL BECAUSE OWLS ARE NIGHT BIRDS HIS NAME WAS PLOP HE FOUND OUT THAT DARK IS FASCINATING THERE IS A GAME CALLED MURDER IN THE DARK AND YOU TURN OFF THE LIGHTS GHOSTS FLOAT IN THE DARK AND YOU CAN SEE THEM BECAUSE THEY ARE WHITE

77C
I LIVE IN A PRETTY LITTLE VILLAGE CALLED KILLEARN THERE
IS A WOOD IN WHICH I LOVE TO PLAY I
MOVED TO KILLEARN LAST SUMMER I LIKE KILLEARN BETTER THAN
MY OTHER VILLAGE BECAUSE I HAVE MORE FRIENDS THERE ARE
LOTS OF BIRDS IN KILLEARN SUCH AS BLUE TITS STARLINGS
BLACKBIRDS I AM GLAD THAT I DO NOT LIVE IN
GLASGOW BECAUSE IT IS SUCH A BIG PLACE THAT I
MIGHT GET LOST THERE IS A SCHOOL IN KILLEARN I
SIT IN IT EVERY DAY THERE IS ONE HOTEL IN
KILLEARN IT IS CALLED THE BLACK BULL MY DAD GOES
THERE EVERY FRIDAY THERE IS ONLY ONE THING I DO
NOT LIKE ABOUT KILLEARN AND THAT IS NEARLY ALL MY
RELATIVES LIVE IN KIRKADY

780
GOD MADE THE EARTH FOR US TO LIVE ON IT
THE FIRST PERSON HE MADE WAS ADAM THE SECOND PERSON
HE MADE WAS EVE WHEN GOD IS NOT HAPPY HE
CRIES HIS TEARS WE CALL RAIN I THINK HE WEARS
A WHITE CLOAK BUT I HAVE NO IDEA WHAT SHAPE
HE IS I DO NOT LIKE WARS I HOPE THERE
ARE NO MORE WARS I WOULD NOT LIKE TO HEAR
THE CANONS AND THE GUNS AND THE CRIES OF PEOPLE
FALLING I HATE TO THINK OF IT

79C
EVERY NIGHT PEOPLE FROM ALL OVER THE WORLD GO TO BED BED IS A VERY COMFORTABLE PLACE TO BE IT IS VERY SOFT AND HAS BLANKETS AND PILLOWS AT NIGHT IT IS VERY COLD AND DARK BED IS MARVELLOUS MUMMY SAYS BEDTIME STORIES FOR ME I RUN UP THE STAIRS BRUSH MY TEETH AND GO TO BED I GO TO BED AT EIGHT OCLOCK SOME TIMES I LISTEN TO MY RADIO OR DO SOME DRAWINGS FROM A BOOK I LOVE TO GO TO BED BECAUSE I WILL NOT BE ANNOYED ANY MORE ONE OF THE PROBLEMS I HAVE AT NIGHT IS THAT DADDY SNORES AND I AM KEPT AWAKE ALL NIGHT

BOC
ONE DAY THE BIG BROWN BARN OWL THAT LIVED IN THE BIG BROWN BARN WAS SAYING TO THE BIG WHITE SNOWY OWL THAT LIVED IN A TREE NEAR BY THAT THERE WAS HARDLY ANY ACTIVITY FOR THE ANIMALS AFTER A WHILE MRS SNOWY OWL SAID WHY NOT HAVE A SPORTS DAY FOR ALL THE WOODLAND CREATURES MR BARN OWL THOUGHT THAT THIS WAS A VERY GOOD IDEA AS SOON AS THE ANIMALS HEARD ABOUT IT THEY HURRIED OFF TO GET READY MRS SILK WORM MADE A SILK FINISH LINE AFTER EVERYTHING WAS ORGANISED MR BARN OWL STARTED THE FIRST RACE WHICH WAS BETWEEN SIX HEDGEHOGS A MOUSE AND A TORTOISE FISRT PRIZE WAS PRESENTED TO THE MOUSE SECOND TO A HEDGEHOG AND THIRD TO THE TORTOISE THEN CAME THE SLOW RACE THE TORTOISE WON THAT OF COURSE HE WOULD SAID THE HARE THE THIRD AND FINAL GAME WAS THE LONG JUMP IN WHICH THE TOAD CAME FIRST THE FROG CAME SECOND AND THE HARE CAME THIRD

81C
ONE DAY A PASSENGER PLANE WENT OVER THE BERMUDA TRIANGLE
SUDDENLY IT STARTED TO DROP AND CRASHED ON THE WATER
IT WAS ABOUT HALF A MILE TO THE SHORE OF
BERMUDA IT HAPPENED THAT ONE OF THE SURVIVORS WAS A
POLICE DETECTIVE HE SWAM ASHORE AND STARTED TO WALK ABOUT
AFTER HE HAD WALKED FOR A WHILE HE SAW A
TREE AS HE WAS PASSING IT HE TRIPPED OVER A
STONE A DOOR OPENED AND HE WENT IN IN THE
TREE THERE WAS LOTS OF COMPUTORS AND AT THE TOP
THERE WAS A TRANSMITTER HE KNEW ALL THE ANSWERS HE
NEEDED HE RAN TO THE BEACH BUT AN ALIEN SHOT
HIM THE BERMUDA SECRET IS STILL KEPT

B2C
IN THE SIXTEEN ACRE WOOD A LITTLE EASTER BUNNY SKIPS
ALONG WITH HIS BASKET OF EASTER EGGS AT THE END
OF THE SIXTEEN ACRE WOOD IS A LITTLE HUT WERE
A BOY LIVES WITH HIS MOTHER AND FATHER EVERY EASTER
THE LITTLE BUNNY SKIPS ALONG TO THE HUT THE BOYS
PARENTS CAN NOT AFFORD TO BUY ANY EASTER EGGS THE
BUNNY LIVES IN A HOLLOW OF A TREE TRUNK IN
THE MIDDLE OF THE WOOD HE HAS THREE ACRES OF
LAND WHERE HE GROWS HIS EASTER EGGS ONE DAY A
MAN HEARD ABOUT THIS BUNNY AND WANTED TO KILL THE
BUNNY AND TAKE HIS EASTER EGGS HE KILLED THE EASTER
BUNNY AND TOOK OVER HIS LAND BUT HE COULD NOT
GROW THEM HE DID NOT KNOW HOW TO GROW THEM
SO HE SADLY WENT BACK TO HOLLAND WELL HOWEVER THE
EASTER BUNNYS COUSIN TOOK OVER HIS JOB AND EVERYBODY WAS
HAPPY THIS BUNNY WAS VERY CLEVER AND HE KNEW HOW
TO GROW EASTER EGGS

B3C
CHUGALUG WAS A TRAIN HE WAS BRIGHT RED WITH A
BLUE BOILER ONE DAY CHUGALUG TRAVELLED TO EDINBURGH HE WAS
CARRYING LOTS OF PASSENGERS BUT CHUGALUG WAS SAD WHY BECAUSE
TOMORROW CHUGALUG WOULD BE GOING TO THE SHUNTING YARD BECAUSE
THE TRAIN DRIVER THOUGHT HE WAS TOO OLD SO WHEN
THEY CAME BACK FROM EDINBURGH CHUGALUG RAN AWAY HE RAN
OVER PURPLE MOUNTAINS AND GREEN VALLEYS UNTIL HE CAME TO
A SUDDEN STOP IT WAS HILLMADA QUEEN OF THE SUN
HILLMADA SAID WHY DO YOU RUN AWAY FRON THE SHUNTING
YARD BECAUSE I DO NOT WANT MY NICE RED PAINT
AND MY BLUE BOILER DIRTY FUSSINESS WILL GET YOU NOWHERE
SO GO BACK AND YOU WILL BE HAPPY SO CHUGALUG
WENT BACK AND TRUE ENOUGH HE WAS HAPPY AND TILL
THAT DAY ON CHUGALUG WAS NEVER FUSSY AGAIN

84C
ONE DAY A LITTLE GIRL CALLED LOUISE DECIDED TO PUT
ON HER NEW SHOES NO ONE EXCEPT THE LITTLE ELF
IN THE SHOP KNEW THEY WERE MAGIC SHE PUT THEM
ON AND SUDDENLY SHE FELT A STRONG WIND SHE LOOKED
AROUND TO FIND SHE WAS FLYING THROUGH THE AIR SHE
MURMURED I AM HUNGRY I SHOULD GO TO THE LAND
OF EATABLES IF THERE IS ONE TO HER SURPRISE SHE
FOUND SHE WAS FLYING OUT OF THE DOOR AND THEN
NOTICED SHE WAS ABOVE THE CLOUDS THEN LOUISE LANDED THERE
WERE HOUSES MADE OF FRUIT CAKE WITH CHIMNEYS OF MARZIPAN
IN THE GARDENS THERE WERE CHOCOLATE BISCUIT AND DUMPLING TREES
THE GRASS WAS GREEN SUGAR AND ON THE GRASS THERE
WERE LEMON CURD AND STRAWBERRY JAM TARTS THE ROAD THE
PAVEMENT AND THE CARS WERE LIQUORICE SHE WALKED ALONG THE
PAVEMENT AND CAME TO A HUMBUG FOREST SHE WALKED INTO
IT AND DECIDED TO TAKE A LONG WALK AFTER A
WHILE SHE BECAME TIRED HOT HUNGRY AND THIRSTY SHE CAME
TO A LEMONADE BROOK AND LAY DOWN UNDER A NEARBY
TREE SHE PULLED SOME HUMBUGS AND DRANK LEMONADE SHE SAID
GO HOME NEXT DAY LOUISE SAID TAKE ME TO FAIRYLAND
LOUISE FLEW TO FAIRYLAND LATER SHE WALKED TO THE PALACE
WHERE SHE WAS TURNED INTO A FAIRY BY THE KING
THEN SHE THREW AWAY THE SHOES BECAUSE SHE HAD WINGS
SHE WAS DRESSED IN BUTTERCUP PETALS AND SHE WAS NAMED
BUTTERCUP SHE NEVER WENT HOME AGAIN AND LIVED HAPPILY EVER
AFTER IN A COTTAGE IN THE TOWN OF BRENDOLLA NEXT
DOOR TO TULIP

B5C
I WANT TO TELL YOU ABOUT MY HAPPY LIFE WELL
YOU SEE MY DADDY WORKS AT A SCHOOL FOR BOARDING
SCHOOL BOYS HE IS A HOUSEMASTER THERE THERE ARE FIFTY
BOYS IN THE SCHOOL THE BOYS CALL ME THEIR HOUSESISTER
I GO ON DUTY WITH MY DADDY BECAUSE IT WOULD
BE BORING BY MYSELF IN THE HOUSE I PLAY WITH
THE BOYS THEY ARE VERY NICE TO ME MY DADDY
SENDS ME DOWN AT NINE OCLOCK THEN I PUT MY
PYJAMAS OR NIGHTDRESS ON THEN I CAN LAY IN THE
SETTEE TILL HE COMES DOWN FROM WORK THERE ARE TWO
BIG UNITS ONE FOR THE YOUNG LITTLE ONES AND THE
OTHER ONE FOR THE OLDER ONES MY DADDY USED TO
BE IN THE BOTTOM UNIT THATS FOR THE LITTLE ONES
BUT NOW HE WORKS IN THE TOP UNIT THERE WHERE
THE OLDER BOYS ARE EVERY MORNING MY DADDY WAKES ME
UP FOR SCHOOL HE GOES TO WORK AT THE SAME
TIME AS I DO I HAVE BREAKFAST WITH THE BOYS
WHEN MY DADDY IS ON DUTY IN THE MORNING THEN
THERE IS A FRIEND TO PICK ME UP TO SCHOOL
EVERY TUESDAY THE BOYS GO SWIMMING I AM ALLOWED TO
GO WITH THEM I LOVE IT THEN WHEN WE COME
HOME SOME OF THE OTHER BOYS MAKE THE SUPPER FOR
THEM THAT IS THE TIME I AM SEND DOWN MY
DADDY HAS THEN BOUGHT ME MY OWN SUPPER THEN AS
I SAID I WOULD PUT MY PYJAMAS OR NIGHTDRESS ON
THEN I WILL SWITCH THE TELEVISION ON AND LAY IN
THE SETTEE THEN IF I FEEL SLEEPY I WOULD SWITCH
OFF AND FALL ASLEEP OR I WOULD JUST FALL ASLEEP
WHEN THE TELEVISION WAS ON THEN WHEN MY DADDY COMES
DOWN HE WILL CARRY ME TO MY BED I WANT
TO TELL YOU ABOUT MY SCHOOL WELL IN THE MORNING
AT 730 MY DADDY WAKES ME UP OF COURSE I
DO NOT WANT TO BE WAKEN UP BUT I GET
UP AND GET DRESSED AND THEN I GET MY BREAKFAST
AND THEN I GO TO SCHOOL THE SCHOOL IS NORMALLY
EMPTY THEN AT NINE OCLOCK THE SCHOOL IS FULL THEN
WHEN THE BELL RINGS SCHOOL BEGINS WE ALL PUSH TO
GET IN THE DOOR I AND GILLIAN SIT AT THE
TOP THE FIRST THING WE DO IS DIARY THEN SUMS
THEN ENGLISH AND THEN WE DO SOMETHING FUN ON MONDAY
WE HAVE CHOIR PRACTICE ON TUESDAY WE HAVE A TELEVISION
PROGRAM ON WEDNESDAY WE HAVE SERVICE PRACTICE THURSDAY GYM AND
THEN ON SATURDAY AND SUNDAY WE HAVE WEEKEND AND ON
MONDAY WE START ALL OVER AGAIN I LIKE SCHOOL A
LOT NO I DO NOT LIKE SCHOOL I LOVE SCHOOL
I HAVE GOT A VERY VERY NICE TEACHER SHE IS
CALLED MISS YOUNG SHE IS ALWAYS NICE TO US WE
GET THREE BREAKS THE LUNCH TIME BELL RINGS AT 12
OCLOCK TO 1 OCLOCK WE GET 4 CHOICES SNACKS PACKS
GOING HOME AND SCHOOL DINNERS WE ALSO GET A BREAK
AFTER DINNER THE CHILDREN THAT I PLAY WITH ARE MY
FRIENDS THEY ARE VERY NICE TO ME WE ALSO GET
A BOTTLE OF MILK A DAY IF WE ARE LUCKY
WE GET EXTRA SOME TIMES THE DENTIST COMES UP THE

BOSS THAT WE HAVE GOT IS HORRIBLE SHE IS CALLED
MISS WODDELL BUT I CALL HER MISS WOMBLE THE SECRETARY
MISS YOUNG IS VERY NICE MOST OF THE CHILDREN HATE
SCHOOL THERE ARE ALSO RULES THESE ARE THE RULES NOT
TO THROW STONES NOT TO KICK BE NICE TO EVERYBODY
TREAT THE SCHOOL LIKE YOUR HOME AND NOT

90C
MRS WYLLIE WAS TELLING US A STORY IT WAS THE
LITTLE DONKEY SHE HAD READ A FEW PAGES WHEN I
LOOKED OUT OF THE WINDOW I THOUGHT I SAW A
MOVEMENT BEHIND A TREE I TURNED BACK TO THE STORY
YES I WAS RIGHT THERE WAS A GIANT DINOSAUR PLODING
UP THE FIELD I SUDDENLY RUSHED OUT TO MRS WYLLIES
DESK SHOUTING AAA DINOSAUR IS CCCOMING THE FFFIELD SHE SUDDENLY
JUMPED OUT OF HER CHAIR THEN SHE SHOUTED LINE UP
CHILDREN KATE HAD FAINTED I SUDDENLY RAN TO HER AND
LIFT HER UP I TOOK HER OUT OF THE CLASSROOM
I SOUNDED THE ALARM THE DINOSAUR WAS NEARLY ONE METRE
AWAY FROM ME I THREW KATE DOWN AND PICKED SOME
STONES AND TWIGS IT WAS NO GOOD THEN I PICKED
HER UP AGAIN THE GIANT HEAD OPENED ITS MOUTH AND
GAVE A ROAR I STARTED TO RUN A LARGE HELICOPTER
CAME DOWN EVERYONE QUICKLY HOPED EXCEPT KATE AND I THE
HELICOPTER ROSE UP INTO THE AIR AND SUDDENLY THEY SAW
ME IT CAME BACK DOWN THE DRIVER SAID ONLY ROOM
FOR ONE WE ARE CRAMPED AS IT IS I QUICKLY
PUT KATE IN THEN I CLIMBED UP ONTO THE ROOF
THE HELICOPTER WENT UP IN THE AIR IT WAS WATCHING
ME I QUICKLY GOT A BRANCH OF A TREE THE
DINOSAUR BENT DOWN I POKED HIM IN THE EYE HE
WAS DYING THE DEAD BODY OF THE DINOSAUR WAS GOING
TO LAND ON THE ROOF I SUDDENLY CLIMBED DOWN THE
SIDE BUMP IT WAS DEAD THE HELOCOPTER CAME DOWN TO
LAND AND EVERYONE THROUGH ME UP IN THE AIR THEN
KATE AWOKE AND I TOLD HER ABOUT WHAT HAD HAPPENED

91C
ONE NIGHT I HAD A DREAM I WOKE UP I
TOLD MYSELF THAT I HAD TO GO TO THE OLD
COTTAGE BY THE DISUSED BREWERY SO I GOT DRESSED AND
I WENT OUT I TOOK A TORCH JUST IN CASE
IT WAS VERY DARK WHEN I GOT THERE IT WAS
VERY DARK SO I WENT IN I SAW AN OLD
DUSTY CHEST I OPENED IT AND FOUND SOME BITS OF
PAPER THEN SUDDENLY I HEARD A BANG I TURNED ROUND
AND THE DOOR HAD SHUT I SHONE MY TORCH AND
THERE WAS A GHOST I WAS GOING TO CHARGE AT
IT THEN I REMEMBERED GHOSTS ARE TRANSPARENT BUT IT MIGHT
BE DRESSED UP SO I PUT MY TORCH DOWN AND
RAN I PULLED OFF THE SHEET AND THERE WAS MR
RADLEY I SAID WHAT ARE YOU DOING HERE NOTHING NOW
GO HOME HE SAID SO I PICKED UP MY TORCH
AND WENT HOME IN THE MORNING I WENT TO THE
POLICE AND THEY CAME WITH ME THERE WE FOUND MR
RADLEY AND SOME OF HIS FRIENDS WHEN THEY SAW THE
POLICE THEY JUMPED OUT OF THE WINDOW BUT THEY DID
NOT KNOW THAT THE POLICE HAD GONE ROUND TO THE
WINDOW AND THEY WERE ALL CAUGHT NEXT DAY I WENT
BACK AND I FOUND 600 POUNDS SO I TOOK IT
TO THE POLICE AND THE PEOPLE WERE TRYING TO SMUGGLE
THE MONEY INTO AMERICA SO THEY WERE PUT INTO PRISON
FOR SEVEN YEARS AND I RETURNED THE MONEY THE END

93C
I WAS COLLECTING DRIFTWOOD FOR THE FIRE WHEN I SAW
SOME SHIPS THEY WERE VIKING SHIPS I WAS FROZEN WITH
FEAR I SHOOK THE FEAR OFF AND COLLECTED THE WOOD
I RAN OFF HOME THEY WERE LANDING I DROPPED THE
WOOD AND RAN UP THE HILL THE DRIFTWOOD WONT MATTER
I TOLD MY FATHER THERE IS NOT MUCH TIME GATHER
THE WEAPONS WHILE I GIVE THE ALARM SO I GOT
ALL THE WEAPONS THEN I SAW THE VIKINGS COMING UP
THE PATH I TOOK A PIKE I RAN OUT THE
FIRST I RAMMED INTO WITH MY PIKE THE SECOND PUT
UP A FIGHT THE OTHERS STARTED UP IT WAS ONE
AGAINST NINE I WAS SAVED BY THE CRIES OF THE
OTHERS NOW IT WAS TWENTY AGAINST NINE INCLUDING ME I
GOT A GOOD RUN AT ONE OF THEM I RAMMED
MY PIKE AT HIM HE FELL DOWN IT WAS NOW
TWENTY AGAINST EIGHT THEY HAD NO CHANCE SOON THEY SURRENDERED
WE TOOK THEM PRISONER I THINK I DID JOLLY WELL
FOR A GIRL I GOT A REWARD I DID NOT
HAVE TO COLLECT DRIFTWOOD ANYMORE

92C
HELLO I AM SULTANA THE FIRST KING OF THE RAISINS
YOU SEE ALL THE KINGS AND QUEENS ARE CALLED SULTANAS
AND ALL THE REST ARE RAISINS I AM ALL EXITED
BECAUSE I AM GOING TO BE ON THIS IS YOUR
LIFE AT THE STUDIO SULTANA THE FIRST I PRESUME IN
1973 YOU SAILED ON A GIANT SHIP OVER TO ENGLAND
AND ON THAT SHIP WAS FAMOUS CAPTAIN RAISIN COOK AND
HERE HE IS HI LIKE TO GO BACK AGAIN I
REALLY REALLY WOULD RATHER THAN BEING BURNT IN A CHRISTMAS
CAKE IS IT NOT OF COURSE SAID CAPTAIN RAISIN COOK
NOT NOW TOMORROW WE WILL SET SAIL NEXT DAY OH
HELLOW SULTANA I CAN RESCUE EVERY RAISIN AND SULTANA IN
THAT TIN WELL GET ON WITH IT SAID SULTANA SOON
THEY WERE ALL ABOARD THEY SAILED FOR NINE DAYS AND
LANDED IN THE WRONG PLACE BUT THERE WERE NO HUMANS
ON IT SO FOR ALL I KNOW IF YOU FIND
THE ISLAND YOU WILL FIND MILLIONS OF SULTANAS ANS RAISINS

94C
I AM A APPLE HANGING ON A TREE ONE DAY
I DROPPED AND ROLLED DOWN A HILL AND A BOY
KICKED ME ON SO I ROLLED ON AND ON SOON
A WIND CAUGHT UP AND BLEW ME ON I WENT
OVER A STONE OW I HAD A BRUISE ON ME
NOW SOON I SAW WATER IN SIGHT OH YES IT
WAS THE RIVER ENDRICK OH NO I AM HADING FOR
IT SOON I WAS RIGHT BESIDE THE RIVER ENDRICK SUDDENLY
I BOUNCED RIGHT INTO THE RIVER I FLOATED ON SOON
I SAW ANOTHER APPLE THE WATER WAS GETTING DEEPER AND
DEEPER AND A WHOLE LOAD OF STONES WERE COMING INTO
THE WATER WE ARE NEARLY IN LOCH LOMOND JUST A
WEE BIT MORE AH WE ARE IN IT OH GOSH
I AM SINKING OH THAT WAS CLOSE WE ARE COMING
UP FOR RIVER LEVEN LOOK I CAN SEE A LITTLE
STICKS JOINED TOGETHER IT IS A MINITURE RAFT I THINK
I WILL TRY TO GET ON IT NO IT HAS
SUNK HERE COMES THE RIVER CLYDE I THINK I AM
DROWNING OH NO HERE IS THE SEA GOOD BYE

95C
MY NAME IS ANNE SOFIE GRAFF AND I WAS BROUGHT UP WITH MY DADDY MY DADDY IS A HOUSEMASTER AT A BOARDING SCHOOL FOR BOYS CALLED BALLIKINRAIN SCHOOL AND WITH THESE BOYS I HAVE BEEN BROUGHT UP ALL MY LIFE SINCE I WAS THREE I GO TO KILLEARN PRIMARY THIS COMMING YEAR I WILL BE GOING IN TO PRIMARY SIX MY SCHOOL IS NOT THAT BAD BUT WE HAVE GOT A HORRIBLE HEADMISTRESS WHO IS VERY STRICT TO THE CHILDREN IN PRIMARY ONE THERE IS MISS NORDON SHE IS TERRIBLE IN PRIMARY TWO MISS GARY SHE IS OKAY AND IN THE OTHER PRIMARY TWO THERE IS MISS LEONARD SHE IS HORRIBLE IN PRIMARY THREE THERE IS TWO TEACHERS MISS YOUNG AND MISS FLEMMING MISS YOUNG IS LOVELY AND KIND AND GENEROUS BUT MISS FLEMMING IS QUITE THE OPPOSITE IN PRIMARY FOUR THERE IS MISS DAVIES HER HUSBAND IS MY DADDYS BOSS AND SHE WAS HORRIBLE I HATED HER AND I STILL DO AND LAST YEAR I HAD MRS WYLLIE WHOM I LOVED VERY DEARLY I HAD A LOVELY YEAR WITH HER HER HUSBAND WORKS WITH MY DADDY SHE WAS HONEST SWEET INTELLIGENT AND GOOD WITH CHILDREN AND NEXT YEAR I FEAR I GET MISS LINDSAY LUCKELY SHE IS NOT STRICT BUT SHE IS SO BORING IN PRIMARY SEVEN THERE IS ANOTHER MISS YOUNG FROM WHAT I HEAR SHE IS ALLRIGHT WELL THAT IS IT ABOUT MY SCHOOL DADDY AND I HAVE MOVED TO A NEW HOUSE DOWN NTHE ROAD IT IS A BEAUTIFUL LITTLE OLDFASHIONED ENGLISH COTTAGE WITH SPIRAL STAIRCAS

AND STRANGE SQUINT WALLS FOR MY BIRTHDAY I AM GETTING A KITTEN DADDY IS GIVING ME THE KITTEN AND CAT TRAY AND A LOVELY TIME AND NANNA IS GIVING ME A CAT BASKET I AM GOING TO BY IT LOTS OF THINGS DO NOT ASK ME WHERE I GET THE MONEY FROM BECAUSE I DO NOT KNOW MYSELF EVERY YEAR DADDY AND I GO TO DENMARK FOR OUR SUMMER HOLIDAY TO SEE NANNA THIS IS OUR HOME COUNTRY WHERE BOTH DADDY AND I WERE BORN WE ALWAYS HAVE A LOVELY TIME WE HAVE JUST COME BACK A FEW WEEKS AGO WE HAD A LOVELY TIME IT ALL STARTED EARLY ON SUNDAY MORNING AT SEVENTHIRTY WHEN WE BOTH HAD TO WAKE UP AND GET READY TO LEAVE WE HAD PACKED OUR SUITCASES THE NIGHT BEFORE SO WHEN WE WERE READY WE LEFT TO CATCH THE BOAT AT NEWCASTLE TO ESBJERG WE SAILED ON THE WINSTON CHURCHILL AND HAD THE COLD TABLE WHEN WE WERE IN DENMARK THE NEXT DAY WE HAD TO DRIVE TO ANOTHER SHIP THAT WAS ONLY FOR AN HOUR ON IT I HAD A BOTTLE OF FIZZY DRINK IN DANISH CALLED SODAVAND THEN WHEN WE CAME OFF THAT BOAT DAD HAD TO DRIVE TO NANNA IN THE COUNTRYSIDE FOR SHE HAS ALSO ONE IN TOWN IT WAS GOOD TO SEE NANNA AGAIN AND MY OLD ROOM NOTHING HAD CHANGED ON WEDNESDAY WE WENT TO COPENHAGEN TO THE CINEMA TO SEE PRIVATE BENJAMIN AND LIFE OF BRIAN WE SPEND MOST OF OUR TIME WITH OUR GREAT FRIEND DITTE WE ALSO WENT TO A FAMOUS FARE GROUND CALLED TIVOLI WE WENT ON THE HELTER SKELTER AND THE CART IN FRONT

OF US BROKE DOWN BUT LUCKELY IT WAS LOW DOWN
AND NOBODY WAS HURT I GOT A LOVELY RED BALLOON
CALLED TEDDY WHICH I AM VERY FOND OF IN TIVOLI
THERE IS LOTS OF WATERFALLS WHICH CHANGE ABOUT EVERY FIVE
MINUTES AND ON THE SAME NIGHT WE SAW THE FIREWORKS
THE BOYS FROM BALLIKINRAIN ARE AGES FROM SEVEN TO SIXTEEN
SOME ARE THIEVES SOME GLUESNIFFERS AND SOME DODGE SCHOOL AND
SOME ARE JUST THERE BECAUSE THEIR PARENTS DO NOT WANT
THEM MOST OF THE BOYS HAVE BEEN BROUGHT UP BY
OTHER PEOPLE BECAUSE THEIR PARENTS DID NOT CARE OR SOME
HAVE NOT BEEN BROUGHT UP ATT ALL THEY HAVE JUST
WANDERED AROUND LOOKING FOR FOOD IN BINS AND ALSO STEALING
FOR FOOD THE ONES THAT DODGE SCHOOL ARE NORMALLY THE
KINDEST FOR THEY HAVE NOT BEEN INVOLVED IN VIOLENCE BUT
SOME OF THEM DO ALL IN THE SCOOL NOW THERE
ARE TWO BOYS WHO MURDERED AN OLD LADY BY BREAKING
IN TO HER HOUSE TYING HER TO HER BED AND
GAGGING HER THEN SETTING FIRE TO HER HOUSE BUT ON
ONE OF THE BOYS NO ONE WOULD THINK THAT HE
WAS A MURDERER HE IS KIND FUNNY AND CLEVER BUT
ON THE OTHER BOY HE IS SELFISH GREEDY A SLAGGER
AND STARTS FIGHTS I DO NOT REALLY LIKE HIM MY
FAVORITE BOYS ARE SIMON JAMES AND ROBERT BALLIKINRAIN ITSELF IS
AN OLD CASTLE BUILD BY A MAN CALLED ARCHIBALD ORR
EWING WHICH HE USED AS HIS HOUSE IT WAS THEN
USED AS A HOTEL THEN IT WAS A GIRLS SCHOOL
CALLED SAINT HILDAS AND NOW IT IS A BOARDING SCHOOL
FOR BOYS BALLIKINRAIN WAS BURNT DOWN IN 1916 BUT WAS
REBUILD AGAIN A FEW MONTHS AGO THERE WAS A ROBBERY
AT BALLIKINRAIN THEY STOLE GOODS WORTH 1000 POUNDS ONE OF
THE BOYS DID IT AND WAS FOUND OUT BY THE
STAFF LISTENING IN ON HIS PHONECALLS THEY STOLE A VIDEORECORDER
CASSETTE CAR TV AND BOYS POCKET MONEY

96C
DADDY AND I HAVE GOT SOME VERY GOOD FRIENDS CALLED
TOM AND ROSEMARY THEY HAVE GOT TWO CHILDREN MICHAEL IS
THE OLDEST AND FREDERICK WHO IS THE YOUNGEST WE KNOW
THEM THROUGH TOM WHO WAS A HOUSEMASTER AT BALLIKINRAIN WORKING
WITH MY DADDY I LOVE BOTH FREDERICK AND MICHAEL AS
MY LITTLE BROTHERS MICHAEL IS THREE AND FREDERICK IS JUST
COMMING UP FOR ONE SO OF COURSE I FEEL CLOSER
TO MICHAEL THAN I DO TO FREDERICK BUT FREDERICK IS
STILL SWEET BEFORE DERRI WAS BORN WE CALL HIM DERRI
IT IS SHORTER ANYWAY A FEW YEARS BEFORE DERRI WAS
BORN TOM ROSEMARY AND MICHAEL WENT TO DENMARK WITH US
DADDY ME AND NANNA STAYED IN THE COUNTRYSIDE WHILE TOM
ROSEMARY AND MICHAEL HAD THE FLAT IN COPENHAGEN WE ALL
WENT TO TIVOLI BUT MICHAEL WAS ONLY COMING UP FOR
ONE SO OF COURSE HE COULD NOT UNDERSTAND MUCH I
WOULD LOVE IT IF MICHAEL AND HIS FAMILY COULD COME
TO DENMARK WITH US THIS COMING SUMMER BECAUSE MICKY WOULD
BE OLD ENOUGH TO COME ON ALL THE GAMES WITH
ME IT WOULD BE SUCH FUN I WOULD BUY HIM
ONE OF TIVOLIS SPECIAL ICECREAMS WITH A CHOCOLATE MARSHMALLOW ON
TOP A SPOONFULL OF WHIPPED CREAM AROUND IT AND UNDER
THAT STRAWBERRY JAM AND UNDER THAT FIVE DIFFERENT KINDS OF
ICECREAM RED YELLOW GREEN AND WHITE THEN I COULD TAKE
HIM ON THE VIKING BOATS THAT GO UP AND DOWN
ROUND AND ROUND I WOULD NOT TAKE HIM ON THE
HELTER SKELTER I THINK HE WOULD BE TOO FRIGHTENED I
WOULD TAKE HIM IN THE GOST HOUSE BUT I WOULD
TELL HIM NOT TO BE SCARED BECAUSE IT WAS NOT
REAL AND THAT IT WAS QUITE PRETTY BECAUSE IT WAS
WITH A RED LIGHT SHINING AND LEAVES AND PLANTS DROOPING
DOWN EVERYWHERE THERE WAS A LOCH NESS MONSTER BUT THAT
WAS NOT FRIGHTENING IT WAS JUST FUNNY

100C
CRACK WENT ANOTHER OF PROFESSOR DANIEL MACNABS TEST TUBES OH DEAR AS HE SPILT SOME ACID ON THE FLOOR THIS WEEK HAD BEEN A TERRIBLE ONE FOR THE PROFESSOR HE HAD BROKEN EIGHTEEN TEST TUBES AND SET ALIGHT HIS JACKET TWICE THAT NIGHT AFTER HE HAD DONE ALL HIS EXPERIMENTS HE SAID WHY DONT I TAKE A HOLIDAY TO GET AWAY FROM ALL THIS CHEMISTRY AND HE DID THE NEXT DAY HE DECIDED TO GO TO BLACKPOOL WHEN HE WAS THERE HE HAD GREAT FUN BESIDES A FEW UPS AND DOWNS FOR INSTANCE WHILE ON A BOAT TOUR HE FELL OVERBOARD ANOTHER TIME HE WAS WALKING ALONG THE BEACH AND HE STEPPED IN A BUCKET AND FELL IN TO A HOLE WHICH SOMEONE HAD DUG AND IT WAS SO DEEP HE WAS THERE FOR THE NIGHT ANOTHER INCIDENT WAS WHEN HE WAS POSTING A POSTCARD HIS HAND GOT STUCK IN THE SLIT AND THE FIRE BRIGADE HAD TO COME TO FREE IT AFTER A WEEK HE WENT BACK HOME THEN HE HAD A BRAINWAVE TO HIMSELF HE SAID WHY DONT I WRITE A BOOK ABOUT MYSELF AND HE DID THE BOOK WAS A GREAT SUCCESS AND SOON THE PROFESSOR WAS PRETTY RICH WHICH HE SPENT NEARLY ALL OF HIS MONEY ON REPLACING BROKEN TEST TUBES

101C
IT WAS A MONDAY MORNING AND I WOKE UP IN
A TERRIBLE MOOD I WAS JUST ABOUT TO GET OUT
OF BED WHEN THE SPRINGS WENT AND I FELL THROUGH
THE SPRINGS ONTO EMMA AND WOKE HER UP WITH A
SCREAM THEN WHEN I WAS JUST ABOUT TO GET OFF
EMMA WHEN I BUMPED MY HEAD I THOUGHT I HAD
BETTER GET DRESSED BUT COULD NOT FIND MY CLOTHES IN
A TERRIBLE RAGE I WENT DOWN STAIRS INTO THE KITCHEN
AND TRIPPED OVER A HOT WATER BOTTLE THAT WAS ON
THE KITCHEN FLOOR I LOOKED AT THE TOAST IT WAS
BURNT THEN I SAW SOME FRIED RUBBER EGGS YUG SUDDENLY
THE DOORBELL WENT IT WAS MY FRIEND I MANAGED TO
FIND SOME CLOTHES I PUT THEM ON EVENTUALLY AT ONE
MINUTE TO NINE MUM GAVE A LIFT TO SCHOOL I
SLAMMED THE CAR DOOR AND IT FELL OFF I GOT
TO SCHOOL AT NINETHIRTY THE DAY ACTUALLY WENT QUITE SMOOTHLY
UNTIL I WAS WALKING HOME WHEN I TRIPPED AND FELL
HEAD FIRST INTO A COWS PANCAKE I WENT HOME BUT
MUM WAS NOT THERE SO I GRABBED THE NEAREST THING
WHICH I FOUND OUT WAS A 100 YEAR OLD CLOTH
IT WAS MUMS ONLY GOOD ONE I TURNED ON THE
TELEVISION AND IT EXPLODED I THOUGHT I HAD BETTER LISTEN
TO THE WIRELESS BUT THE BATTERIES HAD GONE I WENT
TO DO MY HOMEWORK WITH THE CALCULATOR BUT IT HAD
GONE WRONG AT LAST I WENT TO BED AND HAD
QUITE A GOOD NIGHTS SLEEP

102C
HAPPINESS TO ME IS A GOOD HOME NICE PARENTS AND
GORGEOUS PETS AND ALSO FRIENDS HAPPINESS IS IN YOUR SURROUNDINGS
HAPPINESS IS IN THE AIR BEING HAPPY COMES NATURAL TO
MOST PEOPLE LIFE IS HAPPINESS CHILDREN AND BABIES THAT CRY
ARE HAPPINESS TO THEIR MOTHERS JESUS IS HAPPINESS TO EVERYBODY
JESUS IS LIFE LITTLE THINGS LIKE DOLLS ARE HAPPINESS TO
THE CHILDREN HAPPINESS IS WORK AT WORK YOU EARN MONEY
TO GIVE YOUR FAMILY HAPPINESS HAPPINESS IS REST AT REST
YOU DRINK JUICE AND SIT DOWN THAT GIVES HAPPINESS TO
YOURSELF PLAYING IS HAPPINESS WHEN YOU PLAY YOU GIVE YOURSELF
HAPPINESS AND YOUR FRIENDS YOUR FRIENDS ENJOY YOUR COMPANY AND
YOUR FRIENDS HAVE FUN AS WELL AS HAPPINESS WHEN YOU
WORK REST AND PLAY YOU BRING HAPPINESS TO EVERYONE HAPPINESS
WILL LAST I HOPE FOR ETERNITY IT WILL NEVER DIE
LOVE IS HAPPINESS TO EVERY SINGLE HUMAN ON EARTH WHEN
THE SUN SHINES I AM VERY HAPPY I AM SOMETIMES
SAD BUT THEN I REGRET IT AND SMILE

103C
THE BEST PRESENT I HAVE EVER RECEIVED WAS MY PONY
I GOT HIM A BIT EARLIER THAN MY BIRTHDAY BECAUSE
I WANTED TO SEE WHAT HE WAS LIKE ACTUALLY I
WENT TO SEE HIM IN NOVEMBER AND MY BIRTHDAY IS
IN JANUARY BUT I COULD NOT RIDE HIM THEN BECAUSE
IT IS TOO ICY AND SNOWY ANYWAY WHEN WE GOT
THERE HE WAS IN THE FIELD HE LOOKED LOVELY HE
WAS QUITE BIG THOUGH AND HE WAS VERY VERY WHITE
THE LADY CAME OUT AND WE TRIED TO CATCH HIM
YOU SEE HE IS HARD TO CATCH WE HAD TO
TAKE SOME OTHER PONIES OUT OF THE FIELD THEN WE
CAUGHT HIM AFTER THAT WE GAVE HIM A WEE BRUSH
AND PUT HIS SADDLE AND BRIDLE ON THEN I JUMPED
ON AND I RODE HIM DOWN TO A FIELD WHICH
HAD BARLEY GROWING IN IT I STARTED TO TROT THEN
I JUST NEEDED TO SQUEEZE HIM AND HE TOOK OFF
INTO A CANTER IT WAS LOVELY THEN THE LADY PUT
UP A JUMP AND HE JUMPED IT ONCE OR TWICE
THEN WE WENT BACK AND WE PUT HIM BACK IN
THE FIELD WHEN WE GOT HOME I DECIDED THAT I
WANTED HIM AND THAT I WOULD LOOK AFTER HIM PROPERLY
SO I GOT HIM ON MY BIRTHDAY MY BEST PRESENT
YET

104C
ALAN ROUGH STEPPED OUT ONTO THE FOOTBALL PITCH READY TO PLAY HIS FIRST GAME FOR SCOTLAND I WAS IN THE CROWD WATCHING HIM THE REFEREE CALLED THE TWO CAPTAINS UP IT WAS SCOTLAND VERSUS A WORLD TEAM AT WEMBLEY STADIUM THE TWO CAPTAINS WERE KENNY DALGLISH FOR SCOTLAND AND PELE FOR THE WORLD TEAM DALGLISH WON THE TOSS AND ELECTED TO KICK OFF DALGLISH KICKED THE BALL BACK TO SOUNESS WHO LOST IT TO KROL A GREAT BALL BY KROL SENT KEEGAN RACING THROUGH HE BEAT MCGRAIN AND HIT THE BALL TOWARDS THE GOAL BUT SOMEHOW ROUGH MANAGED TO PUSH THE BALL AWAY FOR A CORNER THE CORNER WAS TAKEN BY BONHOF WHO FLIGHTED THE BALL INTO THE AREA BUT MCQUEEN HEADED THE BALL AWAY THEN ZICO VOLLEYED THE BALL STRAIGHT TOWARDS THE GOALS BUT ROUGH SOMEHOW NOT ONLY STOPPED IT HE CAUGHT IT HE HIT A LONG BALL RIGHT INTO THE OTHER TEAMS PENALTY AREA DALGLISH AND KEEGAN WERE HAVING A TUSSLE FOR THE BALL WHEN KEEGAN BROUGHT DOWN DALGLISH IT WAS A PENALTY THE SCOTTISH TEAM DID NOT KNOW WHO SHOULD TAKE IT THEY FINALLY MADE UP THEIR MINDS THAT IT WAS TO BE ROUGH HE STEPPED UP AND SENT SHILTON THE WRONG WAY ALAN ROUGH REALLY LIVED UP TO HIS NAME

11OC
KIRSTY AND I WERE WALKING THROUGH THE WOODS WHEN WE
SAW A SPACESHIP THERE WAS NO SIGN OF MOVEMENT INSIDE
SO WE WENT INSIDE TO HAVE A LOOK KIRSTY TRIPPED
OVER A STONE THAT WAS CARELESSLY DROPPED ON THE FLOOR
SHE HIT A BUTTON THAT SAID VEBER ON IT THERE
WAS A SUDDEN JERK THE DOOR CLOSED I LOOKED OUT
THE WINDOW AND FOUND WE WERE FLYING THROUGH SPACE I
CALLED KIRSTY TO HAVE A LOOK IT WAS WONDERFUL TO
SEE STARS SO CLOSE UP BUMP BUMP WE HAD HIT
SOMETHING HARD IT WAS A PLANET WE PRESUMED IT WAS
VEBER KIRSTY PRESSED A BUTTON IT OPENED THE DOOR ALL
WE COULD SEE WAS BLACK AND BLUE STONES THEY WERE
FUNNY KIRSTY STEPPED OUT AS SOON AS HER FOOT TOUCHED
THE GROUND SHE TURNED INTO STONE I WAS AFRAID TO
TOUCH HER IN CASE I TURNED TO STONE AS WELL
I WENT TO HAVE A DRINK BECAUSE A DRINK ALWAYS
MAKES ME FEEL BETTER WHEN I WAS DRINKING A DROP
OF WATER FELL FROM MY CUP AND FELL ON TO
KIRSTY SUDDENLY SHE CAME ALIVE AGAIN SHE JUMPED INTO THE
SPACESHIP AND TOLD ME THAT WE HAD TO GO HOME
I PPRESSED THE BUTTON WHICH SAID EARTH ON IT IN
FIVE SECONDS THERE WAS A THUD WE HAD REACHED EARTH
AS SOON AS WE WERE OUT THE SPACESHIP IT DISAPPEARED
AND KIRSTY AND I FOUND OURSELVES BACK IN THE WOODS
THIS IS THE FIRST TIME I HAVE EVER TOLD THIS
STORY TO SOMEONE BECAUSE FOR A WHILE KIRSTY AND I
COULD NOT BELIEVE IT HAD HAPPENED

111C
I AM ON OLD PINE TREE I LIVE IN THE
SUBURBS OF LONDON IN A SMALL WOOD IN MY TIME
I HAVE SEEN MANY GOINGS ON AND MANY STRANGE BIRDS
ONE SUMMER TWO STRANGE YELLOW BIRDS CAME TO ME AND
NESTED IN MY BRANCHES A FEW MONTHS LATER SOME CHICKS
HATCHED OUT THEN A BIRD WATCHER CAME AND STUDIED THEM
HE DISCOVERED THAT THEY WERE A VERY RARE BREED AND
I WAS HONOURED TO HAVE THEM AS GUESTS ANOTHER TIME
TWO YOUNG LOVERS WERE PASSING WHEN THE BOY TOOK OUT
A PENKNIFE AND CARVED HIS AND HIS GIRLFRIENDS NAME IN
ME IT WAS VERY SORE BUT NOT VERY DEEP SO
IT SOON HEALED ONE STORMY NIGHT IT STARTED THUNDERING AND
LIGHTNING I WAS VERY SCARED THEN SUDDENLY IT HIT ME
AS SOON AS IT STRUCK I WENT ON FIRE BUT
SOME KIND PEOPLE SAW ME AND PUT OUT THE FIRE
IMMEDIATELY ONE DAY SOME MEN CAME AND CUT ALL MY
NEIGHBOURS DOWN I THOUGHT THEY WERE GOING TO CUT ME
DOWN WHEN I HAD SOMETHING SHOVED ON TOP OF ME
AND THEN IT WAS NAILED ON IT HURT DREADFULLY IT
STILL DOES WHEN THE WIND BLOWS ME SOME PASSERS BY
SAY TO ME MY MY THEN YOU ARE THE OLDEST
TREE IN THE CITY ARE YOU SO I GUESS THAT
IS WHAT IT SAYS

112C
I HAVE JUST GOT A NEW JOB AT ST ANDREWS
GOLF COURSE AS A GREEN KEEPER I WANTED TO TAKE
UP THIS SPORT SO THAT I COULD SEE THE DIFFERENT
COURSES AND THE DIFFERENT PLAYERS ON MY FIRST DAY I
WENT TO THE PROFESSIONALS SHOP TO SEE IF I COULD
GET A MINI CAR TO GO ROUND THE HOLES TO
GET USED TO THEM I WENT TO THE SHOP EVERY
WEEK TO LEARN TO PLAY GOLF AND AFTER FIVE WEEKS
I WAS PLAYING GOLF WELL SO NOW I GO ROUND
PLAYING GOLF AND SORTING THE GREENS AS WELL WHEN I
HAD BEEN AT THE JOB FOR FOUR YEARS THE MANAGER
PUT ME TO THE TEST OF BEING A PROFESSIONAL I
DID WELL SO HE GAVE ME THE JOB ONE WEEK
LATER I GOT A PHONE CALL AND THE MAN SAID
WOULD YOU LIME TO PLAY IN AMERICA OPEN I SAID
YES SO I WENT AND WON A BIG TROPHY

113C
SOME PEOPLE THINK THAT ALL THE ANIMALS IN THE WORLD
HAVE BEEN DISCOVERED WELL THIS STORY SHOWS JUST HOW WRONG
THEY ARE THERE IS AN ANIMAL THAT LIVES IN EGYPT
CALLED THE ELEPHEROO IT HAS A TRUNK THE SAME LENGTH
AS AN ELEPHANTS IT HAS THE BODY AND THE HEAD
OF A KANGAROO AND THE LEGS OF AN ELEPHANT IT
IS GREEN WITH PINK AND YELLOW SPOTS AND EATS SAND
AN ANIMAL CALLED A RABBADOG IS FOUND IN DESOLATE PARTS
OF SOUTH AFRICA IT HAS A RABBITS TAIL RABBIT EARS
AND A RABBITS HEAD IT HAS A DOGS BODY AND
A DOGS LEGS IT IS A VERY SMALL ANIMAL BUT
ALSO VERY VICIOUS AND STRONG IT EATS GRASS AND IS
BLUE WITH YELLOW STRIPES THE ZEBRINGO HAS THE HEAD OF
A ZEBRA AND THE BODY AND LEGS OF A FLAMINGO
IT CAN FLY AND EATS MICE AND GRASS IT CAN
RUN VERY FAST AND HAS BEEN KNOWN TO RUN AT
35 MPH IT IS PINK AND WHITE WITH BLACK STRIPES

114C
THE DEW HAD NOT YET SETTLED ON THE GROUND WHEN
THE SQUADRON WAS TO EMBARK ON A MISSION ALREADY TWO
PLANES HAD TAKEN OFF INTO THE FROSTY MORNING HEADING EITHER
TO DEATH OR GLORY TEN OR SO MINUTES LATER BLOCKBUSTER
SQUADRON AS WE WERE KNOWN WAS OVER NO MANS LAND
AND INTO THE FORBIDDING ENEMYS TERRITORY OUR TARGET THE POISONOUS
GAS FACTORY AT COLOGNE IN GERMANY BY THE TIME WE
WERE HALFWAY THERE WE CAME UNDER HEAVY ENEMY FLAK ONE
PLANE WAS HIT IN THE FUEL TANK AND BLEW UP
ANOTHER THE PILOT WAS HIT IN THE STOMACH AND WAS
SENT TO HEAVEN OR HELL WE PRESSED ON BRAVELY THE
COLD BITING AIR NIPPING OUR FACES RELUCTANTLY I SOUNDED THE
FALL BACK AND BY THE TIME WE HAD REACHED THE
BASE I HAD LOST HALF THE SQUADRON 12 MEN IN
ALL I WOULD HAVE A LOT OF LETTERS TO WRITE
IN THE NEXT DAY OR SO A WEEK PASSED UNTIL
ONE DAY A GERMAN PLANE FLEW LOW OVER OUR BASE
AND DROPPED A NOTE AND THEN FLEW OFF INTO THE
CLOUDY SKY I PICKED UP THE NOTE AND IT READ
I ERNST VON SHONVAST CHALLENGES THE BLOCKBUSTER SQUADRON TO A
DUEL A 0600 HRS TOMORROW I DECIDED TO ACCEPT SINCE
VON SHONVAST WAS A THORN IN THE SIDE AND NEEDED
TO BE TAUGHT A LESSON THE MORNING WAS SURPRISINGLY BRIGHT
AND WE HAD THE ADVANTAGE OF THE SUN AT OUR
BACK BY THE TIME WE HAD TAKEN OFF IT WAS
0600 HRS AND TIME FOR THE DOG FIGHT TEN MINUTES
PAST AND WE MET VON SHONVASTS SQUADRON ALMOST IMMEDIATELY VON
SHONVAST A GREAT ACE SHOT DOWN ONE PLANE I DECIDED
TO TRY AND END HIS PLIGHT I CAME SCHREECHING IN
FOR THE KILL AND SQUEEZED ON THE TRIGGER 100 OR
SO BULLETS CAME SCHREECHING THROUGH THE SKY AND HIT THE
GERMAN ACES TAIL ALMOST IMMEDIATELY THE PLANE EXPLODED INTO FLAMES
KILLING VON SHONVAST BY NOW WE HAD LOST 3 PLANES
OUT OF 14 AND DESTROYED 8 OUT OF THEIR 14
PLANES SOON WE WERE BLASTING THE DEMOROLIZED GERMANS OUT OF
THE SKY THE REMAINING THREE GERRIES HAD ENOUGH AND RETREATED
THE BATTLE WAS WON

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130C
ONE DAY OLD COCKER WENT TO ROB A BANK AND
HE GOT ALL THE MONEY OUT IT AND TWO OF
HIS MATES WERE WAITING IN THE CAR AND OLD COCKER
SHOT THEM BOTH AND KICKED THEM OUT OF THE CAR
AND HE DRIVES OFF TO AN OLD BARN AND ONE
OF HIS MATES WAS STILL ALIVE AND HE TOLD THE
POLICE AND THEY GOT TOGETHER AND WENT TO THE BARN
BUT HE WAS NOT THERE BUT SOME FIVE POUND NOTES
WAS ON THE FLOOR AND THEY TRIED TO PICK UP
HIS TRAIL BUT FAILED MR COCKER WAS HIDING IN A
HOTEL IN LONDON BUT THERE WAS A SPY WATCHING HIM
AND MR COCKER SAW THIS MAN SPYING ON HIM AND
HE SNEAKED UP ON HIM AND STABBED HIM AND WENT
BACK TO THE HOTEL THE POLICE WAS THERE IN THE
MORNING AND FOUND HIM AT THE EDGE OF THE WALL
THEN MR COCKER CAME TO THE WINDOW AND SAW THE
POLICE AND ONE OF THE POLICE LOOKED UP AT THE
HOTEL AND SAW THE BANK ROBBER MR COCKER MR COCKER
GOT OUT THE BACK WAY BEFORE THE POLICE GOT UP
TO HIS ROOM HE HAD GOT AWAY MR COCKER WENT
TO TEXAS HE WAS FLYING ON THE PLANE FOR ABOUT
FIVE HOURS THE PILOT SAID THEY WERE LANDING IN TEN
MINUTES HE GOT OFF THE PLANE AND TWO MEN TOOK
HIM TO THE POLICE STATION AND HE GOT TOOK TO
COURT AND HE HAD A PLAN TO ESCAPE WHEN HE
WAS IN THE COURT WHEN THE JUDGE SAID HE WAS
SENTENCED TO LIFE IN JAIL HE WAS LISTENING FOR A
TRUCK AND HEARD THE TRUCK COMING HE DIVED OUT OF
THE WINDOW AND LANDED ON A HAYSTACK AND GOT AWAY
AND HE WAS DOING MURDERS AND ROBBING BANKS MR COCKER
WAS IN A LITTLE HOUSE IN THE COUNTRY AND THE
HOUSE WAS SURROUNDED AND THEY SAID COME OUT WITH YOUR
HANDS UP AND DROP YOUR GUNS IF YOU DO NOT
WE WILL COME AND MR COCKER SAID COME AND GET
US YOU RATS AND STARTED TO FIRE AT THE POLICE
MR COCKER AND BOBO HIS MATE HE SAID TO THE
REST OF HIS MATES ME AND BOBO ARE GOING TO
GET AWAY IF YOU COME OUT OF THIS ALIVE WE
WILL MEET YOU AT KONG HOTEL BOBO AND COCKER WENT
AND GOT AWAY BUT THERE WAS A ROAD BLOCK AT
THE END AND SMASHED RIGHT THROUGH THEM AND GOT AWAY
AND ROUND THE CORNER WAS THE HOTEL THEY WERE THERE
FOR A FEW DAYS ONE OF HIS MATES BURST THROUGH
THE DOOR AND SAID I WANT MY MONEY YOU RAT
IF YOU DO NOT GIVE IT TO ME I WILL
BLOW YOUR HEAD OFF THE MATE SAID WHERE IS BOBO
HE IS RIGHT BEHIND YOU PUNK KILL HIM BOBO AND
BOBO SHOT HIM SIX TIMES IN THE HEAD THE POLICE
GOT THERE AND BURST THROUGH THE DOOR AND SHOT OLD
COCKER IN THE HEAD TWICE IN THE LEG AND BOBO
SHOT THE POLICEMAN IN THE BACK AND THE REST OF
THE FORCE CAME IN AND SHOT BOBO AND MR COCKER
AND IT WAS ALL OVER THEY GOT MOST OF THE
MONEY BACK BUT MR COCKER HE GOT TOOK TO HOSPITAL

AND THE POLICE ASKED HIM WHERE THE MONEY WAS HE
TOLD IT WAS IN AN OLD BARN IN THE TOWN
AND THE POLICE GOT MOST OF THE MONEY BACK

AND THE POLICE ASKED HIM WHERE THE MONEY WAS HE
TOLD IT WAS IN AN OLD BARN IN THE TOWN
AND THE POLICE GOT MOST OF THE MONEY BACK

140C
IT ALL STARTED ON A STORMY AFTERNOON WHEN I WAS IN TOWN TO GET MY WEEKEND SHOPPING WHEN I PAST A MAN WHO LOOKED VERY SURPRISED SO I STOPPED HIM AND SAID WHAT IS YOUR NAME HE DID NOT ANSWER ME SO I SAID YOU LOOK AS IF YOU HAVE DONE WRONG SO HE STARTED TO STRUGGLE SO I GRABBED HIM BY HIS ARM AND SAID YOU ARE STAYING HERE AND HE SAID YOU CAN NOT KEEP ME HERE SO LET ME GO BEFORE I CALL THE POLICE YOU DO NOT HAVE TO CALL THE POLICE BECAUSE I AM A POLICE SO YOU JUST SHUT YOUR MOUTH BEFORE I BANG IT YOU CAN NOT DO THIS YOU ARE NOT ON DUTY I DO NOT HAVE TO BE ON DUTY TO ARREST SOMEONE YOU DO NOT THINK YOU ARE GOING TO ARREST ME DO YOU THAT IS RIGHT I AM SO COME ALONG QUIETLY OR I WILL DRAG YOU ALONG YOU WILL TRY AND DRAG ME ALONG DO YOU WANT TO SEE ME DO IT NOW DO YOU BECAUSE I DO NOT CARE IF I GET FIRED BECAUSE I AM JUST ABOUT TO LEAVE THE FORCE ANYWAY SO DO NOT GIVE ME ANY OF YOUR LIP I AM NOT GIVING YOU ANY LIP BECAUSE YOU ARE HEADING FOR A DOING SO JUST SHUT YOUR MOUTH WE WERE WALKING DOWN THE STREET WHEN HE STARTED TO STRUGGLE I SWORE TO HIM THAT IF HE DID NOT BUCKLE UP HIS IDEAS I WILL BURST HIM SO WE STARTED WALKING AGAIN AND HE STARTED SHOUTING AT THE PUBLIC AND SWEARING AT THEM SO I GRABBED HIM INTO A CLOSE AND BATTERED HELL OUT OF HIM AS I WAS DOING SO A MAN WALKED PAST AND LOOKED AT ME AND SAID WHAT DO YOU THINK YOU ARE DOING TO TAHT YOUNG MAN I TOLD HIM TO GET LOST BUT HE JUST STAYED THERE HE SAID I WILL GO AND PHONE THE POLICE IF YOU DO NOT LET THAT MAN GO I SAID YOU GO AND PHONE THE COPS BUT YOU ARE GOING TO REGRET IT I AM TELLING YOU BECAUSE I AM A COP SO YOU GO AND GET SOME HELP THE MAN WENT AND PHONED THE POLICE STATION THEY CAME THE MAN SAID I AM GOING TO TAKE YOU TO COURT AND GET YOU JAILED FOR LIFE I DO NOT KNOW WHAT CAME OVER ME BUT I PICKED UP A BOLDER AND THREW IT AT HIM HE JUST FELL TO THE GROUND AND AS HE FELL TO THE GROUND MY SERGEANT CAME AND GRABBED ME AND SAID WHAT DO YOU THINK YOU ARE DOING THAT WAS ASSAULT I DO NOT CARE BECAUSE HE WAS ASKING FOR THAT AND I GAVE HIM IT BUT THAT IS NOT THE POINT THIS YOUNG MAN WAS GOING TO TAKE YOU TO COURT AND SAVE YOU BECAUSE YOU HAVE JUST ASSAULTED THAT GUY YOU BLOODY IDIOT YOU DO NOT CARE ABOUT OTHER PEOPLE DO YOU ALL YOU THINK YOU CAN DO IS ATTACKING PEOPLE IN THE STREETS WELL THAT IS NOT ON THE TRIAL IS NEXT WEEK I HOPE YOU HAVE GOT A GOOD EXCUSE BECAUSE WE CAN NOT DO ANYTHING FOR YOU NOW THE TRIAL CAME AND I

WENT UP TO COURT THE COURT CASE LASTED A VERY
LONG TIME MORE THAN I WOULD HAVE EXPECTED IT TO
BUT AS THE CASE WENT ON THE JUDGE WAS BEGINNING
TO LOOK AT ME AS IF I WAS A MURDERER
THEN THE FINAL VERDICT CAME THE JUDGE SAID VERDICT PLEASE
THE VERDICT WAS GUILTY OF MANSLAUGHTER I COULD NOT BELIEVE
IT AND I GOT JAILED FOR LIFE

141C
IT ALL STARTED ON A SATURDAY MORNING WHEN I GOT A LETTER FROM MY DAD SAYING YOU ARE TO GO TO AFRICA FOR AN ASSIGNMENT SO THAT AFTERNOON I GOT A PLANE TO AFRICA AND THEN GOT A JEEP TO THE CAMP WHERE I WAS TO STAY FOR THE TWO WEEKS I WAS THERE I UNPACKED MY KIT AND HAD SOMETHING TO EAT AND THEN I MADE MY BED AND WENT TO BED AS I WAS SLEEPY NEXT MORNING I WOKE UP AND HAD A CUP OF TEA THEN I WENT DOWN TO THE STREAM AND HAD A SWIM THEN I CAME BACK UP AND PUT MY CLOTHES ON THEN I WENT DOWN TO THE NEAREST VILLAGE AND BOUGHT SOME FOOD FOR MYSELF I CAME BACK UP AND READ THE PAPER THEN I HEARD A BANG IT SEEMED TO COME FROM THE BACK OF MY HOUSE I GRAB MY GUN AND RAN TO WHERE I HEARD IT FROM I MANAGED TO FIND WHAT WAS UP IT WAS A HUNTER HE HAD JUST SHOT A MOTHER KANGOROO BY THE LOOKS OF IT THE MOTHER IS PREGNANT SO I CARRIED IT TO MY HOUSE AND PUT IT IN MY KITCHEN I CLEANED THE WOUND AND GOT THE BULLET OUT THE KANGOROO SEEMED TO BE ALLRIGHT SO I GOT A BLANKET AND WRAPPED IT TO KEEP IT WARM I DO NOT KNOW WHEN SHE IS DUE BUT I HOPE IT IS SOON BECAUSE I CAN NOT LEAVE HER AND THE BABY BEHIND SO THREE DAYS LATER I WOKE UP TO FIND THE KANGOROO HAD HAD THE BABY SO I WENT TO SEE IF THE MOTHER WAS ALLRIGHT I BENT DOWN TO CLAP HER BUT SHE WAS COLD I RECKONED SHE WAS DEAD SO I BURIED HER AND I DID NOT KNOW WHAT TO DO WITH THE BABY SO I BOILED SOME MILK UP AND GAVE IT THAT MY TWO WEEKS ARE NEARLY UP AND I DO NOT KNOW WERE TO PUT THE BABY KANGOROO SO I DECIDED THAT I WOULD TAKE IT BACK TO ENGLAND I DONATED IT TO CHESTER ZOO FOR PEOPLE TO COME AND SEE IT AND MAYBE THE KANGOROO MIGHT HAVE BABIES AND THEN WE WILL HAVE OUR OWN KANGOROOES BORN IN CAPTIVITY AND THAT WOULD MAKE FRONT PAGE IN THE DAILY RECORD AND MAYBE PEOPLE WOULD DONATE MONEY TO HELP THE KANGOROOES SO I GOT THE KANGOROO AND PUT IT IN A BOX AND WENT TO LONDON ZOO I TOLD THE MANAGER THAT I BROUGHT IT FROM AFRICA I TOLD HIM ALL THE STORY AND WHAT WAS GOING TO HAPPEN TO THE BABY KANGOROO SO WE FOUND A CAGE FOR IT TO STAY IN FOR THE MEANTIME SO I LEFT IT THERE FOR A FEW WEEKS WHEN I CAME TO VISIT IT THE MAN SAIS IT WAS VERY ILL AND HE SAIS IT MIGHT DIE WITHIN TWO OR TREE DAYS AT THE MOST I WAS VERY UPSET BECAUSE I LOVED THAT LITTLE THING IT WAS VERY CUTE AND IF IT DIES I WILL NEVER FORGIVE MYSELF BECAUSE IT WAS ME WHO BROUGHT IT OVER HERE I STARTED TO WALK TOWARDS MY CAR WHEN I HEARD THE VOICE OF THE DOCTOR SAYING COME BACK THE KANGOROO IS GOING TO LIVE

I RAN IN TO THE VET ROOM AND SAID IS
HE ALLRIGHT THEY SAID HE WILL LIVE I WAS SO
GLAD THAT I HUGGED THE LITTLE THING AND KISSED IT
AND SAID I AM GOING TO TAKE YOU HOME WITH
ME AND YOU CAN LIVE WITH ME AND I WILL
LOOK AFTER YOU FOR EVER AND EVER AND I WILL
NEVER GIVE YOU AWAY FOR ANYTHING IN THE WHOLE WORLD
SO I TOOK HIM HOME AND MADE A BOX FOR
HIM AND PUT IT NEXT TO THE FIRE TO KEEP
HIM WARM I GAVE HIM SOME WARM MILK AND SOME
APPLES AND SOME ORANGES AFTER THAT I GAVE HIM A
BLANKET THEN I PUT HIM IN HIS BOX PUT THE
BLANKET ON HIM AND THEN I PUT THE LIGHTS OUT
AND WENT UPSTAIRS AND GOT INTO MY BED AND I
READ FOR A WHILE THEN I PUT THE LIGHT OUT
AND WENT TO SLEEP

TEXT STRINGS WRITTEN BY ADULTS.

As a compromise between, on the one hand, the demand for a variety of styles, and on the other hand the limited scope of micro computing in terms of space and time, the following 22 text samples have been chosen from the three categories 'NEWSPAPERS', 'BOOKS FOR CHILDREN' and 'SCIENTISTS' as the data base of text strings written by adults. All text samples can be found in full on the following pages (pp.92 to 128) and comprise at least 600 words from the sources listed below:

SOURCE:	LABEL:	FILENAME:
SCIENTISTS:		
W.Frankena: Ethics	1FRK	FRANK
N.Chomsky: Aspects of Syntax	CHOM	CHOM
W.Labov: Logic of Non stand.Engl.	LAB	LABOV
J.S.Bruner: Study of Thinking.	BRU	BRUNER
B.Russell:History of W.Philosophy (2)	1/2RUS	RUS1/2
B.Russell:Principles of Mathematics	3RUS	RUS3
B.Russell:Hist.as it was never told	4RUS	RUS4
B.Russell:Childrens Stories.	5RUS	RUS5
NEWSPAPERS:		
Glasgow Herald	HRLD	HERALD
The Guardian	GUAR	GUARD
Daily Mail	MAIL	MAIL
Daily Record (2)	1REC and 2REC	DREC1 and DREC2
BOOKS FOR CHILDREN:		
A.A.Milne: Winnie the Pooh	POOH	POOH
L.Carroll: Alice in Wonderland	ALIB	ALICEB
L.Carroll: The Nursery Alice	ALIL	ALICEL
M.Bond: Paddington (4)	1/4PAD	PAD1/4
R.Bach: Jonathan Livingst.Seagull	GULL	GULL

Table 4.1 List of text samples written by adults

As the case was with the indexing of the children's text strings, the limitations of my computer system has necessitated slight variations in the labeling of each 'adult' string. On graphs and outputs of numerical data where the reference to the string appears with many other parameters, the text strings will always be referred to by their (shorter) label. As before, I have kept labels as informative as possible, even if it meant expanding the short three to four letter labels at the beginning of each text sample, eg. BRU has become BRUNER, and HRLD has become HERALD whenever possible in text and tables. It may sound confusing, but I believe it to helpful.

In the following all text samples are printed in full, and each category is introduced with a few comments.

TEXT STRINGS WRITTEN BY ADULTS

INDEX: PAGE:

SCIENTISTS:

In my selection of the first 7 of the following 9 text samples, the emphasis has been on complexity of information, a complexity which is sometimes, but not always mirrored in complexity of style. The last two samples, 'History as it was never told' and 'Children's stories' both by B.Russell, have been included in this category to facilitate comparison with the three preceding text samples by Russell.

M.Frankena's 'Ethics' (W.K. Frankena, 1963) is an introduction to ethics, which, in spite of the ethereal complexity of its subject, is down to earth, often almost Socratic in its approach.

The next two samples are written by language scientists. Chomsky's 'Aspects of the theory of syntax' is well known to most and does not need further introduction. Labov is one of the foremost American socio-linguists, well known for his analysis of the use of language as a means of social 'ranking'. The text sample used here is taken from W.Labov 'The logic of nonstandard English' (Labov,1969). I consider Labov's style to be very relaxed and uncomplex, quite different from that of Chomsky which tends to be 'super charged', one might even say: heavy.

Somewhere in between the styles of these two gentlemen I would place that of Jerome S. Bruner. The present sample is taken from 'A study of thinking' (J.S.Bruner,1967).

Bertrand Russell was a sublimely competent writer. One is bound to be impressed by the ease with which he brings over any subject matter, be it philosophy, mathematical theory or fiction, and the multitude of samples from his writings used in the present research, reflects basically the enjoyment I have experienced reading through his works. Particularly his 'History as it was never told' can be recommended.

The first two text samples of Russell is from his 'History of Western Philosophy' (B.Russell, 1969) and is really one string of 1200 words cut in to two strings of 600 each.

The next sample, in which he sets out his class theory, is from his 'The Principles of Mathematics' (B.Russell, 1956).

The last two text samples by B.Russell are from his 'Anecdotes' (B.Russell, 1972). 'History as it was never told' puts the spice back into history, and in 'Children's Stories' Russell recalls the stories he used to make up for his children when they were young. These, as well as the aforementioned samples are printed on the following pages.

1FRK

WE ARE TALKING HERE ABOUT DISTRIBUTIVE JUSTICE JUSTICE IN THE DISTRIBUTION OF GOOD AND EVIL THERE IS ALSO RETRIBUTIVE JUSTICE PUNISHMENT ETC ABOUT WHICH A LITTLE WILL BE SAID IN CHAPTER 4 DISTRIBUTIVE JUSTICE IS A MATTER OF THE COMPARATIVE TREATMENT OF INDIVIDUALS THE PARADIGM CASE OF INJUSTICE IF THERE IS ONE IS THAT IN WHICH THERE ARE TWO SIMILAR INDIVIDUALS IN SIMILAR CIRCUMSTANCES AND ONE OF THEM IS TREATED BETTER OR WORSE THAN THE OTHER IN THIS CASE THE CRY OF INJUSTICE RIGHTLY GOES UP AGAINST THE RESPONSIBLE AGENT OR GROUP AND UNLESS THAT AGENT OR GROUP CAN ESTABLISH THAT THERE IS SOME RELEVANT DISSIMILARITY AFTER ALL BETWEEN THE INDIVIDUALS CONCERNED AND THEIR CIRCUMSTANCES HE OR THEY WEILL BE GUILTY AS CHARGED THIS IS WHY SIDGWICK SUGGESTED HIS FORMULA ACCORDING TO WHICH JUSTICE IS THE SIMILAR AND INJUSTICE THE DISSIMILAR TREATMENT OF SIMILARS THIS FORMULA DOES GIVE A NECESSARY CONDITION OF JUSTICE SIMILAR CASES ARE TO BE TREATED SIMILARLY SO FAR AS THE REQUIREMENTS OF JUSTICE ARE CONCERNED ALTHOUGH THESE REQUIREMENTS MAY BE OUTWEIGHED BY OTHER CONSIDERATIONS BUT SIDGWICKS FORMULA IS NOT SUFFICIENT ALL IT REALLY SAYS IS THAT WE MUST ACT ACCORDING TO RULES IF WE MEAN TO BE JUST ALTHOUGH THIS FORMULA IS TRUE IT TELLS US NOTHING ABOUT WHAT THE RULES ARE TO BE AND THIS IS WHAT WE WANT TO KNOW SINCE WE HAVE ALREADY SEEN THAT RULES THEMSELVES MAY BE UNJUST IF THIS WERE NOT SO THERE COULD NOT BE UNJUST LAWS OR PRACTICES FOR LAWS AND PRACTICES ARE RULES MUCH DEPENDS ON WHICH SIMILARITIES AND DISSIMILARITIES OF INDIVIDUALS ARE TAKEN AS A BASIS FOR SIMILARITY OR DISSIMILARITY OF TREATMENT THE QUESTION WHICH REMAINS TO BE ANSWERED IS HOW WE ARE TO TELL WHAT RULES OF DISTRIBUTION OF COMPARATIVE TREATMENT WE ARE TO ACT ON WE HAVE SEEN THAT THESE RULES CANNOT BE DETERMINED ON THE BASIS OF BENEFICENCE OR BENEVOLENCE ALONE AS THE RULES OF NOT INJURING ANYONE AND OF KEEPING COVENANTS CAN BE I THINK A NUMBER CRITERIA HAVE BEEN PROPOSED ONE THAT JUSTICE IS DEALING WITH PEOPLE ACCORDING TO THEIR DESERT OR MERITS TWO THAT IT IS TREATING HUMAN BEINGS AS EQUALS IN THE SENSE OF DISTRIBUTING GOOD AND EVIL EQUALLY AMONG THEM EXCEPTING PERHAPS IN THE CASE OF PUNISHMENT THREE THAT IT IS TREATING PEOPLE ACCORDING TO THEIR NEEDS THEIR ABILITIES OR BOTH THE FIRST IS THE CLASSICAL MERITARIAN CRITERION OF JUSTICE FOUND IN ARISTOTLE THIS CRITERION IS ALSO ACCEPTED BY SIR DAVID ROSS ACCORDING TO THIS VIEW THE CRITERION OF DESERT OR MERIT IS VIRTUE AND JUSTICE IS DISTRIBUTING THE GOOD HAPPINESS IN ACCORDANCE WITH VIRTUE ONE MIGHT OF COURSE ADOPT SOME OTHER CRITERION OF MERIT FOR EXAMPLE ABILITY CONTRIBUTION INTELLIGENCE BLOOD COLOUR SOCIAL RANK OR WEALTH AND THEN JUSTICE WOULD CONSIST IN DISTRIBUTING GOOD AND EVIL IN ACCORDANCE WITH THIS CRITERION THE SECOMD CRITERION IS THE EQUALITARIAN ONE WHICH IS CHARACTERISTIC OF MODERN DEMOCRATIC THEORY THE THIRD IS ALSO A MODERN VIEW AND MAY TAKE VARIOUS FORMS ITS MOST PROMINENT FORM TODAY IS THE MARXIST DICTUM FROM EACH ACCORDING TO HIS ABILITY TO EACH ACCORDING TO HIS NEEDS SOME OF THE CRITERIA OF MERIT MENTIONED SEEM TO BE PALPABLY NONMORAL OR EVEN UNJUST FOR EXAMPLE THE USE OF BLOOD COLOUR INTELLIGENCE SOCIAL RANK OR WEALTH AS A BASIS FOR ONES RULES OF DISTRIBUTION USE OF ABILITY AS A BASIS WOULD GIVE US A FORM OF THE THIRD VIEW THIS LEAVES MORAL VIRTUE AND CONTRIBUTION TO SOCIETY AS POSSIBLE CRITERIA OF MERIT BUT WE

MUST THEN HAVE A CRITERION OF CONTRIBUTION AND MORAL VIRTUE BY WHAT MEASURE IS A PERSONS MORAL VIRTUE OR CONTRIBUTION TO SOCIETY TO BE DETERMINED

CHOM
IN PARAGRAPH 4.3 OF CHAPTER 2 WE SUGGESTED A THAT THE
DISTRIBUTIONAL RESTRICTIONS OF LEXICAL ITEMS BE DETERMINED BY
CONTEXTUAL FEATURES LISTED IN LEXICAL ENTRIES AND B THAT THESE
CONTEXTUAL FEATURES BE REGARDED AS DEFINING CERTAIN SUBSTITUTION
TRANSFORMATIONS THUS STRICT SUBCATEGORIAL AND SELECTIONAL
RESTRICTIONS OF LEXICAL ITEMS ARE DEFINED BY TRANSFORMATIONAL
RULES ASSOCIATED WITH THESE ITEMS WE HAVE NOW OBSERVED THAT THE
TRANSFORMATIONAL RULES MUST ALSO CARRY THE BURDEN OF DETERMINING
THE DISTRIBUTIONAL RESTRICTIONS ON BASE PHRASEMARKERS THUS THE
CATEGORIAL RULES THAT GENERATE THE INFINITE SET OF GENERALIZED
PHRASEMARKERS CAN APPARENTLY BE CONTEXTFREE WITH ALL
DISTRIBUTIONAL RESTRICTIONS WHETHER OF BASE PHRASEMARKERS OR
LEXICAL ENTRIES BEING DETERMINED BY THE SINGULARY TRANSFORMATIONS
SUCH A DESCRIPTION OF THE FORM OF THE SYNTACTIC COMPONENT MAY
SEEM STRANGE IF ONE CONSIDERS THE GENERATIVE RULES AS A MODEL FOR
THE ACTUAL CONSTRUCTION OF A SENTENCE BY A SPEAKER THUS IT SEEMS
ABSURD TO SUPPOSE THAT THE SPEAKER FIRST FORMS A GENERALIZED
PHRASEMARKER BY BASE RULES AND THEN TESTS IT FOR WELLFORMEDNESS
BY APPLYING TRANSFORMATIONAL RULES TO SEE IF IT GIVES FINALLY A
WELLFORMED SENTENCE BUT THIS ABSURDITY IS SIMPLY A COROLLARY TO
THE DEEPER ABSURDITY OF REGARDING THE SYSTEM OF GENERATIVE RULES
AS A POINT BY POINT MODEL FOR THE ACTUAL CONSTRUCTION OF A
SENTENCE BY A SPEAKER CONSIDER THE SIMPLER CASE OF A PHRASE
STRUCTURE GRAMMAR WITH NO TRANSFORMATIONS FOR EXAMPLE THE GRAMMAR
OF A PROGRAMMING LANGUAGE OF ELEMENTARY ARITHMETIC OR SOME SMALL
PART OF ENGLISH THAT MIGHT BE DESCRIBED IN THESE TERMS IT WOULD
CLEARLY BE ABSURD TO SUPPOSE THAT THE SPEAKER OF SUCH A LANGUAGE
IN FORMULATING AN UTTERANCE FIRST SELECTS THE MAJOR CATEGORIES
THEN THE CATEGORIES INTO WHICH THESE ARE ANALYZED AND SO FORTH
FINALLY AT THE END OF THE PROCESS SELECTING THE WORDS OR SYMBOLS
THAT HE IS GOING TO USE DECIDING WHAT HE IS GOING TO TALK ABOUT
TO THINK OF A GENERATIVE GRAMMAR IN THESE TERMS IS TO TAKE IT TO
BE A MODEL OF PERFORMANCE RATHER THAN A MODEL OF COMPETENCE THUS
TOTALLY MISCONCEIVING ITS NATURE ONE CAN STUDY MODELS OF
PERFORMANCE THAT INCORPORATE GENERATIVE GRAMMARS AND SOME RESULTS
HAVE BEEN ACHIEVED IN SUCH STUDIES BUT A GENERATIVE GRAMMAR AS IT
STANDS IS NO MORE A MODEL OF THE SPEAKER THAN IT IS A MODEL OF
THE HEARER RATHER AS HAS BEEN REPEATEDLY EMPHASIZED IT CAN BE
REGARDED ONLY AS A CHARACTERIZATION OF THE INTRINSIC TACIT
KNOWLEDGE OR COMPETENCE THAT UNDERLIES ACTUAL PERFORMANCE THE
BASE RULES AND THE TRANSFORMATIONAL RULES SET CERTAIN CONDITIONS
THAT MUST BE MET FOR A STRUCTURE TO QUALIFY AS THE DEEP STRUCTURE
EXPRESSING THE SEMANTIC CONTENT OF SOME WELLFORMED SENTENCE GIVEN
A GRAMMAR CONTAINING A BASE COMPONENT AND A TRANSFORMATIONAL
COMPONENT ONE CAN DEVELOP INNUMERABLE PROCEDURES FOR ACTUALLY
CONSTRUCTING DEEP STRUCTURES THESE WILL VARY IN EXHAUSTIVENESS
AND EFFICIENCY AND IN THE EXTENT TO WHICH THEY CAN BE ADAPTED TO
THE PROBLEMS OF PRODUCING OR UNDERSTANDING SPEECH ONE SUCH
CONSTRUCTIVE PROCEDURE IS TO RUN THROUGH THE BASE RULES OBSERVING
ORDER SO AS TO FORM A GENERALIZED PHRASEMARKER M AND THEN THROUGH
THE TRANSFORMATIONAL RULES OBSERVING ORDER SO AS TO FORM A
SURFACE STRUCTURE MM FROM M IF MM IS WELL FORMED THEN M WAS A
DEEP STRUCTURE OTHERWISE IT WAS NOT ALL DEEP STRUTURES CAN BE
ENUMERATED IN THIS WAY JUST AS THEY CAN ALL BE ENUMERATED IN MANY

OTHER WAYS GIVEN THE GRAMMAR AS NOTED EARLIER THE GRAMMAR DEFINES THE RELATION THE DEEP STRUCTURE M UNDELIES THE WELLFORMED SURFACE STRUCTURE MM OF THE SENTENCE SS AND DERIVATIVELY IT DEFINES THE NOTIONS M IS A DEEP STRUCTURE MM IS A WELFORMED SURFACE STRUCTURE S IS A WELLFORMED SENTENCE AND MANY OTHERS SUCH AS S IS STRUCTURALLY AMBIGUOUS S AND SS ARE PARAPHRASES

LAB
IN THE BALANCE OF THIS PAPER I WILL THEREFORE REFER TO CHILDREN FROM URBAN GHETTO AREAS RATHER THAN LOWERCLASS CHILDREN THE POPULATION WE ARE CONCERNED WITH ARE THOSE WHO PARTICIPATE FULLY IN THE VERNACULAR CULTURE OF THE STREET AND WHO HAVE BEEN ALIENATED FROM THE SCHOOL SYSTEM WE ARE OBVIOUSLY DEALING WITH THE EFFECTS OF THE CASTE SYSTEM OF AMERICAN SOCIETY ESSENTIALLY A COLOR MARKING SYSTEM EVERYONE RECOGNIZES THIS THE QUESTION IS BY WHAT MECHANISM DOES THE COLOR BAR PREVENT CHILDREN FROM LEARNING TO READ ONE ANSWER IS THE NOTION OF CULTURAL DEPRIVATION PUT FORWARD BY MARTIN DEUTSCH AND OTHERS THE NEGRO CHILDREN ARE SAID TO LACK THE FAVORABLE FACTORS IN THEIR HOME ENVIRONMENT WHICH ENABLE MIDDLECLASS CHILDREN TO DO WELL IN SCHOOL THESE FACTORS INVOLVE THE DEVELOPMENT OF VARIOUS COGNITIVE SKILLS THROUGH VERBAL INTERACTION WITH ADULTS INCLUDING THE ABILITY TO REASON ABSTRACTLY SPEAK FLUENTLY AND FOCUS UPON LONGRANGE GOALS IN THEIR PUBLICATIONS THESE PSYCHOLOGISTS ALSO RECOGNIZE BROADER SOCIAL FACTORS HOWEVER THE DEFICIT THEORY DOES NOT FOCUS UPON THE INTERACTION OF THE NEGRO CHILD WITH WHITE SOCIETY SO MUCH AS ON HIS FAILURE TO INTERACT WITH HIS MOTHER AT HOME IN THE LITERATURE WE FIND VERY LITTLE DIRECT OBSERVATION OF VERBAL INTERACTION IN THE NEGRO HOME MOST TYPICALLY THE INVESTIGATORS ASK THE CHILD IF HE HAS DINNER WITH HIS PARENTS AND IF HE ENGAGES IN DINNERTABLE CONVERSATION WITH THEM HE IS ALSO ASKED WHETHER HIS FAMILY TAKES HIM ON TRIPS TO MUSEUMS AND OTHER CULTURAL ACTIVITIES THIS SLENDER THREAD OF EVIDENCE IS USED TO EXPLAIN AND INTERPRET THE LARGE BODY OF TESTS CARRIED OUT IN THE LABORATORY AND IN THE SCHOOL THE MOST EXTREME VIEW WHICH PROCEEDS FROM THIS ORIENTATION AND ONE THAT IS NOW BEING WIDELY ACCEPTED IS THAT LOWERCLASS NEGRO CHILDREN HAVE NO LANGUAGE AT ALL THE NOTION IS FIRST DRAWN FROM BASIL BERNSTEINS WRITINGS THAT MUCH OF LOWERCLASS LANGUAGE CONSISTS OF A KIND OF INCIDENTAL EMOTIONAL ACCOMPANIMENT TO ACTION HERE AND NOW BERNSTEINS VIEWS ARE FILTERED THROUGH A STRONG BIAS AGAINST ALL FORMS OF WORKINGCLASS BEHAVIOR SO THAT MIDDLECLASS LANGUAGE IS SEEN AS SUPERIOR IN EVERY RESPECT AS MORE ABSTRACT AND NECESSARILY SOMEWHAT MORE FLEXIBLE DETAILED AND SUBTLE ONE CAN PROCEED THROUGH A RANGE OF SUCH VIEWS UNTIL ONE COMES TO THE PRACTICAL PROGRAM OF CARL BEREITER SIGFRIED ENGELMANN AND THEIR ASSOCIATES. BEREITERS PROGRAM FOR AN ACADEMICALLY ORIENTED PRESCHOOL IS BASED UPON THEIR PREMISE THAT NEGRO CHILDREN MUST HAVE A LANGUAGE WITH WHICH THEY CAN LEARN AND THEIR EMPIRICAL FINDING THAT THESE CHILDREN COME TO SCHOOL WITHOUT SUCH A LANGUAGE IN HIS WORK WITH FOURYEAROLD NEGRO CHILDREN FROM URBANA BEREITER REPORTS THAT THEIR COMMUNICATION WAS BY GESTURES SINGLE WORDS AND A SERIES OF BADLYCONNECTED WORDS OR PHRASES SUCH AS THEY MINE AND ME GOT JUICE HE REPORTS THAT NEGRO CHILDREN COULD NOT ASK QUESTIONS THAT WITHOUT EXAGGERATING THESE FOURYEAROLDS COULD MAKE NO STATEMENTS OF ANY KIND FURTHERMORE WHEN THESE CHILDREN WERE ASKED WHERE IS THE BOOK THEY DID NOT KNOW ENOUGH TO LOOK AT THE TABLE WHERE THE BOOK WAS LYING IN ORDER TO ANSWER THUS BEREITER CONCLUDES THAT THE CHILDRENS SPEECH FORMS ARE NOTHING MORE THAN A SERIES OF EMOTIONAL CRIES AND HE DECIDES TO TREAT THEM AS IF THE CHILDREN HAD NO LANGUAGE AT ALL HE IDENTIFIES THEIR SPEECH WITH HIS INTERPRETATION OF BERNSTEINS RESTRICTED CODE THE LANGUAGE OF CULTURALLY DEPRIVED

CHILDREN IS NOT MERELY AN UNDERDEVELOPED VERSION OF STANDARD ENGLISH BUT IS A BASICALLY NONLOGICAL MODE OF EXPRESSIVE BEHAVIOR THE BASIC PROGRAM OF HIS PRESCHOOL IS TO TEACH THEM A NEW LANGUAGE DEVISED BY ENGELMANN WHICH CONSISTS OF A LIMITED SERIES OF QUESTIONS AND ANSWERS SUCH AS WHERE IS THE SQUIRREL THE SQUIRREL IS IN THE TREE THE CHILDREN WILL NOT BE PUNISHED IF THEY USE THEIR VERNACULAR SPEECH ON THE PLAYGROUND BUT THEY WILL NOT BE ALLOWED TO USE IT IN THE SCHOOLROOM

BRU

WE HAVE CHOSEN SO FAR TWO SIMPLE CASES OF CATEGORIZING DECISION ONE WHERE THE EXPECTED OUTCOME VALUES ARE BALANCED AND WHERE THE DIFFERENCES IN EXPECTED EVENT PROBABILITIES SWAY DECISION THE OTHER WHERE EXPECTED EVENT PROBABILITIES ARE BALANCED AND WHERE DIFFERENCES IN OUTCOME VALUES BIAS DECISION ONE NEED NOT BE LIMITED TO SUCH SIMPLE CASES IN GEREAL THE ARGUMENT CAN BE MADE THAT WHEN OUTCOME VALUES ARE EQUAL FOR PLACEMENT IN ONE CATEGORY OR ANOTHER CATEGORIZING DECISIONS WILL CORRESPOND TO THE EXPECTED EVENT PROBABILITIES AND WHEN OUTCOME VALUES ARE NOT EQUAL CATEGORIZING DECISIONS WILL BE BIASSED IN THE DIRECTION OF THE MOST FAVORABLE ALTERNATIVE EXPERIMENTAL STUDIES SUPPORTING THIS ARGUMENT WILL BE FOUND IN CHAPTER 7 IT MUST BE NOTED HOWEVER THAT WE ARE ALWAYS LIMITED TO STATEMENTS ABOUT THE DIRECTION THAT BIAS WILL TAKE AS LONG AS WE REMAIN ON THE DESCRIPTIVE LEVEL WE CAN MAKE NO PREDICTIONS ABOUT THE AMOUNT OF BIAS OR DEPARTURE FROM EXPECTED EVENT PROBABILITIES THAT WIL OCCUR PREDICTIONS OF AMOUNT CALL FIRST FOR REPLACING OUR DESCRIPTIVE STATEMENTS OF VALUE WITH NUMERICAL STATEMENTS ONCE SUCH NUMERICAL VALUES HAVE BEEN ASSIGNED ONE CAN FOLLOW THE TRADITIONAL MATHEMATICAL THECHNIQUE OF MULTIPLYING OUTCOME VALUES BY PROBABILITY ESTIMATES TO OBTAIN A MEASURE OF EXPECTED UTILITY AND ONE CAN ALSO ARGUE FOR A GENERAL PRINCIPLE SUCH AS MAXIMIZING UTILITY TO DETERMINE WHICH ALTERNATIVE SHOULD BE CHOSEN THERE ARE HOWEVER A NUMBER OF PROBLEMS IN DETERMINING HOW THE EXPECTED VALUES OF AN OUTCOME FOR ANY GIVEN INDIVIDUAL CAN BE QUANTITATIVELY STATED AGAIN THESE QUESTIONS ARE MORE FULLY DISCUSSED IN CHAPTER 7 FOR THE MOMENT WE WISH TO ANTICIPATE THE DISCUSSION ONLY TO THE EXTENT OF STATING OUR GENERAL CONCLUSION THIS IS THAT WE ARE NOT PREPARED TO DEVELOP OR TO UTILIZE AS YET ANY FORMAL OR MATHEMATICAL MODEL TO PREDICT THE EFFECT OF ANTICIPATED CONSEQUENCES ON CATEGORIZING JUDGMENTS WE HAVE CHOSEN TO BE SATISFIED WITH LESS PRECISE PREDICTION AND TO CONCERN OURSELVES WITH THE PSYCHOLOGICAL QUESTIONS WHICH MUST EVENTUALLY UNDERLIE ANY MODEL THE MOST IMPORTANT OF THESE QUESTIONS CONCERN THE OBJECTIVES DETERMINING OUTCOME VALUES AND THE CONDITIONS AFFECTING AN INDIVIDUALS ESTIMATE OF EVENT PROBABILITY FOR ALL ITS PRESENT LIMITATION THE CONCEPT OF A PAYOFF MATRIX IS A USEFUL AND A SUGGESTIVE ONE IN THE FIRST PLACE IT SUGGESTS PROBLEMS THAT HAVE FAR TOO LONG BEEN OVERLOOKED PSYCHOPHYSICS CONCERNED AS IT IS WITH THE CATEGORIZATION OF MAGNITUDES COULD WELL BE REEXAMINED FOR THE MANNER IN WHICH OUTCOME VALUES AND LIKELIHOOD ESTIMATES AFFECT CATEGORIZING BEHAVIOR IT COULD WE BELIEVE THEREBY BE BROUGHT MUCH CLOSER TO THE JUDGMENTAL BEHAVIOR OF PEOPLE IN EVERYDAY SITUATIONS ANALYSIS OF THE EFFECTS OF ANTICIPATED CONSEQUENCES IN TERMS OF PAYOFF MATRICES MAY ALSO SERVE AS A LINK BETWEEN MOTIVATIONAL STATES AND JUDGMENTAL BEHAVIOR SPECIFICALLY ONES SET IN JUDGING IS PARTIALLY DESCRIBABLE IN SUCH TERMS AGAIN WE MAY BENEFIT BY EXAMINING THE JUDGING ACTS THAT PREVAIL IN EVERYDAY LIFE ONE EXAMPLE IS THE PERSONNEL OFFICER WHO MUST CATEGORIZE APPLICANTS INTO ACCEPTABLE AND UNACCEPTABLE GROUPS AND WHO IS PUNISHED ONLY WHEN HIS INCORRECT CATEGORIZATION TAKES THE FORM OF CLASSING AS ACCEPTABLE A MAN WHO LATER FAILS THE PRACTICES OF THE PROGRESSIVE SCHOOL PROVIDE ANOTHER EXAMPLE THERE THE CHILD IS REWARDED FOR HIS CORRECT CATEGORIZATIONS ONLY THE OTHERS BEING

OVERLOOKED THE SITUATION IN THE BASIC TRAINING CAMP IS YET ANOTHER EXAMPLE ONLY ERRORS ARE NOTED AND PUNISHED CORRECT ACTS ARE OVERLOOKED EACH TIME A SUBJECT WALKS INTO AN EXPERIMENTAL ROOM HE IMPOSES A PAYOFF MATRIX ON THE SITUATION THE EXPERIMENTER PRESENTS TO HIM AND OFTEN THE EXPERIMENTER NEEDS TO SET HIM STRAIGHT WE END WITH WHAT MAY SEEM LIKE A TRIVIAL PROBLEM IN COMPARISON WITH THE ONE JUST DISCUSSED THE RESTRICTIONS IMPOSED UPON

TRUE

THE CONCEPTIONS OF LIFE AND THE WORLD WHICH WE CALL PHILOSOPHICAL ARE A PRODUCT OF TWO FACTORS ONE INHERITED RELIGIOUS AND ETHICAL CONCEPTIONS THE OTHER THE SORT OF INVESTIGATION WHICH MAY BE CALLED SCIENTIFIC USING THIS WORD IN ITS BROADEST SENSE INDIVIDUAL PHILOSOPHERS HAVE DIFFERED WIDELY IN REGARD TO THE PROPORTIONS IN WHICH THESE TWO FACTORS ENTERED INTO THEIR SYSTEMS BUT IT IS THE PRESENCE OF BOTH IN SOME DEGREE THAT CHARACTERIZES PHILOSOPHY PHILOSOPHY IS A WORD WHICH HAS BEEN USED IN MANY WAYS SOME WIDER SOME NARROWER I PROPOSE TO USE IT IN A VERY WIDE SENSE WHICH I WILL NOW TRY TO EXPLAIN PHILOSOPHY AS I SHALL UNDERSTAND THE WORD IS SOMETHING INTERMEDIATE BETWEEN THEOLOGY AND SCIENCE LIKE THEOLOGY IT CONSISTS OF SPECULATIONS ON MATTERS AS TO WHICH DEFINITE KNOWLEDGE HAS SO FAR BEEN UNASCERTAINABLE BUT LIKE SCIENCE IT APPEALS TO HUMAN REASON RATHER THAN TO AUTHORITY WHETHER THAT OF TRADITION OR THAT OF REVELATION ALL DEFINITE KNOWLEDGE SO I SHOULD CONTEND BELONGS TO SCIENCE ALL DOGMA AS TO WHAT SURPASSES DEFINITE KNOWLEDGE BELONGS TO THEOLOGY BUT BETWEEN THEOLOGY AND SCIENCE THERE IS A NO MANS LAND EXPOSED TO ATTACK FROM BOTH SIDES THIS NO MANS LAND IS PHILOSOPHY ALMOST ALL THE QUESTIONS OF MOST INTEREST TO SPECULATIVE MINDS ARE SUCH AS SCIENCE CANNOT ANSWER AND THE CONFIDENT ANSWERS OF THEOLOGIANS NO LONGER SEEM SO CONVINCING AS THEY DID IN FORMER CENTURIES IS THE WORLD DIVIDED INTO MIND AND MATTER AND IF SO WHAT IS MIND AND WHAT IS MATTER IS MIND SUBJECT TO MATTER OR IS IT POSSESSED OF INDEPENDENT POWERS HAS THE UNIVERSE ANY UNITY OR PURPOSE IS IT EVOLVING TOWARDS SOME GOAL ARE THERE REALLY LAWS OF NATURE OR DO WE BELIEVE IN THEM ONLY BECAUSE OF OUR INNATE LOVE OF ORDER IS MAN WHAT HE SEEMS TO THE ASTRONOMER A TINY LUMP OF IMPURE CARBON AND WATER IMPOTENTLY CRAWLING ON A SMALL AND UNIMPORTANT PLANET OR IS HE WHAT HE APPEARS TO HAMLET IS HE PERHAPS BOTH AT ONCE IS THERE A WAY OF LIVING THAT IS NOBLE AND ANOTHER THAT IS BASE OR ARE ALL WAYS OF LIVING MERELY FUTILE IF THERE IS A WAY OF LIVING THAT IS NOBLE IN WHAT DOES IT CONSIST AND HOW SHALL WE ACHIEVE IT MUST THE GOOD BE ETERNAL IN ORDER TO DESERVE TO BE VALUED OR IS IT WORTH SEEKING EVEN IF THE UNIVERSE IS INEXORABLY MOVING TOWARDS DEATH IS THERE SUCH A THING AS WISDOM OR IS WHAT SEEMS SUCH MERELY THE ULTIMATE REFINEMENT OF FOLLY TO SUCH QUESTIONS NO ANSWER CAN BE FOUND IN THE LABORATORY THEOLOGIES HAVE PROFESSED TO GIVE ANSWERS ALL TOO DEFINITE BUT THEIR VERY DEFINITENESS CAUSES MODERN MINDS TO VIEW THEM WITH SUSPICION THE STUDYING OF THESE QUESTIONS IF NOT THE ANSWERING OF THEM IS THE BUSINESS OF PHILOSOPHY WHY THEN YOU MAY ASK WASTE TIME ON SUCH INSOLUBLE PROBLEMS TO THIS ONE MAY ANSWER AS A HISTORIAN OR AS AN INDIVIDUAL FACING THE TERROR OF COSMIC LONELINESS THE ANSWER OF THE HISTORIAN IN SO FAR AS I AM CAPABLE OF GIVING IT WILL APPEAR IN THE COURSE OF THIS WORK EVER SINCE MEN BECAME CAPABLE OF FREE SPECULATION THEIR ACTIONS IN INNUMERABLE IMPORTANT RESPECTS HAVE DEPENDED UPON THEIR THEORIES AS TO THE WORLD AND HUMAN LIFE AS TO WHAT IS GOOD AND WHAT IS EVIL THIS IS AS TRUE IN THE PRESENT DAY AS AT ANY FORMER TIME TO UNDERSTAND AN AGE OR A NATION WE MUST UNDERSTAND ITS PHILOSOPHY AND TO UNDERSTAND ITS PHILOSOPHY WE MUST OURSELVES BE IN SOME DEGREE PHILOSOPHERS THERE IS HERE A RECIPROCAL CAUSATION THE CIRCUMSTANCES

IRUS
CAUSATION THE CIRCUMSTANCES OF MENS LIVES DO MUCH TO DETERMINE THEIR PHILOSOPHY BUT CONVERSELY THEIR PHILOSOPHY DOES MUCH TO DETERMINE THEIR CIRCUMSTANCES THIS INTERACTION THROUGHOUT THE CENTURIES WILL BE THE TOPIC OF THE FOLLOWING PAGES THERE IS ALSO HOWEVER A MORE PERSONAL ANSWER SCIENCE TELLS US WHAT WE CAN KNOW BUT WHAT WE CAN KNOW IS LITTLE AND IF WE FORGET HOW MUCH WE CANNOT KNOW WE BECOME INSENSITIVE TO MANY THINGS OF GREAT IMPORTANCE THEOLOGY ON THE OTHER HAND INDUCES A DOGMATIC BELIEF THAT WE HAVE KNOWLEDGE WHERE IN FACT WE HAVE IGNORANCE AND BY DOING SO GENERATES A KIND OF IMPERTINENT INSOLENCE TOWARDS THE UNIVERSE UNCERTAINTY IN THE PRESENCE OF VIVID HOPES AND FEARS IS PAINFUL BUT MUST BE ENDURED IF WE WISH TO LIVE WITHOUT THE SUPPORT OF COMFORTING FAIRY TALES IT IS NOT GOOD EITHER TO FORGET THE QUESTIONS THAT PHILOSOPHY ASKS OR TO PERSUADE OURSELVES THAT WE HAVE FOUND INDUBITABLE ANSWERS TO THEM TO TEACH HOW TO LIVE WITHOUT CERTAINTY AND YET WITHOUT BEING PARALYSED BY HESITATION IS PERHAPS THE CHIEF THING THAT PHILOSOPHY IN OUR AGE CAN STILL DO FOR THOSE WHO STUDY IT PHILOSOPHY AS DISTINCT FROM THEOLOGY BEGAN IN GREECE IN THE SIXTH CENTURY BC AFTER RUNNING ITS COURSE IN ANTIQUITY IT WAS AGAIN SUBMERGED BY THEOLOGY AS CHRISTIANITY ROSE AND ROME FELL ITS SECOND GREAT PERIOD FROM THE ELEVENTH TO THE FOURTEENTH CENTURIES WAS DOMINATED BY THE CATHOLIC CHURCH EXCEPT FOR A FEW GREAT REBELS SUCH AS EMPEROR FREDERICK THIS PERIOD WAS BROUGHT TO AN END BY THE CONFUSIONS THAT CULMINATED IN THE REFORMATION THE THIRD PERIOD FROM THE SEVENTEENTH CENTURY TO THE PRESENT DAY IS DOMINATED MORE THAN EITHER OF ITS PREDECESSORS BY SCIENCE TRADITIONAL RELIGIOUS BELIEFS REMAIN IMPORTANT BUT ARE FELT TO NEED JUSTIFICATION AND ARE MODIFIED WHEREVER SCIENCE SEEMS TO MAKE THIS IMPERATIVE FEW OF THE PHILOSOPHERS OF THIS PERIOD ARE ORTHODOX FROM A CATHOLIC STANDPOINT AND THE SECULAR STATE IS MORE IMPORTANT IN THEIR SPECULATIONS THAN THE CHURCH SOCIAL COHESION AND INDIVIDUAL LIBERTY LIKE RELIGION AND SCIENCE ARE IN A STATE OF CONFLICT OR UNEASY COMPROMISE THROUGHOUT THE WHOLE PERIOD IN GREECE SOCIAL COHESION WAS SECURED BY LOYALTY TO THE CITY STATE EVEN ARISTOTLE THOUGH IN HIS TIME ALEXANDER WAS MAKING THE CITY STATE OBSOLETE COULD SEE NO MERIT IN ANY OTHER KIND OF POLITY THE DEGREE TO WHICH THE INDIVIDUALS LIBERTY WAS CURTAILED BY HIS DUTY TO THE CITY VARIED WIDELY IN SPARTA HE HAD AS LITTLE LIBERTY AS IN MODERN GERMANY OR RUSSIA IN ATHENS IN SPITE OF OCCASIONAL PERSECUTIONS CITIZENS HAD IN THE BEST PERIOD A VERY EXTRAORDINARY FREEDOM FROM RESTRICTIONS IMPOSED BY THE STATE GREEK THOUGHT DOWN TO ARISTOTLE IS DOMINATED BY RELIGIOUS AND PATRIOTIC DEVOTION TO THE CITY ITS ETHICAL SYSTEMS ARE ADAPTED TO THE LIVES OF CITIZENS AND HAVE A LARGE POLITICAL ELEMENT WHEN THE GREEKS BECAME SUBJECT FIRST TO THE MACEDONIANS AND THEN TO THE ROMANS THE CONCEPTIONS APPROPRIATE TO THEIR DAYS OF INDEPENDENCE WERE NO LONGER APPLICABLE THIS PRODUCED ON THE ONE HAND A LOSS OF VIGOUR THROUGH THE BREACH WITH TRADITION AND ON THE OTHER HAND A MORE INDIVIDUAL AND LESS SOCIAL ETHIC THE STOICS THOUGHT OF THE VIRTUOUS LIFE AS A RELATION OF THE SOUL TO GOD RATHER THAN AS A RELATION OF THE CITIZEN TO THE STATE THEY THUS PREPARED THE WAY FOR CHRISTIANITY WHICH LIKE STOICISM WAS ORIGINALLY UNPOLITICAL SINCE DURING ITS FIRST THREE CENTURIES ITS ADHERENTS WERE DEVOID OF INFLUENCE ON GOVERNMENT SOCIAL COHESION

DURING THE SIX AND A HALF CENTURIES FROM ALEXANDER TO CONSTANTINE
WAS SECURED NOT BY PHILOSOPHY AND NOT BY ANCIENT LOYALTIES BUT BY
FORCE FIRST THAT OF ARMIES AND THEN THAT OF CIVIL ADMINISTRATION

CF JS

TO BRING CLEARLY BEFORE THE MIND WHAT IS MEANT BY CLASS AND TO DISTINGUISH THIS NOTION FROM ALL THE NOTIONS TO WHICH IT IS ALLIED IS ONE OF THE MOST DIFFICULT AND IMPORTANT PROBLEMS OF MATHEMATICAL PHILOSOPHY APART FROM THE FACT THAT CLASS IS A VERY FUNDAMENTAL CONCEPT THE UTMOST CARE AND NICETY IS REQUIRED IN THIS SUBJECT ON ACCOUNT OF THE CONTRADICTION TO BE DISCUSSED IN CHAPTER X I MUST ASK THE READER THEREFORE NOT TO REGARD AS IDLE PEDANTRY THE APPARATUS OF SOMEWHAT SUBTLE DISCRIMINATIONS TO BE FOUND IN WHAT FOLLOWS IT HAS BEEN CUSTOMARY IN WORKS ON LOGIC TO DISTINGUISH TWO STANDPOINTS THAT OF EXTENSION AND THAT OF INTENSION PHILOSOPHERS HAVE USUALLY REGARDED THE LATTER AS THE MORE FUNDAMENTAL WHILE MATHEMATICS HAS BEEN HELD TO DEAL SPECIALLY WITH THE FORMER MCOUTARA IN HIS ADMIRABLE WORK ON LEIBNIZ STATES ROUNDLY THAT SYMBOLIC LOGIC CAN ONLY BE BUILT UP FROM THE STANDPOINT OF EXTENSION AND IF THERE REALLY WERE ONLY THESE TWO POINTS OF VIEW HIS STATEMENT WOULD BE JUSTIFIED BUT AS A MATTER OF FACT THERE ARE POSITIONS INTERMEDIATE BETWEEN PURE INTENSION AND PURE EXTENSION AND IT IS ESSENTIAL THAT THE CLASSES WITH WHICH WE ARE CONCERNED SHOULD BE COMPOSED OF TERMS AND SHOULD NOT BE PREDICATES OR CONCEPTS FOR A CLASS MUST BE DEFINITE WHEN ITS TERMS ARE GIVEN BUT IN GENERAL THERE WILL BE MANY PREDICATES WHICH ATTACH TO THE GIVEN TERMS AND TO NO OTHERS WE CANNOT OF COURSE ATTEMPT AN INTENSIONAL DEFINITION OF A CLASS AS THE CLASS OF PREDICATES ATTACHING TO THE TERMS IN QUESTION AND TO NO OTHERS FOR THIS WOULD INVOLVE A VICIOUS CIRCLE HENCE THE POINT OF VIEW OF EXTENSION IS TO SOME EXTENT UNAVOIDABLE ON THE OTHER HAND IF WE TAKE EXTENSION PURE OUR CLASS IS DEFINED BY ENUMERATION OF ITS TERMS AND THIS METHOD WILL NOT ALLOW US TO DEAL AS SYMBOLIC LOGIC DOES WITH INFINITE CLASSES THUS OUR CLASSES MUST IN GENERAL BE REGARDED AS OBJECTS DENOTED BY CONCEPTS AND TO THIS EXTENT THE POINT OF VIEWS OF INTENSION IS ESSENTIAL IT IS OWING TO THIS CONSIDERATION THAT THE THEORY OF DENOTING IS OF SUCH GREAT IMPORTANCE IN THE PRESENT CHAPTER WE HAVE TO SPECIFY THE PRECISE DEGREE IN WHICH EXTENSION AND INTENSION RESPECTIVELY ENTER INTO THE DEFINITION AND EMPLOYMENT OF CLASSES AND THROUGHOUT THE DISCUSSION I MUST ASK THE READER TO REMEMBER THAT WHATEVER IS SAID HAS TO BE APPLICABLE TO INFINITE AS WELL AS FINITE CLASSES WHEN AN OBJECT IS UNAMBIGUOUSLY DENOTED BY A CONCEPT I SHALL SPEAK OF THE CONCEPT AS A CONCEPT OR SOMETIMES LOOSELY AS THE CONCEPT OF THE OBJECT IN QUESTION THUS IT WILL BE NECESSARY TO DISTINGUISH THE CONCEPT OF A CLASS FROM A CLASSCONCEPT WE AGREED TO CALL MAN A CLASSCONCEPT BUT MAN DOES NOT IN ITS USUAL EMPLOYMENT DENOTE ANYTHING ON THE OTHER HAND MEN AND ALL MEN WHICH I SHALL REGARD AS SYNONYMS DO DENOTE AND I SHALL CONTEND THAT WHAT THEY DENOTE IS THE CLASS COMPOSED OF ALL MEN THUS MAN IS THE CLASSCONCEPT MEN THE CONCEPT IS THE CONCEPT OF THE CLASS IT IS NO DOUBT CONFUSING AT FIRST TO USE CLASSCONCEPT AND CONCEPT OF A CLASS IN DIFFERENT SENSES BUT SO MANY DISTINCTIONS ARE REQUIRED THAT SOME STRAINING OF LANGUAGE SEEMS UNAVOIDABLE IN THE PHRASEOLOGY OF THE PRECEDING CHAPTER WE MAY SAY THAT A CLASS IS A NUMERICAL CONJUNCTION OF TERMS THIS IS THE THESIS WHICH IS TO BE ESTABLISHED IN CHAPTER II WE REGARDED CLASSES AS DERIVED FROM ASSERTIONS IE AS ALL THE ENTITIES SATISFYING SOME ASSERTION WHOSE FORM WAS LEFT WHOLLY VAGUE I

SHALL DISCUSS THIS VIEW CRITICALLY IN THE NEXT CHAPTER FOR THE PRESENT WE MAY CONFINE OURSELVES TO CLASSES AS THEY ARE DERIVED FROM PREDICATES LEAVING OPEN THE

4RUS
THE EMPRESS JOSEPHINE HAD A VERY INTERESTING AND VERY REMARKABLE LIFE FULL OF UPS AND DOWNS AS EVERYBODY KNOWS SHE CAME FROM THE WEST INDIES AND WAS IN PARIS AT THE TIME OF THE REIGN OF TERROR NOT ONLY THAT BUT SHE WAS IMPRISONED DURING THE REIGN OF TERROR AND WAS IN IMMINENT DANGER OF BEING GUILLOTINED BUT HOWEVER SHE SUCCEEDED IN NOT BEING GUILLOTINED AND IN GETTING INTO INTIMATE RELATIONS WITH BARRAS WHO BECAME THE FIRST OF THE DIRECTORS AND WHEN ASKED WHAT HE HAD DONE DURING THE TERROR REMARKED I SURVIVED AND SO SHE SURVIVED THROUGH THE PERIOD OF THE DIRECTOIRE HOWEVER BARRAS WAS GETTING A LITTLE TIRED OF HER BECAUSE SHE WAS ALREADY ELDERLY AND HE DECIDED TO MARRY HER OFF TO NAPOLEON WHO WAS VERY VERY YOUNG AND WHO WANTED A REWARD FOR SUCH AN ACT OF SELFABNEGATION AND WAS GIVEN COMMAND OF THE FRENCH ARMY IN ITALY AS A REWARD THAT WAS HOW SHE BECAME NAPOLEONS WIFE ONCE SHE HAD ACHIEVED THIS POSITION SHE MADE MUCH USE OF IT SHE WAS A SOMEWHAT EXTRAVAGANT LADY AND AFTER A TIME NAPOLEON BEGAN TO OBJECT TO PAYING HER BILLS ON ONE OCCASION WHEN HE HAD BEEN PARTICULARLY ADAMANT ABOUT HER BILLS SHE WENT TO THE WAR MINISTER AND SAID NOW LOOK HERE YOU KNOW PERFECTLY WELL THAT IF I SAY ONE WORD AGAINST YOU TO NAPOLEON YOU WILL BE DISMISSED FROM OFFICE NOW WHAT I WANT YOU TO DO IS TO TAKE SOME PART OF THE FUNDS DEVOTED TO THE WAR TO PAY MY DEBTS THE WAR MINISTER UNDER THIS PRESSURE RELUCTANTLY CONSENTED THROUGHOUT THE WHOLE OF THE FORTHCOMING YEAR FRENCH ARMS SUFFERED ONE REVERSE AFTER ANOTHER GENOA WHICH THE FRENCH HAD CONQUERED FELL BACK AND WAS LOST TO THEM AND ALL THIS IN ORDER TO PAY JOSEPHINES DRESSMAKERS BILL HOWEVER NAPOLEON WAS NOT ALWAYS COMPLIANT WHEN HE RETURNED UNEXPECTEDLY FROM EGYPT AND NOBODY KNEW THAT HE WAS GOING TO COME SHE WAS DINING TETEATETE WITH BARRAS NAPOLEON MANAGED SOMEHOW TO CONVEY THAT HE WAS JUST GOING TO ARRIVE AND SHE FLED QUICKLY FROM BARRAS TO NAPOLEONS AND HER FLAT THE DOOR WAS LOCKED AND SHE REMAINED OUTSIDE NAPOLEON WAS INSIDE HAVING ARRIVED BEFORE HER FOR TWENTYFOUR HOURS HE KEPT HER SITTING ON THE DOORSTEP SHE HAD ANOTHER MORE SERIOUS MISFORTUNE AFTER NAPOLEONS FALL WHEN THE EMPEROR ALEXANDER CAME TO PARIS SHE THOUGHT WELL EMPERORS ARE MY MEAT I OUGHT TO BE ABLE TO CATCH HIM SHE TRIED VERY HARD SHE INVITED HIM TO DINNER AND FOLLOWING THE CUSTOM OF FASHIONABLE LADIES OF THAT TIME SHE WORE HER DRESS WET IN ORDER THAT IT MIGHT CLING TO THE FIGURE THE RESULT WAS THAT SHE CAUGHT A CHILL AND DIED AND THE EMPEROR ALEXANDER REMAINED UNAFFECTED BY HER CHARMS HER RELATIONS WITH NAPOLEAN HAD A SOMEWHAT UNFORTUNATE BEGINNING ON THEIR WEDDING NIGHT JUST AS NAPOLEON WAS GETTING INTO BED JOSEPHINES DOG BIT HIM IN THE CALF WHICH COMPLETELY SPOILT THIS IMPORTANT OCCASION MANY YEARS AFTERWARDS WHEN HE WAS DIVORCING HER HE BROUGHT THIS UP AS A GRIEVANCE AND IT APPEARED TO BE ONE OF THE REASONS WHY HE WISHED TO DIVORCE HER PEOPLE ARE ACCUSTOMED TO TREATING GREEK HISTORY IN A SPIRIT OF REVERENCE WHICH MAKES EVENTS UNREAL THEY DO NOT SEE THOSE EVENTS AS BEING VERY SIMILAR TO THOSE OF OUR TIME TAKE FOR INSTANCE THE AGE OF PERICLES ALWAYS REGARDED AS A SORT OF GREAT AND GLORIOUS AND SHIMMERING WONDER AND NEVER TREATED IN TERMS OF REALISM BUT IN FACT PERICLES WAS A PARTY BOSS WHO SUCCEEDED IN ESTABLISHING HIMSELF VERY LARGELY BY CORRUPT MEANS AND WHO WHEN HE SET TO WORK TO BUILD TEMPLES ON

SRUS

WHEN MY CHILDREN WERE VERY YOUNG WE SPENT THE SUMMERS A MILE FROM THE SEA UP A STEEP HILL AT THE END OF A DAY ON THE BEACH THEY WOULD FIND THE HILL TIRING AND I TRIED TO TAKE THEIR MINDS OFF FATIGUE BY INVENTING STORIES HERE ARE THREE OF THEM THE POST OFFICE OF PINKIE PONK TOWN HAD GROWN TIRED OF THE SMALL VILLAGE TO WHICH IT BELONGED AND OF THE VERY RESTRICTED OUTLOOK FROM ITS WINDOWS IT LEARNT FROM THE ADVERTISEMENTS WHICH PASSED THROUGH IT THAT NOWADAYS IT IS POSSIBLE TO FLY AND IT THOUGHT IF ONLY I COULD FLY WHAT JOURNEYS I COULD MAKE IT DISCOVERED THAT ON THE TOP OF A STEEP AND LONELY CLIFF THERE LIVED A VERY VERY OLD WOMAN WHO HAD INHERITED MAGIC POWERS FROM A LONG LINE OF ANCESTRAL WITCHES WHEN IT ASKED HER WHETHER SHE COULD ENABLE IT TO FLY SHE REPLIED NOTHING EASIER YOU MUST GET THE POST MASTER TO STAND ON A HILLTOP AT MIDNIGHT WHEN THERE IS A FULL MOON AND TO SAY IN A LOUD VOICE JINKIE PINKIE FLY PIE CHINKIE CHONKIE RATTLE RIE UP UP TO THE SKY ONE TWO THREE GO IF SHE CONTINUED HE CAN GET THIS EXACTLY RIGHT YOU WILL FLY AND QUICKLY BE OUT OF SIGHT THE POST MASTER WHO ALSO WAS TIRED OF PINKIE PONK TOWN TRIED IT ON AT THE NEXT FULL MOON BUT DURING THE INTERVENING MONTH HE MADE MANY VISITS TO THE OLD SORCERESS AND AT LAST BECAME WORD PERFECT WHEN THE INHABITANTS OF PINKIE PONK TOWN WOKE UP IN THE MORNING AFTER THE NEXT FULL MOON THEY WERE ASTONISHED TO FIND AN EMPTY GAP WHERE THE POST OFFICE HAD STOOD THE PASSENGERS ON A CROSSCHANNEL STEAMER AVERRED THAT THEY HAD SEEN IT FLYING THROUGH THE AIR TOWARDS DIEPPE THEY WOULD HAVE BEEN REGARDED AS LUNATICS BUT FOR THE FACT THAT ONE OF THEM WAS THE ARCHBISHOP OF CANTERBURY AND ANOTHER WAS PRESIDENT OF THE ROYAL SOCIETY NEXT DAY THE NEWSPAPERS REPORTED THAT A BUILDING CLEARLY LABELLED PINKIE PONK TOWN POST OFFICE HAD DESCENDED UPON A SMALL VILLAGE IN THE SOUTH OF FRANCE COMPLETE WITH POST MASTER BUT ALAS THE POST MASTER AND THE POST OFFICE FOUND THEIR NEW HABITAT JUST AS DULL AS PINKIE PONK TOWN AND AT THE NEXT FULL MOON THEY FLEW HOME AGAIN AND THENCE FORTH TRAVELLED NO MORE CLOSE TO WHERE WE LIVED THERE WAS A VERY LARGE AREA OF MARSH FILLED WITH THE SORT OF VEGETATION APPROPRIATE TO SUCH A PLACE MY CHILDREN EXPLORED THE EDGES OF THIS REGION AND WERE INTERESTED BY THE STRANGE SUCKING NOISE THAT THEIR SHOES MADE AS THEY PULLED THEM OUT OF THE MIRE IN THE VERY CENTRE OF THE SLOUGH SO I ASSURED MY CHILDREN LIVED THE GREAT GOD ZOOMP THE TUTELARY DEITY OF ALL SWAMPS AND QUAGMIRES ONCE UPON A TIME AN EMINENT ZOOLOGIST IN PURSUIT OF RARE FERNS HAD COME UPON THE GOD AND PULLED HIM OUT WITH EXTRAORDINARY LABOUR THE ZOOLOGIST DRIED HIM OUT AND PUT HIM IN A GLASS CASE IN THE NATURAL HISTORY MUSEUM BUT THE NIGHT WATCHMAN COMPLAINED THAT THROUGHOUT THE HOURS OF DARKNESS HE HEARD A MELANCHOLY VOICE WAILING ZOOMP ZOOMP ZOOMP THE ZOOLOGIST INVESTIGATED AND FOUND THAT THE POOR GOD WAS SUFFERING UNBEARABLE DESICCATION THE ZOOLOGIST TOOK PITY UPON HIM AND TRANSPORTED HIM IN THE DEAD OF NIGHT TO THE WETTEST PART OF THE SWAMP AFTER THIS THOUGH THE GODS WORDS WERE UNCHANGED THE EMOTION THAT THEY STRESSED WAS ENTIRELY DIFFERENT AND ALL WHO HEARD HIM REJOICED IN THE CHEERFULNESS OF HIS ZOOMP ZOOMP ZOOMP MY CHILDREN AT ONE TIME BECAME INTERESTED IN TALES OF THE FIERCE BEASTS OF THE JUNGLE AND THE STRANGE LUMINOUS FISHES THAT LIVE IN THE DEEPER PARTS OF THE OCEAN THIS LEAD ME TO TELL THEM ABOUT THE VERY REMARKABLE ZOO NEAR

SOUTHAMPTON WHICH WAS THE PRIVATE PROPERTY OF THAT EMINENT WEALTHY NATURALIST SIR THEOPHILUS TWACKUM

NEWSPAPERS:

This category is made up of 5 long articles, so called 'features' of varying style and quality. They appear in table 4.1 in descending order of factual writing - and ascending order of 'juiciness' - with the REC1 as an example of what I earlier called 'seductive pandering', a highly conducive and, to many people, palatable style, which contrary to common belief is neither unskilled nor low in vocabulary.

The article from GLASGOW HERALD (Glasgow Herald,1981) reports on the Governments failure to back up gas piping from the North Sea oil fields. Although the writer allows his personal view to shine through, there is no direct declaration of his or his paper's emotional bias. I have picked this article for its factual subject matter, and the writers detachment.

The writer of the article from THE GUARDIAN (Guardian,1983) is a vicar who unashamedly admits to having remarried in church a number of divorcees in spite of the moral stands of his Church. Although the writing is biased in the sense, that it airs a personal view, the writer rarely departs from a sober conveying of his views. I have picked this article because its subject is emotional, but the style is relatively un-emotional.

With the article from THE DAILY MAIL (Daily Mail,1981) we enter the fleemarket of journalism. In a rather pompous and self-assured style the writer gives a vivid account of two teachers' fight to break the spell cast upon some of their pupils by the 'Moonies'. Both subject matter and style are highly emotional.

The DAILY RECORD has provided me with two gems, DREC1 and DREC2. DREC2 (Daily Record,1983) is a feature on the television series 'To the manor born' revealing inside information about the filming of the series and generally establishing a pseudo relationship of pseudo intimacy between the reader and the actors. The style can - if anything - best be classed as hallucinogenic.

DREC1 (Daily Record,1981) as a text string is not easy to describe, let alone classify. I can best describe DREC1 as being like an adolescent day dream: word-play and action-repeat-with-minor-changes. As stated above, it is not the result of lack of skill or simple-mindedness. The vocabulary of this article, being the highest of any text I have measured (see next chapter), bears witness to the manipulative skills of the writer. In a style which sways hither and dither with the emotional charge of the 'action', the reader can live out this infatuation with the life of a 'master criminal' turned super-grass, in around 1000 words.

HRLD

THE GOVERNMENT IS NOT TO BACK THE HUGE 27 BILLION POUND NORTH SEA GAS GATHERING PIPELINE PROJECT AFTER WEEKS OF MEETINGS AND NEGOTIATIONS IT ANNOUNCED YESTERDAY THAT IT WILL BE LEFT TO THE INDIVIDUAL OIL COMPANIES TO MAKE THEIR OWN ARRANGEMENTS FOR BRINGING THE GAS ASHORE THE GOVERNMENTS WITHDRAWAL FROM THE PROJECT REGARDED AS THE MOST AMBITIOUS OPEN TO BRITAIN FOR MANY YEARS IS A BITTER BLOW TO SCOTLANDS ECONOMY AND JOB HOPES IT WAS EXPECTED THE PROJECT WOULD LEAD TO LARGE INVESTMENT IN PETROCHEMICAL DEVELOPMENTS AT NIGG IN THE CROMARTY FIRTH AND IN BUCHAN IN ABERDEENSHIRE AS WELL AS GIVING A MAJOR BOOST TO BRITISH STEEL WHO WOULD HAVE PROVIDED MOST OF THE 14 BILLION POUND WORTH OF PIPE REQUIRED IF THE OIL COMPANIES ARE TO GO IT ALONE THE FIRST OBSTACLE TO BE OVERCOME IS THE PRICE THEY WILL BE PAID BY BRITISH GAS FOR THE FEEDSTOCK WHEN IT COMES ASHORE THE SCHEME FINALLY FOUNDERED BECAUSE THE GOVERNMENT DECIDED NOT TO FINANCE IT AS A STATE ENTERPRISE THEY WANTED THE OIL COMPANIES TO INVEST ABOUT 70 PERCENT OF THE NECESSARY CAPITAL BUT WITHOUT GOVERNMENT BACKING BANKS AND OTHER CITY INSTITUTIONS WERE NOT PREPARED TO ADVANCE FUNDS WHICH WOULD HAVE ALLOWED THE INITIAL WORK TO START ON THE PIPELINE AND THE RECEPTION TERMINAL AT ST FERGUS IN ABERDEENSHIRE IT HAS BEEN ESTIMATED THAT AS MUCH AS 50 BILLION POUND WORTH OF GAS COULD BE AT RISK IF SOME METHOD IS NOT FOUND OF BRINGING IT ASHORE AT PRESENT ALTHOUGH SOME OF THE GAS IS BEING FLARED OFF MOST OF IT IS BEING REINJECTED INTO THE FIELD BUT THIS CAN ONLY BE DONE FOR A CERTAIN LENGTH OF TIME A GOVERNMENT SPOKESMAN SAID THE OIL COMPANIES SHOULD FINANCE THEIR OWN PIPELINE IT IS CLEAR TO THE GOVERNMENT THAT EITHER BY THE INTEGRATED SCHEME OR BY A NUMBER OF SEPARATE SCHEMES THE VAST VOLUME OF GAS RESERVES CAN AND WILL BE BROUGHT ASHORE SAID THE SPOKESMAN THE GOVERNMENT THEREFORE HAS DECIDED THAT THE COMPANIES SHOULD IN THE FUTURE AS IN THE PAST MAKE THEIR OWN ARRANGEMENTS FOR BRINGING THE GAS ASHORE THERE WAS ANGRY REACTION FROM ALL SECTIONS OF SCOTTISH INDUSTRY THE SCOTTISH TRADES UNION CONGRESS DESCRIBED IT AS A KICK IN THE TEETH TO SCOTLAND IN ALL SORT OF RESPECTS MR DOUG HARRISON OF THE STUC SAID MRS THATCHER ON ADVICE FROM THE TREASURY AND CLEARLY DISREGARDING ADVICE FROM OTHER DEPARTMENTS AND MINISTERS IS PREPARED YET AGAIN TO PUT POLITICAL DOGMA BEFORE THE NEEDS OF THIS COUNTRY OVER THE NEXT 30 YEARS A SPOKESMAN FOR THE CBI IN SCOTLAND SAID WE TAKE A VERY SERIOUS VIEW OF THIS INDEED IT WAS ONE OF THE MAJOR FACTORS LIKELY TO GET THE SCOTTISH ECONOMY GOING AGAIN IT IS NOT JUST THE PIPELINE PROJECT ITSELF BUT ALL THE SPINOFFS FOR THE CONSTRUCTION AND STEEL INDUSTRIES AND THE SUPPLIERS OF ALL THE NECESSARY EQUIPMENT MR JOHN SMITH SHADOW TRADE SECRETARY SAID THE DECISION WAS APPALLING NEGLECT OF OUR NATIONAL INTERESTS THE DEAD HAND OF SHORT TERM POLITICAL DOGMA HAD KILLED THE MOST VISIONARY OF ALL NORTH SEA PLANS HE SAID IT WAS NOW LIKELY THAT THE VAST RESOURCES OF THE NORTH SEA WOULD BE WASTED AND IT WAS THE END OF A PIONEERING PARTNERSHIP BETWEEN PUBLIC AND PRIVATE INDUSTRY WHICH SUCH AN ENORMOUS PROJECT REQUIRED COUNCILLOR SANY MUTCH CONVENER OF GRAMPIAN REGION SAID THE DECISION WAS A SETBACK TO THE REGIONS HOPES OF GETTING A SHARE OF THE PETROCHEMICAL AND OTHER DOWNSTREAM DEVELOPMENTS WHICH WOULD BRING PERMANENT JOBS TO THE AREA WE HAVE MADE IT CLEAR WE ARE NOT CONTENT TO SEE RESOURCES OF

THE NORTH SEA COMING ASHORE IN GRAMPIAN ONLY TO BE PIPED AWAY ELSEWHERE FOR PROCESSING HE SAID MR ALBERT MACQUARRIE CONSERVATIVE MP FOR EAST ABERDEENSHIRE WHERE OCCIDENTAL PLAN TO BUILD A CRACKER PLANT WITH GAS FROM THE NORTH SEA SAID WE ARE LOSING 100000 POUND A WEEK BY GAS BEING FLARED OFF AND THIS CANNOT GO ON MR JAMES RASMUSSEN OIL CONSULTANT TO THE SCOTTISH COUNCIL DEVELOPMENT AND INDUSTRY SAID THE OPTIONS OPEN TO THE INDUSTRY WERE TO USE THE EXISTING PIPELINES WHICH BOTH HAD SPARE CAPACITY HE WOULD ALSO NOT RULE OUT THE POSSIBILITY OF A MODIFIED PIPELINE BEING BUILD THE MAIN REASON THE OIL COMPANIES ARE RELUCTANT TO GO IT ALONE IS THAT THE PRICE BEING OFFERED FOR THE GAS IS NOT HIGH ENOUGH HE SAID MR BRUCE MILLAN SHADOW SCOTTISH SECRETARY SAID THE DECISION WAS ANOTHER VICTORY FOR THE HATCHET MEN OF THE TREASURY AND MEANT THAT THE GOVERNMENT WAS GOING TO SQUANDER A VAST NATIONAL RESOURCE

GUAR

SINCE I CAME TO MY PARISH IN 1977 I HAVE REMARRIED IN CHURCH SIX COUPLES IN FULL KNOWLEDGE OF THE FACT THAT BY SO DOING I WAS GOING AGAINST THE LAW OF THE CHURCH OF ENGLAND BUT NOT AGAINST THE LAW OF THE LAND THE PROCEDURE IS SIMPLE THE COUPLE CONCERNED NEED TO TAKE THEIR DECREE ABSOLUTE TO THE LOCAL SUPERINTENDENT REGISTRAR TOGETHER WITH A LETTER FROM THE VICAR TO SAY THAT HE IS PREPARED TO MARRY THEM ON THE ISSUE OF THE REGISTRARS CERTIFICATE A FORMALITY THE COUPLE MAY THEN BE MARRIED ACCORDING TO THE RITES AND CEREMONIES OF THE CHURCH THE MAIN REASON WHY I HAVE PERFORMED THESE WEDDINGS IS THAT THE CHURCH PROVIDES NO ALTERNATIVE WHICH IS BOTH LOGICAL AND COMPASSIONATE THE OFFICIAL LINE IS NOTHING BUT HYPOCRISY IT SAYS THAT DIVORCED PERSONS MAY NOT BE REMARRIED IN CHURCH BUT THAT THEY MAY HAVE A SERVICE OF BLESSING BUT A MARRIAGE SERVICE IS A BLESSING THAT IS WHY NEWLY ORDAINED DEACONS ARE NOT ALLOWED TO PERFORM MARRIAGES ONLY A PERSON IN PRIESTS ORDERS CAN PRONOUNCE A BLESSING IF THE CHURCH IS PREPARED TO BLESS A REGISTER OFFICE REMARRIAGE IT FOLLOWS THAT IT THEREBY RECOGNISES THAT REMARRIAGE AS VALID IN WHICH CASE WHY NOT ALLOW A CHURCH WEDDING IN THE FIRST PLACE IF IT IS CLAIMED THAT THE CHURCH IN ITS SERVICE OF BLESSING BY NO MEANS RECOGNISES THE VALIDITY OF CIVIL REMARRIAGE THEN WE CAN ONLY WONDER AT THE SOCIAL MORAL AND THEOLOGICAL STATUS OF THESE UNIONS THAT ARE PRONOUNCED BLESSED IT SEEMS TO ME THEREFORE THAT THE ONLY POSSIBLE MEANS BY WHICH THE HAPLESS VICAR CAN AVOID HYPOCRISY ARE EITHER TO REFUSE ALL REQUESTS FOR REMARRIAGE ON THE GROUNDS THAT REMARRIAGE IS A THEOLOGICAL IMPOSSIBILITY OR TO ALLOW ALL SUCH REQUESTS ON THE GROUNDS OF COMPASSION LIKE A DOZEN OTHER PARSONS I COULD NAME I HAVE CHOSEN THE SECOND COURSE AT FIRST GLANCE THE NEW REPORT TO THE JULY SYNOD MARRIAGE AND THE STANDING COMMITTEES TASK WOULD SEEM TO PUT AN END TO ALL THIS TROUBLE FOR IT RECOMMENDS REMARRIAGE IN CHURCH BUT THIS TURNS OUT TO BE AT THE COST OF MAKING THE LOCAL VICAR INTO A COMMISSAR AND THE CHURCH IN GENERAL LIKE THE ASSOCIATION OF SCRIBES AND PHARISEES FIRST THE COUPLE INTENDING REMARRIAGE MUST APPLY TO THE VICAR WHO WILL INQUIRE INTO THE FULL CIRCUMSTANCES SURROUNDING THE APPLICATION WHY WHAT RIGHT HAS THE VICAR TO CONDUCT A FULL EXAMINATION OF PEOPLES PRIVATE AFFAIRS AFTER ALL HE IS NOT EXPECTED TO DO THIS WITH FIRST MARRIAGES A SINGLE MAN MAY TURN UP AT THE VICARAGE ARM IN ARM WITH A SINGLE WOMAN WITH WHOM HE HAS SPENT A SINGLE NIGHTS DRUNKEN LECHERY IF HE ASKS FOR MARRIAGE THE VICAR CANNOT AND RIGHTLY CANNOT LEGALLY REFUSE IT BUT IF AFTER A DISASTROUS FIRST MARRIAGE IN WHICH HIS WIFE WAS POSSESSED OF THE MORALS OF LUCREZIA BORGIA A MAN COMES NOW WISHING TO BE MARRIED TO THE SECRETARY OF THE WOMENS INSTITUTE THE VICAR IS OBLIGED TO CONDUCT A FULL EXAMINATION INTO THEIR AFFAIRS SUCH A MORAL INTERROGATION IS ITSELF IMMORAL THAT IS NOT ALL THE VICAR IS NOT TO BE THE SOLE INTERROGATOR HE MUST CONSULT GUIDE LINES TO BE PROVIDED IN THE SYNODS GREEN BOOK AND THEN FILL IN A FORM OF APPLICATION TO THE BISHOP BUT EVEN THE BISHOP IS NOT LEFT TO DECIDE THE ISSUE HE MUST PASS ON THE APPLICATION TO A PANEL OF ADVISERS THOSE INTENDING REMARRIAGE MIGHT BE PLEASED TO LEARN THAT ONLY A MINORITY OF THOSE WHO PRODUCED THE CHURCHS REPORT THINK THAT THE COUPLES PERSONAL ATTENDANCE BEFORE THIS PANEL SHOULD BE MANDATORY BUT HALF OF THE COMMITTEE DO THINK THAT IN WHATEVER SUPPLANTS

BANNS IN THE RUNUP TO REMARRIAGE THERE SHOULD BE A PUBLIC STATEMENT POINTING OUT THAT A DIVORCED PERSON IS INVOLVED ALL THIS MUST SOUND VERY FINE IN THE CORRIDORS OF ECCLESIASTICAL BUREAUCRACY BUT WHAT ABOUT THE REAL WORLD OF HUMAN RELATIONSHIPS COUPLES WHO APPLY FOR REMARRIAGE CERTAINLY ALL WHO HAVE EVER APPLIED TO ME DO NOT DO SO LIGHTLY IT IS FAR EASIER TO BE REMARRIED IN THE REGISTER OFFICE AFTER THE HURT AND RECRIMINATIONS AND THE SHOUTING IN PUBLIC OF ONES PERSONAL MATTERS THAT CONSTITUTE DIVORCE PROCEEDINGS IT REQUIRES COURAGE AND PERSISTENCE TO APPROACH THE VICARAGE WITH AN EYE ON A SECOND CHANCE IT IS CHURLISH OF THE VICAR TO REWARD THEM BY RUMMAGING IN HIS DRAWERS FOR LITTLE GREEN BOOKS AND APPLICATION FORMS WHEN HE SEES THEM COMING UP THE DRIVE AND TO ACCOMPANY EVERY PUBLIC REFERENCE TO THEIR FORTHCOMING NUPTIALS WITH THE SHRILL UTTERANCE OF DIVORCED DIVORCED AS IF LEPROSY HAD VISITED THE PARISH BUT THE MOST OBJECTIONABLE ASPECT OF THE NEW PROPOSALS IS NEITHER THEIR POOR LOGIC NOR THEIR BAD MANNERS BUT THEIR COLOSSAL SANCTIMONIOUSNESS THE IDEA OF VICARS AND BISHOPS LET ALONE A PANEL OF ADVISERS AGAINST WHICH BY THE WAY NO APPEAL IS ENVISAGED SETTING THEMSELVES UP IN JUDGMENT OVER COUPLES WHO HAVE MADE THE CONSIDERABLE EFFORT TO SEEK SPIRITUAL SUPPORT IS REPUGNANT TO THE SPIRIT OF CHRISTIANITY ARE CLERGYMEN SAINTS IS THE ANONYMOUS PANEL OF ADVISERS TO BE MADE UP OF ALL THE HOLY VIRGINS AND MARTYRS CHAIRED BY THE ARCHANGEL MICHAEL HIMSELF WHEREAS THE FOUNDER OF CHRISTIANITY WELL KNOWN FOR HIS HARSH WORDS AGAINST THOSE WHO THOUGHT THEMSELVES RIGHTEOUS AND DESPISED OTHERS AND WHO WOULD SCARCELY ALLOW EVEN THE SINLESS TO CAST THE FIRST STONE WOULD NOT PERMIT EVEN THE BUREAUCRACY OF THE CHURCH OF ENGLAND DEVISED TO HURL SUCH PEBBLES OF SELFRIGHTEOUSNESS AGAINST MEN AND WOMEN SEEKING BLESSING OF HIS CHURCH

MAIL

EVERY MORNING TWO TEACHERS MEET IN A STAFFROOM AND WONDER WILL TODAY BE THE DAY THE MOONIES KEEP THEIR PROMISE FOR THE PAST YEAR MR CASEY MCCANN AND THE REV PETER HULLAH HAVE BEEN GETTING UNDER THE CULT LEADERS GUARD WITH AN AMAZING DOUBLE ACT OF STRAIGHT TALKING AND DIPLOMACY BUT ONLY WHEN THE NEW TERM STARTS NEXT WEEK WILL THEY KNOW IF THEIR EFFORTS TO SAVE STUDENTS SUCKED IN BY THE MOONIES HAVE SUCCEEDED MCCANN AND HULLAH GOT INVOLVED IN THE STRUGGLE AGAINST THE UNIFICATION CHURCH WHEN TWO EXPUPILS BECAME MOONIES ON A VISIT TO AMERICA DURING THEIR UNIVERSITY HOLIDAYS THEN THEY WIDENED THEIR NO NONSENSE CAMPAIGN TO COVER ALL BRITISH STUDENTS WHO HAD ABANDONED THEIR EDUCATION TO FOLLOW THE REV SUN MYUNG MOON AND WRUNG AN IMPORTANT PLEDGE OUT OF ONE OF THE CULTS LEADERS IN JUNE DR MOSE DURST PRESIDENT OF THE AMERICAN MOONIES PROMISED CASEY MCCANN THAT BRITISH RECRUITS IN AMERICA WOULD BE ENCOURAGED TO RETURN HOME TO FINISH THEIR STUDIES IF THE MOONIES KEPT TO THEIR WORD THE DIRECTNESS USED BY MCCANN AND HULLAH WILL HAVE TRIUMPHED WHERE OTHER PEOPLES SUBTLETY FAILED BUT IF THEY DO NOT THERE WILL BE A NEW WAVE OF PUBLIC ANSER AGAINST THE MOONIES AND VERY LITTLE TIME REMAINS FOR THE PROMISE TO BE KEPT IT ALL BEGAN WHEN MR MCCANN AN ENERGETIC 39 YEAR OLD HOUSEMASTER AT SEVENOAKS PUBLIC SCHOOL KENT AND MR HULLAH ITS JOVIAL CHAPLAIN WERE ALERTED BY A LETTER FROM THE MOTHER OF TWO FORMER PUPILS WHO HAD JOINED THE CULT WITHIN 24 HOURS THEY WERE ON THE DOORSTEP TO OFFER HELP WITHIN 48 HOURS MR MCCANN WAS IN SAN FRANCISCO HE WENT STRAIGHT FROM THE AIRPORT TO THE CULTS HEADQUARTERS IN BUSH STREET THE MOONIES INVARIABLY ASK VISITORS TO REMOVE THEIR SHOES SIGN THE VISITORS BOOK AND GO UPSTAIRS TO THE MAIN RECEPTION ROOMS BUT CASEY MCCANN WAS HAVING NONE OF THAT I JUST TOLD THEM IF YOU CAME TO MY HOUSE I WOULD NOT ASK YOU TO TAKE YOUR SHOES OFF AND BESIDES I HAVE GOT VERRUCA AND WITH THAT INTRODUCTION HE WALKED STRAIGHT UPSTAIRS WITH HIS BOOTS STILL ON BUTTONHOLED THE TOP BRASS AND INSISTED ON SEEING THE BOYS AFTER MUCH PERSISTENCE HE WAS ABLE TO TALK TO ONE OF THEM SINCE THEN MR MCCANN HAS MET MOST OF THE TOP MOONIES IN THE UNITED STATES AND BRITAIN AND HAS FREQUENTLY DROPPED IN UNANNOUNCED AT THEIR BRITISH HEADQUARTERS IN LONDON THE MEETINGS HAVE BEEN SOMETIMES TENSE AND ANGRY SOMETIMES RELAXED OVER HALF A DOZEN PINTS IN A LOCAL NOT ALL TOP MOONIES RESPECT THE SECTS BAN ON ALCOHOL THERE HAVE BEEN MOMENTS WHEN HE FELT HE WAS REACHING AN UNDERSTANDING INTERSPERSED WITH STAND UP SHOUTING MATCHES MCCANN DOES NOT BELIEVE IN LEAVING HURTFUL THINGS UNSAID THERE CAN NOT BE MANY SCHOOLMASTERS LEFT WITH HIS NO NONSENSE MANNER HE IS SIX FOOT TWO INCHES TALL WITH A FLORID COMPLEXION AND A WITHERING COMMAND OF THE ENGLISH LANGUAGE MR MIKE MARSHALL ACTING DIRECTOR OF THE MOONIES IN BRITAIN CHIDES HIM FOR TREATING THEM LIKE SCHOOLKIDS CASEY DOES NOT MIND THE JIBE HE THINKS IT MEANS HIS MESSAGE IS GETTING THROUGH PETER HULLAH IS A 33 YEAR OLD YORKSHIREMAN WITH A RUGBY FORWARD FIGURE AND A JOVIAL MANNER HE THINKS OF HIMSELF AS CASEYS DUSTPAN AND SUPERGLUE BEARER CASEY BREAKS THE CROCKERY AND PETER PICKS IT UP AND PUTS IT TOGETHER AGAIN NEITHER MCCANN NOR HULLAH WOULD GET ANYWHERE WITH THE MOONIES ON THEIR OWN EACH NEEDS THE OTHERS BALANCING QUALITIES MCCANN WOULD RAISE TOO MANY HACKLES IF HE DID NOT HAVE THE CHAPLAIN TO SMOOTH THEM OUT AGAIN THEIR JOINT EFFORTS WERE FIRST REWARDED AT EASTER WHEN THE YOUNGER OF THE TWO

BROTHERS LEFT THE MOONIES I HAD INVITED HIM TO DINNER AND ASKED HIM WHAT HE WOULD LIKE TO DRINK SAID MCCANN I THOUGHT HE WOULD SAY CARROT JUICE OR SQUASH BECAUSE MOONIES ARE NOT SUPPOSED TO DRINK INSTEAD HE ASKED FOR A DOUBLE GIN I ASKED IF THAT MEANT WE HAD SOMETHING TO CELEBRATE HE SAID YES AND HE WAS OUT THE ELDER BROTHER REMAINS IN THE MOONIES BUT MCCANN AND HULLAHS CAMPAIGN HAS FOREWARNED OTHER PUPILS FROM THEIR SCHOOL THEY HAVE ALSO CAMPAIGNED HARD FOR MANY OTHERS UNCONNECTED WITH SEVENOAKS AND IF THE PROMISE MADE TO THEM IS KEPT THEY WILL HAVE ENGINEERED A MAJOR BREAKTHROUGH IN THE STRUGGLE AGAINST THE MOONIES MR MCCANN HAS FLOWN TO AMERICA THREE TIMES AND MR HULLAH TWICE AT THEIR OWN EXPENSE THEY HAVE HAD ONLY TWO SMALL DONATIONS TO HELP THE MOTIVATION FOR BOTH MEN WAS A FEELING THAT THEY HAD A DUTY TO THEIR FORMER PUPILS THAT DUTY TO TWO BOYS BECAME A DUTY TO THOUSANDS AND NOW THEY ARE BUSILY SPREADING THE WORD IN OTHER SCHOOLS MCCANN AND HULLAH HAVE ALWAYS GONE THEIR OWN WAY AND HAVE NOT JOINED ANY OF THE ESTABLISHED ANTI MOONIE GROUPS SO WHAT DO THESE GROUPS MOST OF WHOM HAVE BEEN WORKING ON THE SAME PROBLEMS FOR FAR LONGER THINK OF THEM MR MCCANN IS A FIERY INDEPENDENT SPIRIT WHO HAS BLUSTERED HIS WAY INTO LANCASTER GATE THE MOONIE HEADQUARTERS SAID ONE EXPERIENCED WORKER HE IS ESSENTIALLY A PROBLEM SOLVER AND HE SEES NO REASON WHY THIS PROBLEM SHOULD NOT BE SOLVED LIKE ANY OTHER THE TEST OF HIS SUCCESS WILL BE WHETHER ANY OF THESE BRITISH BOYS AND GIRLS COME HOME TO COMPLETE THEIR EDUCATION I WISH THEM WELL

1REC

AT THE AGE OF 28 ROGER DENNHARDT HAD REACHED THE PINNACLE OF HIS CHOSEN PROFESSION ARMED ROBBERY HE WAS HOLDING UP BANKS SECURITY FIRMS AND SHOPS TWO OR THREE TIMES A WEEK WHEN HIS CAREER CAME TO A SUDDEN STOP HE WAS NICKED AND AFTER THREE YEARS IN PRISON DENNHARDT THE MOST ACCOMPLISHED VILLAIN OF HIS GENERATION BECAME A SUPERGRASS THIS IS HIS AMAZING CHILLING STORY ROGER DENNHARDT BECAME HOOKED ON THE THRILL OF WRONGDOING FROM THE VERY BEGINNING HE FOUND IT EASY AND HE LOVED THE FEELING OF POWER THE FIRST TIME I FELT LIKE A CRIMINAL HE SAYS WAS WHEN I FIRST HELD A GUN IN MY HAND WITH MALICIOUS INTENT THE KIDS I STARTED OUT WITH HAD BEEN DOING ARMED ROBBERY WITH PICKHANDLES AND A KNIFE THEY JUST DID NOT PRODUCE THE FEAR PEOPLE WERE NOT IMPRESSED THEY WOULD TRY TO FIGHT BACK HE RECALLS A SCENE FROM HIS APPRENTICESHIP IN CRIME I REMEMBER SITTING IN THE CAR HIGH AS A KITE ABSOLUTELY TINGLING BECAUSE THIS WAS THE FIRST REAL CRIME I HAD EVER COMMITTED SATURATED WITH ADRENALIN SIZZLING INSIDE EVEN NOW IT IS DIFFICULT FOR DENNHARDT TO GRASP THAT IT MIGHT HAVE BEEN LESS THAN HEROIC TO DOMINATE UNARMED PEOPLE WITH A DEADLY WEAPON IT WAS BETTER THAN WORKING THE VERY FIRST JOB WE DID WITH A GUN I GOT A SHAREOUT OF ABOUT 30 POUNDS IT WAS MORE THAN I EARNED IN A WEEK DOING THE JOB I HAD GOT AS A PLASTERER ABOVE ALL CRIME MADE DENNHARDT FEEL LIKE SOMEBODY A STRING OF HOLDUPS LABELLED THE BONNIE AND CLYDE CAPER BROUGHT HIM NOTORIETY WHEN HE WAS STILL A TEENAGER THEY ALSO BROUGHT HIS FIRST PRISON SENTENCE AND HIS COMING TO CRIMINAL MANHOOD ANY NUMBER OF REASONS COULD EXPLAIN WHY ROGER LOUIS DENNHARDT BECAME AN ARMED ROBBER HIS UNSTABLE BOYHOOD CONTAINED ALL THE CLASSIC INGREDIENTS WARRING PARENTS THE NONEXISTENT HOME LIFE INCONSISTENT SUPERVISION BAD COMPANIONS STRANGELY ENOUGH THAT IS NOT THE WAY IT SEEMED OR SEEMS NOW TO DENNHARDT HE RESPECTS HIS FATHER STILL ALTHOUGH THEY HAVE NOT MET FOR MANY YEARS AND LOVES HIS MOTHER DEEPLY HE DID NOT LACK AFFECTION BUT AS A VERY YOUNG CHILD HE CAME TO ACCEPT VIOLENCE AS PART OF EVERYDAY LIFE I REMEMBER CONSTANT BUMPING AND BANGING SOUNDS AND MY MUM SCREAMING HE SAYS THE FAMILY LIVED ON THE BARNHILL HOUSING ESTATE AT HAYES MIDDLESEX DENNHARDTS FIRST ILLICIT THRILL CAME FROM BORROWING THEIR CAR FOR JOY RIDES THEN IT WAS PUSHING PEP PILLS TO OTHER YOUNGSTERS THEN TAKING CARS WHICH LED EVENTUALLY TO LOCKUP FOR YOUNG OFFENDERS AT REDHILL SURREY DENNHARDT WENT ON THE RUN FROM REDHILL BUT HIS FATHER AND UNCLE TOOK HIM BACK AT REDHILL THEY TOOK ME INTO THIS ROOM LOCKED THE DOOR AND THESE MASTERS LEAPT ON ME THEY PULLED MY TROUSERS DOWN AND BIRCHED ME I WAS OUTRAGED THAT BEATING WAS A CHASTENING EXPERIENCE WHAT HURT MORE WAS THE FACT THAT THESE BASTARDS THESE GROWN MEN ALL GATHERED TOGETHER AND JUMPED ON ME A 15 YEAR OLD BOY THE STEP FROM WAYWARD YOUTH TO HARDENED CRIMINAL PROVED A SHORT ONE WHEN HE WAS 19 DENNHARDT TEAMED UP WITH TWO OTHER TEENAGERS AND A GIRL IN THE BONNIE AND CLYDE RAMPAGE AROUND HALF A DOZEN COUNTIES DENNHARDT MET THE TWO OTHER CLYDES CHRIS HAGUE AND TERRY THARME BY CHANCE HAGUE AND THARME WHO WERE ALREADY ROBBING ALLNIGHT GARAGES RECOGNISED A KINDRED SPIRIT THEIR FIRST RAID TOGETHER WAS A SUBPOST OFFICE THARNE AND HAGUE WENT IN WEARING CARDBOARD CISCO KID MASKS FROM WOOLWORTHS MINUTES LATER THEY WERE BACK IN THE STOLEN GETAWAY CAR EMPTYHANDED BUT BAWLING WITH LAUGHTER THE POSTMASTER HAD IGNORED THEIR CLUBS AND KNIFE

AND SWUNG A CHAIR AT THEM WE CAN NOT HAVE THAT HE SAID AFTER THE RAID HIS SENSE OF ORGANISATION AFFRONTED HE WAS NOT FRIGHTENED WE HAVE GOT TO GET A GUN THEY STOLE A SHOTGUN SAWED OFF THE BARREL AND STORMED ANOTHER POST OFFICE THIS TIME THEY COLLECTED 88 POUNDS THE GANG DID MORE POST OFFICE ROBBERIES BEFORE TRYING THEIR FIRST BANK AT HANWORTH MIDDLESEX IT WAS A PUSHOVER NO COUNTER SCREEN NOT EVEN AUTOMATIC LOCKING TILLS THEY JUST WAVED THE GUN AND TOOK ALL THE MONEY IN SIGHT 3000 POUNDS ENOUGH IN THOSE DAYS AS DENNHARDT REMEMBERS WITH GREEDY RELISH TO BUY A NEW ETYPE JAGUAR AND PETROL FOR 10 YEARS WHEN THE GANG WERE FINALLY COUGHT THEY ADDED TO THEIR FASTGROWING LEGEND BY BREAKING OUT OF ASHFORD REMAND CENTRE THEY TOOLED UP FOR MORE ROBBERIES BY RAMMING A GUNSMITHS WINDOW WITH THEIR CAR ONLY WHEN AWED PARENTS INCLUDING DENNHARDTS FATHER WENT ON TELEVISION PLEADING WITH THEIR CHILDREN TO SURRENDER DID BRITAINS BIGGEST MANHUNT COME TO AN END FIVE YEARS AGO ROGER DENNHARDT HAD IT MADE EACH OF HIS FOUR BANK ACCOUNTS STOOD COMFORTABLY IN FOUR OR FIVE FIGURES HE ZIPPED AROUND LONDON IN FAST CARS THEN ONE DAY HE FOUND A GUN MUZZLE PRESSED TO HIS OWN WELLBARBERED HEAD HE HAD WALKED INTO A POLICE TRAP IN JAIL THE MASTER CRIMINAL HAD TIME TO REFLECT ON HIS PAST AND AFTER THREE YEARS HE TURNED INFORMER DENNHARDTS INFORMATION PUT DOZENS OF CROOKS IN PRISON AND RESULTED IN THE RECOVERY OF CASH AND STOLEN PROPERTY WORTH HUNDREDS OF THOUSANDS OF POUNDS HE APPLIED HIMSELF TO HIS NEW ROLE WITH ALL THE VIGOUR AND DEDICATION HE HAD SPENT ON HIS CRIMINAL CAREER THE TASK OF UNLOADING SUCH A MASS OF NAMES AND NUMBERS WAS AIDED BY A NEAR PHOTOGRAPHIC MEMORY THAT AND THE ATTENTION TO DETAIL WHICH SERVED DENNHARDT SO WELL DURING THE YEARS OF BANDITRY HE HAD THOUGHT OF HIMSELF WITH SOME JUSTIFICATION AS THE MOST HIGHLY SKILLED ROBBER IN THE LAND A THOROUGH PROFESSIONAL HIS PARTICULAR STRENGTH WAS PLANNING DEALING WITH THE INTRICACIES OF VEHICLES WEAPONS APPROACH AND ESCAPE ROUTES THE BACKUP OPERATION THE HABITS OF VICTIMS DENNHARDT STOOD HIGH IN THE RANKS OF VILLAINY BEFORE HE WAS 20 HE WAS ACKNOWLEDGED AS A FACE A CRIMINAL CELEBRITY AT HIS PEAK HE RAN A BLACK AND WHITE OPEL AND A HONEYBROWN BMW HE ALSO RAN A MISTRESS MELISSA A PALESKINNED BRUNETTE WITH THE BODY OF A GIRL OF 15 WHICH SHE WAS AND THE FACE OF A WOMAN OF 20 HAD AN ENDEARING WAY OF DOING JUST WHAT SHE WAS TOLD NIGHT AFTER NIGHT AND OFTEN IN BROAD DAYLIGHT DENNHARDT WOULD CHANGE HIS SHARP SUIT FOR THE SINISTER RIG OF HIS TRUE CALLING AND TAKE UP THE LETHAL TOOLS OF HIS TRADE ON HIS LAST JOB A 30000 POUNDS RAID ON A SECURITY VAN HE CARRIED A PUMPACTION SHOTGUN ONE OF THE GANGS GETAWAY CARS LED POLICE TO DENNHARDT HE WAS ARRESTED IN FEBRUARY 1977 AND LATER RECEIVED A 13 YEARS SENTENCE THE MORNING OF THE ARREST IN NORTH LONDON DENNHARDT AND MELISSA HAD MADE LOVE AFTER PATCHING UP A QUARREL HE RECALLS I KEPT THINKING IT WILL BE YEARS NOW BEFORE I SEE HER AGAIN YEARS MATE BLOODY STINKING YEARS I WOULD NOT SAY ANYTHING BUT I CRIED DENNHARDT HAD TAKEN PART IN A MILLION POUNDS SERIES OF CRIMES OVER MORE THAN A DECADE THE POLICE HE SAYS HAVE RECOVERED HIS SHARE OF THE LOOT GOING QE FOR QUEENS EVIDENCE EARNED DENNHARDT HIS FREEDOM

2REC
THE BARMAID IN THE COUNTRY PUB NEAR THE QUAINTLY NAMED CRICKET ST
THOMAS IN SOMERSET TALKED EXPERTLY ABOUT THE HIT TV SERIES THAT
HAS ALMOST BECOME PART OF HER COMMUNITYS LIFE SHE KNEW EVERYTHING
ABOUT TO THE MANOR BORN AND ITS CHARACTERS RIGHT DOWN TO THE
PROPER SPELLING OF AUDREY FFORBES HAMILTON THE TWEEDY LADY SO
BEAUTIFULLY PORTRAYED BY PENELOPE KEITH BUT SOON THE SERIES FOR
WHOM THE SOMERSET FOLK HOLD A SPECIAL AFFECTION WILL BE NO MORE
DURING FILMING AT THE WEEKEND PENELOPE REVEALED THAT THE NEW
SERIES THE THIRD WILL ALSO BE THE LAST AT THE END OF THESE SEVEN
PROGRAMMES WHICH START IN NOVEMBER IT WILL BE FAREWELL TO THE
ARISTOCRATIC BUT IMPOVERISHED AUDREY AND RICHARD DE VERE THE
WEALTHY OWNER OF THE MANOR PLAYED BY PETER BOWLES AND THE
MILLIONS OF VIEWERS WHO REGULARLY TUNE IN WANT TO KNOW IF AUDREY
AND RICHARD FINALLY GET TOGETHER IN THE LAST EPISODE THE ROMANTIC
MYSTERY AT THE MANOR THICKENS WHEN ANOTHER WOMAN ENTERS THE LIFE
OF RICHARD DE VERE SHE IS A FRENCH BUSINESSWOMAN PLAYED BY RULA
LENSKA WHO IN THE EPISODE WHICH WAS FILMED AT THE WEEKEND ARRIVES
TO VISIT THE MANOR EVERYONE IS TIGHTLIPPED ABOUT THE POSSIBILITY
OF A ROMANTIC ENDING IT IS ALL LISTED AS TOP SECRET BY THE BBC
WHO HAVE DECIDED TO DO A DALLAS PENELOPE WHO LOOKS MUCH MORE
ATTRACTIVE IN THE FLESH HAS NO REGRETS THAT SHE IS PLAYING AUDREY
FOR THE LAST TIME I FELT THE SERIES HAD RUN ITS COURSE SHE TOLD
ME ONE OF THE REASONS WHY I AM SUCCESSFUL IS THAT I KNOW WHEN TO
SAY NO WITH THE GOOD LIFE WE ALL DECIDED THAT IT WAS OVER AND I
THINK IT IS FAR BETTER TO LEAVE THE PUBLIC WANTING MORE THAN
HAVING THEM SAY THE SHOW IS DETERIORATING PENELOPE WHO WAS
DRESSED IN A SMARTLY TAILORED COUNTRY SUIT AND GREEN WELLIES
ADDED THAT SHE THOUGHT IT WAS A GOOD IDEA OF BUILDING UP SUSPENSE
BY NOT REVEALING HOW THE SERIES WOULD END YOU WANT PEOPLE TO BE
WONDERING WHAT IS GOING TO HAPPEN SHE SAID WHILE SHE WAS TALKING
HER HUSBAND DETECTIVE CONSTABLE RODNEY TIMPSON SAT NEARBY AS THE
COUPLE CUDDLED HAPPILY PENELOPE AGREED THAT SHE LIKED HAVING
RODDY WITH HER WHEN SHE IS WORKING WHEN YOU ARE ON LOCATION IT
SUDDENLY BECOMES THE MOST IMPORTANT THING IN THE WORLD SO IT IS
MARVELLOUS TO HAVE A TOUCHSTONE AND MINE IS MY HUSBAND SHE ALSO
TALKED ABOUT THE POSSIBILITY OF STARTING A FAMILY IF A CHILD
COMES ALONG IT WOULD BE LOVELY SHE SAID BUT WE ARE NOT SORT OF
DESPERATE BY THE END OF THIS SERIES PENELOPE WILL HAVE PLAYED
AUDREY FOR TEN AND A HALF HOURS BUT SHE HAS NO DESIRE TO APPEAR
IN A FEATURE FILM VERSION OF TO THE MANOR BORN I DO NOT BELIEVE
THAT IT WOULD TRANSFER TO THE CINEMA I HAVE NEVER SEEN A FILM OF
A TV SERIES WHICH WORKED SHE SAID EMPHATICALLY SHE HAS MADE A
FILM HOWEVER PRIEST OF LOVE WHICH STARS IAN MCKELLEN AS
DHLAWRENCE AND HERSELF AS DOROTHY BRETT THE SOCIETY GIRL WHO FELL
PASSIONATELY FOR HIM PENELOPE DESCRIBED THE CHARACTER SHE PLAYS
AS A CHALLENGING ROLE DOROTHY BRETT WAS STONE DEAF AND I FOUND IT
TERRIBLY DIFFICULT AT FIRST TO UNDERSTAND HOW A DEAF PERSON WOULD
RESPOND TO THINGS THE PART REALLY APPEALED TO ME PENELOPE HOWEVER
HAS NO IDEA ABOUT WHICH ROLES SHE WOULD LIKE TO TACKLE NEXT SHE
TOLD ME WHEN I FINISH THIS I WILL BE ABLE TO HAVE CHRISTMAS
WITHOUT WORKING THEN I WILL TAKE A DEEP BREATH AND SEE WHAT THE
NEXT THING IS THE THING ABOUT BEING AN ACTRESS IS NOT KNOWING
WHAT THE FUTURE WILL BRING I LIKE THAT BUT I DO NOT FEEL
ARROGANTLY OR NOT THAT I HAVE TO PROVE THAT I CAN ACT SO I DO NOT

2REC
THE BARMAID IN THE COUNTRY PUB NEAR THE QUAINTLY NAMED CRICKET ST THOMAS IN SOMERSET TALKED EXPERTLY ABOUT THE HIT TV SERIES THAT HAS ALMOST BECOME PART OF HER COMMUNITYS LIFE SHE KNEW EVERYTHING ABOUT TO THE MANOR BORN AND ITS CHARACTERS RIGHT DOWN TO THE PROPER SPELLING OF AUDREY FFORBES HAMILTON THE TWEEDY LADY SO BEAUTIFULLY PORTRAYED BY PENELOPE KEITH BUT SOON THE SERIES FOR WHOM THE SOMERSET FOLK HOLD A SPECIAL AFFECTION WILL BE NO MORE DURING FILMING AT THE WEEKEND PENELOPE REVEALED THAT THE NEW SERIES THE THIRD WILL ALSO BE THE LAST AT THE END OF THESE SEVEN PROGRAMMES WHICH START IN NOVEMBER IT WILL BE FAREWELL TO THE ARISTOCRATIC BUT IMPOVERISHED AUDREY AND RICHARD DE VERE THE WEALTHY OWNER OF THE MANOR PLAYED BY PETER BOWLES AND THE MILLIONS OF VIEWERS WHO REGULARLY TUNE IN WANT TO KNOW IF AUDREY AND RICHARD FINALLY GET TOGETHER IN THE LAST EPISODE THE ROMANTIC MYSTERY AT THE MANOR THICKENS WHEN ANOTHER WOMAN ENTERS THE LIFE OF RICHARD DE VERE SHE IS A FRENCH BUSINESSWOMAN PLAYED BY RULA LENSKA WHO IN THE EPISODE WHICH WAS FILMED AT THE WEEKEND ARRIVES TO VISIT THE MANOR EVERYONE IS TIGHTLIPPED ABOUT THE POSSIBILITY OF A ROMANTIC ENDING IT IS ALL LISTED AS TOP SECRET BY THE BBC WHO HAVE DECIDED TO DO A DALLAS PENELOPE WHO LOOKS MUCH MORE ATTRACTIVE IN THE FLESH HAS NO REGRETS THAT SHE IS PLAYING AUDREY FOR THE LAST TIME I FELT THE SERIES HAD RUN ITS COURSE SHE TOLD ME ONE OF THE REASONS WHY I AM SUCCESSFUL IS THAT I KNOW WHEN TO SAY NO WITH THE GOOD LIFE WE ALL DECIDED THAT IT WAS OVER AND I THINK IT IS FAR BETTER TO LEAVE THE PUBLIC WANTING MORE THAN HAVING THEM SAY THE SHOW IS DETERIORATING PENELOPE WHO WAS DRESSED IN A SMARTLY TAILORED COUNTRY SUIT AND GREEN WELLIES ADDED THAT SHE THOUGHT IT WAS A GOOD IDEA OF BUILDING UP SUSPENSE BY NOT REVEALING HOW THE SERIES WOULD END YOU WANT PEOPLE TO BE WONDERING WHAT IS GOING TO HAPPEN SHE SAID WHILE SHE WAS TALKING HER HUSBAND DETECTIVE CONSTABLE RODNEY TIMPSON SAT NEARBY AS THE COUPLE CUDDLED HAPPILY PENELOPE AGREED THAT SHE LIKED HAVING RODNEY WITH HER WHEN SHE IS WORKING WHEN YOU ARE ON LOCATION IT SUDDENLY BECOMES THE MOST IMPORTANT THING IN THE WORLD SO IT IS MARVELLOUS TO HAVE A TOUCHSTONE AND MINE IS MY HUSBAND SHE ALSO TALKED ABOUT THE POSSIBILITY OF STARTING A FAMILY IF A CHILD COMES ALONG IT WOULD BE LOVELY SHE SAID BUT WE ARE NOT SORT OF DESPERATE BY THE END OF THIS SERIES PENELOPE WILL HAVE PLAYED AUDREY FOR TEN AND A HALF HOURS BUT SHE HAS NO DESIRE TO APPEAR IN A FEATURE FILM VERSION OF TO THE MANOR BORN I DO NOT BELIEVE THAT IT WOULD TRANSFER TO THE CINEMA I HAVE NEVER SEEN A FILM OF A TV SERIES WHICH WORKED SHE SAID EMPHATICALLY SHE HAS MADE A FILM HOWEVER PRIEST OF LOVE WHICH STARS IAN MCKELLEN AS DHLAWRENCE AND HERSELF AS DOROTHY BRETT THE SOCIETY GIRL WHO FELL PASSIONATELY FOR HIM PENELOPE DESCRIBED THE CHARACTER SHE PLAYS AS A CHALLENGING ROLE DOROTHY BRETT WAS STONE DEAF AND I FOUND IT TERRIBLY DIFFICULT AT FIRST TO UNDERSTAND HOW A DEAF PERSON WOULD RESPOND TO THINGS THE PART REALLY APPEALED TO ME PENELOPE HOWEVER HAS NO IDEA ABOUT WHICH ROLES SHE WOULD LIKE TO TACKLE NEXT SHE TOLD ME WHEN I FINISH THIS I WILL BE ABLE TO HAVE CHRISTMAS WITHOUT WORKING THEN I WILL TAKE A DEEP BREATH AND SEE WHAT THE NEXT THING IS THE THING ABOUT BEING AN ACTRESS IS NOT KNOWING WHAT THE FUTURE WILL BRING·I LIKE THAT BUT I DO NOT FEEL ARROGANTLY OR NOT THAT I HAVE TO PROVE THAT I CAN ACT SO I DO NOT

FEEL THAT THERE IS ONE PART WHICH I PARTICULARLY WANT TO PLAY BUT I IMAGINE GOING ON TILL I AM QUITE AN OLD LADY SMILED THE STAR UNLIKE PENELOPE COSTAR PETER BOWLES KNOWS EXACTLY WHAT HIS NEXT ROLES WILL BE AFTER HE FINISHES PLAYING RICHARD DE VERE AND HE ADMITS THAT IT IS THE SUCCESS OF THIS SERIES WHICH HAS SENT HIS CAREER SOARING SO I SHALL TAKE A BIT OF DE VERE WITH ME WHEN WE FINISH BECAUSE HE HAS HAD A TREMENDOUS EFFECT ON MY CAREER THE DAPPER ACTOR TOLD ME INDEED HE HAS BECAUSE PETER NOW HAS THREE BIG TV PROJECTS COMING UP A COMEDY SERIES HAS BEEN WRITTEN FOR HIM HE HAS SOLD THE IDEA FOR A DRAMA SERIAL ABOUT A GOSSIP COLUMNIST TO THAMES TV ON TOP OF ALL THIS HE IS SOON TO STAR IN THE ITV SERIAL VICE VERSA PLAYING DE VERE HAS MADE ME MORE SARTORIALLY AWARE I HAVE LIKED TO DRESS WELL AND NOW BECAUSE OF THIS SUCCESS I HAVE BEEN ABLE TO BE A BIT MORE EXTRAVAGANT AND IT IS ONLY BECAUSE OF MY RECENT SUCCESS THAT I WAS ABLE TO AFFORD TO BUY A MERCEDES THEN PETER AND PENELOPE NOT FORGETTING BERTIE THE BEAGLE WENT BACK TO WORK IN FRONT OF THE CAMERAS EXACTLY TO THE MANOR BORN

BOOKS FOR CHILDREN.

For this category I first chose some well established children's books like 'Alice's Adventures in Wonderland' (L.Carroll,1865), 'Winnie the Pooh' (A.A.Milne,1926) and 'Paddington Bear' (M.Bond,1958) which between them cover nearly a century of story telling for children. The next step was to make the best possible use of this particular choise in terms of finding other stories for children by the same authors. The first obvious choise was to use Lewis Carroll's 'The Nursery Alice' (L.Carroll, 1890) which Carroll intended to be an easier version of 'Alice in Wonderland' with a target audience of eight to ten year olds depending on the child's social class 'since I concider children of the lower orders to be 2 or 3 years behind the upper orders' (F.B. Lennon: Life of Lewis Carroll). It would have been interesting too, to compare an analysis of these text strings for children with those of Mr Dodgson's text books on logic and mathematics, but it turns out to be very difficult to find around 600 words in his text books which are not interrupted by formulas or notes.

To secure variety in the more recent litterature, I have selected four text samples from different books in the 'Paddington' series (M.Bond,1958,59,60,62) Lastly I have picked R.Bach's 'Jonathan Livingston Seagull' (R.Bach,1973), which deals with - for a child - rather complex human issues.

As most of these text samples are already well known, I shall not go into details regarding each of them, but refer the reader to the samples themselves on the following pages.

POOH

THE PIGLET LIVED IN A VERY GRAND HOUSE IN THE MIDDLE OF A BEECHTREE AND THE BEECHTREE WAS IN THE MIDDLE OF THE FOREST AND THE PIGLET LIVED IN THE MIDDLE OF THE HOUSE NEXT TO HIS HOUSE WAS A PIECE OF BROKEN BOARD WHICH HAD TRESPASSERS W ON IT WHEN CHRISTOPHER ROBIN ASKED THE PIGLET WHAT IT MEANT HE SAID IT WAS HIS GRANDFATHERS NAME AND HAD BEEN IN THE FAMILY FOR A LONG TIME CHRISTOPHER ROBIN SAID YOU COULD NOT BE CALLED TRESPASSERS W AND PIGLET SAID YES YOU COULD BECAUSE HIS GRANDFATHER WAS AND IT WAS SHORT FOR TRESPASSERS WILL WHICH WAS SHORT FOR TRESPASSERS WILLIAM AND HIS GRANDFATHER HAD HAD TWO NAMES IN CASE HE LOST ONE TRESPASSERS AFTER AN UNCLE AND WILLIAM AFTER TRESPASSERS I HAVE GOT TWO NAMES SAID CHRISTOPHER ROBIN CARELESSLY WELL THERE YOU ARE THAT PROVES IT SAID PIGLET ONE FINE WINTERS DAY WHEN PIGLET WAS BRUSHING AWAY THE SNOW IN FRONT OF HIS HOUSE HE HAPPENED TO LOOK UP AND THERE WAS WINNIE THE POOH POOH WAS WALKING ROUND AND ROUND IN A CIRCLE THINKING OF SOMETHING ELSE AND WHEN PIGLET CALLED TO HIM HE JUST WENT ON WALKING HALLO SAID PIGLET WHAT ARE YOU DOING HUNTING SAID POOH HUNTING WHAT TRACKING SOMETHING SAID WINNIE THE POOH VERY MYSTERIOUSLY TRACKING WHAT SAID PIGLET COMING CLOSER THAT IS JUST WHAT I ASK MYSELF I ASK MYSELF WHAT WHAT DO YOU THINK YOU WILL ANSWER I SHALL HAVE TO WAIT UNTIL I CATCH UP WITH IT SAID WINNIE THE POOH NOW LOOK THERE HE POINTED TO THE GROUND IN FRONT OF HIM WHAT DO YOU SEE THERE TRACKS SAID PIGLET PAWMARKS HE GAVE A LITTLE SQUEAK OF EXCITEMENT OH POOH DO YOU THINK IT IS A A A WOOZLE IT MAY BE SAID POOH SOMETIMES IT IS AND SOMETIMES IT IS NOT YOU NEVER CAN TELL WITH PAWMARKS WITH THESE FEW WORDS HE WENT ON TRACKING AND PIGLET AFTER WATCHING HIM FOR A MINUTE OR TWO RAN AFTER HIM WINNIE THE POOH HAD COME TO A SUDDEN STOP AND WAS BENDING OVER THE TRACKS IN A PUZZLED SORT OF WAY WHAT IS THE MATTER ASKED PIGLET IT IS A VEERY FUNNY THING SAID BEAR BUT THERE SEEM TO BE TWO ANIMALS NOW THIS WHATEVERITWAS HAS BEEN JOINED BY ANOTHER WHATEVERITIS AND THE TWO OF THEM ARE NOW PROCEEDING IN COMPANY WOULD YOU MIND COMING WITH ME PIGLET IN CASE THEY TURN OUT TO BE HOSTILE ANIMALS PIGLET SCRATCHED HIS EAR IN A NICE SORT OF WAY AND SAID THAT HE HAD NOTHING TO DO UNTIL FRIDAY AND WOULD BE DELIGHTED TO COME IN CASE IT REALLY WAS A WOOZLE YOU MEAN IN CASE IT REALLY IS TWO WOOZLES SAID WINNIE THE POOH AND PIGLET SAID THAT ANYHOW HE HAD NOTHING TO DO UNTIL FRIDAY SO OFF THEY WENT TOGETHER THERE WAS A SMALL SPINNEY OF LARCHTREES JUST HERE AND IT SEEMED AS IF THE TWO WOOZLES IF THAT IS WHAT THEY WERE HAD BEEN GOING ROUND THIS SPINNEY SO ROUND THIS SPINNEY WENT POOH AND PIGLET AFTER THEM PIGLET PASSING THE TIME BY TELLING POOH WHAT HIS GRANDFATER TRESPASSERS W HAD DONE TO REMOVE STIFFNESS AFTER TRACKING AND HOW HIS GRANDFATHER TRESPASSERS W HAD SUFFERED IN HIS LATER YEARS FROM SHORTNESS OF BREATH AND OTHER MATTERS OF INTEREST AND POOH WONDERING WHAT A GRANDFATHER WAS LIKE AND IF PERHAPS THIS WAS TWO GRANDFATHERS THEY WERE AFTER NOW AND IF SO WHETHER HE WOULD BE ALLOWED TO TAKE ONE HOME AND KEEP IT AND WHAT CHRISTOPHER ROBIN WOULD SAY AND STILL THE TRACKS WENT ON IN FRONT OF THEM SUDDENLY WINNIE THE POOH STOPPED

ALICE
THERE WAS A TABLE SET OUT UNDER A TREE IN FRONT OF THE HOUSE AND THE MARCH HARE AND THE HATTER WERE HAVING TEA AT IT A DOORMOUSE WAS SITTING BETWEEN THEM FAST ASLEEP AND THE OTHER TWO WERE USING IT AS A CUSHION RESTING THEIR ELBOWS ON IT AND TALKING OVER ITS HEAD VERY UNCOMFORTABLE FOR THE DOORMOUSE THOUGHT ALICE ONLY AS IT IS ASLEEP I SUPPOSE IT DOES NOT MIND THE TABLE WAS A LARGE ONE BUT THE THREE WERE ALL CROWDED TOGETHER AT ONE CORNER OF IT NO ROOM NO ROOM THEY CRIED OUT WHEN THEY SAW ALICE COMING THERE IS PLENTY OF ROOM SAID ALICE INDIGNANTLY AND SHE SAT DOWN IN A LARGE ARMCHAIR AT ONE END OF THE TABLE HAVE SOME WINE THE MARCH HARE SAID IN AN ENCOURAGING TONE ALICE LOOKED ALL ROUND THE TABLE THERE WAS NOTHING ON IT BUT TEA I DO NOT SEE ANY WINE SHE REMARKED THERE IS NOT ANY SAID THE MARCH HARE THEN IT WAS NOT VERY CIVIL OF YOU TO OFFER IT SAID ALICE ANGRILY IT WAS NOT VERY CIVIL OF YOU TO SIT DOWN WITHOUT BEING INVITED SAID THE MARCH HARE I DID NOT KNOW IT WAS YOUR TABLE SAID ALICE IT IS LAID FOR A GREAT MANY MORE THAN THREE YOUR HAIR WANTS CUTTING SAID THE HATTER HE HAD BEEN LOOKING AT ALICE FOR SOME TIME WITH GREAT CURIOSITY AND THIS WAS HIS FIRST SPEECH YOU SHOULD LEARN NOT TO MAKE PERSONAL REMARKS ALICE SAID WITH SOME SEVERITY IT IS VERY RUDE THE HATTER OPENED HIS EYES VERY WIDE ON HEARING THIS BUT ALL HE SAID WAS WHY IS A RAVEN LIKE A WRITINGDESK COME WE SHALL HAVE SOME FUN NOW THOUGHT ALICE I AM GLAD THEY HAVE BEGUN ASKING RIDDLES I BELIEVE I CAN GUESS THAT SHE ADDED ALOUD DO YOU MEAN THAT YOU THINK YOU CAN FIND OUT THE ANSWER TO IT SAID THE MARCH HARE EXACTLY SO SAID ALICE THEN YOU SHOULD SAY WHAT YOU MEAN THE MARCH HARE WENT ON I DO ALICE HASTILY REPLIED AT LEAST AT LEAST I MEAN WHAT I SAY THAT IS THE SAME THING YOU KNOW NOT THE SAME THING A BIT SAID THE HATTER WHY YOU MIGHT JUST AS WELL SAY THAT I SEE WHAT I EAT IS THE SAME THING AS I EAT WHAT I SEE YOU MIGHT JUST AS WELL SAY ADDED THE MARCH HARE THAT I LIKE WHAT I GET IS THE SAME THING AS I GET WHAT I LIKE YOU MIGHT JUST AS WELL SAY ADDED THE DORMOUSE WHO SEEMED TO BE TALKING IN HIS SLEEP THAT I BREATHE WHEN I SLEEP IS THE SAME THING AS I SLEEP WHEN I BREATHE IT IS THE SAME THING WITH YOU SAID THE HATTER AND HERE THE CONVERSATION DROPPED AND THE PARTY SAT SILENT FOR A MINUTE WHILE ALICE THOUGHT OVER ALL SHE COULD REMEMBER ABOUT RAVENS AND WRITINGDESKS WHICH WAS NOT MUCH THE HATTER WAS THE FIRST TO BREAK THE SILENCE WHAT DAY OF THE MONTH IS IT HE SAID TURNING TO ALICE HE HAD TAKEN HIS WATCH OUT OF HIS POCKET AND WAS LOOKING AT IT UNEASILY SHAKING IT EVERY NOW AND THEN AND HOLDING IT TO HIS EAR ALICE CONSIDERED A LITTLE AND SAID THE FOURTH TWO DAYS WRONG SIGHED THE HATTER I TOLD YOU BUTTER WOULD NOT SUIT THE WORKS HE ADDED LOOKING ANGRILY AT THE MARCH HARE IT WAS THE BEST BUTTER THE MARCH HARE MEEKLY REPLIED YES BUT SOME CRUMBS MUST HAVE GOT IN AS WELL THE HATTER GRUMBLED YOU SHOULD NOT HAVE PUT IT IN WITH THE BREADKNIFE THE MARCH HARE TOOK THE WATCH AND LOOKED

ALIL
THIS IS THE MAD TEAPARTY YOU SEE ALICE HAD LEFT THE CHESHIRECAT
AND HAD GONE OFF TO SEE THE MARCH HARE AND THE HATTER AS THE
CHESHIRECAT HAD ADVISED HER AND SHE FOUND THEM HAVING TEA UNDER A
GREAT TREE WITH A DORMOUSE SITTING BETWEEN THEM THERE WERE ONLY
THOSE THREE AT THE TABLE BUT THERE WERE QUANTITIES OF TEACUPS SET
ALL ALONG IT YOU CAN NOT SEE ALL THE TABLE YOU KNOW AND EVEN IN
THE BIT YOU CAN SEE THERE ARE NINE CUPS COUNTING THE ONE THE
MARCH HARE HAS GOT IN HIS HAND THAT IS THE MARCH HARE WITH THE
LONG EARS AND STRAWS MIXED UP WITH HIS HAIR THE STRAWS SHOWED HE
WAS MAD I DO NOT KNOW WHY NEVER TWIST UP STRAWS AMONG YOUR HAIR
FOR FEAR PEOPLE SHOULD THINK YOU ARE MAD THERE WAS A NICE GREEN
ARMCHAIR AT THE END OF THE TABLE THAT LOOKED AS IF IT WAS JUST
MEANT FOR ALICE SO SHE WENT AND SAT DOWN IN IT THEN SHE HAD QUITE
A LONG TALK WITH THE MARCH HARE AND THE HATTER THE DORMOUSE DID
NOT SAY MUCH YOU SEE IT WAS FAST ASLEEP GENERALLY AND IT ONLY
JUST WOKE UP FOR A MOMENT NOW AND THEN AS LONG AS IT WAS ASLEEP
IT WAS VERY USEFUL TO THE MARCH HARE AND THE HATTER BECAUSE IT
HAD A NICE ROUND SOFT HEAD JUST LIKE A PILLOW SO THEY COULD PUT
THEIR ELBOWS ON IT AND LEAN ACROSS IT AND TALK TO EACH OTHER
QUITE COMFORTABLY YOU WOULD NOT LIKE PEOPLE TO USE YOUR HEAD FOR
A PILLOW WOULD YOU BUT IF YOU WERE FAST ASLEEP LIKE THE DORMOUSE
YOU WOULD NOT FEEL IT SO I SUPPOSE YOU WOULD NOT CARE ABOUT IT I
AM AFRAID THEY GAVE ALICE VERY LITTLE TO EAT AND DRINK HOWEVER
AFTER A BIT SHE HELPED HERSELF TO SOME TEA AND BREADANDBUTTER
ONLY I DO NOT QUITE SEE WHERE SHE GOT THE BREADANDBUTTER AND SHE
HAD NO PLATE FOR IT NOBODY SEEMS TO HAVE A PLATE EXCEPT THE
HATTER I BELIEVE THE MARCH HARE MUST HAVE HAD ONE AS WELL BECAUSE
WHEN THEY ALL MOVED ONE PLACE ON THAT WAS THE RULE AT THIS
CURIOUS TEAPARTY AND ALICE HAD TO GO INTO THE PLACE OF THE MARCH
HARE SHE FOUND HE HAD JUST UPSET THE MILKJUG INTO HIS PLATE SO I
SUPPOSE HIS PLATE AND THE MILKJUG ARE HIDDEN BEHIND THAT LARGE
TEAPOT THE HATTER USED TO CARRY ABOUT HATS TO SELL AND EVEN THE
ONE THAT HE HAS GOT ON HIS HEAD IS MEANT TO BE SOLD YOU SEE IT
HAS GOT ITS PRICE ON IT A TEN AND A SIX THAT MEANS TEN SHILLINGS
AND SIX PENCE WAS NOT THAT A FUNNY WAY OF SELLING HATS AND HAS
NOT HE GOT A BEAUTIFUL NECKTIE ON SUCH A LOVELY YELLOW TIE WITH
LARGE RED SPOTS HE HAS JUST GOT UP TO SAY TO ALICE YOUR HAIR
WANTS CUTTING THAT WAS A RUDE THING TO SAY WAS NOT IT AND DO YOU
THINK HER HAIR DOES WANT CUTTING I THINK IT IS A VERY PRETTY
LENGTH JUST THE RIGHT LENGTH THIS IS A LITTLE BIT OF THE
BEAUTIFUL GARDEN I TOLD YOU ABOUT YOU SEE ALICE HAD MANAGED AT
LAST TO GET QUITE SMALL SO THAT SHE COULD GO THROUGH THE LITTLE
DOOR I SUPPOSE SHE WAS ABOUT AS TALL AS A MOUSE IF IT STOOD ON
ITS HINDLEGS SO OF COURSE THIS WAS A VERY TINY ROSETREE AND THESE
ARE VERY TINY GARDENERS WHAT FUNNY LITTLE MEN THEY ARE BUT ARE
THEY MEN DO YOU THINK I THINK THEY MUST BE LIVE CARDS WITH JUST

ALIL

THIS IS THE MAD TEAPARTY YOU SEE ALICE HAD LEFT THE CHESHIRECAT AND HAD GONE OFF TO SEE THE MARCH HARE AND THE HATTER AS THE CHESHIRECAT HAD ADVISED HER AND SHE FOUND THEM HAVING TEA UNDER A GREAT TREE WITH A DORMOUSE SITTING BETWEEN THEM THERE WERE ONLY THOSE THREE AT THE TABLE BUT THERE WERE QUANTITIES OF TEACUPS SET ALL ALONG IT YOU CAN NOT SEE ALL THE TABLE YOU KNOW AND EVEN IN THE BIT YOU CAN SEE THERE ARE NINE CUPS COUNTING THE ONE THE MARCH HARE HAS GOT IN HIS HAND THAT IS THE MARCH HARE WITH THE LONG EARS AND STRAWS MIXED UP WITH HIS HAIR THE STRAWS SHOWED HE WAS MAD I DO NOT KNOW WHY NEVER TWIST UP STRAWS AMONG YOUR HAIR FOR FEAR PEOPLE SHOULD THINK YOU ARE MAD THERE WAS A NICE GREEN ARMCHAIR AT THE END OF THE TABLE THAT LOOKED AS IF IT WAS JUST MEANT FOR ALICE SO SHE WENT AND SAT DOWN IN IT THEN SHE HAD QUITE A LONG TALK WITH THE MARCH HARE AND THE HATTER THE DORMOUSE DID NOT SAY MUCH YOU SEE IT WAS FAST ASLEEP GENERALLY AND IT ONLY JUST WOKE UP FOR A MOMENT NOW AND THEN AS LONG AS IT WAS ASLEEP IT WAS VERY USEFUL TO THE MARCH HARE AND THE HATTER BECAUSE IT HAD A NICE ROUND SOFT HEAD JUST LIKE A PILLOW SO THEY COULD PUT THEIR ELBOWS ON IT AND LEAN ACROSS IT AND TALK TO EACH OTHER QUITE COMFORTABLY YOU WOULD NOT LIKE PEOPLE TO USE YOUR HEAD FOR A PILLOW WOULD YOU BUT IF YOU WERE FAST ASLEEP LIKE THE DORMOUSE YOU WOULD NOT FEEL IT SO I SUPPOSE YOU WOULD NOT CARE ABOUT IT I AM AFRAID THEY GAVE ALICE VERY LITTLE TO EAT AND DRINK HOWEVER AFTER A BIT SHE HELPED HERSELF TO SOME TEA AND BREADANDBUTTER ONLY I DO NOT QUITE SEE WHERE SHE GOT THE BREADANDBUTTER AND SHE HAD NO PLATE FOR IT NOBODY SEEMS TO HAVE A PLATE EXCEPT THE HATTER I BELIEVE THE MARCH HARE MUST HAVE HAD ONE AS WELL BECAUSE WHEN THEY ALL MOVED ONE PLACE ON THAT WAS THE RULE AT THIS CURIOUS TEAPARTY AND ALICE HAD TO GO INTO THE PLACE OF THE MARCH HARE SHE FOUND HE HAD JUST UPSET THE MILKJUG INTO HIS PLATE SO I SUPPOSE HIS PLATE AND THE MILKJUG ARE HIDDEN BEHIND THAT LARGE TEAPOT THE HATTER USED TO CARRY ABOUT HATS TO SELL AND EVEN THE ONE THAT HE HAS GOT ON HIS HEAD IS MEANT TO BE SOLD YOU SEE IT HAS GOT ITS PRICE ON IT A TEN AND A SIX THAT MEANS TEN SHILLINGS AND SIX PENCE WAS NOT THAT A FUNNY WAY OF SELLING HATS AND HAS NOT HE GOT A BEAUTIFUL NECKTIE ON SUCH A LOVELY YELLOW TIE WITH LARGE RED SPOTS HE HAS JUST GOT UP TO SAY TO ALICE YOUR HAIR WANTS CUTTING THAT WAS A RUDE THING TO SAY WAS NOT IT AND DO YOU THINK HER HAIR DOES WANT CUTTING I THINK IT IS A VERY PRETTY LENGTH JUST THE RIGHT LENGTH THIS IS A LITTLE BIT OF THE BEAUTIFUL GARDEN I TOLD YOU ABOUT YOU SEE ALICE HAD MANAGED AT LAST TO GET QUITE SMALL SO THAT SHE COULD GO THROUGH THE LITTLE DOOR I SUPPOSE SHE WAS ABOUT AS TALL AS A MOUSE IF IT STOOD ON ITS HINDLEGS SO OF COURSE THIS WAS A VERY TINY ROSETREE AND THESE ARE VERY TINY GARDENERS WHAT FUNNY LITTLE MEN THEY ARE BUT ARE THEY MEN DO YOU THINK I THINK THEY MUST BE LIVE CARDS WITH JUST

ALIC

THIS IS THE MAD TEAPARTY YOU SEE ALICE HAD LEFT THE CHESHIRECAT AND HAD GONE OFF TO SEE THE MARCH HARE AND THE HATTER AS THE CHESHIRECAT HAD ADVISED HER AND SHE FOUND THEM HAVING TEA UNDER A GREAT TREE WITH A DORMOUSE SITTING BETWEEN THEM THERE WERE ONLY THOSE THREE AT THE TABLE BUT THERE WERE QUANTITIES OF TEACUPS SET ALL ALONG IT YOU CAN NOT SEE ALL THE TABLE YOU KNOW AND EVEN IN THE BIT YOU CAN SEE THERE ARE NINE CUPS COUNTING THE ONE THE MARCH HARE HAS GOT IN HIS HAND THAT IS THE MARCH HARE WITH THE LONG EARS AND STRAWS MIXED UP WITH HIS HAIR THE STRAWS SHOWED HE WAS MAD I DO NOT KNOW WHY NEVER TWIST UP STRAWS AMONG YOUR HAIR FOR FEAR PEOPLE SHOULD THINK YOU ARE MAD THERE WAS A NICE GREEN ARMCHAIR AT THE END OF THE TABLE THAT LOOKED AS IF IT WAS JUST MEANT FOR ALICE SO SHE WENT AND SAT DOWN IN IT THEN SHE HAD QUITE A LONG TALK WITH THE MARCH HARE AND THE HATTER THE DORMOUSE DID NOT SAY MUCH YOU SEE IT WAS FAST ASLEEP GENERALLY AND IT ONLY JUST WOKE UP FOR A MOMENT NOW AND THEN AS LONG AS IT WAS ASLEEP IT WAS VERY USEFUL TO THE MARCH HARE AND THE HATTER BECAUSE IT HAD A NICE ROUND SOFT HEAD JUST LIKE A PILLOW SO THEY COULD PUT THEIR ELBOWS ON IT AND LEAN ACROSS IT AND TALK TO EACH OTHER QUITE COMFORTABLY YOU WOULD NOT LIKE PEOPLE TO USE YOUR HEAD FOR A PILLOW WOULD YOU BUT IF YOU WERE FAST ASLEEP LIKE THE DORMOUSE YOU WOULD NOT FEEL IT SO I SUPPOSE YOU WOULD NOT CARE ABOUT IT I AM AFRAID THEY GAVE ALICE VERY LITTLE TO EAT AND DRINK HOWEVER AFTER A BIT SHE HELPED HERSELF TO SOME TEA AND BREADANDBUTTER ONLY I DO NOT QUITE SEE WHERE SHE GOT THE BREADANDBUTTER AND SHE HAD NO PLATE FOR IT NOBODY SEEMS TO HAVE A PLATE EXCEPT THE HATTER I BELIEVE THE MARCH HARE MUST HAVE HAD ONE AS WELL BECAUSE WHEN THEY ALL MOVED ONE PLACE ON THAT WAS THE RULE AT THIS CURIOUS TEAPARTY AND ALICE HAD TO GO INTO THE PLACE OF THE MARCH HARE SHE FOUND HE HAD JUST UPSET THE MILKJUG INTO HIS PLATE SO I SUPPOSE HIS PLATE AND THE MILKJUG ARE HIDDEN BEHIND THAT LARGE TEAPOT THE HATTER USED TO CARRY ABOUT HATS TO SELL AND EVEN THE ONE THAT HE HAS GOT ON HIS HEAD IS MEANT TO BE SOLD YOU SEE IT HAS GOT ITS PRICE ON IT A TEN AND A SIX THAT MEANS TEN SHILLINGS AND SIX PENCE WAS NOT THAT A FUNNY WAY OF SELLING HATS AND HAS NOT HE GOT A BEAUTIFUL NECKTIE ON SUCH A LOVELY YELLOW TIE WITH LARGE RED SPOTS HE HAS JUST GOT UP TO SAY TO ALICE YOUR HAIR WANTS CUTTING THAT WAS A RUDE THING TO SAY WAS NOT IT AND DO YOU THINK HER HAIR DOES WANT CUTTING I THINK IT IS A VERY PRETTY LENGTH JUST THE RIGHT LENGTH THIS IS A LITTLE BIT OF THE BEAUTIFUL GARDEN I TOLD YOU ABOUT YOU SEE ALICE HAD MANAGED AT LAST TO GET QUITE SMALL SO THAT SHE COULD GO THROUGH THE LITTLE DOOR I SUPPOSE SHE WAS ABOUT AS TALL AS A MOUSE IF IT STOOD ON ITS HINDLEGS SO OF COURSE THIS WAS A VERY TINY ROSETREE AND THESE ARE VERY TINY GARDENERS WHAT FUNNY LITTLE MEN THEY ARE BUT ARE THEY MEN DO YOU THINK I THINK THEY MUST BE LIVE CARDS WITH JUST

PAD1
MR AND MRS BROWN FIRST MET PADDINGTON ON A RAILWAY PLATFORM IN
FACT THAT WAS HOW HE CAME TO HAVE SUCH AN UNUSUAL NAME FOR A BEAR
FOR PADDINGTON WAS THE NAME OF THE STATION THE BROWNS WERE THERE
TO MEET THEIR DAUGHTER JUDY WHO WAS COMING HOME FROM SCHOOL FOR
THE HOLIDAYS IT WAS A WARM SUMMERDAY AND THE STATION WAS CROWDED
WITH PEOPLE ON THEIR WAY TO THE SEASIDE TRAINS WERE WHISTLING
TAXIS HOOTING PORTERS RUSHING ABOUT SHOUTING AT ONE ANOTHER AND
ALTOGETHER THERE VAS SO MUCH NOISE THAT MR BROWN WHO SAW HIM
FIRST HAD TO TELL HIS WIFE SEVERAL TIMES BEFORE SHE UNDERSTOOD A
BEAR ON PADDINGTON STATION MRS BROWN LOOKED AT HER HUSBAND IN
AMAZEMENT DO NOT BE SILLY HENRY THERE CAN NOT BE MR BROWN
ADJUSTED HIS GLASSES BUT THERE IS HE INSISTED I DISTINCTLY SAW IT
OVER THERE BEHIND THOSE MAILBAGS IT WAS WEARING A FUNNY KIND OF
HAT WITHOUT WAITING FOR A REPLY HE CAUGHT HOLD OF HIS WIFES ARM
AND PUSHED HER THROUGH THE CROWD ROUND A TROLLEY LADEN WITH
CHOCOLATE AND CUPS OF TEA PAST A BOOKSTALL AND THROUGH A GAP IN A
PILE OF SUITCASES TOWARDS THE LOST PROPERTY OFFICE THERE YOU ARE
HE ANNOUNCED TRIUMPHANTLY POINTING TOWARDS A DARK CORNER I TOLD
YOU SO MRS BROWN FOLLOWED THE DIRECTION OF HIS ARM AND DIMLY MADE
OUT A SMALL FURRY OBJECT IN THE SHADOWS IT SEEMED TO BE SITTING
ON SOME KIND OF SUITCASE AND AROUND ITS NECK THERE WAS A LABEL
WITH SOME WRITING ON IT THE SUITCASE WAS OLD AND BATTERED ON THE
SIDE IN LARGE LETTERS WERE THE WORDS WANTED ON VOYAGE MRS BROWN
CLUTCHED AT HER HUSBAND WHY HENRY SHE EYCLAIMED I BELIEVE YOU
WERE RIGHT AFTER ALL IT IS A BEAR SHE PEERED AT IT MORE CLOSELY
IT SEEMED A VERY UNUSUAL KIND OF BEAR IT WAS BROWN IN COLOUR A
RATHER DIRTY BROWN AND IT WAS WEARING A MOST ODD LOOKING HAT WITH
A WIDE BRIM JUST AS MR BROWN HAD SAID FROM BENEATH THE BRIM TWO
LARGE ROUND EYES STARED BACK AT HER SEEING THAT SOMETHING WAS
EXPECTED OF IT THE BEAR STOOD UP AND POLITELY RAISED ITS HAT
REVEALING TWO BLACK EARS GOOD AFTERNOON IT SAID IN A SMALL CLEAR
VOICE ER GOOD AFTERNOON REPLIED MR BROWN DOUBTFULLY THERE WAS A
MOMENT OF SILENCE THE BEAR LOOKED AT THEM INQUIRINGLY CAN I HELP
YOU MR BROWN LOOKED RATHER EMBARRASED WELL NO ER AS A MATTER OF
FACT WE WERE WONDERING IF WE COULD HELP YOU MRS BROWN BENT DOWN
YOU ARE A VERY SMALL BEAR SHE SAID THE BEAR PUFFED OUT ITS CHEST
I AM A VERY RARE SORT OF BEAR HE REPLIED IMPORTANTLY THERE ARE
NOT MANY OF US LEFT WHERE I COME FROM AND WHERE IS THAT ASKED MRS
BROWN THE BEAR LOOKED ROUND CARREFULLY BEFORE REPLYING DARKEST
PERU I AM NOT REALLY SUPPOSED TO BE HERE AT ALL I AM A STOWAWAY A
STOWAWAY MR BROWN LOWERED HIS WOICE AND LOOKED ANXIOUSLY OVER HIS
SHOULDER HE ALMOST EXPECTED TO SEE A POLICEMAN STANDING BEHIND
HIM WITH A NOTEBOOK AND PENCIL TAKING EVERYTHING DOWN YES SAID
THE BEAR I EMIGRATED YOU KNOW A SAD EXPRESSION CAME INTO ITS EYES
I USED TO LIVE WITH MY AUNT LUCY IN PERU BUT SHE HAD TO GO INTO A
HOME FOR RETIRED BEARS YOU DO NOT MEAN TO SAY YOU HAVE COME ALL
THE WAY FROM SOUTH AMERICA BY YOURSELF EXCLAIMED MRS BROWN THE
BEAR NODDED AUNT LUCY ALWAYS SAID SHE WANTED ME TO EMIGRATE WHEN
I WAS OLD ENOUGH THAT IS WHY SHE TAUGHT ME TO SPEAK ENGLISH BUT
WHATEVER DID YOU DO FOR FOOD ASKED MR BROWN YOU MUST BE STARVING
BENDING DOWN THE BEAR UNLOCKED THE SUITCASE WITH A SMALL KEY
WHICH IT ALSO HAD ROUND ITS NECK AND BROUGHT OUT AN ALMOST EMPTY
GLASS JAR I ATE MARMALADE HE SAID RATHER PROUDLY BEARS LIKE
MARMALADE AND I LIVED IN A LIFEBOAT BUT WHAT ARE YOU GOING TO DO

NOW SAID MR BROWN YOU CAN NOT JUST SIT ON PADDINGTON STATION WAITING FOR SOMETHING TO HAPPEN OH I SHALL BE ALL RIGHT I EXPECT THE BEAR BENT DOWN TO DO UP ITS CASE AGAIN AS HE DID SO MRS BROWN CAUGHT A GLIMPSE OF THE WRITING ON THE LABEL IT SAID SIMPLY PLEASE LOOK AFTER THIS BEAR THANK YOU SHE TURNED APPEALINGLY TO HER HUSBAND OH HENRY WHAT SHALL WE DO WE CAN NOT JUST LEAVE HIM HERE THERE IS NO KNOWING WHAT MIGHT HAPPEN TO HIM LONDON IS SUCH A BIG PLACE WHEN YOU HAVE NOWHERE TO GO CAN NOT HE COME AND STAY WITH US FOR A FEW DAYS MR BROWN HESITATED BUT MARY DEAR WE CAN NOT TAKE HIM NOT JUST LIKE THAT AFTER ALL AFTER ALL WHAT MRS BROWNS VOICE HAD A FIRM NOTE TO IT SHE LOOKED DOWN AT THE BEAR HE IS RATHER SWEET AND HE WOULD BE SUCH COMPANY FOR JONATHAN AND JUDY EVEN IF IT IS ONLY FOR A LITTLE WHILE THEY WOULD NEVER FORGIVE US IF THEY KNEW YOU HAD LEFT HIM HERE IT ALL SEEMS HIGHLY IRREGULAR SAID MR BROWN DOUBTFULLY I AM SURE THERE IS A LAW ABOUT IT HE BENT DOWN WOULD YOU LIKE TO COME AND STAY WITH US HE ASKED THAT IS HE ADDED HASTILY NOT WISHING TO OFFEND THE BEAR IF YOU HAVE NOTHING ELSE PLANNED THE BEAR JUMPED AND HIS HAT NEARLY FELL OFF WITH EXCITEMENT OOOH YES PLEASE I SHOULD LIKE THAT VERY MUCH I HAVE NOWHERE TO GO AND EVERYONE SEEMS IN SUCH A HURRY WELL THAT IS SETTLED THEN SAID MRS BROWN BEFORE HER HUSBAND COULD CHANGE HIS MIND AND YOU CAN HAVE MARMALADE FOR BREAKFAST EVERY MORNING AND SHE TRIED HARD TO THINK OF SOMETHING ELSE THAT BEARS MIGHT LIKE EVERY MORNING THE BEAR LOOKED AS IF IT COULD HARDLY BELIEVE ITS EARS I ONLY HAD IT ON SPECIAL OCCASIONS AT HOME MARMALADE IS VERY EXPENSIVE IN DARKEST PERU THEN YOU SHALL HAVE IT EVERY MORNING STARTING TOMORROW CONTINUED MRS BROWN AND HONEY ON SUNDAY A WORRIED EXPRESSION CAME OVER THE BEARS FACE WILL IT COST VERY MUCH HE ASKED YOU SEE I HAVE NOT VERY MUCH MONEY

P.02
THE OLD BOXROOM WAS FINISHED AT LAST AND EVERYONE INCLUDING PADDINGTON AGREED THAT HE WAS A VERY LUCKY BEAR TO MOVE INTO SUCH A NICE ROOM NOT ONLY WAS THE PAINTWORK A GLEAMING WHITE SO THAT HE COULD ALMOST SEE HIS FACE IN IT BUT THE WALLS WERE GAILY PAPERED AND HE EVEN HAD NEW FURNITURE OF HIS OWN AS WELL IN FOR A PENNY IN FOR A POUND MR BROWN HAD SAID AND HE HAD BOUGHT PADDINGTON A BRAND NEW BED WITH SPECIAL SHORT LEGS A SPRING MATTRESS AND A CUPBOARD FOR HIS ODDS AND ENDS THERE WERE SEVERAL OTHER PIECES OF FURNITURE AND MRS BROWN HAD BEEN EXTRAVAGANT AND BOUGHT A THICK PILE CARPET FOR THE FLOOR PADDINGTON WAS VERY PROUD OF HIS CARPET AND HE HAD CAREFULLY SPREAD SOME OLD NEWSPAPERS OVER THE PARTS WHERE HE WALKED SO THAT HIS PAWS WOULD NOT MAKE IT DIRTY MRS BIRDS CONTRIBUTION HAD BEEN SOME BRIGHT NEW CURTAINS FOR THE WINDOWS WHICH PADDINGTON LIKED VERY MUCH IN FACT THE FIRST NIGHT HE SPENT IN HIS NEW ROOM HE COULD NOT MAKE UP HIS MIND WHETHER TO HAVE THEM DRAWN TOGETHER SO THAT HE COULD ADMIRE THEM OR LEFT APART SO THAT HE COULD SEE THE VIEW HE GOT OUT OF BED SEVERAL TIMES AND EVENTUALLY DECIDED TO HAVE ONE DRAWN AND THE OTHER LEFT BACK SO THAT HE COULD HAVE THE BEST OF BOTH WORLDS THEN SOMETHING STRANGE CAUGHT HIS EYE PADDINGTON MADE A POINT OF KEEPING A TORCH BY THE SIDE OF HIS BED IN CASE THERE WAS AN EMERGENCY DURING THE NIGHT AND IT WAS WHILE HE WAS FLASHING IT ON AND OFF TO ADMIRE THE DRAWN CURTAIN THAT HE NOTICED IT EACH TIME HE FLASHED THE TORCH THERE WAS AN ANSWERING FLICKER OF LIGHT FROM SOMEWHERE OUTSIDE HE SAT UP IN BED RUBBING HIS EYES AND STARED IN THE DIRECTION OF THE WINDOW HE DECIDED TO TRY A MORE COMPLICATED SIGNAL TWO SHORT FLASHES FOLLOWED BY SEVERAL LONG ONES WHEN HE DID SO HE NEARLY FELL OUT OF BED WITH SURPRISE FOR EACH TIME HE SENT A SIGNAL IT WAS REPEATED IN EXACTLY THE SAME WAY THROUGH THE GLASS PADDINGTON JUMPED OUT OF BED AND RUSHED TO THE WIMDOW HE STAYED THERE FOR A LONG WHILE PEERING OUT AT THE GARDEN BUT HE COULD NOT SEE ANYTHING AT ALL HAVING MADE SURE THE WINDOW WAS TIGHTLY SHUT HE DREW BOTH CURTAINS AND HURRIED BACK TO BED PULLING THE CLOTHES OVER HIS HEAD A LITTLE FARTHER THAN USUAL IT WAS ALL VERY MYSTERIOUS AND PADDINGTON DID NOT BELIEVE IN TAKING ANY CHANCES IT WAS MR BROWN AT BREAKFAST THE NEXT MORNING WHO GAVE HIM HIS FIRST CLUE SOMEONE HAS STOLEN MY PRIZE MARROW HE ANNOUNCED CROSSLY THEY MUST HAVE GOT IN DURING THE NIGHT FOR SOME WEEKS PAST MR BROWN HAD BEEN CAREFULLY NURSING A HUGE MARROW WHICH HE INTENDED TO ENTER FOR A VEGETABLE SHOW HE WATERED IT MORNING AND EVENING AND MEASURED IT EVERY NIGHT BEFORE GOING TO BED MRS BROWN EXCHANGED A GLANCE WITH MRS BIRD NEVER MIND HENRY DEAR SHE SAID YOU HAVE GOT SEVERAL OTHERS ALMOST AS GOOD I DO MIND GRUMBLED MR BROWN AND THE OTHERS WILL NEVER BE AS GOOD NOT IN TIME FOR THE SHOW PERHAPS IT WAS ONE OF THE OTHER COMPETITORS DAD SAID JONATHAN PERHAPS THEY DID NOT WANT YOU TO WIN IT WAS A JOLLY GOOD MARROW THAT IS QUITE POSSIBLE SAID MR BROWN LOOKING MORE PLEASED AT THE THOUGHT I HAVE A GOOD MIND TO OFFER A SMALL REWARD MRS BIRD HASTILY POURED OUT SOME MORE TEA BOTH SHE AND MRS BROWN APPEARED ANXIOUS TO CHANGE THE SUBJECT BUT PADDINGTON PRICKED UP HIS EARS AT THE MENTION OF A REWARD

PADD
PADDINGTON SAT UP IN BED LATE THAT NIGHT WRITING HIS MEMORIES HE HAD A LARGE LEATHER BOUND SCRAP BOOK GIVEN TO HIM BY MR GRUBER IN WHICH HE KEPT A RECORD OF ALL HIS ADVENTURES TOGETHER WITH ANY INTERESTING PICTURES AND HE CAREFULLY PASTED IN THE RECEIPT FOR HIS TENPENCE WHICH THE AUCTIONEER HAD GIVEN HIM WHEN HE DID EVENTUALLY FALL ASLEEP IT WAS ONLY TO DREAM HE WAS AT THE AUCTION SALE AGAIN HE WAS STANDING IN THE MIDDLE OF THE AUCTION ROOMS WAVING HIS PAWS AND BIDDING FOR EVERYTHING THAT WAS OFFERED FOR SALE THE PILE OF THINGS HE HAD BOUGHT GOT BIGGER AND BIGGER AS THEY WERE PLACED AROUND HIM UNTIL HE COULD HARDLY SEE OUT SEVERAL OF THE LARGER ITEMS WERE STICKING IN HIS SIDE WHEN HE WOKE HE WAS VERY RELIEVED TO FIND HE WAS STILL IN HIS OWN ROOM AND THAT THE BANGING OF THE AUCTIONEERS HAMMER WAS REALLY ONLY SOMEONE KNOCKING AT HIS DOOR AS HE SAT UP IN BED RUBBING HIS EYES PADDINGTON ALSO FOUND TO HIS SURPRISE THAT THE MARMALADE DISH WAS IN BED WITH HIM AND HE HAD IN FACT BEEN LYING ON IT PADDINGTON EXCLAIMED MRS BROWN AS SHE ENTERED CARRYING THE BREAKFAST THINGS WHAT ON EARTH IS THE MATTER I KEPT HEARING A LOT OF BANGING AND SHOUTING COMING FROM YOUR ROOM IN THE NIGHT I EXPECT IT WAS THE NOISE OF THE FURNITURE MRS BROWN EXPLAINED PADDINGTON HASTILY DRAWING THE SHEETS UP ROUND HIS EARS SO THAT SHE WOULD NOT SEE THE MARMALADE STAINS THE FURNITURE EXCLAIMED MRS BROWN AS SHE PUT THE TRAY DOWN ON THE BED WHAT FURNITURE THE FURNITURE I BOUGHT IN MY DREAM SAID PADDINGTON PATIENTLY MRS BROWN SIGHED SOMETIMES SHE COULD NOT MAKE HEAD OR TAIL OF WHAT PADDINGTION WAS TALKING ABOUT I HAVE BROUGHT YOU YOUR BREAKFAST IN BED SHE SAID BECAUSE MRS BIRD AND I HAVE TO GO OUT THIS MORNING WE ARE TAKING JONATHAN AND JUDY TO THE DENTIST AND WE THOUGHT PERHAPS YOU WOULD NOT MIND BEING LEFT ON YOUR OWN UNLESS SHE ADDED YOU WOULD LIKE TO COME TOO OH NO SAID PADDINGTON HASTILY I DO NOT THINK I SHOULD LIKE TO GO TO THE DENTIST THANK YOU VERY MUCH I WOULD MUCH RATHER STAY AT HOME THERE IS A BIG BOX ARRIVED FROM MR GRUBER CONTINUED MRS BROWN I THINK IT IS THE CARPENTRY TOOLS YOU BOUGHT IN THE SALE YESTERDAY I HAVE HAD THEM PUT IN THE SHED THANK YOU MRS BROWN SAID PADDINGTON HOPING SHE WOULD SOON GO AS IT WAS GETTING VERY HOT UNDER THE BLANKETS AND THE MARMALADE DISH WAS STICKING IN HIS SIDE AGAIN MRS BROWN PAUSED IN THE DOORWAY WE SHALL NOT BE ANY LONGER THAN WE CAN HELP YOU ARE SURE YOU WILL BE ALL RIGHT I EXPECT I SHALL FIND SOMETHING TO DO SAID PADDINGTON VAGUELY MRS BROWN HESITATED BEFORE SHUTTING THE DOOR SHE WOULD HAVE LIKED TO ASK PADDINGTON A FEW MORE QUESTIONS HE HAD A FAR AWAY LOOK IN HIS EYES WHICH SHE DID NOT LIKE THE LOOK OF AT ALL BUT SHE WAS ALREADY LATE FOR THE APPOINTMENT AND THE CONVERSATION WITH PADDINGTON PARTICULARLY IN THE EARLY MORNING WAS LIABLE TO BECOME COMPLICATED WHEN MRS BIRD HEARD ALL ABOUT PADDINGTONS STRANGE BEHAVIOUR SHE HURRIED UPSTAIRS TO SEE WHAT WAS GOING ON BUT SHE ARRIVED BACK A FEW MOMENTS LATER WITH THE NEWS THAT HE WAS SITTING UP IN BED EATING HIS BREAKFAST AND READING A CATALOGUE OH WELL SAID MRS BROWN LOOKING MOST RELIEVED HE CAN NOT COME TO MUCH HARM DOING THAT IN RECENT WEEKS PADDINGTON HAD BEGUN TO COLLECT CATALOGUES AND WHENEVER HE SAW AN INTERESTING ONE ADVERTISED IN THE NEWSPAPERS HE USUALLY SENT AWAY FOR IT

PAD4
MRS BIRD PAUSED FOR A MOMENT AND SNIFFED THE AIR AS SHE AND MRS BROWN TURNED THE CORNER INTO WINDSOR GARDENS CAN YOU SMELL SOMETHING SHE ASKED MRS BROWN STOPPED BY HER SIDE NOW THAT MRS BIRD MENTIONED IT THERE WAS A VERY PECULIAR ODOUR COMING FROM SOMEWHERE NEAR AT HAND IT WAS NOT EXACTLY UNPLEASANT BUT IT WAS RATHER SWEET AND SICKLY AND IT SEEMED TO BE MADE UP OF A NUMBER OF THINGS SHE COULD NOT QUITE PLACE PERHAPS THERE HAS BEEN A BONFIRE SOMEWHERE SHE REMARKED SO THEY PICKED UP THEIR SHOPPING AND CONTINUED ALONG THE ROAD WHAT EVER IT IS SAID MRS BIRD DARKLY IT SEEMS TO BE GETTING WORSE IN FACT SHE ADDED AS THEY NEARED NUMBER 32 IT IS MUCH TOO CLOSE TO HOME FOR MY LIKING I KNEW IT SHE EXCLAIMED AS THEY MADE THEIR WAY ALONG THE DRIVE AT THE SIDE OF THE HOUSE JUST LOOK AT MY KITCHEN WINDOWS OH DEAR SAID MRS BROWN AS SHE FOLLOWED THE DIRECTION OF MRS BIRDS GAZE WHAT ON EARTH HAS THAT BEAR BEEN UP TO NOW LOOKING AT MRS BIRDS KITCHEN WINDOWS IT SEEMED JUST AS IF IN SOME STRANGE WAY SOMEONE HAD CHANGED THEM FOR FROSTED GLASS WHILE THEY HAD BEEN OUT WORSE STILL NOT ONLY DID THE GLASS HAVE A FROSTED APPEARANCE BUT THERE WERE SEVERAL TINY RIVERS OF A RATHER NASTY LOOKING BROWN LIQUID TRICKLING DOWN THEM AS WELL AND FROM A SMALL PARTLY OPEN WINDOW AT THE TOP THERE CAME A STEADY CLOUD OF ESCAPING STEAM WHILE MRS BIRD EXAMINED THE OUTSIDE OF HER KITCHEN WINDOWS MRS BROWN HURRIED ROUND TO THE BACK OF THE HOUSE I DO HOPE PADDINGTON IS ALL RIGHT SHE EXCLAIMED WHEN SHE RETURNED I CAN NOT GET IN THROUGH THE BACK DOOR IT SEEMS TO BE STUCK HMM SAID MRS BIRD IF ONLY IF THE WINDOWS LOOK LIKE THIS FROM THE OUTSIDE HEAVEN ALONE KNOWS WHAT WE SHALL FIND WHEN WE GET INDOORS NORMALLY THE WINDOWS AT NUMBER 32 WINDSOR GARDENS WERE KEPT SPOTLESSLY CLEAN WITH NEVER A TRACE OF A SMEAR BUT EVEN MRS BIRD BEGAN TO LOOK WORRIED AS SHE PEERED IN VAIN FOR A GAP IN THE MIST THROUGH WHICH SHE COULD SEE WHAT WAS GOING ON HAD SHE BUT KNOWN THE CHANCES OF SEEING ANYTHING AT ALL THROUGH THE HAZE WERE MORE UNLIKELY THAN SHE IMAGINED FOR ON THE OTHER SIDE OF THE GLASS EVEN PADDINGTON WAS HAVING TO ADMIT TO HIMSELF THAT THINGS WERE GETTING A BIT OUT OF HAND IN FACT AS HE GROPED HIS WAY ACROSS THE KITCHEN IN THE DIRECTION OF THE STOVE WHERE SEVERAL LARGE SAUCEPANS STOOD BUBBLING AND GIVING FORTH CLOUDS OF STEAM HE DECIDED HE DID NOT MUCH LIKE THE LOOK OF THE FEW THINGS HE COULD SEE CLIMBING UP ON A KITCHEN CHAIR HE LIFTED THE LID OFF ONE OF THE SAUCEPANS AND PEERED HOPEFULLY INSIDE AS HE POKED AT THE CONTENTS WITH ONE OF MRS BIRDS TABLESPOONS THE MIXTURE WAS MUCH STIFFER THAN HE HAD EXPECTED AND IT WAS AS MUCH AS HE COULD MANAGE TO PUSH THE SPOON IN LET ALONE STIR WITH IT PADDINGTONS WHISKERS BEGAN TO DROOP IN THE STEAM AS HE WORKED THE SPOON BACK AND FORTH BUT IT WAS NOT UNTIL HE TRIED TO TAKE IT OUT IN ORDER TO TEST THE RESULT OF HIS LABOURS THAT A REALLY WORRIED EXPRESSION CAME OVER HIS FACE FOR TO HIS SURPRISE HOWEVER MUCH HE PULLED AND TUGGED IT WOULD NOT EVEN BUDGE THE MORE HE STRUGGLED THE HOTTER THE SPOON BECAME AND AFTER A MOMENT OR TWO HE GAVE IT UP AS A BAD JOB AND HURRIEDLY LET GO OF THE HANDLE AS HE CLIMBED DOWN OFF THE CHAIR IN ORDER TO CONSULT A LARGE MAGAZINE WHICH WAS LYING OPEN ON THE FLOOR MAKING TOFFEE WAS NOT AT ALL THE EASY THING THE ARTICLE IN THE MAGAZINE MADE IT OUT TO BE

GULL
IT WAS MORNING AND THE NEW SUN SPARKLED GOLD ACROSS THE RIPPLES OF A GENTLE SEA A MILE FROM SHORE A FISHING BOAT CHUMMED THE WATER AND THE WORD FOR BREAKFAST FLOCK FLASHED THROUGH THE AIR TILL A CROWN OF A THOUSAND SEAGULLS CAME TO DODGE AND FIGHT FOR BITS OF FOOD IT WAS ANOTHER BUSY DAY BEGINNING BUT WAY OFF ALONE OUT BY HIMSELF BEYOND BOAT AND SHORE JONATHAN LIVINGSTON SEAGULL WAS PRACTICING A HUNDRED FEET IN THE SKY HE LOWERED HIS WEBBED FEET LIFTED HIS BEAK AND STRAINED TO HOLD A PAINFUL HARD TWISTING CURVE THROUGH HIS WINGS THE CURVE MEANT THAT HE WOULD FLY SLOWLY AND NOW HE SLOWED UNTIL THE WIND WAS A WHISPER IN HIS FACE UNTIL THE OCEAN STOOD STILL BENEATH HIM HE NARROWED HIS EYES IN FIERCE CONCENTRATION HELD HIS BREATH FORCED ONE SINGLE MORE INCH OF CURVE THEN HIS FEATHERS RUFFLED HE STALLED AND FELL SEAGULLS AS YOU KNOW NEVER FALTER NEVER STALL TO STALL IN THE AIR IS FOR THEM DISGRACE AND IT IS DISHONOUR BUT JONATHAN LIVINGSTON SEAGULL UNASHAMED STRETCHING HIS WINGS AGAIN IN THAT TREMBLING HARD CURVE SLOWING SLOWING AND STALLING ONCE MORE WAS NO ORDINARY BIRD MOST GULLS DO NOT BOTHER TO LEARN MORE THAN THE SIMPLEST FACTS OF FLIGHT HOW TO GET FROM SHORE TO FOOD AND BACK AGAIN FOR MOST GULLS IT IS NOT FLYING THAT MATTERS BUT EATING FOR THIS GULL THOUGH IT WAS NOT EATING THAT MATTERED BUT FLIGHT MORE THAN ANYTHING ELSE JONATHAN LIVINGSTON SEAGULL LOVED TO FLY THIS KIND OF THINKING HE FOUND IS NOT THE WAY TO MAKE ONES SELF POPULAR WITH OTHER BIRDS EVEN HIS PARENTS WERE DISMAYED AS JONATHAN SPENT WHOLE DAYS ALONE MAKING HUNDREDS OF LOWLEVEL GLIDES EXPERIMENTING HE DID NOT KNOW WHY FOR INSTANCE BUT WHEN HE FLEW AT ALTITUDES LESS THAN HALF HIS WINGSPAN ABOVE THE WATER HE COULD STAY IN THE AIR LONGER WITH LESS EFFORT HIS GLIDES ENDED NOT WITH THE USUAL FEET DOWN SPLASH INTO THE SEA BUT WITH A LONG FLAT WAKE AS HE TOUCHED THE SURFACE WITH HIS FEET TIGHTLY STREAMLINED AGAINST HIS BODY WHEN HE BEGAN SLIDING IN TO FEETUP LANDINGS ON THE BEACH THEN PACING THE LENGTH OF HIS SLIDE IN THE SAND HIS PARENTS WERE VERY MUCH DISMAYED INDEED WHY JON WHY HIS MOTHER ASKED WHY IS IT SO HARD TO BE LIKE THE REST OF THE FLOCK JON WHY CAN NOT YOU LEAVE LOW FLYING TO THE PELICANS THE ALBATROSS WHY DO NOT YOU EAT JON YOU ARE BONE AND FEATHERS I DO NOT MIND BEING BONE AND FEATHERS MUM I JUST WANT TO KNOW WHAT I CAN DO IN THE AIR AND WHAT I CAN NOT THAT IS ALL I JUST WANT TO KNOW SEE HERE JONATHAN SAID HIS FATHER NOT UNKINDLY WINTER IS NOT FAR AWAY BOATS WILL BE FEW AND THE SURFACE FISH WILL BE SWIMMING DEEP IF YOU MUST STUDY THEN STUDY FOOD AND HOW TO GET IT THIS FLYING BUSINESS IS ALL VERY WELL BUT YOU CAN NOT EAT A GLIDE YOU KNOW DO NOT YOU FORGET THAT THE REASON YOU FLY IS TO EAT JONATHAN NODDED OBEDIENTLY FOR THE NEXT FEW DAYS HE TRIED TO BEHAVE LIKE THE OTHER GULLS HE REALLY TRIED SCREECHING AND FIGHTING WITH THE FLOCK AROUND THE PIERS AND FISHING BOATS DIVING ON SCRAPS OF FISH AND BREAD BUT HE COULD NOT MAKE IT WORK IT IS ALL SO POINTLESS HE THOUGHT DELIBERATELY DROPPING A HARDWON ANCHOVY TO A HUNGRY OLD GULL CHASING HIM I COULD BE SPENDING ALL THIS TIME LEARNING TO FLY THERE IS SO MUCH TO LEARN IT WAS NOT LONG BEFORE JONATHAN GULL WAS OFF HIMSELF AGAIN FAR OUT AT SEA HUNGRY HAPPY LEARNING THE SUBJECT

CHAPTER 5.

EVALUATION OF STRUCTURE IN TEXT STRINGS USING SIMPLE STATISTICAL ANALYSES.

In this chapter I shall examine the relationship between structure and vocabulary in text strings. 'Structure' is here taken to mean structure in the information theoretical sense (see chapters 1 and 2), and 'vocabulary' is the 'raw' concept of vocabulary. Vocabulary in this sense means: numbers of different words in a text string. There is some common notion of a great vocabulary being a sign of great litteracy, and consequently most people put an emphasis on their producing a rich and varied vocabulary. This they use as a mean of posturing and impressing their fellow men, who - given the chance - will respond with an equally impressive display of such verbal plumage.

We suffer from a peculiar misapprehension. Even if normal physical development in young children is associated with increasing size we do not therefore automatically deduce that this applies to adults as well in the sense that bigger means better. And yet, the common attitude to the concept of vocabulary seems to be just that: The use of an increasing number of words rightly associated with childrens language development has become an accepted part of lay - and not so lay - assessment of the mental development of adults.

Whereas a small vocabulary may (but not: does) indicate arrested language development - just as small weight may (but not: does) mean stunned growth - this simplistic approach has sadly led to a pre-occupation with one minor, but easily assessed, aspect of language behaviour and consequently to a general lack of appreciation of the finer and richer features of human language. It is frequently said about some popular newspapers that their vocabulary is so small, that it is equivalent to that of a child of such and such an age, thereby infering, that this is why they are read by people who are so and so 'dum'. I shall later demonstrate, that the idea of the popular press relying on a smaller vocbulary, is a myth. In actual fact, of all the text strings used in this present research, the text strings with the highest vocabulary were features from the popular press.

To establish the usefulness - or limitations - of this established concept of vocabulary, let us imitate the reading - by a computer program which we can call INFOR - of a particular text string according to this concept:

> ONCE UPON A TIME THERE WAS A LITTLE GIRL
> CALLED ALICE AND SHE HAD A VERY CURIOUS
> DREAM WOULD YOU LIKE TO HEAR WHAT IT WAS
> THAT SHE DREAMED ABOUT WELL THIS WAS THE (5.1)
> FIRST THING THAT HAPPENED A WHITE RABBIT
> CAME RUNNING BY IN A GREAT HURRY AND JUST
> BEFORE IT PASSED ALICE IT STOPPED AND
> TOOK ITS WATCH OUT OF ITS POCKET......

Do not let the lack of grammatical signs: periods, commas and so forth upset you. At the moment I only want to explain to you the basics of INFOR and will leave the trickier bits out for a while. First problems first, and the first must be that of continuity.

The continuity of a text string is of course limited by the sheer fact, that a text string, even one constituted by a whole book, must begin and end somewhere. This sounds trivially true, but as we shall soon see, this is in fact going to cause us some problems. Let us however proceed according to the raw concept of vocabulary and fill in an information array IA so that each place in IA represents a word in the text string. If there are say, 64 words in the text string, the array IA will have 64 places to be filled. If a word is 'new' in the text, its place in the array IA will be set to '1'. If the word is a repeat, its place in the array will be set to '0'.

The first word in the text string is of course a 'new' word. The first place in the information array IA is therefore set to 1, which we will express like this:

IA[1]:=1;

The program INFOR now stores this first word in the computer's memory and proceeds to the next word: "UPON". INFOR reads the word, examines the memory store and since it does not find "UPON" in the memory, the word is a new word and accordingly INFOR sets the second place to 1 in array IA: IA[2]:=1. We can express whether the words read so far were new or repeats in this way:

IA[1:2]:=1,1;

INFOR now stores "UPON" in the computer's memory and proceeds to the third word. Any word will be stored in the computer's memory first time it is encountered. By repeating the processes stated above, INFOR will find the first 6 words of the text string to be new, set the first 6 places of IA equal to 1 and store the words in the memory. When INFOR encounters the 7th word "A" and checks the memory, it will find, that this word is a repeat and will accordingly set IA[7] to 0. Array IA now looks like this

IA[1:7]:=1,1,1,1,1,1,0;

After all the words of text string (5.1) have been read by INFOR, we have an array which, if we remove the commas between the ones and the zeros, will look like this:

IA[1:64]:=1111110111111101111111111111101110
1111010111111011011010010111111101; (5.2)

Array IA is now an ordered account of whether the words were new or repeats during the reading by INFOR of (5.1), and the vocabulary at any point of the string can be established simply by counting the numbers of '1's. In (5.2) there are 51 '1's so the vocabulary of text string (5.1) is 51.

In this way any text string can be reduced to an array of ones and zeros, and what I am interested in is this: Is there any particular structure in this array of zeros and ones, or were the new words merely arriving at random during the reading of the text string (5.1)?

It is clear. even from a short array like (5.2) and without any further analysis, that the zeros in this array become more and more frequent as the reading goes on. All samples of normal natural text analysed in this way yield the same result: new words become less, and repeated words more frequent as the reading continues. This has already answered my question as to the randomness of the elements in (5.1). The obvious question must now be: By which rate do new words become less, and repeated words more frequent?

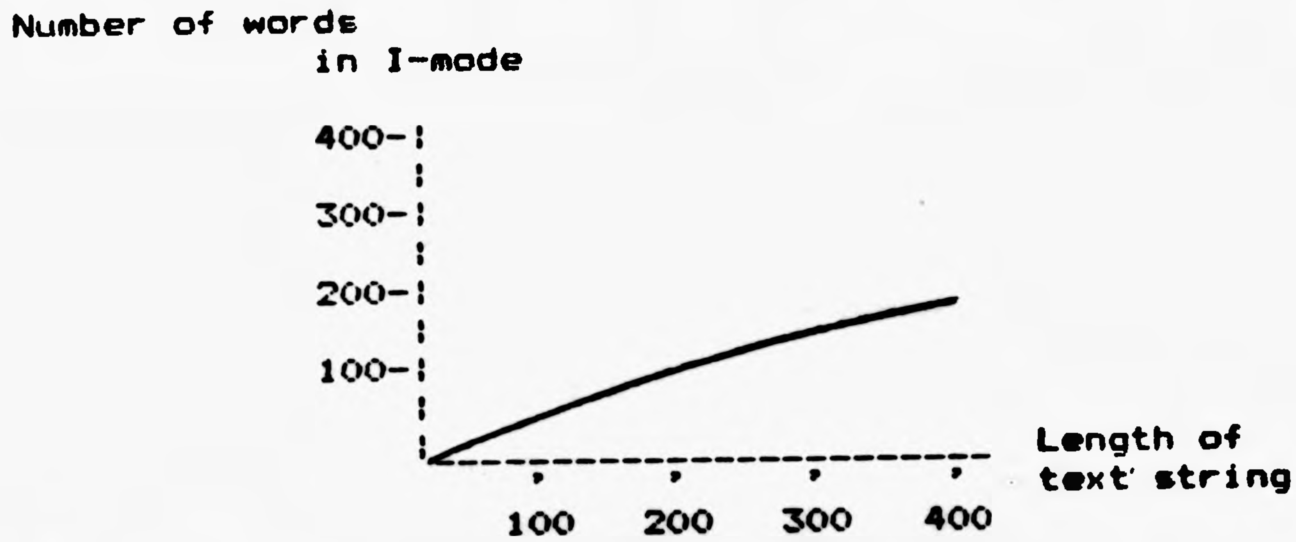

Figure 5.3. Vocabulary plotted against length of text string.

If we plot number of new words against length of text string in a co-ordinate system, we get a graphic representation of the vocabulary at any given point of the text string. In the unlikely event of all the words in the string being different ie. the number of new words at any point of the string equaling the number of read words, we get a straight line F(x) = x through (1,1), (2,2), (3,3) etc. This 'every word is a new word' situation only exists at the start of a natural text string. After a few words, rarely more than 30, the words begin to repeat themselves, and as we read along the string, the ratio of new words falls steadily. The graph representing a natural text string, would reflect this mixture of slowly increasing numbers of new words and fast increasing numbers of repeats and its 'steepness' would decline every time a repeat was encountered. Figure 5.3 shows such a typical graph. A graph of this shape can be represented by an equation of the form

F(x) = A * x to the B power (5.4)

where the factor A and power B depend on individual properties of the text string being analysed, and therefore vary from text string to text string.

As it is not immediately obvious why I have chosen the curve F(x) = A * x to the B power as an expression of the relationship between vocabulary and length of text string I shall explain what my reasons are.

In the initial stage of my research, after I had realised that the relationship between vocabulary and length of text string is NOT one of linearity, I made a number of attempts to plot this relationship in different kinds of coordinate systems to see if it would plot as a straight line in any of them. I eventually found out, that this would be the case only in a double logarithmic coordinate system, i.e. a system where both axes are logarithmic.

In a normal equidistant coordinate system the equation for a straight line is the well known

$$y = Bx + A$$

where B is the gradient of the line and A is the intersection with the y-axis. In a double logarithmic system, the expression of a straight line is correspondingly

$$\ln(y) = B*\ln(x) + \ln(A)$$

where B as before is the gradient of the line and A is the intersection with the ln(y) axis. If we 'take the logarithm on both sides' we get the expression

$$y = A * x \text{ in the B power}$$

or

$$F(x) = A * x \text{ in the B power}$$

which is the equation 5.4.

The fact, that the relationship between vocabulary and length of text string for any text is NOT one of linearity (in an equidistant coordinate system), but one of exponential decay, has considerable bearing on the 'type token ratio' mentioned in chapter 2 (page 18), since, if the relationship between vocabulary and length of a text string was one of linearity, the 'type token ratio' would make some sense. However, as the relationship is one of exponential decay, 'type token ratio' is a fiction, a bogus which should never have found its way into communication analysis.

When we know that in the original double logarithmic coordinate system, A is the y-intercept and B is the gradient of the straight line, it is quite easy to apprehend the relationship between A and B. The text strings analysed in this paper gave values for the gradient B between +0.64 to +0.91, and values for the y-intercept A of between 0.88 and 2.96.

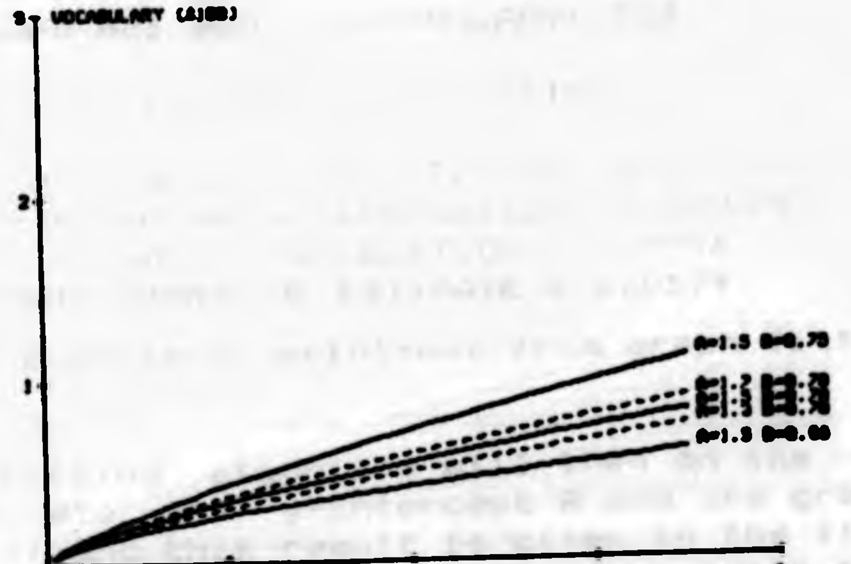

Figure 5.6. Graphic expression of equation 5.4
for different values of A and B

To visualise how the slope and shape of the graph depends on different values of A and B in equation (5.4), a number of graphs have been plotted in the same coordinate system with different values of A and B (fig. 5.6). The values of A and B are stated next to each graph.

The curve fitting algorithm explained in next chapter has been developed to find the intercept A and gradient B from a given text sample. This analysis has been carried out on all the childrens text strings and on a number of the text strings written by adults. As an example, a print-out from this curve fitting algorithm is enclosed here (fig. 5.7). I shall explain the contents of this print-out, which happens to be an analysis of an article from the Daily Record, an article with an amasingly high vocabulary.

In this print-out the vocabulary is given after each interval of 50 words. The size of vocabulary given at each interval constitutes a point on the graph, and after 10 intervals we have 10 points of a graph. The size of the interval is fixed by the operator, and depends on the length of the text string to be analysed. In all cases I have fixed the interval such that the number of points have been around 10. For very short text strings, like some of the childrens strings in this work, this has meant an interval of only 5 words between each point. The size of the interval in itself is not so important as long as we get around 10 points spread over the entire string.

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B:DREC1.TXT:

AT WORD NR: 50    VOCABULARY: 41
AT WORD NR: 100   VOCABULARY: 72
AT WORD NR: 150   VOCABULARY: 101
AT WORD NR: 200   VOCABULARY: 130
AT WORD NR: 250   VOCABULARY: 148
AT WORD NR: 300   VOCABULARY: 174
AT WORD NR: 350   VOCABULARY: 200
AT WORD NR: 400   VOCABULARY: 226
AT WORD NR: 450   VOCABULARY: 249
AT WORD NR: 500   VOCABULARY: 274
AT WORD NR: 550   VOCABULARY: 297
AT WORD NR: 600   VOCABULARY: 324

GEOMETRIC REGRESSION ANALYSIS:

F(x) = 1.60110e0 * X TO THE 8.26290e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9993
COEFFICIENT OF CORRELATION = 0.9996
STANDARD ERROR OF ESTIMATE = 0.0179
```

Fig.5.7. Example of print-out from graph fitting algorithm

The curve fitting algorithm will then on the basis of these points calculate the y-intercept A and the gradient B in the equation (5.4) and this result is given in the first line of the 'geometric regression analysis', together with the 'closeness of fit': the correlation coefficient and the standard error of estimate. As the correlation coefficient of this example shows, the closeness of fit is very high (higher than + 0.999). This is not a particular feature of this print-out. All the print-outs in the appendix to this chapter show the same high closeness of fit and thus demonstrate, that equation 5.4 in all cases is a faithful representation of the relationship between vocabulary and length of text string.

To give an idea of the differences between such graphic representations of the vocabulary in specific text strings, I have plot-

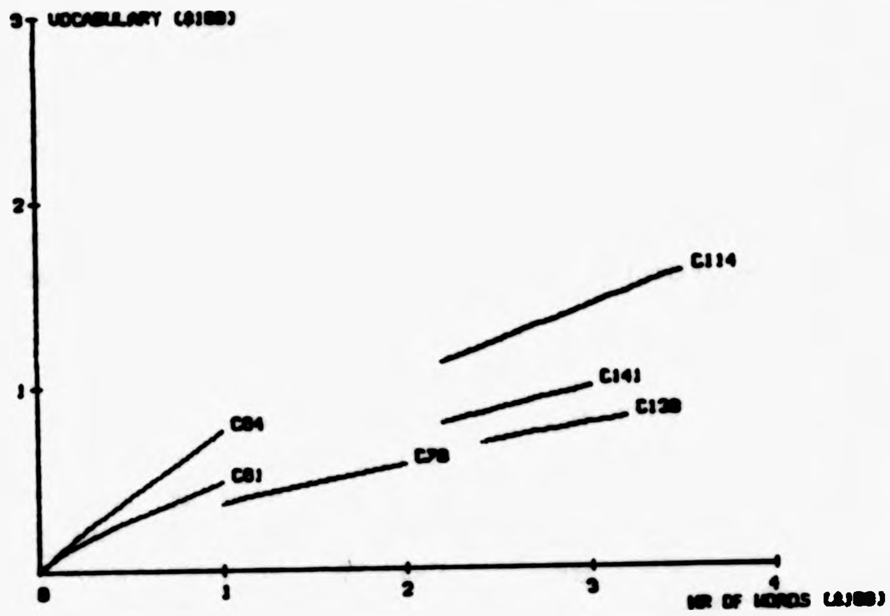

Figure 5.8. The relationship between vocabulary and length of text strings for 6 text strings written by children.

ted 6 graphs from childrens text strings in figure 5.8. These graphs have been plotted on the basis of the print-outs from the curve fitting algorithm mentioned above. They have been picked so as to give a fair representation of the data, from the smallest to the steepest gradient. For reasons of clarity only the latter part of the graphs of C70, C114, C130 and C141 has been plotted.

The same relationship between vocabulary and length of string - but representing adult text strings - is presented in the following graph (Figure 5.9). The texts can all be found in full in chapter 4 and are (from top to bottom of the graph) Daily Record 1, Bertrand Russell 4, The Guardian, 'Winnie the Pooh', Russell 3, 'Alice in Wonderland', 'The Nursery Alice'. It is interesting to see, that Daily Record 1 is high above Russell's 'The Principles of Mathematics' and that 'The Nursery Alice', which Lewis Carrol wrote as an easy "Alice in Wonderland" comes out only marginally lower than the work it was supposed to replace for younger children.

If you go through the trouble of reading the above mentioned text samples in chapter 4, and look at the graphs in figure 5.9, you will again find, that there is no obvious link between a high vocabulary of a text string and its litterary quality. This may come as a surprise to some and as a confirmation to others. I belong to the latter group, so my next step shall be to further demonstrate how little weight can be given to the size of vocabulary as a measure of litterary quality.

To assess whether there is a simple and direct relationship between age, competence, style and vocabulary, I arranged all text samples in descending order of vocabulary. However, as

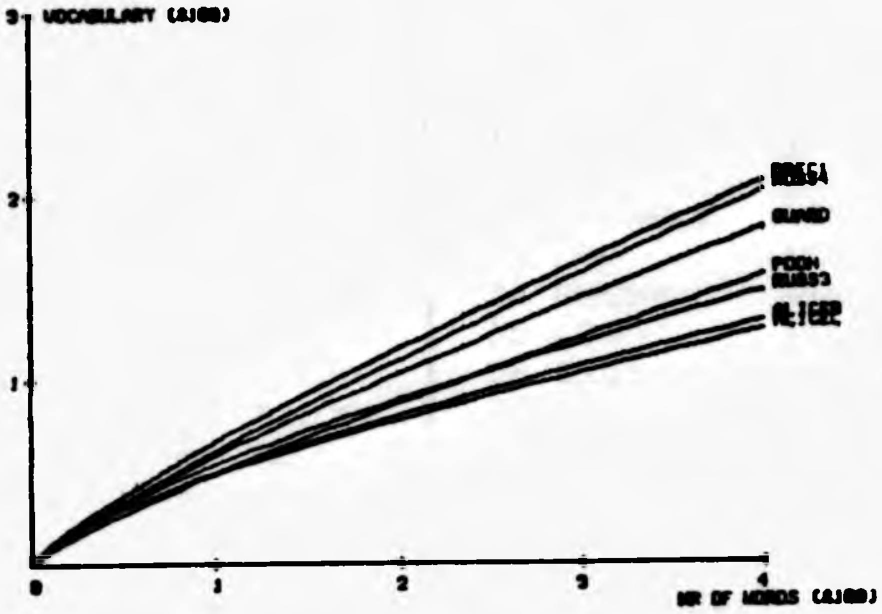

Figure 5.9: The relationship between vocabulary and length of text strings for 7 text strings written by adults.

1	MAIL	VOC(50) =	44.00
2	PAD3	VOC(50) =	43.00
3	C76	VOC(50) =	42.00
4	HERALD	VOC(50) =	42.00
5	RUSS5	VOC(50) =	42.00
6	PAD2	VOC(50) =	42.00
7	C140	VOC(50) =	42.00
8	C100	VOC(50) =	41.00
9	C114	VOC(50) =	41.00
10	C64	VOC(50) =	41.00
11	PAD1	VOC(50) =	41.00
12	DREC1	VOC(50) =	41.00
13	DREC2	VOC(50) =	41.00
14	PAD4	VOC(50) =	41.00
15	RUSS1	VOC(50) =	40.00
16	C104	VOC(50) =	40.00
17	C113	VOC(50) =	40.00
18	C72	VOC(50) =	39.00
19	C78	VOC(50) =	39.00
20	RUSS2	VOC(50) =	39.00
21	C110	VOC(50) =	39.00
22	C85	VOC(50) =	38.00
23	LABOV	VOC(50) =	38.00
24	C84	VOC(50) =	38.00
25	C111	VOC(50) =	38.00
26	ALICEL	VOC(50) =	38.00
27	C112	VOC(50) =	38.00
28	SEAGULL	VOC(50) =	38.00
29	C79	VOC(50) =	37.00
30	ALICEB	VOC(50) =	37.00
31	C96	VOC(50) =	37.00
32	RUSS3	VOC(50) =	37.00
33	CHOMSKY	VOC(50) =	37.00
34	C77	VOC(50) =	37.00
35	OLGA	VOC(50) =	36.00
36	C91	VOC(50) =	36.00
37	C83	VOC(50) =	36.00
38	C67	VOC(50) =	36.00
39	FRANKENA	VOC(50) =	36.00
40	C103	VOC(50) =	36.00
41	C74	VOC(50) =	36.00
42	C141	VOC(50) =	36.00
43	C90	VOC(50) =	36.00
44	C63	VOC(50) =	35.00
45	C65	VOC(50) =	35.00
46	C102	VOC(50) =	35.00
47	RUSS4	VOC(50) =	35.00
48	C75	VOC(50) =	34.00
49	C70	VOC(50) =	34.00
50	C81	VOC(50) =	34.00
51	C62	VOC(50) =	34.00
52	C95	VOC(50) =	34.00
53	GUARD	VOC(50) =	34.00
54	C130	VOC(50) =	33.00
55	C92	VOC(50) =	33.00
56	C80	VOC(50) =	33.00
57	C71	VOC(50) =	32.00
58	C66	VOC(50) =	32.00
59	C73	VOC(50) =	32.00
60	C101	VOC(50) =	32.00
61	BRUNER	VOC(50) =	31.00
62	C61	VOC(50) =	31.00
63	C93	VOC(50) =	30.00
64	C94	VOC(50) =	29.00
65	C82	VOC(50) =	29.00
66	POOH	VOC(50) =	26.00

Table 5.10: Vocabulary (per 50 words) arranged in descending order of magnitude.

demonstrated above, the relationship between the vocabulary and length of text string is non-linear. Therefore, the numerical values of vocabulary for two or more text strings are not comparable unless the text strings are of equal length. So, if we want

1	MAIL	VOC(100) =	75.00
2	DREC2	VOC(100) =	74.00
3	C114	VOC(100) =	73.00
4	HERALD	VOC(100) =	73.00
5	PAD4	VOC(100) =	73.00
6	RUSS5	VOC(100) =	72.00
7	C100	VOC(100) =	72.00
8	SEAGULL	VOC(100) =	72.00
9	DREC1	VOC(100) =	72.00
10	PAD2	VOC(100) =	70.00
11	PAD1	VOC(100) =	70.00
12	LABOV	VOC(100) =	69.00
13	RUSS2	VOC(100) =	69.00
14	OLGA	VOC(100) =	69.00
15	RUSS3	VOC(100) =	69.00
16	C111	VOC(100) =	69.00
17	C104	VOC(100) =	68.00
18	RUSS1	VOC(100) =	68.00
19	ALICEB	VOC(100) =	67.00
20	PAD3	VOC(100) =	67.00
21	GUARD	VOC(100) =	67.00
22	C83	VOC(100) =	66.00
23	C84	VOC(100) =	66.00
24	C96	VOC(100) =	66.00
25	ALICEL	VOC(100) =	65.00
26	C92	VOC(100) =	65.00
27	C85	VOC(100) =	64.00
28	C72	VOC(100) =	63.00
29	C95	VOC(100) =	63.00
30	C140	VOC(100) =	63.00
31	C113	VOC(100) =	62.00
32	CHOMSKY	VOC(100) =	62.00
33	C80	VOC(100) =	62.00
34	RUSS4	VOC(100) =	62.00
35	C74	VOC(100) =	61.00
36	C110	VOC(100) =	61.00
37	C90	VOC(100) =	61.00
38	C77	VOC(100) =	61.00
39	C79	VOC(100) =	61.00
40	C112	VOC(100) =	60.00
41	C101	VOC(100) =	60.00
42	FRANKENA	VOC(100) =	60.00
43	C91	VOC(100) =	60.00
44	C103	VOC(100) =	60.00
45	C93	VOC(100) =	59.00
46	C141	VOC(100) =	57.00
47	C81	VOC(100) =	57.00
48	C130	VOC(100) =	56.00
49	C102	VOC(100) =	56.00
50	C82	VOC(100) =	54.00
51	C94	VOC(100) =	53.00
52	C62	VOC(100) =	53.00
53	C70	VOC(100) =	51.00
54	BRUNER	VOC(100) =	50.00
55	C71	VOC(100) =	50.00
56	POOH	VOC(100) =	50.00
57	C73	VOC(100) =	47.00

Table 5.10: Vocabulary (per 100 words) in descending order of magnitude.

1	DREC1	VOC(500) =	274.00
2	MAIL	VOC(500) =	273.00
3	OLGA	VOC(500) =	269.00
4	LABOV	VOC(500) =	269.00
5	RUSS2	VOC(500) =	261.00
6	SEAGULL	VOC(500) =	252.00
7	RUSS4	VOC(500) =	250.00
8	RUSS5	VOC(500) =	249.00
9	HERALD	VOC(500) =	248.00
10	DREC2	VOC(500) =	246.00
11	PAD1	VOC(500) =	241.00
12	PAD2	VOC(500) =	239.00
13	RUSS1	VOC(500) =	238.00
14	GUARD	VOC(500) =	236.00
15	PAD4	VOC(500) =	235.00
16	BRUNER	VOC(500) =	232.00
17	PAD3	VOC(500) =	228.00
18	FRANKENA	VOC(500) =	219.00
19	C95	VOC(500) =	217.00
20	CHOMSKY	VOC(500) =	216.00
21	RUSS3	VOC(500) =	211.00
22	ALICEL	VOC(500) =	198.00
23	ALICEB	VOC(500) =	194.00
24	C141	VOC(500) =	192.00
25	POOH	VOC(500) =	188.00
26	C85	VOC(500) =	188.00
27	C130	VOC(500) =	172.00
28	C140	VOC(500) =	164.00

Table 5.11: Vocabulary (per 500 words).

to compare numerical values of vocabulary, it is essential that we compare vocabulary for text strings of the same length say, 50 words or 100 words or whatever length is suitable, as long as the vocabulary is given for strings of equal length. Accordingly when I have given in table 5.10 to 5.12 the vocabulary of different text strings, I have stated at which length of string the vocabulary was measured. In table 5.10 to table 5.12 the vocabulary is given for text strings of length 50, 100 and 500 respectively. As many of the childrens text strings were too short to figure in the vocabulary per 100 and all but 5 were too short to figure in

the vocabulary per 500 words, tables 5.10 to 5.12 become progressively shorter as more and more text samples 'drop out'.

The hypothesis, that the four categories: newspapers, scientists, childrens books and children are drawn from different populations with regard to the numerical vocabulary, was tested with the Kruskal-Wallis one-way analysis of variance of the vocabulary per 50, 100 and 500 words respectively.

Tables 5.13 to 5.15 are schematic representations of the level of significance when any one category was tested against all other categories. An "ns" stands for "not significant" and means, that the 5% significance level was not reached. When the hypothesis, that any two categories are drawn from different populations, is confirmed on a significance level better than 5%, the significance level is stated where the horizontal line from one category crosses the vertical line from another category. Thus, the hypothesis that newspapers constitute a different category from children, judged on their vocabulary per 50 words (table 5.13b), is confirmed on a 3% significance level.

	mean	s.d.
children	35.8	3.5
scientists	37.2	3.2
papers	40.4	3.8
ch.books	38.0	5.1

Table 5.13a Mean vocabulary per 50 words.

	children	scientists	papers	ch.books
children	--	ns	3%	4%
scientists		--	ns	ns
papers			--	ns
ch.books				--

Table 5.13b Significance of Kruskal-Wallis test of difference between categories in vocabulary per 50 words.

	mean	s.d.
children	60.6	6.0
scientists	64.6	6.8
papers	72.2	3.1
ch.books	66.8	6.8

Table 5.14a Mean vocabulary per 100 words.

	children	scientists	papers	ch.books
children	--	ns	0.1%	0.1%
scientists		--	3%	ns
papers			--	5%
ch.books				--

Table 5.14b Significance of Kruskal-Wallis test of difference between categories in vocabulary per 100 words.

	mean	s.d.
children	173.4	36.9
scientists	238.3	20.5
papers	255.4	17.1
ch.books	227.1	27.9

Figure 5.15a Mean vocabulary per 500 words.

	children	scientists	papers	ch.books
children	--	1%	1%	2%
scientists		--	ns	ns
papers			--	ns
ch.books				--

Table 5.15b Significance of Kruskal-Wallis test of difference between categories in vocabulary per 500 words.

From table 5.13b it would appear, that the vocabulary of children, measured over 50 words, is not significantly different from that of scientists, but is significantly different from that of newspapers and - interestingly enough - from that of childrens books.

Table 5.14b shows that as the length of text string goes up from 50 to 100, newspapers show significant differences from the other categories, and the difference between childrens text strings on the one hand and childrens books and newpapers on the other, become more pronounced.

In text strings of 500 words, there is significant difference between childrens vocabulary and that of all other categories, but it is clear too, that none of the other categories vary significantly from each other in this respect.

It is clear too, that newspapers have the highest vocabulary whatever the length of text string.

The values for the categories of children in tables 5.13 to 5.15 were based on the 5 strings C85, C95, C130, C140 and C141 which were all longer than 500 words.

To assess more fully the dependence between the four parameters: vocabulary, intercept A, gradient B and age of writer, the correlation between these parameters was calculated over 100 words for 25 childrens text strings and - for comparative reasons - for all adult text strings. This length of text string - 100 words - is somewhat arbitrary. It was chosen as a compromise between, on the one hand, the wish to accommodate as many of the younger writers as possible, on the other, the wish to preserve enough of the adult strings to retain the subject matter. Table 5.16a gives the correlation coefficients and table 5.16b gives the statistical significance of these coefficients.

	A	B	VOCABULARY	AGE
A	-	-0.94696	-0.59826	-0.02029
B		-	+0.81154	+0.21889
VOCAB.			-	+0.38888

Table 5.16a Coefficients of correlation between A, B, vocabulary and age over 100 words from 25 text strings written by children aged 6 to 14 years.

	A	B	VOCABULARY	AGE
A	-	0.1%	0.2%	ns
B		-	0.1%	ns
VOCAB.			-	5%

Table 5.16b Coefficients of table 5.16a translated into statistical significance for N = 25.

The highly significant reciprocal relationship between intercept A and gradient B seen in table 5.16b we already knew about. The relationship between A and B on the one hand and the vocabulary on the other we too did know about, and as expected the parameter B, being the exponent, would contribute more to the relationship with the vocabulary (significant on the 0.1% level) than will the intercept A (significant on a 0.2% level). More surprising is the level of significance between age and vocabulary. This level of 5% has only just been reached and only because it would be reasonable to apply the less stringent demands of a one-tailed test since we would expect a direct relationship. If the two tailed test had been applied, as the case has been with the other values of table 5.16a, the relationship between age and vocabulary would have been significant on a 10% level only i.e. not significant.

In table 5.16b we can see too, that A or B on their own are not significantly dependent on the age of the children. The Kruskal-Wallis test gave that there was little difference (difference confirmed on a 50% level) between A and age of child, and B and age of child respectively.

We touched earlier in this chapter on the possibility that the parameters A and B were somehow related to the amount of structure in the text string. However, we have not quite settled what we mean by 'structure'. Is it the kind of structure which a child develops as he becomes aware of the operational rules we call grammar or is it a kind of structure we develop later when we learn to manipulate whole segments of text strings in order to achieve a special effect?

On the basis of the 25 childrens text strings of 100 words, and the 22 adults' text strings equally of 100 words each, all the categories: younger children, older children, scientists, newspapers and childrens books were tested against each other with the Kruskal-Wallis test for difference with regard to A, B and vocabulary. The results of these analyses are presented on the following three pages, for intercept A, exponent B and the vocabulary respectively.

INTERCEPT A MEASURED OVER 100 WORDS:

	mean	s.d.
younger children	1.49	0.55
older children	1.65	0.30
scientists	1.55	0.34
papers	1.20	0.19
ch.books	1.35	0.21

Table 5.17a A (mean) of different categories.

The difference between the younger children and the older children as measured with the Kruskal-Wallis test did not confirm that there was any significant difference between the two categories (significance level = 50%). In spite of this, I have wanted to keep the two categories separate in the following analysis to judge how each category is faring when compared to each of the adult categories.

	children younger	children older	scientists	papers	chbooks
children-Y	--	0.5	0.05	3.69	1.70
children-O		--	1.24	5.38	5.01
scientists			--	3.75	1.56
papers				--	1.05
chbooks					--

Table 5.17b Kruskal-Wallis test of difference between categogories in values of intercept A.

	children younger	children older	scientists	papers	chbooks
children-Y	--	ns	ns	ns	ns
children-O		--	ns	5%	5%
scientists			--	ns	ns
papers				--	ns
chbooks					--

Table 5.17c Significance of test in table 5.17b.

It is somewhat surprising to find in tables 5.17b and 5.17c that the older children show greater difference to any of the adult categories than do the younger children, to the extent, that 'older children' are significantly different from 'papers' and 'childrens books', whereas none of the younger children are significantly different from any of the adult categories. A higher value of intercept A in the strings of older children means that these strings initially has a higher vocabulary than the other categories, but that the high vocabulary is not sustained througout the string. This could well reflect older childrens deliberate 'flaunting' of recently acquired language behaviour and - in vocabulary terms - exhausting themselves in so doing.

GRADIENT B MEASURED OVER 100 WORDS:

	mean	s.d.
young children	0.78	0.06
old children	0.80	0.06
scientists	0.81	0.06
papers	0.90	0.05
chbooks	0.85	0.06

Table 5.18a B (mean) of different categories.

Again the Kruskal-Wallis test for difference shows that there is no significant difference between the values of B for the younger and older children. Again - and for the same reasons as above - the two categories shall be kept separate in the following analysis of difference between categories (Tables 5.18b and 5.18c).

	children younger	children older	scientists	papers	chbooks
children-Y	--	0.30	1.07	9.64	8.39
children-O		--	0.51	5.91	4.67
scientists			--	4.84	1.56
papers				--	4.82
chbooks					--

Table 5.18b Kruskal-Wallis test of difference between categogories in values of exponent B.

	children younger	children older	scientists	papers	chbooks
children-Y	--	ns	ns	1%	1%
children-O		--	ns	2%	5%
scientists			--	3%	ns
papers				--	3%
chbooks					--

Table 5.18c Significance of test in table 5.18b.

Tables 5.18b and 5.18c show that with regard to the gradient B, the difference between younger children and all adult categories is geater than between older children and any of the adult categories. This seems intuitively right if we are talking about parameters which represent developmental features. It may after all be, that B - but not A - is a mesure of some kind of developmental linguistic feature. It is interesting to see (table 5.18c), that not only are younger and older children significantly different from childrens books, but from newspapers as well. Scientists are not significantly different from neither younger nor older children.

VOCABULARY MEASURED OVER 100 WORDS:

	mean	s.d.
younger children	57.3	6.2
older children	63.1	6.0
scientists	64.6	6.8
papers	72.2	3.1
ch.books	66.8	7.2

Table 5.19a Vocabulary (mean) of different categories.

When 'younger children' was tested against 'older children' with the Kruskal-Wallis test for difference with regard to vocabulary, the difference was - as above - not significant. However, instead of a significance level of 50% as the case was with the A and B values, the significance level with regard to vocabulary for younger versus older children is nearer 7%.

	children younger	children older	scientists	papers	chbooks
children-y	--	3.24	5.04	10.28	8.21
children-o		--	0.56	6.43	2.57
scientists			--	5.21	0.94
papers				--	3.69
chbooks					--

Table 5.19b Kruskal-Wallis test of difference in vocabulary between categories.

	children younger	children older	scientists	papers	chbooks
children-y	--	ns	5%	1%	1%
children-o		--	ns	2%	ns
scientists			--	5%	ns
papers				--	ns
chbooks					--

Table 5.19c Significance of test in table 5.19b.

The above analysis of difference of vocabulary between the various categories gives a very similar picture to that of the analysis of gradient B on the preceding page. This is not surprising considering the high correlation between B and vocabulary in table 5.16. In both cases, the difference between the various categories is greater for the younger children than for the older children, and it seems reasonable to suggest, that B as well as vocabulary are directly related to some kind of developmental feature. The question is: which, since, as we have seen in table 5.16b, gradient B is not significantly correlated with age - and with vocabulary only just.

DISCUSSION OF THE ABOVE ANALYSES.

If A and B are related to early linguistic development, we would have expected to see a difference in the values of A and B of younger children as compared to those of older children. As we saw in table 5.16b, this does not seem to be the case. A and B are not significantly correlated with age. Tables 5.17 and 5.18 confirmed that the two categories 'younger children' and 'older children' do not seem to be drawn from different population with regard to A and B. Consequently we would assume that A and B are either not related to linguistic development or are related to developments which take place later on in life i.e. during or after adolescence. The difference between children as a whole and adults as a whole, as measured with the Kruskal-Wallis test seemed to confirm the latter view; the difference in the features between the childrens and adults' language as represented by A or B was confirmed on a better than 5% (A) and better than 1% (B), thus confirming, that the parameters A and B may be related to linguistic developments which have taken place sometimes between the age of the child writers and the adult writers. So much said, tables 5.18 (a) and (b) do show, that even if there are no significant differences between the two categories 'younger children' and 'older children' per se, these two categories tested against the different adult categories, gave that the 'younger children' consistently showed greater difference to the adult categories than the 'older children' with regard to the gradient B, whereas the opposite was the case with regard to the intercept A (tables 5.17 (a) and (b)).

The parameters A and B may still contain elements of basic developmental features. The analysis of gradient B certainly looks that way. The analysis of intercept A is puzzling and inconclusive.

Not unexpectedly we can conclude that vocabulary is a significant developmental feature of text strings, but only just! Children measured against adults gave that the difference is confirmed on a better than 0.1% level. However, when we divided the children into 2 categories: the younger (6 to 9, n=13) and the older (10-14, n=12) we found that when each category is tested against the adults (n=22), the difference between the younger category and the adults is confirmed on a better than 0.01% level, while the difference between the older children and the adults doesn't quite make it to the 5% level. This is interesting, since it means, that the strings written by the age group 10-14 are not significantly different from the adult text strings with regard to vocabulary.

It would be interesting to contemplate further on the structural features measured by the parameters A, B and vocabulary. To that end let us look at different kinds of structure in text strings.

DISTRIBUTIVE, SEQUENTIAL AND CONTENT STRUCTURE.

As you may recall from the examination of Information Theory in chapter 1, the structure of a system according to this theory is invertly related to the amount of entropy in the system; high entropy equals little structure and low entropy equals a high level of structure, and on the whole we can express the level of structure by one single parameter, the entropy. We also saw, that entropy was related to the concept of randomness, but whether we want to associate structure with entropy or randomness, is not important. The important point is that in a simple physical system, we only need one parameter to express the level of structure.

When we talk about structure in text strings however, the concept of structure is not equally simple. For a start, the generation of a text string is more than a matter of different degrees of random distribution. In a simple physical system we arrive at a structure which normally depends on only one thing, the level of entropy. Even though there is some variation and oscillation within this physical state or structure, basically the level of entropy determines which kind of bonding and at which orientation this bonding is to take place between units. In most physical systems we can predict pretty accurately the level of structure if we know the initial entropy of the system and the amount of energy which is going in to, or taken out of, the system.

In those physical systems which we call cognitive - and a text string is one such - there are at least three kinds of structure. First there is what I will term 'distributive' structure. This is the structure constituted by the different distribution of words in different text strings. If we analyse a text string and count the number of different words and how often each word has been used in the same string, we get a discription - graphic or other - of the distribution of the words, and this distribution constitutes one kind of structure. If we shuffle the words of the text string as the case is if we permutate the words in the string, we do not alter the number of times each word has been used, and the distribution, as calculated before, remains unchanged.

Secondly there is the 'sequential' structure. This is the structure which is most important in the semantic sense and it arises from the words being arranged sequentially. We can not normally change the sequence of the words in a text string without altering the semantic content of the string or loose it all together, even though in this case the particular words used in the string often will be able to convey some information as to what the string was a statement about i.e. the strings subject matter, even though we may have lost the statement itself. This information remnant, this ability to convey information about the string's subject matter even though the string has been 'broken up' is a third kind of structure which I shall term 'content' structure, but not make a subject of a special examination since this paper is about automatic analysis of text strings, and the content structure is a purely cognitive feature.

Even though the distributive, sequential and content structures are all related since they are basically three 'side-effects' of the same capacity to generate natural language, they express different features of this generative capacity, or to put it another way, they express this generative capacity on three different levels. On the surface level we have the distributive structure which is a purely mathematical feature. On the deep level we have the content structure which is a purely semantical or cognitive feature. Neither of these structures change when the text string is permutated.

In between we have the sequential structure which ties the content structure (a semantic feature) to the distributive structure (a mathematical feature). As such it is half semantic, half mathematical and contrary to the other two structures it changes - it breakes down - if we permutate the text string. Thus, if equation 5.4 can be seen as an expression of the average structure in a text string, this equation should render different values if it was applied to a text string before and after permutation of the text string, and if this is the case, the difference should be equal to the break down of the sequential structure since the distributive structure and the content structure both remain unchanged by the permutation.

To test this hypothesis, the 22 adult text strings of 600 words used throughout this research and 5 text strings written by children, each 550 words long, were subsequently subjected to the same routine: the values of A and B were found by the graph fitting algorithm, as explained earlier, BEFORE and AFTER permutation of each text string. The reason for selecting only the longer text strings for this experiment is solely that the effect I am looking for is so small, that relatively short strings would not exhibit any significant change. This has however meant, that all but 5 text strings written by children has had to be excluded from the experiment.

In the majority of cases i.e. in 20 out of the 27 samples, A, the intercept, increased and B, the gradient, decreased with permutation. Recalling, that equation 5.4 originates from a straight line in a double logarithmic coordinate system, we can now see that what happens, when we permutate the words of a text string, is that the graph - which is a straight line in the original double logarithmic system - tilts clockwise, so causing B, the gradient to decrease, and A, the y-intercept to increase.

The relationship between vocabulary and length of text string before and after permutation is illustrated in figure 5.20 where BRUNER NAT refers to the the text sample by Bruner in its natural form, and BRUNER PERM refers to the text string after permuta-

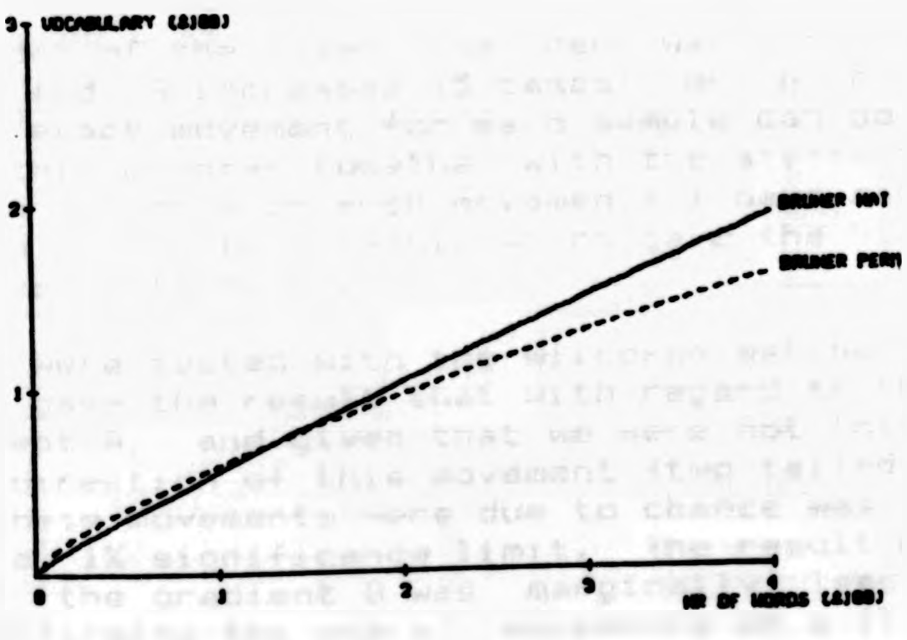

Figure 5.20 Relationship between vocabulary and length of text string before and after permutation (Bruner).

tion. This particular sample was chosen because it most clearly shows how the graph fitting algorithm 'sees' the difference: The dashed line (the permutated text) rises more steeply, than the full line (the natural text) until around word number 150, as a result of the ratio (new words) to (length of text string) being greater in the beginning of the permutated string than in the na-

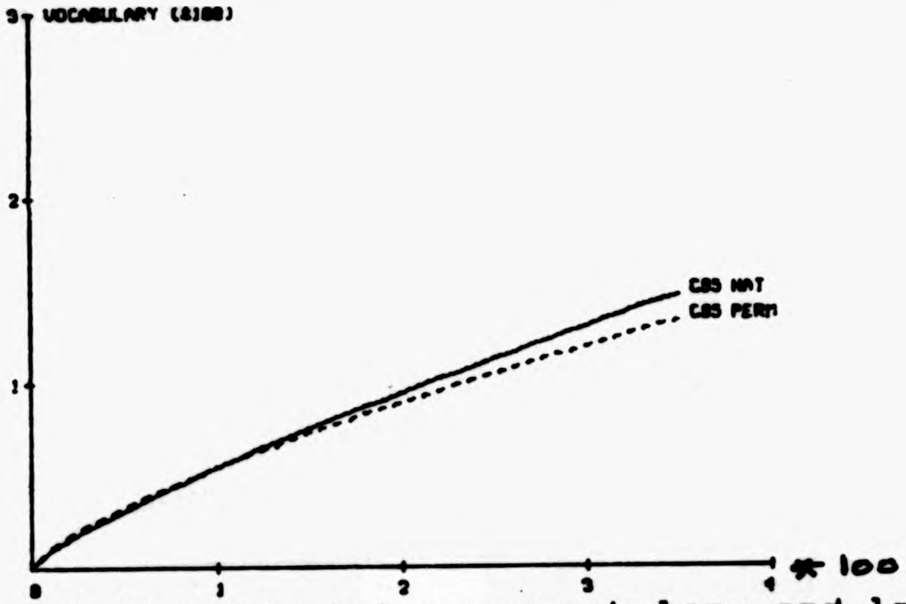

Figure 5.21 Relationship between vocabulary and length of text string before and after permutation (C95).

tural string and consequently smaller later in the text string. A simple way of putting it would be: In the permutated string it looks like there are more new words in the beginning and fewer new words later than in the natural string.

As stated above, the text sample used in figure 5.20 was chosen because it most clearly illustrated the difference between the natural and the permutated text string i.e. it was the sample wich showed the greatest difference before and after permutation. More typical of the majority of the samples, but of course less instructive, is the sample used in figure 5.21 which is one of the childrens text strings. However, even if the difference is much smaller, the situation is the same as above.

In the remainder of the cases, the trend was either the opposite: A decreased and B increased (5 cases) or both increased (2 cases). The exact movement for each sample can be found in the appendix to this chapter together with the statistical calculations. As an example of such movements I have made a graphic representation of the text sample which gave the biggest movement the opposite way (figure 5.22).

All movements were tested with the Wilcoxon matched pairs signed-rank test and gave the result that with regard to the movement of the y-intercept A, and given that we were not initially able to predict the direction of this movement (two tailed) the overall chance that these movements were due to chance was 0.0014, well below even a 1% significance limit. The result regarding the movements of the gradient B was marginally less significant, but still confirming the overall movements on a 1% significance level.

On the whole, we have confirmed on a 1% level the hypothesis that the equation 5.4 is indeed associated with the sequential structure of a text string and that the y-intercept A is inversely related to this structure (A increases when the structure decreases, is 'broken') while the gradient B is directly related (B decreases when the structure decreases).

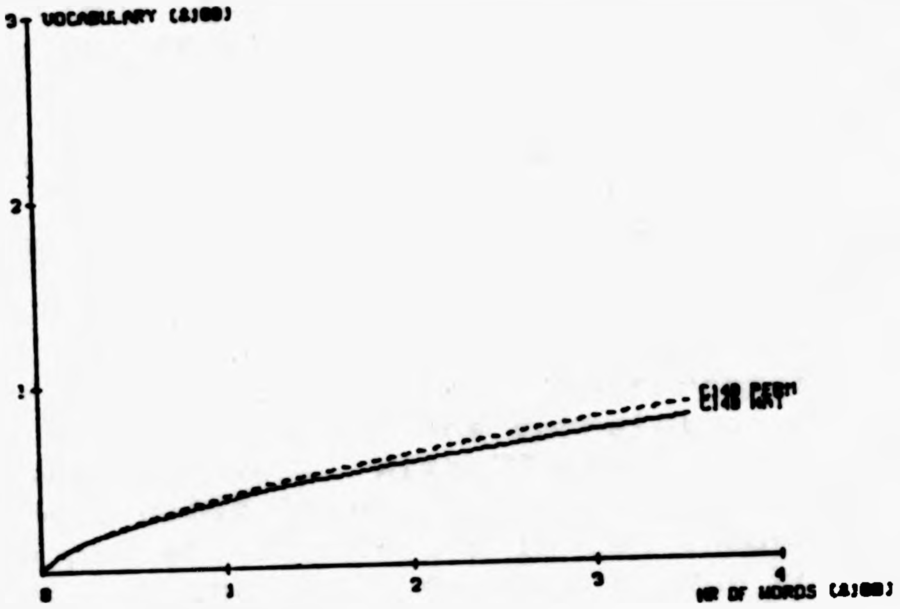

Figure 5.22 Relationship between vocabulary and length of text string before and after permutation (C140).

However, the situation is more complex than this. If we examine the A values which went the 'wrong' way after permutation i.e. where A (perm) was smaller after permutation than before, it becomes apparent, that all the A values which went the 'wrong' way originated from maximum values. If you care to look at a couple of examples in the appendix to this chapter, you can see what I mean.

Let us look at the only one text string (C140) of the childrens text strings which had a smaller A value after permutation than before. The A value before permutation (A text) is by far the greatest of all the A values in this group (children). The same is the case with all other text strings, which had a smaller A after permutation. This must lead to the conclusion, that the graph 5.4 does not just tilt clockwise as a result of the string having been permutated, but adjusts itself to some hypothetical pre-determined A value. If the initial A value is smaller than this hypothetical value, as the case is with most of the text strings in this analysis, the graph tilts clockwise; if the initial A value is greater than the same hypothetical A value, the graph tilts anti-clockwise. Presumably, this hypothetical A value constitutes some minimum structure level and the initial A value of the natural text string - be it bigger or smaller than this hypothetical A value - will 'slip back' to the low structure value of A, as soon as some kind person releases the bindings between the words of the string. We say that we do this by permutating the words, but in a physical sense, we break the bonds between the units by adding energy to the system.

This kind of 'behaviour' is well known from simpler so-called 'exo-thermal' physical systems. By adding a small amount of energy, it is possible to 'lift' the system over a 'barrier' and release energy while the system 'falls' into a minimum energy state from which it was suspended by 'weak' bonds.

If we look at the B values in the same table, in the appendix, of values before and after permutations, we find exactly the same behaviour. It is thus not only a question of an A value or a B value: we find to our amasement - at least to mine - that the graph 5.4 not only is connected to the sequential structure of the text string, but that this graph tends to seek towards a minimum structure position when the sequential structure is being broken down.

The best way to assess if this behaviour is significant is to measure the correlation between A of the natural text (A text) and the movement of A (delta A). If A is big, then - if this theory is correct - delta A should be small and vice versa, i.e. we should get a negative correlation coefficient. The correlation coefficients between all values of A and delta A, and all values of B and delta B were calculated. The correlation between all A's and delta A's was -0.7098. The correlation between all B's and delta B's was -0.6707. With 27 observations this feature is significant on a 0.01% level (A) and a 0.03% level (B). There is thus only a probability of one in ten thousand (A) and one in three thousand (B) that this feature is due to chance.

The question is now: which is the minimum structure position of the graph 5.4? Is there one common position for all text samples or is the minimum structure position determined by features particular to each text string or to each type of text string.

If the minimum structure position is common to all text strings, one would presume, that the mean values of A (perm) and B (perm) for all the text strings would constitute this position. These mean values are stated in the appendix after all the values of A and B respectively. The mean value of A (perm) of all samples is 2.3556. If the minimum structure position was common to all text strings, one would expect this value to be the value, which all text strings would move towards when 'released', i.e. if the A value of a natural text was greater than 2.3556, then we would expect the result of a permutation of the string to be that A decreased. If on the other hand the initial A value of a natural text string was smaller than 2.3556, we would expect the A value of the string to have increased after the permutation. Looking through the table of A and B values however, this is clearly not the case. Each group, children, newspapers, scientists and childrens books seem to have each their own minimum structure values of A and B.

Testing for difference between the A (perm) and B (perm) values of the 4 groups with the Kruskal-Wallis one-way analysis of variance we do indeed find, that the hypothesis that the four groups are drawn from different populations is confirmed on a better than 5% level for the A perm values, and on a better than 1% level for the B perm values.

In an attempt to establish what exactly causes the change in the values of A and B when the text string is permutated, I have tried to assess the length of 'runs' of new and repeated words before and after permutation. The reason for my wanting to examine the length of runs before and after permutation had to do with my experience throughout this work, that particularly the first long run of new words in the beginning of a natural text string often was broken into several shorter runs when the string had been permutated. This could well influence the final equation of the graph due to the fact, that the fitting of an exponential graph to a number of coordinate pairs is more "sensitive" to the first, lower values of coordinate pairs than to the later (as on logarithmic graph paper), and it would therefore seem reasonable to suggest, that a few - to the Information Theory irrelevant - changes in the succession of the first words of the sample caused by the permutation could account for the change in the values of A and B. As this may not be immediately apparent, I shall explain:

As stated before, the number of new words in a text string, as demonstrated in this work, will generally be falling exponentially along the string. In many cases however, there are a substantial number of 'new words' in the beginning of a natural text string. In some cases the string of new words before a word is repeated in the beginning of a text can amount to 20 or 30. What often happens during the permutation of this kind of text string is that the uninterrupted long string of new words in the beginning of a text string is broken down into smaller segments by one or two of the small words 'and', 'or', 'the' etc. moving from later parts of the text string to the beginning of the text, where they would not normally occur.

To assess if this feature could account for the consistent changes in the A and B values after permutation, the number of 'new' words in the beginning of each text string was counted before and after permutation and evaluated with the Wilcoxon matched-pairs signed-rank test. The hypothesis, that the breakdown of the first long 'run' of new words IN THE BEGINNING of a text string into two or more shorter 'runs' was a feature correlated with the permutation of the string, had to be rejected (11% confidence level).

Instead of length of runs we can measure number of runs; this makes no difference since the number of runs is invertedly related to the length of runs: many runs equals short runs, few runs equals long runs - everything else equal.

To test whether the breaking down of long segments of new words, not only in the beginning of the text string as analysed above, but IN THE STRING AS A WHOLE, was a constant feature of the permutation of a text string and thus could account for the other constant feature of A increasing and B decreasing in value due to permutation, a program was made which measured the length of runs of new words and repeated words both before and after permutation and made a suitable print-out. This analysis was carried out on all the 27 text samples above. Two examples of such a print-out are shown below (figure 5.23) and (figure 5.24), the first being runs measured before permutation, the second being runs measured after permutation. The remaining print-outs can be found in the appendix to this chapter.

I shall explain the lay-out of figures 5.23 and 5.24. The print-out begins with the name of the sample, in this case 'B:BRUNER.TXT'. The 'B:' in front of the name refers to a disk drive and is irrelevant in this connection. The TXT after the period in the name is the type of file and indicates, that this file contains the natural text string, whereas if the type had been file contained the permutated text string. The next line is:

B:BRUNER.TXT
1B600RF0

```
111111111111111111110011011100100000000000000001001111
110001011011100011100111011100000000000000000100100
11111110001011110110001001100000111001101100111001
00011100011000110110001110100001100101110100111011
10010001100110010011010010001010110000100111001111
10111000001010101100101001010000101001010100101010
11001000001011100110010001100001000001000001101100
001111010011001001000010100001001110000001011101001
00000101010001101110010010111001000010011010011110
00111010110000001010010100101001110111101100010011
01010100010110100111000010100110011001001110000010
000000011011000111000000001101010010001010101101101
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        79 *******************************************************:
  2        34 **********************************
  3        24 ************************
  4         4 ****
  5         1 *
  6         1 *
  7         1 *
  8         0
  9         0
 10         0
 11         0
 12         0
 13         0
 14         0
 15         0
 16         0
 17         0
 18         0
 19         0
 20         1 *
SUM= 273         144
```

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        59 *******************************************************
  2        46 **********************************************
  3        17 *****************
  4         9 *********
  5         8 ********
  6         1 *
  7         1 *
  8         1 *
  9         0
 10         0
 11         0
 12         1 *
 13         0
 14         0
 15         0
 16         1 *
SUM= 327         144
```

Figure 5.23 Print-out of runs in text string before permutation.

```
B:BRUNER.PRM
1B600RF0

1111101111111111101111110111101111101111111111101110
1111101111111111101110111101011101101001111111110101
0111011010011011101100010010000100101101101010100110
0101110010101011011010100100001100001101001101001 1
0000001110101100010101110001010100111111000010000101
0110110001011111000111011000110000010111000111 10000
0011000000010100001110010000100011000100100110 0000
0000001000011000011101000101011011000110000100 1011
0110100111101100000010000001001000100000000010000000
0001100000111000000111110010111000000001001000010000 1
1100001010110000100001000010000000100001000011 1001
0000001100000000010100000100110100001010110010 1100
```

```
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        68 ********************************************************************
   2        34 **********************************
   3        17 *****************
   4         3 ***
   5         6 ******
   6         1 *
   7         0
   8         1 *
   9         1 *
  10         1 *
  11         1 *
SUM= 273
```

133

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        63 ***************************************************************
   2        23 ***********************
   3        13 *************
   4        19 *******************
   5         3 ***
   6         5 *****
   7         3 ***
   8         1 *
   9         2 **
  10         0
  11         1 *
SUM= 327
```

133

Figure 5.24 Print-out of runs in text string after permutation.

1B600RF0. This means, that the measurement is B for binary, that it starts at word number 1 and continues to word number 600. The 'RF zero' I shall not explain here. It refers to a technique which will be developed in the last half of this thesis and which is not being employed in this present measurement, for which reason the RF is set to zero.

The next 12 lines represent the text string which was analysed. The first line of fifty 1's or 0's covers the first fifty words. The next line of fifty 1's or 0's covers the next fifty words and so on. A '1' means that the word was a new word, a '0' means, that a word was a repeat. As there were 600 words in the text string, there are 12 lines of fifty 1's or 0's which together give the pattern of new and repeated words in the 600 word long text string. We can see, that in figure 5.23 - before permutation - there are 20 new words in the beginning of the text string before we encounter the first repeat. If we then turn to figure 5.24, we can see, that the run of twenty in the beginning of the natural text string has been split into one run of 5 plus one run of 11 in the permutated string - just the kind of change that was mentioned above.

Next comes the 'length of runs of ones'. This is a graphich and numerical representation of the length and number of each run of ones, and should be read like this (referring to figure 5.23): There were 79 runs which were one digit long. There were 34 runs which were 2 digits long. There were 24 runs which were 3 digits long etc. Finally we can see, that there was 1 run which was 20 digits long. That was, as we know, the 20 new words in the beginning of the text string. Finally the sum of the product of the length of run and the number of runs is calculated for later control. The number of *'s representing the numerical value of the number of each run were added to give - by means of a histogram - a graphic representation of the one half of the bell-shaped distribution curve constituted by the number of each run length.

The same exercise is repeated for the number of runs of zeroes, and the sum product is calculated for control as before. These two sums should add up to the length of the text string if everything is all right. Furthermore, the first control number in figure 5.23 (before permutation) should be equal to the first control number in figure 5.24 (after permutation), because the number of 1's - the number of different words - should be the same after the permutation as it was before. The same is of course true for the 0's.

Comparing 5.23 with 5.24, we find, that contrary to expectations influenced by ideas about chance and randomness, whereas in 5.23 (before permutation) there was only 1 run each of 5, 6 and 20 (totalling 31), after permutation there were 6 runs of 5, plus 1 run each of 8,9,10,and 11 (totalling 68). Clearly what happened was the opposite of what we (I) had expected: Permutation increased the run lengths rather than reduced them. This is graphically illustrated by the bell-shaped distribution curve from being 'high and narrow' becoming 'flatter and wider' as a result of the permutation of the natural text string.

Clearly , the expectation, that long runs will be broken into several small ones, is not always realistic. As a matter of fact, counting the number of runs (i.e. assessing the length of runs) for all the samples before and after permutation, it turns out, that the opposite is true: The permutation of a natural text string leads almost invariably to fewer and longer runs.

Even maximum length of runs ANYWHERE in a text string is not generally reduced by permutation. The hypothesis, that the maximum length of runs anywhere in a text is decreased by permutation had to be rejected when maximum runs were assessed with the Wilcoxon test before and after permutation (40% significance level for runs of 1's, 38% significance level for runs of 0's).

Table 5.25 shows the considerable difference in the number of runs caused by the permutation of a natural text string. All changes were tested with Wilcoxon's matched-pairs signed-ranks test wich confirmed this feature on a significance level better than 0.0003 i.e. on a 0.03% level.

	mean number of runs		
	before perm.	after perm.	difference
children	263.1	247.2	15.9
scientists	291.0	267.1	23.9
newspapers	299.2	278.8	20.4
childr.books	275.9	267.1	8.8

Table 5.25 Mean values of number of runs in each group of text strings before and after permutation. Childrens values adjusted for differing length of text string (multiplied by 600/550 = 1.0909).

The mean NUMBER of runs easily translates into mean LENGTH of runs. Knowing that the adult text strings are 600 words long and the childrens text strings 550 words long, we simply divide length of text string with the relevant value of the mean number of runs. Table 5.26 gives the length of runs for the different groups

	mean length of runs		
	before perm.	after perm.	difference
children	2.28	2.43	0.07
scientists	2.06	2.25	0.19
newspapers	2.01	2.15	0.14
childr.books	2.17	2.24	0.15

Table 5.26 Mean values of length of runs in each group of text strings before and after permutation.

The next obvious step was to compare number of runs before and after permutation with A and B values before and after permutation for each text string. In this way we would test if the change in the number of runs could account for the changes in A and B which we saw above.

NUMBER OF RUNS BEFORE permutation correlated negatively with the corresponding A-VALUES on a better than 0.1% significance level and positively with the corresponding B-VALUES on a better than 0.1% significance level.

NUMBER OF RUNS AFTER permutation correlated negatively with the corresponding A-VALUES on a better than 2% significance level and positively with the corresponding B-VALUES on a better than 0.1% significance level.

If number of runs is invertedly related to both length of runs, and - as we have just seen - to the values of the intercept A, then length of runs must be DIRECTLY related to the values of A, and we can thus with a high level of confidence conclude, that as the text is permutated and the length of runs increase, so does the value of A.

A parallel argument for the gradient B leads to the conclusion, that as the length of runs increases with permutation, the gradient B decreases.

We have thus been able to tie together a number of loose ends and are now able to reconsider the whole area of structural changes in terms of run lengths.

DISCUSSION OF ANALYSES ABOVE.

It can not be said too often, so I will say it again: it is essential that structure analyses are carried out on strings of equal length. Because of the exponential nature of equation 5.4, there is no such thing as a 'Type Token Ratio'.

We found earlier in this chapter, that the lowest A value of adult text strings was that of newspapers. This is reflected in table 5.26: Of the three adult groups, newspapers have the shortest length of runs. The way adults generate text strings clearly result in shorter runs than when children perform the same task. The text strings written FOR children too showed longer runs than the other adult categories, scientists and newspapers. These two groups, scientists plus newspapers on the one hand and text-strings written FOR children plus text strings written BY children on the other, were tested against each other for independence with the Kruskal-Wallis test of variance and gave that the groups were drawn from different populations with a level of significance of better than 2%.

We have seen too, that text strings with a higher degree of structure, like adult strings, had shorter average runs than had text strings with a lower degree of structure like those of children. So, contrary to what I had expected, within the limits set out by a permutation, run length is not crrelated with structure, but with lack of structure. High structure = short runs, low structure = long runs. Consequently, when we brake down the sequential structure of a text string the average run length increases. That the conscious internal manipulation of text strings, typical for adult language construction, should result in shorter runs, is somehwat different from what I had expected, and I can not offer any explanations as to why this should be so.

Contrary to common belief, we found that the text strings from newspapers came out as having the highest level of structure and the highest vocbulary of all the samples in this research. It was even the case, that the text strings from the most 'popular' press scored higher than the strings from the more 'serious' papers. Since the parameter we have analysed - the gradient B - represents sequential structure, the interpretation of the result is probably that much more sequential manipulation goes on in the mind of the writers of the 'popular' press than in the minds of the more 'serious' press, and certainly more than this category of journalists normally get credit for.

Apart from this apparent anomaly, the level of structure, according to this present analysis, came out very much as one would hav expected, with younger children (Table 5.18a) showing the least amount of structure (lowest B-values), followed by older children, scientists, childrens books and finally with the highest structure - as just stated - newspapers. It may be surprising to see that childrens books should have a higher structure than scientists, but it is quite feasable, that the internal sequential manipulation which goes into the writing of a feature in the popular press is the same as goes into the writing of a text string for children, bearing in mind, that what we have been measuring in the analyses above is not 'childishness', but to what extent the string has been manipulated and polished off before it was put down on paper.

In this chapter, we have looked at different concepts of language structure and applied our analysis to some of them. We have answered some of the questions, but other problems have arisen and some new questions await an answer.

The common concept of vocabulary and the concept of structure of the Information Theory are both one-parameter concepts of structure. Our analysis in this chapter expanded this concept to that of a two-parameter concept (the A-values and B-values), but even this is a long way from a description of the structure of natural language. For this reason we shall now turn our backs to the one or two parameter concepts of structure and look for a more - in linguistic terms - realistic method of structure analysis.

Thus, after the next chapter, which consists of the programs implementing the methods of this chapter, we shall explore the most sensitive multi-component analysis of structure available, namely that of Fourier analysis. Fourier analysis is normally used to analyse electrical signals and - to a lesser extent - for event-analysis. To my knowledge this method of analysis has not before been used to evaluate structures in text strings, and for this reason we shall later have to put considerable effort into adapting Fourier analysis to our particular information carrier: text strings.

CHAPTER 6.

PROGRAMS IMPLEMENTING METHODS OF CHAPTER 5.

In this chapter I shall describe the different programs used in my initial research.

Program VOCOUTEXPGRAPH.

The first program is really two programs in one. The first part, made up by the procedure READWORD and the function NEWWORD, reads the text string and calculates the vocabulary. The second part, the procedures GETDATA and COMPREGRESSANALYSIS, finds the closest fit of a curve and the points constituted by the vocabulary at regular intervals.

Beginning in the main program (line 178) and following the data flow, we see, that the program asks for the beginning and the end of the measuring window (line 187 and 189). The beginning of the window is normally the beginning of the text string.

The next parameter to initiate is the number of words in each interval (line 191). The program is written to calculate the vocabulary of the text string at regular intervals. After each interval the program will provide a print-out. If each interval has been chosen to be 50 words, the program will give the vocabulary (as calculated from the beginning of the text string) after each 50 words. The size of the intervals depends only on how many points we need to establish the graph which constitutes the relationship between vocabulary and length of text string as as figure 5.3 in chapter 5. Normally I have wanted around ten points from each text string, which for adult strings of aorund 500 words meant intervals of around 50 words, and for childrens strings of around 100 words obviously meant intervals of around 10 words.

READWORD (line 27) then reads as much of the string as necessary and feeds the number of words read and the vocabulary between the start of the window and each particular point in to the array POINTS. This array is of course the basis for GETDATA's and COMPREGRESSANALYSIS's calculations which result in the program printing out the equation (Line 217) that was the closest fit to the points in POINTS.

Procedure Readword is a straight forward disk file read-procedure which will accept the words and numbers defined in the set LETTERS in line 180. Words longer than 20 letters will be truncated. Procedure MOVEONE takes the first word of the textstring and allocates it to the array LABL which is the label of the string. After MOVEONE all words have been moved one word forward. Function NEWWORD compares each incoming word with all the preceding words from the start of the window. GETDATA finds A and B of the equation: F(x) = A * X in power B of the curve with the closest fit to the points in POINTS. The usual routine of the 'least squares' method is used, except that it is 'transposed' to a double logarithmic system. Finally COMPREGRESSANALYSIS calculates the coefficients of determination and correlation and the standard error of estimate.

Program PERMUTATE.

This program starts off with the same read procedure as the program above.

The function PRANDOM (line 107) is a pseudo random generator used to pick out word from the textstring at random.

If we start in the main program (line 119) and follow the data flow as usual, we see that after the usual disk file parameter routines, the program asks where we want the permutation to start and where to end. This is important, since the whole point of having a text string permutated - as opposed to randomised - is, that not only are the words of the original text string preserved in the permutated string, but so is their relative distribution. This means of course, that if a word appears 5 times in the natural text string, then it will appear five times in the permutated string as well.

The permutation procedure works by the program moving words from the text string to the permutated string according to the random number appearing from the random generator. This generator has been modified, so it only generates numbers within the range of the number of words in the text string. Each time a random number is generated and the appropriate word moved to the permutated string, that number is stored in the array RANDARRY. Each time a new random number is generated, it is first checked against all the numbers in RANDARRY to make shure that it is not a repeat. If it is a repeat, no word is picked from the original text string and the random generator is asked to provide another number. In this way we are shure, that each word from the original string is picked at random, but only picked once. By reducing the length of the string by 1 every time a word has been picked (line 140) we make sure that the permutation increases in speed as we near the end of the permutation.

Program TESTRUNS.

This program was made to measure the length of 'runs' of 1's and 0's in the information array before and after the text had been permutated with PERMUTATE as explained in chapter 5.

INFARRAY (initiated line 188) is an array with as many places as there are words in a given text string. When we read the first word we put a one in the first place of INFARRAY (because the first word is always a new word). When we read the next word, we put a one in the second place if this is a new word, or a zero if it is a repeat. This is done for every consecutive word. In this way we finish with an array filled with zeros and ones; a zero or a one for each word according to whether the word was a repeat or not.

A 'run' is a number of similar digits. In the beginning of the information array there may be more than 20 ones before they are interrupted by a zero, because it reflects the beginning of the text string and it takes a while before the words in the string start repeating themselves. In the end of the string there may on the other hand be quite long runs of zeros, because many of the words repeat themselves. The shortest run is of course only one digit long, and this is the most common length.

The first procedures in TESTRUNS are just like the first procedures of VOCOUTEXPGRAPH, so these need no further explanation. The only new procedure is RUNDETECTOR beginning at line 117. This procedure measures the length of each run (ones or zeros) and keeps track of how many there are of each length.

Finally the program prints a bar graph of the distribution of the different lengths of runs of 1's and 0's and checks that the number of runs multiplied by the lengths of the runs equal the number of places in INFARRY, or - which is the same - equals the number of words in the analysed text string.

```
PROGRAM VOCOUTEXPGRAPH(TEXTIN,TEXTOUT);
LABEL 1,2,3;
CONST
    MAXWORDLEN=20;
    NUMBOFWORD=1001;
TYPE
    WORDINDEX=1:MAXWORDLEN;
    TEXTINDEX=0:NUMBOFWORD;
    WORDTYPE=PACKED ARRAY[TEXTINDEX,WORDINDEX] OF CHAR;
    TRANSFTYPE=ARRAY[TEXTINDEX] OF REAL;
VAR
    WORD:WORDTYPE;
    LABL:PACKED ARRAY[WORDINDEX] OF CHAR;
    TRANLA:TRANSFTYPE;
    POINTS:ARRAY[1:100,1:2] OF INTEGER;
    START,FIN,VOC,NUMPOINTS,STEP,N,M:INTEGER;
    XCOOR,YCOOR,SUMLOGX,SUMLOGY,COEFFOFDET,STANDERRNUMERATOR,
    SUMXSQR,SUMYSQR,SUMXTIMESY,A,B:REAL;
    CH:CHAR;
    NAME:STRING;
    TEXTIN,TEXTOUT:TEXT;
    LETTERS:SET OF CHAR;
    F:INTERACTIVE;



PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
     BLANK=' ';
VAR
     N,CHARCOUNT:INTEGER;
     CH:CHAR;
BEGIN
      FOR N:=1 TO MAXWORDLEN DO WORD[L,N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
           WHILE NOT EOLN(TEXTIN) DO
           BEGIN
                READ(TEXTIN,CH);
                IF CH=BLANK THEN GOTO 2;
                IF EOLN(TEXTIN) THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     GOTO 2;
                END;
                IF CH IN LETTERS THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     CHARCOUNT:=CHARCOUNT+1;
                     IF CHARCOUNT>MAXWORDLEN THEN
                     BEGIN
                          WHILE CH<>BLANK DO
                          READ(TEXTIN,CH);
                          CHARCOUNT:=1;
                     END;
                     GOTO 1;
                END;
           END;
```

```
          READLN(TEXTIN);
     END;
     IF EOF(TEXTIN) THEN
     BEGIN
          CONACT(O);
          WRITE('EOF AT WORD NR:',L);
          HALT;
     END;
2:   IF WORD[L,1]=BLANK THEN
     BEGIN
          CHARCOUNT:=1;
          GOTO 1;
     END;
END;
PROCEDURE MOVEONE;
VAR
     N,M:INTEGER;
BEGIN
     FOR N:=1 TO 20 DO
     LABL[N]:=WORD[1,N];
     FOR N:=2 TO FIN+1 DO
     WORD[N-1]:=WORD[N];
END;
FUNCTION NEWWORD(RE:INTEGER):INTEGER;
VAR LE:INTEGER;
BEGIN
     NEWWORD:=1;
     FOR LE:=START TO RE-1 DO
     IF WORD[RE]=WORD[LE] THEN
     BEGIN
          NEWWORD:=0;
          EXIT(NEWWORD);
     END;
END;
PROCEDURE BOOKIN;
BEGIN
     CONACT(O);
     WRITELN('NAME OF INPUT FILE:');
     READLN(NAME);
     {$I- I/O OFF}
     RESET(TEXTIN,NAME);
     WHILE IORESULT<>0 DO
     BEGIN
          WRITELN('FILE NOT FOUND, TRY AGAIN');
          READLN(NAME);
          RESET(TEXTIN,NAME);
     END;
END;
```

```
PROCEDURE BOOKOUT;
BEGIN
    REWRITE(TEXTOUT,'PRINTER:');
END;



PROCEDURE GETDATA;
VAR
    I:INTEGER;
BEGIN
    SUMLOGX:=0;
    SUMLOGY:=0;
    SUMXSQR:=0;
    SUMYSQR:=0;
    SUMXTIMESY:=0;
    FOR I:=1 TO NUMPOINTS DO
    BEGIN
        XCOOR:=LN(POINTS[I,1]);
        YCOOR:=LN(POINTS[I,2]);
        SUMLOGX:=SUMLOGX+XCOOR;
        SUMLOGY:=SUMLOGY+YCOOR;
        SUMXSQR:=SUMXSQR+XCOOR*XCOOR;
        SUMYSQR:=SUMYSQR+YCOOR*YCOOR;
        SUMXTIMESY:=SUMXTIMESY+XCOOR*YCOOR;
    END;
    IF NUMPOINTS*SUMXSQR=SUMLOGX*SUMLOGX THEN
    WRITELN('REGRESSION CAN NOT BE CALCULATED')
    ELSE
    BEGIN
        B:=(NUMPOINTS*SUMXTIMESY-SUMLOGY*SUMLOGX)
            /(NUMPOINTS*SUMXSQR-SUMLOGX*SUMLOGX);
        A:=(SUMLOGY-B*SUMLOGX)/NUMPOINTS;
    END;
END;



PROCEDURE COMPREGRESSANALYSIS;
VAR
TEMP:REAL;
BEGIN
    TEMP:=B*(SUMXTIMESY-SUMLOGX*SUMLOGY/NUMPOINTS);
    COEFFOFDET:=ABS(TEMP/(SUMYSQR-SUMLOGY*SUMLOGY/NUMPOINTS));
    STANDERRNUMERATOR:=SUMYSQR-SUMLOGY*SUMLOGY/NUMPOINTS-TEMP;
    WRITELN;
    WRITE(TEXTOUT,'COEFFICIENT OF DETERMINATION (R-SQUARED) =');
    WRITELN(TEXTOUT,COEFFOFDET:0:4);
    WRITE(TEXTOUT,'COEFFICIENT OF CORRELATION =');
    WRITELN(TEXTOUT,SQRT(ABS(COEFFOFDET)):0:4);
    IF NUMPOINTS=2 THEN NUMPOINTS:=3;
    WRITELN(TEXTOUT,'STANDARD ERROR OF ESTIMATE =',
        SQRT(ABS(STANDERRNUMERATOR/(NUMPOINTS-2))):0:4);
END;



BEGIN--MAIN PROGRAM
    RESET(F,'CONSOLE:');
    LETTERS:=['0':'9','A':'Z'];
```

```
1:  BOOKIN;
    BOOKOUT;
    CONACT(0);
    FOR N:=1 TO 4 DO WRITELN(TEXTOUT);
    WRITELN('PRESENT LIMITATION: 1000 WORDS');
    WRITELN;
    WRITELN('WINDOW TO START WITH WORD NR:');
    READLN(F,START);
    WRITELN('WINDOW TO END WITH WORD NR:');
    READLN(F,FIN);
    WRITELN('HOW MANY WORDS BETWEEN INTERVALS?');
    READLN(STEP);
    FOR N:=1 TO FIN+1 DO READWORD(N);
    MOVEONE;
    WRITELN(TEXTOUT,NAME,':');
    WRITELN(TEXTOUT);
    VOC:=0;
    NUMPOINTS:=0;
    FOR N:=START TO FIN DO
    BEGIN
        VOC:=VOC+NEWWORD(N);
        IF N MOD STEP = 0 THEN
        BEGIN
            WRITE(TEXTOUT,'AT WORD NR: ',N);
            IF N < 10 THEN WRITE(TEXTOUT,' ');
            IF N < 100 THEN WRITE(TEXTOUT,' ');
            WRITELN(TEXTOUT,'   VOCABULARY: ',VOC);
            NUMPOINTS:=NUMPOINTS+1;
            POINTS[NUMPOINTS,1]:=N;
            POINTS[NUMPOINTS,2]:=VOC;
        END;
    END;
    WRITELN(TEXTOUT);
    WRITELN(TEXTOUT,'GEOMETRIC REGRESSION ANALYSIS:');
    WRITELN(TEXTOUT);
    GETDATA;
    WRITELN(TEXTOUT,'F(x) = ',EXP(A),' * X TO THE ',B,' POWER');
    COMPREGRESSANALYSIS;
    WRITELN('ANOTHER RUN? (Y/N)');
    READ(F,CH);
    IF CH='Y' THEN
    BEGIN
        CLOSE(TEXTIN);
        GOTO 1;
    END;
END.
```

```
PROGRAM PERMUTATE(TEXTIN,TEXTOUT);
LABEL 1;
CONST
    NOWORDS=620;--MAXIMUM NUMBER OF WORDS IN TEXTSTRING
    MAXLENGTH=20;--MAXIMUM NUMBER OF LETTERS PER WORD
    BLANK=' ';
TYPE
    WORDINDEX=1:NOWORDS;
    LETTERINDEX=1:MAXLENGTH;
    WORDTYPE=PACKED ARRAY[WORDINDEX,LETTERINDEX] OF CHAR;
VAR
    FIXWORD,PERMWORD:WORDTYPE;
    ENDOFSTRING,BEGINPERM,ENDPERM,W,
    NUMBOFPERM,SHRINKSTEP,M,N,RANDNR:INTEGER;
    TEXTIN,TEXTOUT:INTERACTIVE;
    NAME:STRING;
    SEED:LONG_INTEGER;
    CH1:CHAR;


PROCEDURE INITIATE;
BEGIN
    WRITELN('NAME OF INPUT FILE:'); READLN(NAME);
    {$I- I/O OFF}
    RESET(TEXTIN,NAME);
    WHILE IORESULT <> 0 DO
    BEGIN
        WRITELN('FILE NOT FOUND, TRY AGAIN');
        READLN(NAME);
        RESET(TEXTIN,NAME);
    END;
    WRITELN('NAME OF OUTPUT FILE:'); READLN(NAME);
    RESET(TEXTOUT,NAME);
    CLOSE(TEXTOUT,PURGE);
    REWRITE(TEXTOUT,NAME);
    WRITELN('PERMUTATION TO START AT WORD NUMBER:');
    READLN(BEGINPERM);
    WRITELN('PERMUTATION TO FINISH WITH WORD :');
    READLN(ENDPERM);
    NUMBOFPERM:=ENDPERM-BEGINPERM+1;
    WRITELN('SEED:');
    READLN(SEED);
END;


PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
VAR
    N,CHARCOUNT:INTEGER;
    CH:CHAR;
BEGIN

     CHARCOUNT:=1;
1:   WHILE NOT EOF(TEXTIN) DO
     BEGIN
         WHILE NOT EOLN(TEXTIN) DO
         BEGIN
             READ(TEXTIN,CH);
             IF CH=BLANK THEN GOTO 2;
             IF EOLN(TEXTIN) THEN
             BEGIN
                 FIXWORD[L,CHARCOUNT]:=CH;
```

```
                    GOTO 2;
                END;
                IF CH IN ['0':'9','A':'Z'] THEN
                BEGIN
                    FIXWORD[L,CHARCOUNT]:=CH;
                    CHARCOUNT:=CHARCOUNT+1;
                    IF CHARCOUNT>MAXLENGTH THEN
                    BEGIN
                        WHILE CH<>BLANK DO
                        READ(TEXTIN,CH);
                        CHARCOUNT:=1;
                    END;
                    GOTO 1;
                END;
            END;
            READLN(TEXTIN);
        END;
        IF EOF(TEXTIN) THEN
        BEGIN
            CONACT(0);
            WRITE('EOF AT FIXWORD NR:',L);
            HALT;
        END;
2:      IF FIXWORD[L,1]=BLANK THEN
        BEGIN
            CHARCOUNT:=1;
            GOTO 1;
        END;
END;


PROCEDURE MOVEONE;
VAR
    M,N:INTEGER;
BEGIN
    FOR M:=1 TO 4 DO IF FIXWORD[1,M]<>' ' THEN
    WRITE(TEXTOUT,FIXWORD[1,M]); WRITE(TEXTOUT,',');
    WRITE(TEXTOUT,BEGINPERM,'P',ENDPERM,' ');
    FOR N:=2 TO ENDOFSTRING DO
    FIXWORD[N-1]:=FIXWORD[N];
    ENDOFSTRING:=ENDOFSTRING-1;
END;


FUNCTION PRANDOM(VAR SEED:LONG_INTEGER):LONG_INTEGER;

    CONST
        MULTIPLIER=25173;
        INCREMENT=13849;
        MODULUS=65536;
    BEGIN
        PRANDOM:=ABS(SEED);
        SEED:=(MULTIPLIER*SEED+INCREMENT) MOD MODULUS;
    END;


BEGIN--MAINPROGRAM
1:  CONACT(0);
    INITIATE;
    ENDOFSTRING:=ENDPERM+2;
    FOR N:=1 TO ENDOFSTRING DO
    FOR M:=1 TO MAXLENGTH DO
    FIXWORD[N,M]:=BLANK;
```

```
                GOTO 2;
            END;
            IF CH IN ['0':'9','A':'Z'] THEN
            BEGIN
                FIXWORD[L,CHARCOUNT]:=CH;
                CHARCOUNT:=CHARCOUNT+1;
                IF CHARCOUNT>MAXLENGTH THEN
                BEGIN
                    WHILE CH<>BLANK DO
                    READ(TEXTIN,CH);
                    CHARCOUNT:=1;
                END;
                GOTO 1;
            END;
        END;
        READLN(TEXTIN);
    END;
    IF EOF(TEXTIN) THEN
    BEGIN
        CONACT(0);
        WRITE('EOF AT FIXWORD NR:',L);
        HALT;
    END;
2:  IF FIXWORD[L,1]=BLANK THEN
    BEGIN
        CHARCOUNT:=1;
        GOTO 1;
    END;
END;


PROCEDURE MOVEONE;
VAR
    M,N:INTEGER;
BEGIN
    FOR M:=1 TO 4 DO IF FIXWORD[1,M]<>' ' THEN
    WRITE(TEXTOUT,FIXWORD[1,M]); WRITE(TEXTOUT,',');
    WRITE(TEXTOUT,BEGINPERM,'P',ENDPERM,' ');
    FOR N:=2 TO ENDOFSTRING DO
    FIXWORD[N-1]:=FIXWORD[N];
    ENDOFSTRING:=ENDOFSTRING-1;
END;


FUNCTION PRANDOM(VAR SEED:LONG_INTEGER):LONG_INTEGER;

    CONST
        MULTIPLIER=25173;
        INCREMENT=13849;
        MODULUS=65536;
    BEGIN
        PRANDOM:=ABS(SEED);
        SEED:=(MULTIPLIER*SEED+INCREMENT) MOD MODULUS;
    END;


BEGIN--MAINPROGRAM
1:  CONACT(0);
    INITIATE;
    ENDOFSTRING:=ENDPERM+2;
    FOR N:=1 TO ENDOFSTRING DO
    FOR M:=1 TO MAXLENGTH DO
    FIXWORD[N,M]:=BLANK;
```

```
    SHRINKSTEP:=NUMBOFPERM;
    FOR N:=1 TO ENDOFSTRING DO READWORD(N);
    MOVEONE;
    FOR N:=1 TO BEGINPERM-1 DO
    PERMWORD[N]:=FIXWORD[N];
    PERMWORD[ENDPERM+1]:=FIXWORD[ENDPERM+1];
    FOR N:=1 TO NUMBOFPERM DO
    FIXWORD[N]:=FIXWORD[BEGINPERM+N-1];
    FOR N:=1 TO NUMBOFPERM DO
    BEGIN
         RANDNR:=PRANDOM(SEED) MOD SHRINKSTEP+1;
         PERMWORD[BEGINPERM+N-1]:=FIXWORD[RANDNR];
         FOR M:=RANDNR TO SHRINKSTEP+2 DO
         FIXWORD[M]:=FIXWORD[M+1];
         SHRINKSTEP:=SHRINKSTEP-1;
    END;
    W:=0;
    FOR N:=1 TO ENDOFSTRING DO
    BEGIN
         W:=W+1;
         FOR M:=1 TO MAXLENGTH DO IF PERMWORD[N,M] <> BLANK
         THEN WRITE(TEXTOUT,PERMWORD[N,M]);
         IF W<10 THEN WRITE(TEXTOUT,BLANK)
         ELSE IF W>=10 THEN
         BEGIN
              WRITELN(TEXTOUT);
              W:=0;
         END;
    END;
    WRITELN('ANOTHER RUN? (Y/N)');
    READ(CH1);
    IF CH1='Y' THEN
    BEGIN
         CLOSE(TEXTIN);
         CLOSE(TEXTOUT);
         GOTO 1;
    END;
END.
```

```
PROGRAM TESTRUNS(TEXTIN,TEXTOUT);
LABEL 1;
CONST
    MAXWORDLEN=20;
    NUMBOFWORD=1001;
TYPE
    WORDINDEX=1:MAXWORDLEN;
    TEXTINDEX=1:NUMBOFWORD;
    WORDTYPE=PACKED ARRAY[TEXTINDEX,WORDINDEX] OF CHAR;
    TRANSFTYPE=ARRAY[TEXTINDEX] OF INTEGER;
VAR
    WORD:WORDTYPE;
    LABL:PACKED ARRAY[WORDINDEX] OF CHAR;
    INFARRAY:TRANSFTYPE;
    START,FIN,RF,T1,N:INTEGER;
    CH:CHAR;
    NAME:STRING;
    TEXTIN,TEXTOUT:TEXT;
    LETTERS:SET OF CHAR;
    F:INTERACTIVE;
    SECOND:BOOLEAN;


PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
     BLANK=' ';
VAR
     N,CHARCOUNT:INTEGER;
     CH:CHAR;
BEGIN
      FOR N:=1 TO MAXWORDLEN DO WORD[L,N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
           WHILE NOT EOLN(TEXTIN) DO
           BEGIN
                READ(TEXTIN,CH);
                IF CH=BLANK THEN GOTO 2;
                IF EOLN(TEXTIN) THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     GOTO 2;
                END;
                IF CH IN LETTERS THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     CHARCOUNT:=CHARCOUNT+1;
                     IF CHARCOUNT>MAXWORDLEN THEN
                     BEGIN
                          WHILE CH<>BLANK DO
                          READ(TEXTIN,CH);
                          CHARCOUNT:=1;
                     END;
                     GOTO 1;
                END;
           END;
           READLN(TEXTIN);
      END;
      IF EOF(TEXTIN) THEN
      BEGIN
           CONACT(0);
```

```
            WRITE('EOF AT WORD NR:',L);
            HALT;
        END;
2:      IF WORD[L,1]=BLANK THEN
        BEGIN
            CHARCOUNT:=1;
            GOTO 1;
        END;
END;



PROCEDURE MOVEONE;
VAR
     N,M:INTEGER;
BEGIN
     FOR N:=1 TO 20 DO
     LABL[N]:=WORD[1,N];
     FOR N:=2 TO FIN+1 DO
     WORD[N-1]:=WORD[N];
END;



FUNCTION NEWWORD(RE,RFF:INTEGER):INTEGER;
VAR LE:INTEGER;
BEGIN
     NEWWORD:=1;
     FOR LE:=START-RFF TO RE-1 DO
     IF WORD[RE]=WORD[LE] THEN
     BEGIN
          NEWWORD:=0;
          EXIT(NEWWORD);
     END;
END;



PROCEDURE BOOKIN;
BEGIN
     WRITELN('NAME OF INPUT FILE:');
     READLN(NAME);
     {$I- I/O OFF}
     RESET(TEXTIN,NAME);
     WHILE IORESULT<>0 DO
     BEGIN
          WRITELN('FILE NOT FOUND. TRY AGAIN');
          READLN(NAME);
          RESET(TEXTIN,NAME);
     END;
END;



PROCEDURE RUNDETECTOR(STOP1,STOP2:INTEGER);
VAR
     BLOCK:ARRAY[1:40] OF INTEGER;
     SUM,MAX,N,M,RUN:INTEGER;
BEGIN
     FOR N:=1 TO 40 DO BLOCK[N]:=0;
     N:=0; M:=0; MAX:=1;
     REPEAT
```

```
            REPEAT
                RUN:=RUN+1;
                M:=M+1;
            UNTIL (INFARRAY[M+1]=STOP1) OR (M >= TI);

            IF RUN > MAX THEN MAX:=RUN;
            BLOCK[RUN]:=BLOCK[RUN]+1;

             REPEAT
                 M:=M+1;
             UNTIL (INFARRAY[M+1]=STOP2) OR (M >= TI);
        UNTIL M >= TI;
        SUM:=0;
        IF SECOND THEN BLOCK[1]:=BLOCK[1]-1;
        WRITELN(TEXTOUT,'LENGTH    NUMBER');
        WRITELN(TEXTOUT,'OF RUN    OF RUNS');
        FOR M:=1 TO MAX DO
        BEGIN
            WRITE(TEXTOUT,M:3,'      ',BLOCK[M]:3,' ');
            FOR N:=1 TO BLOCK[M] DO IF N<65 THEN WRITE(TEXTOUT,'*');
            WRITELN(TEXTOUT);
            SUM:=SUM+M*BLOCK[M];
        END;
        WRITELN(TEXTOUT,'SUM=',SUM:4);
        SECOND:=TRUE;
    END;



    PROCEDURE BOOKOUT;
    BEGIN
        REWRITE(TEXTOUT,'PRINTER:');
    END;



    BEGIN--MAIN PROGRAM
        CONACT(0);
        RESET(F,'CONSOLE:');
        LETTERS:=['0':'9','A':'Z'];
    1:  SECOND:=FALSE;
        BOOKIN;
        CONACT(0);
        WRITELN(NAME);
        BOOKOUT;
        WRITELN('PRESENT LIMITATION: 1000 WORDS');
        WRITELN;
        WRITE('WINDOW TO START WITH WORD NR: ');
        READLN(F,START);
        WRITE('WINDOW TO END WITH WORD NR: ');
        READLN(F,FIN);
        WRITE('RF: ');
        READLN(F,RF);
        WRITELN(TEXTOUT,NAME);
        WRITELN(TEXTOUT,START,'B',FIN,'RF',RF);
        WRITELN(TEXTOUT);
        FOR N:=1 TO FIN+1 DO READWORD(N);
        MOVEONE;
        TI:=0;
        FOR N:=START TO FIN DO
        BEGIN
            TI:=TI+1;
            INFARRAY[TI]:=NEWWORD(N,RF);
```

```
      END;
      FOR N:=1 TO TI DO
      BEGIN
          WRITE(TEXTOUT,INFARRAY[N]);
          IF N MOD 50 = 0 THEN
          WRITELN(TEXTOUT);
      END;
      WRITELN(TEXTOUT);
      WRITELN(TEXTOUT,'LENGTH OF RUNS OF ONES');
      WRITELN(TEXTOUT);
      RUNDETECTOR(0,1);
      WRITELN(TEXTOUT);WRITELN(TEXTOUT);WRITELN(TEXTOUT);
      WRITELN(TEXTOUT,'LENGTH OF RUNS OF ZEROES');
      WRITELN(TEXTOUT);
      RUNDETECTOR(1,0);
      PAGE(TEXTOUT);
      WRITELN('ANOTHER RUN?');
      READ(F,CH);
      IF CH='Y' THEN
      BEGIN
          CLOSE(TEXTIN);
          GOTO 1;
      END;
  END.
```

CHAPTER 7.

BASIS AND METHOD OF FOURIER ANALYSIS.

In chapter 5 we began our first attempts to analyse structure in text strings, where 'structure' is taken to mean structure in the information theoretical sense as opposed to the concept of structure within the grammar-based structuralism usually associated with structural analysis of text strings.

We established a possible link between the position and gradient of the graphic representation of the vocabulary-decay on the one hand and the sequential structure on the other. Even so, this analysis was still anchored in the 'accumulative' nature of the common concept of vocabulary, ie. all the analysis evaluated structures starting from the first word of the string and accumulated new words and repeated words with no regard for the fact that words have different functions and that this function depends on - and is defined by - the SEQUENTIAL STRUCTURE of the text string and the INTERACTION between the words of the string.

To start with the last feature: the interaction between words. In an analysis of text strings based on the non-cognitive reading by a computer, we have no hope of evaluating this feature since it is semantical and therefore depends on cognitive skill. Regarding the first feature: the sequential structure, we are in a better position. We have already seen that we can analyse this feature. Our first attempt - in chapter 5 - to evaluate sequential structure involved a simple plotting in a double logarithmic system based on the accumulations of new words and repeats in the text string. This evaluation of sequential structure was however very crude and yielded only two values - the position and the gradient of a graph - values which we on the whole were unable to correlate to other parameters.

So, to cater for a more sophisticated approach to the analysis of sequential structures in text strings, let us turn to other fields of pattern and structure analysis and see if we can find such a method which will lend itself to the analysis of text strings. The obvious choise, if we want to analyse sequential structures or patterns, is FOURIER analysis.

Fourier analysis, or spectral analysis, has become one of the most important ways of applying numerical solutions to practical problems in a vide range of fields like optics, electronics, speech processing, image enhancing, engineering, etc. Not that there is anything new about Fourier analysis. This method of numerical analysis was developed by the French mathematician Jean Babtiste Josef Fourier in the beginning of last century, but was considered too complex and impractical to use until a modification, the "Fast Fourier Transform" (abbreviated as FFT) was described by J.M. Cooley and J.W. Tukey in 1965, (Cooley and Tukey, 1965).

To explain how Fourier analysis can be used, I will begin in a field, well known to most: If you look at the groove of one of your grammophone records through a magnifying glass, you will see, that at any point, all the sound is represented by one single groove. This is the case whether the recording is one of a pure sine wave or one of a full symphony orchestra. It is not difficult to understand how a pure sine wave can be represented by a single groove, but how does the human ear hear all of - and indeed distinguish between - the instruments when there is just one single groove. The explanation is of course, that all the sound waves were added together to just one sum wave during the recording and later cutting of the master record. Later - when we listen to this sum wave - our ear and brain - are able to extract the basic wave forms which went into the making of the sum wave. This is how Fourier analysis works. To say that our hearing device does this by means of Fourier transformation is probably to take the analogy a bit too far, since we do not yet understand how our auditory channel is able to do what it does. But the result is the same as that of a Fourier transformation: the sum wave is dissolved into the single basic frequencies.

I shall now describe in greater detail the basis of Fourier transformation. When I have done that, I will introduce you to some applications of the Fourier transformation, and although the connection between these examples and our attempt to analyse text strings may not seem immediately obvious, their relevance will become apparent as our analysis comes along.

In Fourier analysis we talk about two 'domains', a time domain and a frequency domain, and the Fourier analysis is said to move the function which is analysed from the time domain to the frequency domain. This may initially sound difficult, but is really very easy to understand.

Generally, the move from a time domain to a frequency domain involves no more math than any of us would have had in primary school, so I can easily explain the basic principles.

Think about the meaning of the word "frequency". This means a number of events taking place in the space of a given unit. When we talk about sound waves, this unit is a time unit - normally a second - and the events taking place are wave tops. Say we have an event taking place 1 time every 4 seconds. this would be the time domain. If we want to express the frequency of this line of events we would of course get a frequency of events equal to 1/4 per second ie a frequency of 0.25. This would be the frequency domain. Another event taking place 1 time every 10 seconds (time domain) gives a frequency of 0.1 per second (frequency domain). Fourier transformation gives us a means of expressing a - sometimes - complex function in a more intelligible way.

These were simple cases of transformation from a time domain to a frequency domain. Fig 7.1 expresses the first example in graphic form. The graph to the left represents the time domain with a wave which peaks once every 4 seconds. The graph to the right is the Fourier transform of the graph to the left and is said to be in the frequency domain. As the graph to the left peaks once every 4 seconds, the transform in the frequency domain gives a peak on f = 0.25.

Let us now imagine, that the lines of events taking place above were lights flashing rather than the top of a wave, and we would have a light flashing once every 4 seconds, and another light once every 10 seconds. It would not be difficult to establish each of the frequencies by timing each light in turn. But if we connected the two lights so that they were both flashing when only one of them should have flashed, we could not easily establish how many - and which - different freqencies were involved. However, if we timed the now irregular flashing and used Fourier analysis to transform the series of timings into the frequency domain, the Fourier transform would give us a peak over f = 0.1 and a peak over f = 0.25. The real power of the Fourier analysis is its ability to dissolve a complex waveform into all its basic components, and to show how much of each component contributed to the waveform. In the frequency domain, the height of the peaks will show proportionately how much each basic waveform contributed to the final waveform. This is why the vertical

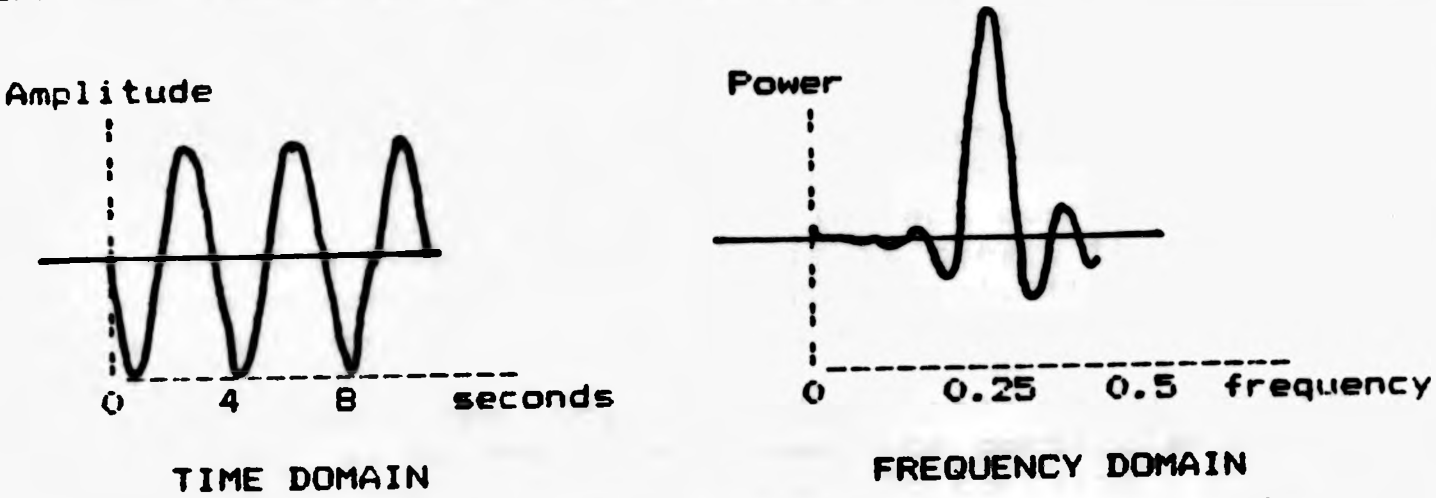

Figure 7.1 Transformation from time domain to frequency domain of a wave form.

axis in the frequency domain is labelled "power". This graph is called a power spectrum of the waveform in the time domain, and the analysis carried out in this way would be a power spectral analysis.

The more peaks a component has in the time domain, the higher will the peak be in the frequency domain after the transformation. This means, that everything else equal, the higher number of events in the time domain will result in a peak with a higher power in the frequency domain.

While Figure 7.1 shows that the transform of a simple wave form is a single pulse, the next transformation (Figure 7.2) shows

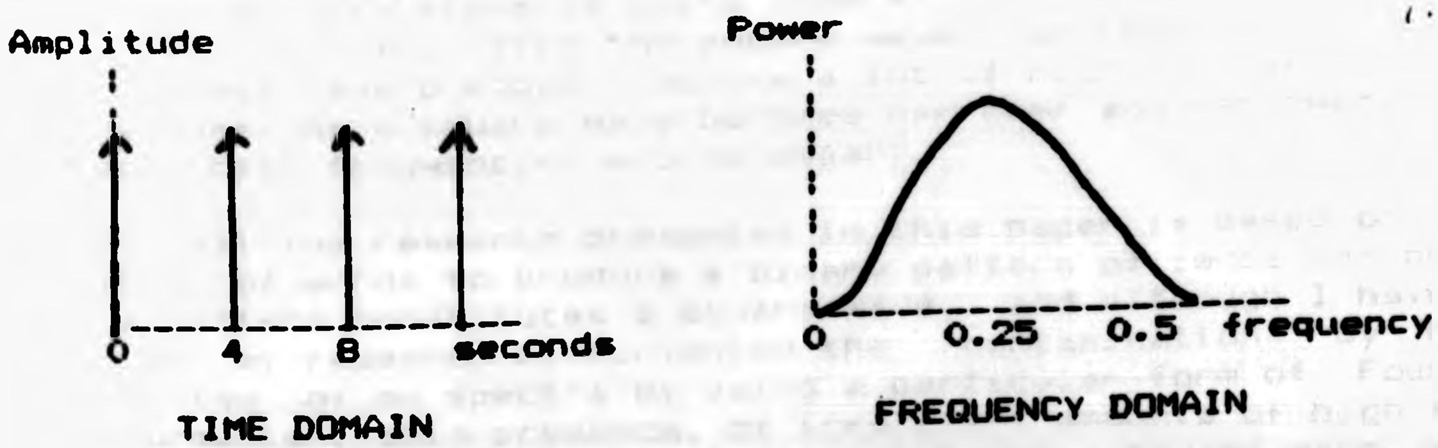

Figure 7.2 Transformation from time domain to frequency domain of a train of pulses.

that the transform of a train of pulses with the same length as in Figure 7.2 is a wave whith a peak at the same frequency as in Figure 7.1.

Fourier transformation goes both ways between the time domain and the frequency domain. If we had applied Fourier transformation to the spectrum to the right in fig 7.1 and 7.2 the resulting waveform would have been the ones to the left in fig 7.1 and 7.2.

Fig 7.3 on the following page shows four pairs of graphs. In each pair, the graph to the left represents a function of time. The graph to the right shows the Fourier transform of the graph to the left and is in the frequency domain. The graph to the right show the amount of the different frequency components needed to make the graph to the left.

Whithout going into unnecessarily great detail, let us see what we can learn from the transform pairs in fig 7.3. Let us examine each pair of graphs in turn.

Figure 7.3 (a). The transform of a constant (a,left) gives a zero-frequency value equal to this constant (a,right). The zero-frequency is said to give the DC (direct current) level of the transform, and from this example it is clear, that if the signal in the time domain is biased by a DC signal, this will show up in the frequency domain as a zero-frequency value equal to the bias.

Figure 7.3 (b). The transform (b,right) of a square pulse (b,left) is, as we shall later see, of particular relevance to the research presented in this paper. It contains a number of low frequencies (to build up the area under the pulse and create the flat topped sections which obviously change little with time), but in addition, there is a fair amount of high frequencies. These reflect the need for "small building blocks" - or a higher resolution - to make the sudden change at the corners of the square pulse.

A triangular pulse (c,left) of the same area has similar requirements for low frequencies (c,right), but needs a lesser amount of high frequencies than (b,right) because the shape of the triangle wave changes less suddenly than the shape of the square wave.

A Gaussian (bell-shaped) curve (d,left) requires very little high frequencies (d,right) to build up its smooth function of time.

The correlation between sudden changes and high frequencies in the Fourier transform is quite general. Functions that change abruptly with time, like the square wave, or that have a lot of fine detail (sharp edges) require a lot of high frequencies to define them. As a square wave becomes narrower and narrower, more and more high freqwencies are necessary.

Nearly all the research presented in this paper is based on the labeling of words to produce a binary pattern of zeros and ones. Such a pattern constitutes a square wave, and although I have in most of my research circumvented the "contamination" by high frequencies of my spectra by using a particular form of Fourier transformation, this presence, of irrelevant amounts of high frequencies solely due to the basic signal being a square wave, will become apparent in the latter part of my research, where I have had to change the Fourier transform.

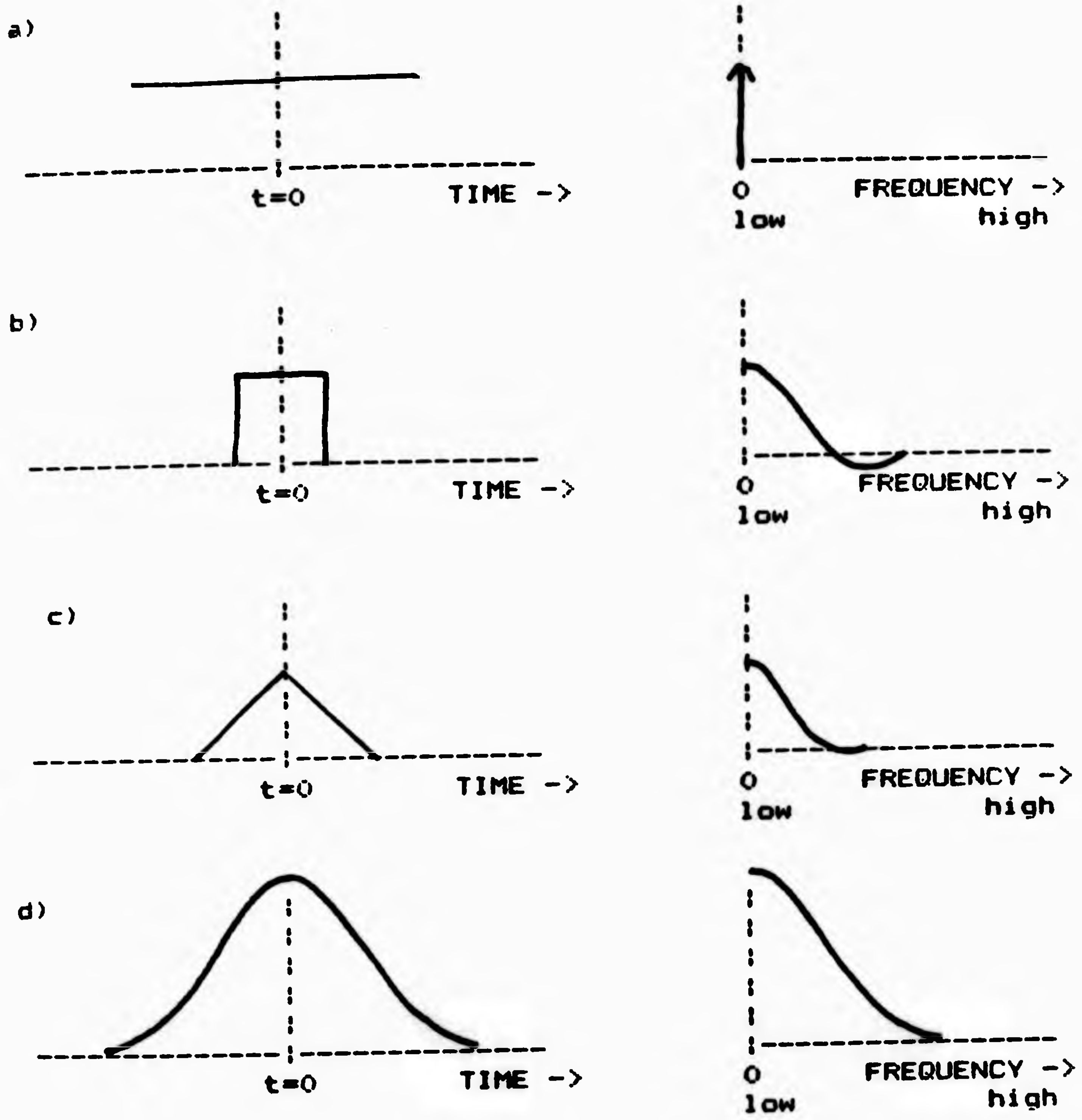

Figure 7.3 Some functions and their Fourier transform.

The general Fourier transform of a continuous function is given by

$$A(f) = \int_{-\infty}^{\infty} a(t)e^{2\pi i f t}\, dt \qquad (7.4)$$

The "i" in equation (7.4) stands for the square root of -1. The constant "e" is the base of the natural logarithm. The variable "t" is often regarded as time while the variable "f" is taken to mean frequency, and then the Fourier transform is interpreted as taking a function of time into a function of frequency as explained above.

This equation can only be applied to continuous functions, but it can be shown, that provided the sample points of a discrete function are equally spaced (equidistant), the corresponding equation

$$A(j) = \sum_{k=0}^{k \leq N-1} a_k e^{2\pi i jk/N} \qquad 0 \leq j \leq N-1 \tag{7.5}$$

can be used, and since our data base consists of words, this is the equation which is of special interest to us. In this equation, "N" is the total number of samples and "k" is the number of each individual sample point. The Fourier transform of a discrete function is closely related to that of a continuous function, two obvious differences being, that (7.5) is a sum instead of an area and that "t" (time) in (7.4) is replaced by k/N (number of individual sample divided by total number of samples) in (7.5). The condition stated above, that the sample points must be equally spaced, is important and I shall return to this later.

There are many ways to express the basic Fourier transform of a discrete function. As I would like to demonstrate two important aspects of Fourier transformation more fully, we shall express the same relationship in polar form. This would ease the handling of the complex numbers involved in the basic Fourier transform, since in polar form, complex numbers can be expressed in terms of sin and cos. I shall not attempt to develop this step by step however, since it would be unnecessary and beyond the scope of this paper, only state, that the Fourier transform of a discrete function F(x) with a period of L and consisting of 2N sample points can be written as the following series

$$F(x) = \frac{A_0}{2} + \sum_{k=1}^{N-1}\left[A_k \cos\left(\frac{2k\pi x}{L}\right) + B_k \sin\left(\frac{2k\pi x}{L}\right)\right] + \frac{A_N}{2}\cos\left(\frac{2N\pi x}{L}\right) \tag{7.6}$$

where

$$A_k = \frac{1}{N}\sum_{n=0}^{2N-1} F(x)\cos\left(\frac{2k\pi X_n}{L}\right) \quad (k=0,1,2,\ldots,N) \tag{7,7}$$

and

$$B_k = \frac{1}{N}\sum_{n=0}^{2N-1} F(x_n)\sin\left(\frac{2k\pi X_n}{L}\right) \quad (k=0,1,2,\ldots,N-1) \tag{7.8}$$

Note, that the number of sampled points in the initial function F(x) were 2N. This is important since it is apparent from (7.6) that the resulting series gives only half that number of points namely N (Sigma "runs" only from k=1 to k=N-1). Thus, if our initial discrete function had 10 sample points, then the resulting power spectrum will have only 5 lines (frequency components). This is a result of the sampling which takes place when we want to Fourier transform a discrete function, and in a physical way we can look at it as if our resulting power spectrum has been folded around the middle of the spectrum i.e. around the sampling frequency divided by two.

At the moment I shall go no further into the intricacies behind the theory of Fourier analysis, only remind you, that we have touched on three important points regarding power spectral analysis: 1) That the sample points of a discrete function must be equallly spaced (equidistant) before we can apply the Fourier transform. 2) That the powerspectrum of a discrete function is folded around a frequency equal to half of the sampling frequency and finally, 3) that because the spectrum is folded, high-frequency components are added to the components in the low-frequency end of the spectrum.

A point wich I should mention before we begin to Fourier analyse text strings in earnest is the fact, that the way we are plotting words along the x-axis, our time domain is not one of pure time. The unit in our time domain is one of words; a word unit.

The use of words as a parameter, instead of real time, is perfectly legitimate and is not at all as confusing as it may seem. Let us look at the transformation between the two domains the way we did it before: the TIME domain and the FREQUENCY domain. If we get a peak at 0.25 in the frequency domain, it is still a transformation of an event taking place every 4 units in the time domain, but the units are no longer seconds, but words. This means, that a peak in the frequency domain at 0.25, reflects a pulse repetition every 4 words instead of every 4 seconds in the time domain. The way we have plotted the y-axis in the time domain ("new words") means, that each pulse constitutes a word which is new to the particular text string being analysed. Thus, a peak in the frequency domain at 0.25 in our interpretation, means a higher than incidental arrival of new words for every 4 words being read, or repeated combinations (patterns) of new and repeated words adding up to segments which are 4 words long.

As an intrinsic part of the development of INFOR, I wrote some simple "text strings" which I knew would give well known and well defined Fourier transforms (Figure 7.11 to 7.14). These strings did not contain words, but numbers because it is easier to construct strings of numbers when you have to keep a check on new 'words' and repeats. This does not interfere with our task, since to INFOR a 'word' is a number of characters (letters or digits) in between two separators (spaces, commaes, line shift) and if two 'words' differ in their content of letters or digits they are considered different. INFOR has of course no notion of the semantical or syntactical content of the units it analyses. So, to test and improve INFOR, these strings of periodically recurring numbers were put together. The strings were of the form

1 2 1 2 3 4 3 4 5 6 5 6 7 8 7 8 9 10 9 10 11 12 11 12 (7.9)

When INFOR reads (7.10) the resulting information array will (in this particular case) look like this

IA[1:24]:=110011001100110011001100; (7.10)

because INFOR compares each information unit (the numbers in 7.10) and checks whether they are repeats or not: at the first "1" and "2" in (7.10) INFOR will register two new words; when "1" and "2" are repeated, INFOR will register two repeats, and so on

LAMBDA-2 1 1 2 2 3 3 4 4 5 5 6 6 7 7 8 8 9 9 10 10 11 11 12 12 13
13 14 14 15 15 16 16 17 17 18 18 19 19 20 20 21 21 22 22 23 23 24
24 25 25 26 26 27 27 28 28 29 29 30 30 31 31 32 32 33 33 34 34 35
35 36 36 37 37 38 38 39 39 40 40 41 41 42 42 43 43 44 44 45 45 46
46 47 47 48 48 49 49 50 50 51 51 52 52 53 53 54 54 55 55 56 56 57
57 58 58 59 59 60 60 61 61 62 62 63 63 64 64 65 65 66 66 67 67 68
68 69 69 70 70 71 71 72 72 73 73 74 74 75 75 76 76 77 77 78 78 79
79 80 80 81 81 82 82 83 83 84 84 85 85 86 86 87 87 88 88 89 89 90
90 91 91 92 92 93 93 94 94 95 95 96 96 97 97 98 98 99 99 100 100
101 101 102 102 103 103 104 104 105 105 106 106 107 107 108 108

Figure 7.11 (a). Artificial text string which generates an information array with a wavelength lambda = 2.

for each pair of numbers. The result is as can be seen in (7.11) a square wave with a wavelength lambda = 4 ('two up, two down') and 6 full oscillations. Such an oscillation with a wavelength of 4 should, as we have already seen, give a peak at 0.25 in the

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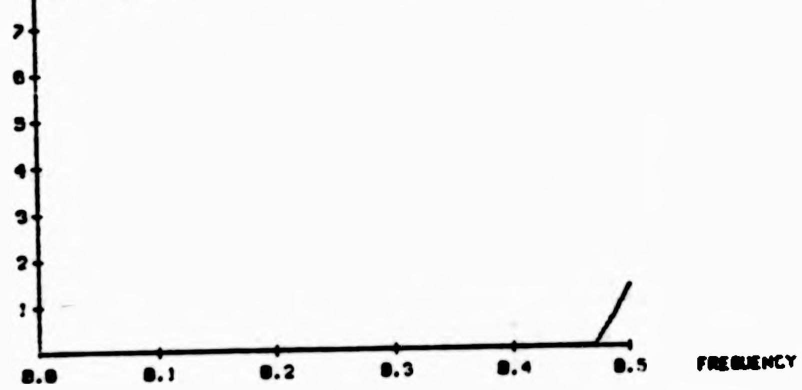

Figure 7.11 (b). Power spectrum of text string in fig 7.11 (a).

LAMBDA-4 1 2 1 2 3 4 3 4 5 6 5 6 7 8 7 8 9 10 9 10 11 12 11 12 13
14 13 14 15 16 15 16 17 18 17 18 19 20 19 20 21 22 21 22 23 24 23
24 25 26 25 26 27 28 27 28 29 30 29 30 31 32 31 32 33 34 33 34 35
36 35 36 37 38 37 38 39 40 39 40 41 42 41 42 43 44 43 44 45 46 45
46 47 48 47 48 49 50 49 50 51 52 51 52 53 54 53 54 55 56 55 56 57
58 57 58 59 60 59 60 61 62 61 62 63 64 63 64 65 66 65 66 67 68 67
68 69 70 69 70 71 72 71 72 73 74 73 74 75 76 75 76 77 78 77 78 79
80 79 80 81 82 81 82 83 84 83 84 85 86 85 86 87 88 87 88 89 90 89
90 91 92 91 92 93 94 93 94 95 96 95 96 97 98 97 98 99 100 99 100
101 102 101 102 103 104 103 104 105 106 105 106 107 108 107 108

Figure 7.12 (a). Artificial text string which generates an information array with a wavelength lambda = 4.

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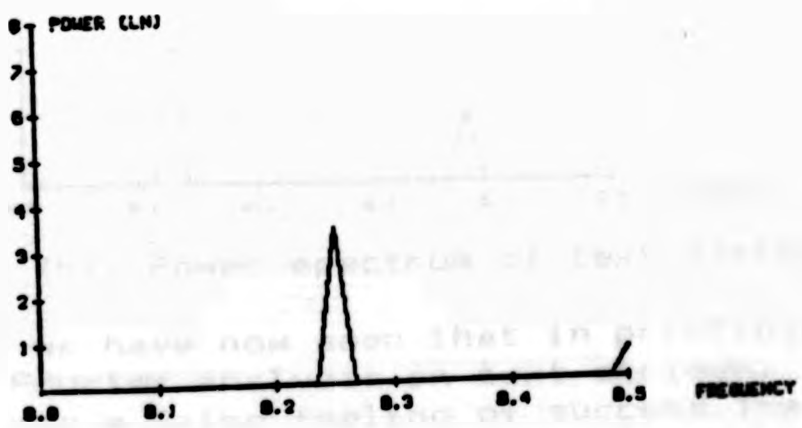

Figure 7.12 (b). Power spectrum of text string in fig 7.12 (a).

frequency domain. Figure 7.12(a) is such a text string which should generate a wavelength of 4, and as the power spectrum figure 7.12(b) shows, this is indeed the case. Figures 7.11(a), 7.12(a), 7.13(a) and 7.14(a) are strings which generate wave-lengths of 2, 4, 8, and 16 respectively and the power spectra give peaks at f=0.5 (7.11b), f=0.25 (7.12b), f=0.125 (7.13b) and f=0.0625 (7.14b) as expected.

The peak to the left in the spectra with periods 4, 8 and 16 are the main peaks; the peaks which indicate the main frequency in the time domain. The smaller peaks to the right of the main peak - in the higher frequency part of the spectrum - only indicate, that a certain amount of these frequencies was necessary to build up the particular shape of our function represented by the 1's and the 0's in the information array as explained in chapter 5. These secondary peaks only show up when the periodicity is highly regular, symmetrical and sharp-edged as the case is with our synthetically generated square waves as explained in the beginning of this chapter. In practice they are not going to interfere with our analysis of natural strings, so we will let them rest with this brief explanation.

LAMBDA-8 1 2 3 4 1 2 3 4 5 6 7 8 5 6 7 8 9 10 11 12 9 10 11 12 13
14 15 16 13 14 15 16 17 18 19 20 17 18 19 20 21 22 23 24 21 22 23
24 25 26 27 28 25 26 27 28 29 30 31 32 29 30 31 32 33 34 35 36 33
34 35 36 37 38 39 40 37 38 39 40 41 42 43 44 41 42 43 44 45 46 47
48 45 46 47 48 49 50 51 52 49 50 51 52 53 54 55 56 53 54 55 56 57
58 59 60 57 58 59 60 61 62 63 64 61 62 63 64 65 66 67 68 65 66 67
68 69 70 71 72 69 70 71 72 73 74 75 76 73 74 75 76 77 78 79 80 77
78 79 80 81 82 83 84 81 82 83 84 85 86 87 88 85 86 87 88 89 90 91
92 89 90 91 92 93 94 95 96 93 94 95 96 97 98 99 100 97 98 99 100
101 102 103 104 101 102 103 104 105 106 107 108 105 106 107 108

Figure 7.13 (a). Artificial text string which generates an information array with a wavelength lambda = 8.

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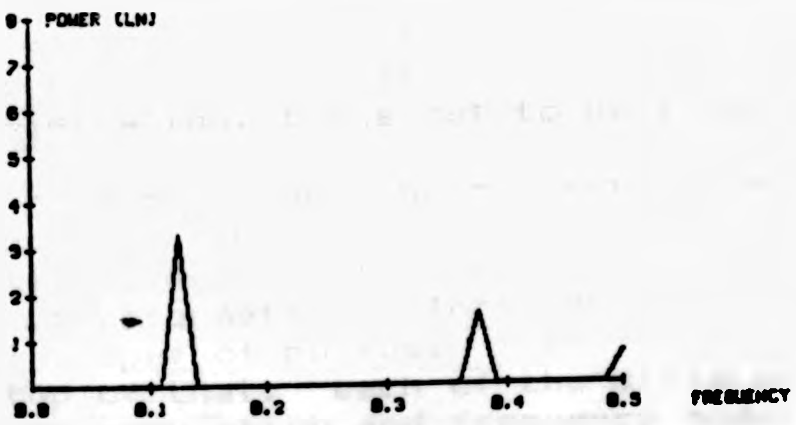

Figure 7.13 (b). Power spectrum of text string in fig 7.13 (a).

Even though we have now seen that in principle it is possible to carry out Fourier analysis on text strings, let us not however, get lured into a false feeling of success.The analysis of synthetic and well defined strings is one thing, the analysis of natural strings quite another. The production of text strings by our linguistic device is not a steady so-and-so-many-words-pr-time-unit kind of affair. The speed with which we create text strings vary considerably. Sometimes the speed itself is part of the information and expresses emotions like intimacy, anxiety or enthusiasm and we talk slowly or fast according to what we want to convey. This is a problem we have not solved, merely worked our way around by letting INFOR use words as the time unit. Our frequency parameter in the power spectra calculated by INFOR is

LAMBDA-16 1 2 3 4 5 6 7 8 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111

Figure 7.14 (a). Artificial text string which generates an information array with a wavelength lambda = 16.

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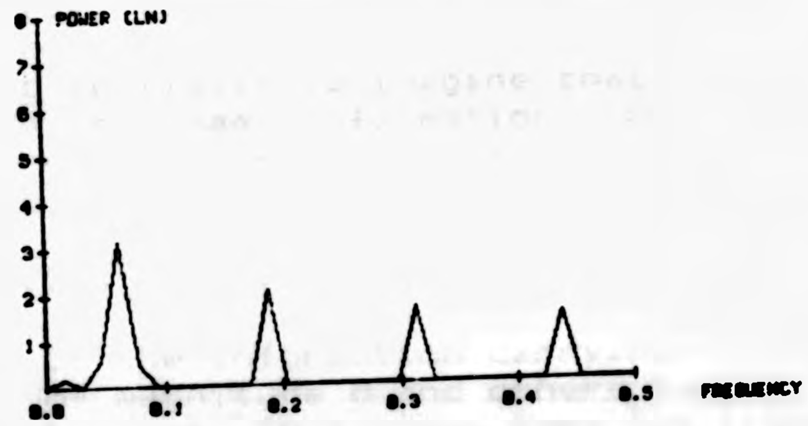

Figure 7.14 (b). Power spectrum of text string in fig 7.14 (a).

therefore not one of real time, but one of word units, but we shall later see, how this feature, which superficially looks like a serious limitation, turns out to be a 'blessing in disguise'.

The way I have described the concept of Fourier transformation, it may appear, that there is only one kind of Fourier transformation. As a matter of fact, there are almost as many different tranformation formulas as there are different geometrical shapes of pulses, i.e. triangular, sawtooth, square etc. On top of that, each of the different kinds of modulation, i.e.amplitude modulation and frequency modulation has got its own set of formulas. It is very much a question of defining what one wants to achieve, and then - somtimes by trial and error - finding the right kind of transform i.e. the transform ahich gives consistent results. But whatever transform is used, the principle of all Fourier analysis is still basically that of 'dissolving' complex wave forms or structures into simple wave forms or structures.

The research presented in this thesis too has had to alternate between different types of transform, one being the Fast Fourier Transform (FFT) and the other being a transform developed particularly for the analysis of time series or event-analysis.

It is important to understand the basic difference between a time series transform and the Fast Fourier Transform. The first transform - the time series transform - can only transform a series of timings i.e. times lapsed between successive events, or distances between events e.g. distances between successive peaks or between the 'ones' of our information array:

IA[1:20] = 1,0,0,1,0,0,0,0,0,1,0,1,0,0,0,0,1,0,0,1

I shall expand more fully on this when I explain the computer programs in chapter 9. Let us just now for the sake of explaining the nature of a time series say, that the information array could be translated into the time series

IT[1:5] = 2,5,1,4,2

by counting the spaces between the 1's in IA. This transform does not take account of the shape of the pulse (square, triangular, sinusoidal etc.) and depends on the pulses of events being very narrow. Since the timeseries transform does not recognise shape - particularly not hight - THE TIME SERIES TRANSFORM DOES NOT TAKE ACCOUNT OF THE AMPLITUDE OF THE SIGNAL.

This inability to provide for a multitude of signal levels is going to become a problem, because - as we shall see in chapter 8 - it is not realistic to imagine that all the words in a text string carry the same information. Our common sense tells us, that some words carry more information than others, so a realistic information array may look like this:

IA[1:20] = 1,0,0,8,0,0,0,0,0,1,0,1,0,0,0,0,8,0,0,1

where some of the information carrying words have transferred information of magnitude 8 and others have transferred information of 1 or nothing. This array does not translate directly into a time series, so to transform this signal with its three signal levels 0,1 and 8 we would use the Fast Fourier Transform instead.

In the Fast Fourier Transform, the amplitude of the signal as well as the shape of its pulses have become part of the analysis and have an impact on the power spectrum. This is important - often essential - in some kinds of analysis, but does on the other hand have its disadvantages: One is, that if the signal is made up of square pulses, as the case is in our application of the transforms, we will get some peaks in the high fequency part of the spectrum, which are not part of the structure of the text string, but rather the high frequencies which go to make up the sharp corners of the square pulses as explained in the beginning of this chapter (figure 7.3 b). Although this high frequency power is genuine in the sense that it is a part of the 'squareness' of the pulses, it is not part of the text string structures themselves, but an arte fact arising from our use of square pulses to carry the information from the text string structures into the FFT.

In cases where this high frequency power is going to 'mask' important high frequency peaks, one would instead try to use the time series transform to reduce the 'noise' in the high frequency part of the spectrum, but in the cases where the amplitude of the signal MUST be taken into account, one would have to use the Fast Fourier Transform and accept the 'disfiguration' or 'noise' in the high frequency part of the power spectrum.

We are primarily going to use the FFT for the analysis of analog signals - signals with more than two signal levels. If the signals we wanted to analyse had only two signal levels like the 1's and 0's of our information arrays, the FFT would still be perfectly usable since, if a transform is sensitive to a continuum of amplitudes or signal levels, it does not matter whether these levels are 1 and 0 - or 2 and five - or whatever, so in that sense the FFT is 'binary' just as much as it is 'analog'. But if FFT caters for 'binary' signals as well as for 'analog' signals, what is the point of having two Fourier transforms - the timeseries and the FFT - instead of just the one, the FFT.

There are a couple of reasons why I have used both transforms. The first one is the necessity - in an experimental set-up like the present - to use at least two different methods so as to compare the spectra resulting from the different transforms. The two transforms used on the same text string should give more or less identical spectra. Figure 12.1 in chapter 12 shows, that this is indeed the case.

The second reason has to do with the demands which the FFT tends to impose on the experiment. The minimum number of frequency points necessary to give a good power spectrum is 32 points. But if we want a spectrum of 32 frequency points, then we need to 'feed' the Fast Fourier Transform with 64 observations since the FFT only yields half as many frequency points as we have observations, whereas with the time series transform we get the same number of frequency points in the power spectrum as we have observations in the time domain. This means, that with the same number of observations, the FFT will give only half the resolution in the power spectrum of that of the timeseries. The FFT spectrum is thus coarser than the spectrum from the timeseries transform, for the same number of observations. Other restrictions imposed on us by the FFT and by the perception model suggested in chapter 8 bring the minimum length of text string up to around 120 words, which is far too great a demand for many of the text strings written by children.

For this reason, the time series transform has been the main tool in my analysis of text strings. Only when the need to analyse amplitudes of the signal arises, will the FFT be called upon.

Two applications of Fourier analysis to 'black box' systems.

I shall now demonstrate a couple of applications of the Fourier transformation to 'enclosed' systems, one of which is a mechanical one, the other a physiological one. Superficially these examples may not have much to do with power spectral analysis of continuous text strings. However, they demonstrate the important application of Fourier analysis to the output information from 'black box' systems; systems which are not directly accessible, or which would alter significantly if accessed. Furthermore, the examples will give you a 'feel' of what Fourier analysis is.

The first example (fig.7.16) from a technical journal (Randall,1980) shows how Fourier analysis is used to distinguish between a worn and a not so worn gear box by picking up, amongst a multitude of different noises, the repetitive sound pattern of one rotating part (worn 1st gear cog-wheel). The graphs to the left are the power spectra resulting from a Fourier transformation of the sound waves emitted from the gear box. On the top graph (left) there is a clear peak at around 30 hz and a number of smaller peaks in fast succession along the entire spectrum emanating from the second biggest peak at around 10 hz. This is the power spectrum and we are now on the frequency domain.

If we only wanted to know which cog-wheel(s) in the gear box were about to break up, we could deduct this information from the power spectrum, and we could terminate our analysis here.

However, we could go a bit further and transform the power spectrum back to where we came from, back to the initial time domain. As you may remember from my initial explanation of the Fourier transformation, it works both ways. So if we apply the Fourier transform to the power spectrum (7.16,left) we will move back to the time domain and our power spectrum turns back into a frequency spectrum. This would give the graphs to the right. The time domain is here called 'quefrency' domain (the unit is seconds) to indicate that it is not the initial time domain, but is derived from a frequency domain by means of a second Fourier transformation. What we have achieved by transforming ourselves back to where we came from, by the means of two Fourier transformations, is basically that we have produced an enhanced picture of the sound waves initially emitted by the gear box. We have, so to speak, produced a less 'noisy' picture of the initial sound spectrum, a noise level which allows us to distinguish features particularly associated with the wear of a gear box.

This demonstrates another and very important use of Fourier transformation. Since structural features in any signal transform into peaks, while 'noise' - in the information theoretical sense - transforms into a low level current normally lying just over the base line throughout the spectrum, it is easy, after the signal has been moved to the frequency domain by the means of Fourier transformation, to extract the noise by simply subtract this low level current in the frequency domain. This is not going to affect the structural information which is contained in the peaks only. In this way, any information masked by noise, may be

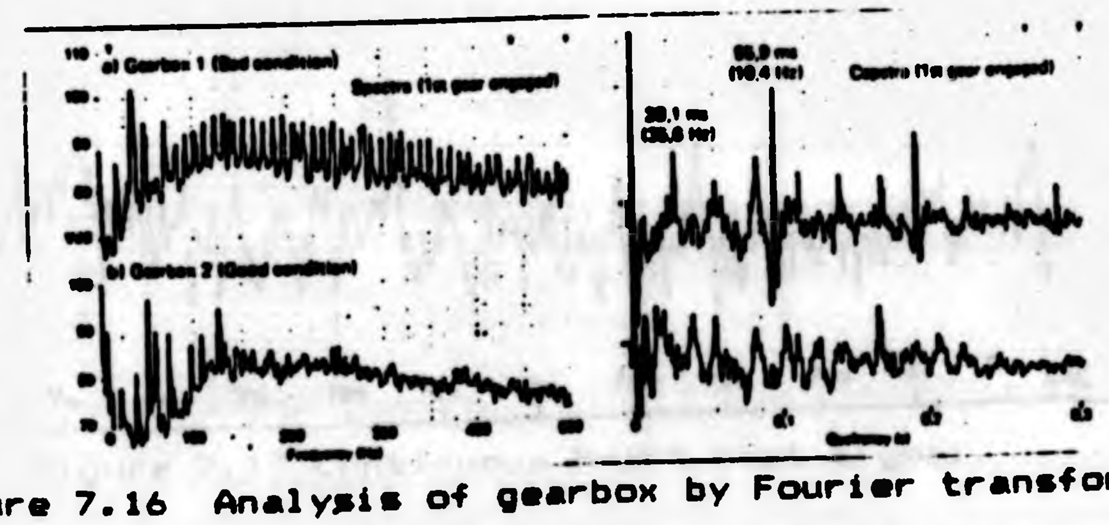

Figure 7.16 Analysis of gearbox by Fourier transformation.

Fourier transformed, the noise subtracted, and the peaks transformed back again. This is the technique behind image enhancing of photographs taken by (spy) satellites.

Although we are concerned with the application of Fourier analysis to "soft machines" rather than to gearboxes, the above example still demonstrates the ability of Fourier analysis to analyse what is inside a "black box" by means of the patterns - sound or otherwise - emitted by the box.

This first example demonstrated the analysis of a mechanical "black box". But if we want to analyse a "black box" then it does not matter whether the box is mechanical or part of a "soft machine" as the human apparition has been termed. If the system we want to analyse emits a signal and if the emitted signal can be put on a form suitable for Fourier analysis, then the origin of the signal is of little importance. The Fourier analysis will dissolve the signal into a number of periodic sub-signals each reflecting the presence of a number of (mechanical) sub-components. But a number of physiological (e.g. neurological) processes emit periodic signals and can therefore be analysed in exactly the same way as the gearbox above. Of course, any signal components present will reflect biological components rather than mechanical components, but apart from this, the method is no different from the one applied above.

Fourier analysis was applied to neurological signals shortly after the first description of the Fast Fourier Transform in 1965. A more recent application of Fourier analysis to a physiological process has been that of power spectral analysis of heart beat signals, developed at the University of Groningen in Holland over the past five years (Mulder,1979). As this research clearly demonstrates the potential of Fourier analysis in establishing the presence of biological sub-control systems, and as this is esentially what I am trying to do in my search for structures in the linguistic signal emitted by humans, my next example shall be Mulder's application of Fourier analysis to the heartbeat signal.

A continuous heart beat signal (Figure 7.17) is obtained with a pressure sensor of some kind. This signal, which is in the time domain, is passed through a digital filter, which smoothes it and converts it into an equidistant time series (Figure 7.18, next page).

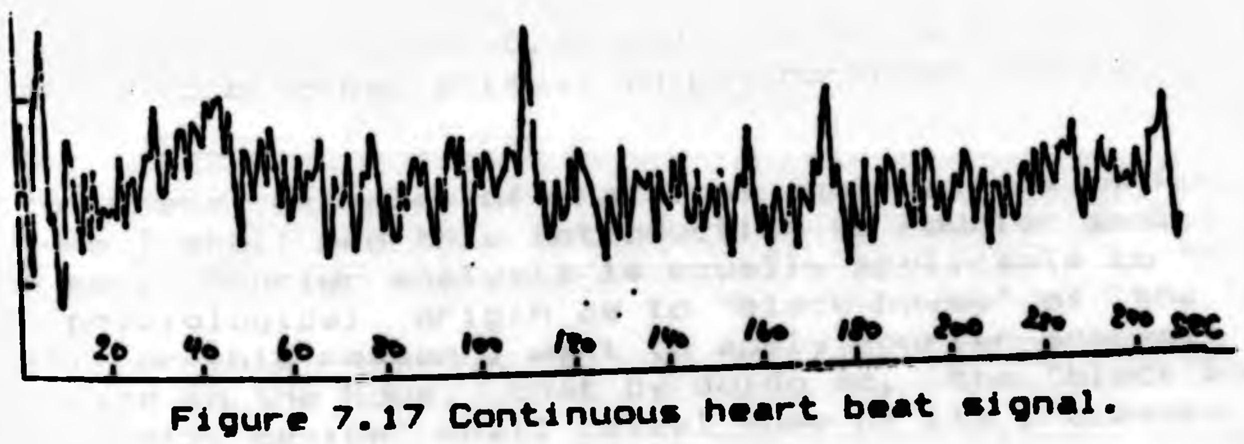

Figure 7.17 Continuous heart beat signal.

After Fourier transformation of the signal in figure 7.18 we get the power spectrum in figure 7.19. In this power spectrum a number of frequency components can be distinguished. It is believed, that each of these reflect a subsystem, a biological control system.

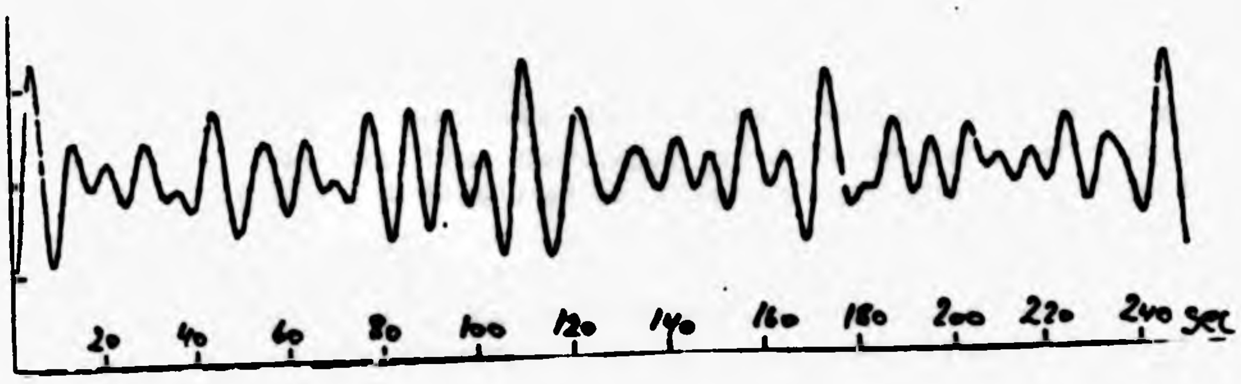

Figure 7.18 Heart beat signal after filtering.

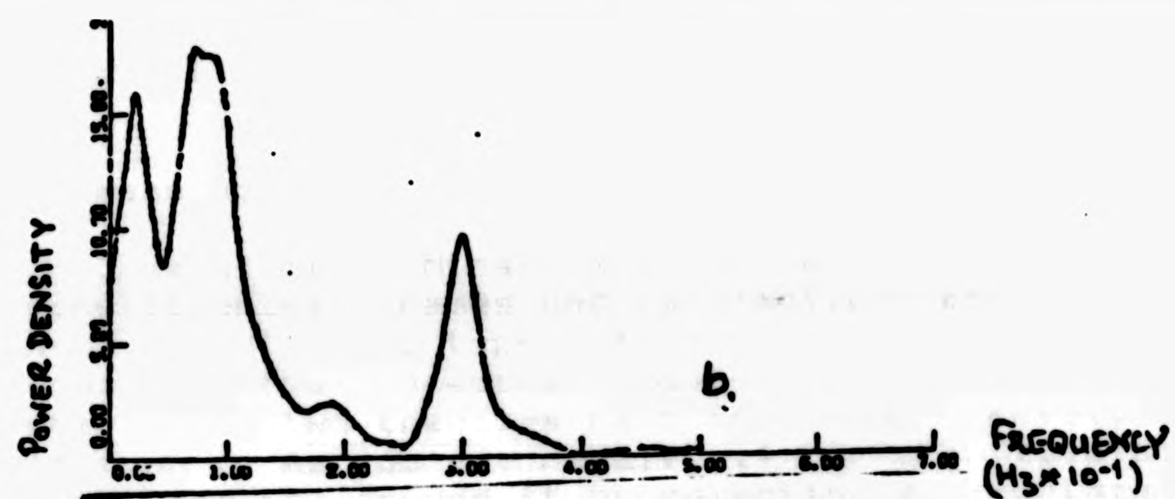

Figure 7.19 Heart beat signal after Fourier transformation.

1) The component around 0.03 Hz is thought to be related to the body temperature control system.

2) The component around 0.10 Hz is caused by oscillations in the blood pressure control system.

3) A component between 0.25 and 0.40 Hz reflecting breathing activity.

4) A component between 0.40 and 0.50 Hz is thought to reflect reactions to external stimuli in psycho-motor tasks.

With these examples of practical applications of Fourier techniques I shall end this introduction to Fourier analysis. As you can see, Fourier analysis is equally applicable to "black boxes" of physiological origin as to 'black boxes' of the mechanical sort. For this reason I want to apply Fourier analysis to natural language in the hope, that by doing so, the 'black box' of our 'linguistic device' shall reveal some of its processes.

CHAPTER 8.

MEANING AND THE PROCESSING OF TEXT STRINGS.

The research presented in this thesis has up to this point been based on different varieties of the commonly accepted concept of vocabulary. Although we have rectified some of the most blatant misapprehensions about the concept of vocabulary and have established the nature of the relationship between vocabulary and length of text string, the analysis up to this point has been based on an entirely statistical - albeit a dynamic rather than a static - evaluation. The time has now come to examine, in some detail, the cognitive processing of text strings. I write 'examine' as if this process was readily accessible, which of course it is not. However, I shall at least be adding my bit of speculation to the already existing corpus which suggests one or two features of cognitive text string processing which it may be possible to model in computer software.

Theories of meaning.

In chapter 3 we examined Minsky's theory of frames and compared its main constituents: frames and information-retrieval network, with Johnson-Laird's two types of mental models: the physical /perceptional and the conceptual models, and we looked at one feature which the two theories have in common, namely that of 'frame selection'. As you may recall, if our cognitive apparatus perceives the reality around it by selecting appropriate frames out of a number of possible frames, the information theory states that every time one frame is selected, entropy is being transformed into information, or put more simply: information is being transferred.

When it comes to our own personal experience of cognitive processing of text strings, as when we read or listen, the most important aspect is whether the text string 'makes sense' or not. There may be several reasons why a text string may not make sense, one of which may be that we are not able to relate it to the real, or at least a possible, world. We refer to this relationship as 'meaning'. We may ask what the meaning is of such and such a word, expression or act, and we would expect the response to be an introduction to the real, or a possible, world. One could of course contend with Wittgenstein that there is no such thing as meaning, but this is probably at odds with most peoples subjective experience of their own cognitive processing of text strings - written or spoken - in so far as this process is accessible by introspection.

It is thus prudent that we in the following should concern ourselves with the various uses and theories of 'meaning' and single out the particular sense in which the term 'meaning' is used in the theoretical basis of the research in this thesis. Later we shall examine in more detail how Minsky sees his theory of frames applied to the cognitive processing of text strings, and we shall

try to establish if there is room for a concept of 'meaning' in the application of the theory of frames to the cognitive processing of text strings.
John Lyons (J. Lyons, 1983) discusses six contemporary theories:

> The referential theory which holds that the meaning of an expression is what it refers to, or stands for: e.g., 'Fido' means Fido, 'dog' means either the class of dogs or the properties they all share.
>
> The ideational, or mentalistic theory which holds that the meaning of an expression is the idea, or concept, associated with it in the mind of anyone who knows it.
>
> The behaviourist theory which holds that the meaning of an expression is either the stimulus that evokes it or the response that it evokes, or a combination of both.
>
> The meaning-is-use theory which holds that the meaning of an expression is determined by its use in language.
>
> The verificationist theory which holds that the meaning of an expression is determined by the verifiability of the sentences containing it.
>
> The truth-conditional theory which holds that the meaning of an expression is its contribution to the truth-conditions of the sentences containing it.

Human language behaviour is undoubtedly the most complex of human activities, and it is inconceivable that any single principle could account for the full complexity of this behaviour. As Austin points out (J.L. Austin, 1962) we use language for many things: We make assertions or statements, we ask questions, issue commands, make promises, threaten, insult, as well as all the things Austin calls 'performative' - to baptize a child, to plight one's troth, to sentence a criminal and so on. Consequently, the nature of the relationship between an expression and a real or a possible world - that relationship we term 'meaning' - may be just as varied as the different uses we make of language.

Consequently the above mentioned theories are not necessarily incompatible; some of them are probably even complementary. For each of the theories above, I can imagine a language act for which that theory holds true. Likewise, for each of them I can imagine a language act for which the theory is clearly false. This is not the place, however, to indulge in this exercise, because, what I am interested in is not so much what each of these theories state about meaning, rather what all these theories have in common.

All the theories above are theories about the meaning of detached language elements. Whether these elements are words, expressions or utterances, each of the theories states something about language elements which have been removed from their natural linguistic environment and prepared for analysis by having all connections to this environment cut off. The overwhelming complexity of human language behaviour may justify such 'in vitro' analyses of language elements in isolation, but few - if any - conclusions can be drawn from the analysis of a detached language element about the nature of general language behaviour. Consequently we can not conclude anything about the nature of 'meaning' in human language behaviour on the basis of an analysis of the meaning of isolated language elements, or to put it another way: we can not extrapolate from 'in vitro' analysis to 'in vivo' functions. Language behaviour is coherent, not only within the information medium itself, but coherent with real or possible worlds. The emphasis on the propositional aspects of language and the analysis 'in vitro' of the truth conditions of detached language elements lead us nowhere.

Johnson-Laird (P.N.Johnson-Laird, 1983) discusses three theories of meaning:

1)The lexical decomposition theory which assumes that words are represented by structured sequences of semantic components (called markers), and that comprehension involves a process of semantic decomposition into a set of 'linguistically universal' components (also called 'semantic primitives'), e.g. underlying the meaning of 'woman' are the fundamental concepts of 'human', 'female' and 'adult', and the meaning of 'child' are the fundamentals of 'human' and 'not adult'.

2)The meaning postulate theory which assumes that words cannot be adequately defined and that each morpheme in the vocabulary of natural language is represented by a corresponding unanalysed token in the mental language (sometimes known as 'mentalese'). E.g. a sentence like 'a man lifts a child' mobilises the 3 words of the mentalese lexicon: 'man', 'child', 'lift', and their corresponding meaning postulates: {man}: FOR ANY X, IF X IS A MAN THEN X IS HUMAN AND X IS ADULT AND X IS MALE. {child}: FOR ANY X, IF X IS A CHILD THEN X IS HUMAN AND NOT (X IS AN ADULT). {lift}: FOR ANY X AND Y. IF X LIFTS Y THEN X CAUSES Y TO MOVE UPWARDS. According to this theory there are no semantic primitives into which the meanings of words can be decomposed, and accordingly there are no mental dictionary entries representing the meaning of words.

3)Semantic networks are essentially means for representing large numbers of related facts in a way that can be readily interrogated by a computer program. The theory assumes that the meaning of a word is its set of verbal associations involving a variety of associative links, including class inclusion, part-whole, property of, and variable relations as specified by other defining words. E.g. people are unlikely to learn that poodles are animals. Rather do they first learn that poodles are dogs, and later that dogs are animals. Consequently the semantic representation of poodles is not linked directly to the semantic representation of animals, but indirectly by a semantic chain: poodle -> dog -> animal. Such a semantic chain is only the most basic element of a semantic network. The fully fledged theory envisages a three-dimensional structure with probabilistic/heuristic chains. Resent research has indeed indicated that mental storage of (at least some) semantic information is hierarchically organised.

These three theories of meaning all assume that meanings are represented by expressions in a mental language. They diverge on the vocabulary of that language, and how inferences based on the meanings of words are made.

The lexical decomposition theory assumes that words are represented by structured sequences of semantic markers, and that comprehension involves a process of semantic decomposition. Johnson-Laird emphasises however, that unless a theory relates language to the world, or to a model of it, it is not a complete theory of meaning. The word 'woman' may be decomposed into the components 'human', 'adult', 'female', but this procedure does not specify the full meaning of the word. It relates words to other words, universals or markers; it does not relate words to the real, or possible, world. The illusion of significance is created by an analysis that uses terms that everyone understands.

By using exotic terms - rather than terms that everyone understands - Johnson-Laird is able to demonstrate that the theory of meaning postulates makes the same basic mistake as does the lexical decomposition theory: that of 'side steppping', rather than relating words to the real world:

> ....consider the status of a semantic theory based on, say, meaning postulates, but using an exotic language that you do not understand. It might well contain the following meaning postulate:
>
> for any x, if x is a ZUG then x is a GEK and x is not a PLEK
>
> where, say ZUG is the token corresponding to the word 'zug'. Such a postulate might well enable you to infer from 'zug brochna' that 'gek brochna', but no matter how complex the system becomes, or how sophisticated the inferences that it can make, it does not provide a complete sematics. It tells you about the relations between words without telling you anything about what they pick out in the world. (P.N. Johnson-Laird, 1983, p.231).

According to Johnson-Laird, the main empirical claim of semantic networks - the inheritance of properties - too appears to be an over-simplification in the light of present experimental results. Networks however, can always be revised to accommodate new empirical phenomena, and are perhaps best thought of as a notation rather than a strong theory of meaning.

Despite their differing inadequacies, the most important characteristic of the three theories is what they have in common. Their main scientific function is to account for the perception of semantic properties such as anomaly and ambiguity and semantic relations such as synonymy and paraphrase. 'On the question of how language is related to the world they are silent'(ibid p.230).

John Lyons' criticism (J.Lyons, 1983) of present meaning theories is similar to that of Johnson-Laird in as much as these theories say little about how language relates to the real world, and he puts the blame for this on the positivistic tradition of American and British linguistic thinking, with its emphasis on the propositional aspects of language and truth-conditonal semantics in an irrelevant meta-linguistic world. If linguistic thinking in Britain had followed a more balanced view between Continental existentialistic and British positivistic thinking, says Lyons, present theories would not have failed so blatantly to account for the most important aspect of language behaviour, that of self-expression or subjectivity. About self-expression and subjectivity of utterance Lyons writes:

> ....I want the term 'self-expression' to be taken literally. The self is not to be understood as being logically and psychologically distinguishable from the beliefs, attitudes and emotions of which it is the seat or location. Still less is it to be taken, as it commonly is in the dominant intellectualist tradition referred to at the beginning of this section, as the reasoning faculty operating dispassionately upon the propositions stored in the mind or brought to it for judgment from observation of the external world....The inadequecy of thruh-conditional semantics as a total theory, not only of utterance-meaning, but also of sentence-meaning, derives ultimately from its restriction to propositional content and its inability to handle the phenomenon of subjectivity. Self-expression cannot be reduced to the expression of propositional knowledge and beliefs.(J.Lyons, 1983, p.240).

John Lyons is here touching on something of great importance, namely that it is all very well to analyse propositional utterances in relation to a well defined world; the problem is that such a world - the positivistic world of propositional calculus and set theory - has nothing to do with the real world. The language of each individual refers to his or her past and present reality and past and present values of a real world. There is my world, and there is your world, just as there is any speaker's world and any listener's world. There are many possible worlds, and the main function of language is to convey worlds - not words.

> ...a speaker must necessarily refer to the world that he is describing from the viewpoint of the world he is in. I might just as well have put it the other way round, saying that a speaker must refer to the actual or non-actual world that he is describing <u>from the viewpoint of the world that is in him</u>. (ibid p.241).

The notion of 'possible worlds', the emphasis on the subjectivity of the language act and its importance as a means of self-expression are the most important moves away from the positivistic theories of meaning. The problem is, that parallel to this development there is considerable research going on into artificial intelligence, and the move away from the positivistic approach to meaning complicates matters considerably when we want to apply computers to fields like cognitive processing of language. Lyons, however, is convinced that there is nothing in subjective linguistics which should make it principally different from positivistic linguistics in terms of 'computer applicability'. It is only a question of developing further our present software to account for the increased complexity of subjective linguistics. It is only a question of time before the increased complexity of subjective linguistics is mirrored in the software controlled reading of natural text strings. Minsky's frame theory is one such attempt to increase the sophistication of a basically positivistic approach to cognitive processing.

Minsky's theory of frames.

In Chapter three we examined Minsky's theory of frames (M.Minsky, 1975) in general terms, and I explained the mechanism of the selection of the 'best match' and its implication for the transfer of information. In the following I shall explain how Minsky sees his theory of frames applied to the cognitive processing of text strings, and we shall examine this application of his theory in the light of Johnson-Laïrd's and Lyons' findings as I have presented them above.

When I explained Minsky's theory of frames in Chapter three, the explanation was based on the visual/cognitive processing of items of the real world, the reason being that the theory of frames lends itself most readily to the processing of non-abstract, well defined objects. When we move from the concrete visual world to the symbolic acts of language, the theory of frames meets with the same problems of other attempts to relate mental representations to the real or possible world.

The structural base for cognitive processing of text strings, as Minsky sees it, is case-grammar which, he suggests, already constitutes a theory of frame recall and slot filling. In the frame theoretical version of case-grammar the different grammatical categories can be seen as frames with slot filling programs. The two most important categories of case-grammar, the noun group and the verb group, contain the following slots; NOUN GROUP: determiner, ordinal, number, adjective(s), classifier, noun, qualifier. VERB GROUP: agent, instrument, co-agent, source, object, destination, former support, conveyance, future support, former surroundings, trajectory, future surroundings. When reading a text string, our linguistic device would first search for a noun group and, on encountering this, fill each slot in turn, or, failing that, our lingusitic device would be looking for the verb group. Once each grammatical category has been identified, the meaning of each is established through the filling of the appropriate slots of the appropriate frame.

Minsky further suggests that there should be a front line understander charged with reducing all action concepts to simple combinations of primitive acts. There are two reasons for reducing all action to primitive acts. The first one is that it would reduce the size of the knowledge library. The second is that reduction is one method by which paraphrases may be recognised.

Primitive acts of the physical world could be: MOVE-BODY-PART, MOVE-OBJECT, EXPEL, INGEST, PROPEL, SPEAK. Primitive acts of perception could be: SEE, HEAR, SMELL, FEEL. And some acts of the mental and social world could be: MOVE-CONCEPT, THINK-ABOUT, CONCLUDE, TRANSFER-POSSESSION.

For illustration let us look at TRANSFER-POSSESSION. 'Take' and 'give' are words that mobilise a frame around TRANSFER-POSSESSION with, amongst other slots, an actor slot, a source slot, a destination slot and an object slot. The sentence 'Sue gives Robin a cake' mobilises the frame around TRANSFER-POSSESSION with the actor slot and source slot both filled by 'Sue', destination slot filled by 'Robin' and object slot filled by 'cake'. If the sentence had instead been 'Robin receives a cake from Sue', the actor slot and destination slot would both be filled by 'Robin', the source slot by 'Sue' and the object slot by 'cake'. Notice that 'giving' implies TRANSFER-POSSESSION with same actor and source, while receiving implies TRANSFER-POSSESSION with same actor and destination.

To deal with eventualities of ungrammatical utterances and the general 'untidiness' of real-life language, Minsky envisages a rich mental library of frames which may be called upon 'on default'. Some library frames would provide general knowledge like plausible cause-effect relationship, actions and state changes; others would provide specialised knowledge like how cause-effect relationship may be altered under special circumstances. All the frames of the mental library could work as subprocessors.

Understanding natural text strings involves frame finding and slot filling. When we start reading a text string, the first sentence or two evoke a frame. Minsky does not specify the minimal unit necessary to make a frame, but - in terms of extent - the parallel to an earlier smallest unit of meaning in linguistics, that of 'semem', seems obvious. As we go on reading, subsequent text segments fill the slots in the first frame. The slot filling may evoke new frames, introducing more open slots, and as the actor-action frames interweaves with state-change frames in cause-effect relationships, the reader pieces together a network of linked frames which constitutes an understanding of the text string.

Several features of Minsky's theory as a semantic model are open to criticism. The first one is that we rarely communicate in neatly arranged, grammatically clear sentences; therefore we can not base our comprehension on grammatical correctness. The second feature, I would question, is Minsky's suggestion that during cognitive processing of text strings we first establish the grammatical structure of an utterance - even if it is in case-grammar terms - and then establish the meaning. Johnson-Laird's sentence 'I saw the Azores flying the Atlantic' is just one example of how context and meaning interact with general knowledge and references to establish intension. The third criticism is that it is difficult to say whether our ability to categorize sentence segments into grammatical types is the condition or the result of the selection and restriction of referents. What is generally called grammatical structure is a complex mixture of functionally different morphologic and semantic features, some of which undoubtedly restrict and select, but most of which are so interwoven with context and meaning as to make it impossible to give a full account of their function.

In semantic terms frames present the same problem as do single words detached from their textual context. Minsky's frame theory acknowledges the influence of the context, but his notion of 'frames' seems to me to be too 'strong' in the sense that the strategy and assignment criteria for a frame is in the frame itself. But if a frame is to contain its own strategy, a statement like: 'particles have wave properties' would not make sense because the assignment rules laid down in the frame 'particle' would not allow the frame to be assigned to 'wave property'. Even if we could draw on a mental lexicon to provide us with a frame of special knowledge, it would effectively destroy the frame 'particle'. But clearly this does not happen; we easily understand the statement 'particles have wave properties'.

As a software approach to a mental model of the world, which is what Minsky's theory of frames is, the theory has several merits. As a <u>semantic</u> model the theory has some merits, although, according to Johnson-Laird, the theory is probably best thought of as a theory of notion rather than as a strong theory of semantics. Even if the 'best match' selection is much more sophisticated, apart from the added feature of recursive constraints on referents (frames), the selection of frames is basically similar to that of Weinreich and Putnam's theories of instantiation (page 195). However, Minsky does not explain how the constraints on a particular meaning arrives from that meaning itself (P.N.Johnson-Laird, 1983,p 235). If the notion of frames is to account for the intense interaction between restriction of reference and restriction of meaning, then a frame is much weaker and has much more flexible bounderies than Minsky envisages. On the question of how language is related to the world, the theory is silent.

Meaning and context.

I have several times emphasised how unrealistic and misleading 'in vitro' analyses of language can be. This state of affair becomes most striking when we focus on the relationship between meaning and context.

The idea of what constitutes context in a text string is generally very intuitive. We know that we should 'not take a word out of its context' by which we mean that the proper content of that word must be assessed in its wider linguistic environment, and not just as a part of a short detached text segment. But how much of the linguistic environment constitutes the context and the constraint of a word?

Referents of homonyms like 'plane' are normally defined by their immediate linguistic environment. 'The plane landed', 'the plane cut the wood' and 'the big plane tree' are minimal linguistic environments which still clearly define the appropriate referents. But even if the constraints of the context has clearly defined a referent, we must not expect referents to remain static. The interesting thing is that we are quite used to our mental models changing without our noticing as we read along. One of the most important features of our cognitive processing of text strings is the continuous defining and re-defining of the mental models which our linguistic device sets up as we read along. The mental model of say, a character in a detective story, alters as we read along, right up to the last page. The success of a detective story depends, among other things, on the writer's ability to keep a number of possible 'worlds' pending.

But we do not have to resort to homonyms or the characters of a detective story to see the subtle changes of referents as the linguistic environment changes.

Let us see what happens when I swing myself to Shakespearean heights and place the word 'tree' in different linguistic environments:

"The tree was
the object of her tender care..." (8.1)

"The tree was
the pride of generations of the family..." (8.2)

"The tree was
a flutter of life; birds shot in and out..." (8.3)

"The tree was
stretching its branches over the naked, cold fields..." (8.4)

I am now going to ask you to look - by introspection - at your own semantical processing of 'tree' in the four different sentences above. What I am asking you to do is to make some processes phenic, which are normally cryptic to you. If you do this and look at your phenic image of 'tree' in each sentence, you will easily recognise that 'tree' has four different referents. I am probably not far wrong, if I suggest, that 'tree-(8.1)' was small and fragile, 'tree-(8.2)' was a big old tree, 'tree-(8.3)' was big and full of leaves and the last one, 'tree-(8.4)' was a dark, naked tree in winter. I could of course right away have informed you that these trees were respectively: young, old, full of leaves, without leaves; however, that is not the way we normally process the linguistic environment. Instead it appears that the potential for this information is already contained in our mental model of 'tree'. and the linguistic environment picks out each particular quality from the mental picture of 'tree'.

Selectional restriction.

The thesis that words do not have a few qualitatively distinct meanings, but rather a whole family of potential meanings was suggested independently by Weinrich (U.Weinrich,1966) and Putnam (H.Putnam,1975). According to this thesis the occurence of a word in a specific linguistic context 'instantiates' a specific sense which is a member of the family. Encountering 'plane' in an utterance our lingusitic device would mobilise a family of meanings: a tool for wood work, an aeroplane, a geometric feature or an even shape, and based on the specific context of the linguistic environment one of the meanings would be selected. In an assertion like 'they are handsome', depending on whether handsome means generous or good looking, the meaning of 'they' is restricted accordingly.

Although in agreement with the principle that some measure of selectional restriction takes place when we process natural language, Johnson-Laird makes two important points. It is nonsense, states Johnson-Laird, to suppose that the meaning of 'they' in 'they are handsome' is affected by a selectional restriction: what changes is its referent, and, in general, what have to be constrained are the referents of expression. If we take a sentence like 'it attacked the swimmer' chances are that we would suggest that 'it' stands for a shark. However, even if 'it' may refer to indefinitely many entities, it still only has one meaning. What is being selected is not a specific meaning, but a specific referent.

Johnson-Laird also points out that in focusing on selectional restriction we often forget the interaction between meaning, referents and context. Meaning and context are complementary. In the interaction between meaning and context in natural language, context and meaning may restrict referents, but just as important is it that referents in their turn determine context and meaning. Likewise, the reference of some expressions may equally play a role in determining the senses of other expressions. Resorting to small text segments to demonstrate - 'in vitro' - the impact of the context on the meaning of words, as is the usual practice, tends to demonstrate only one side of this complex interaction.

Pondering over the different (im)possible interpretations of a sentence like 'I saw the Azores flying the Atlantic' Johnson-Laird (P.N.Johnson-Laird,1983) concludes that <u>the constraints on a particular meaning derive from that meaning itself</u>. What a listener really does in interpreting the sentence 'I saw the Azores flying the Atlantic' is to determine whether it <u>is</u> possible for the Azores to 'travel' through the air over the Atlantic Ocean. This proposition can only be decided by making an implicit inference based on general knowledge:

> .....such inferences often depend on the particular situation that is being referred to: e.g., in the context of a story about how the earth explodes, the Azores might well fly over the Atlantic Ocean. The evaluation of what is a possible referent for, say, the subject of a verb is almost invariably a matter that depends on the nature of the events to which reference is made......The subject of the verb to love, for example, must be classifiable as human or animal. There is thus a semantic anomaly in the sentence: 'The chair loved the table'. Yet in a context where the dish ran away with the spoon, there may be nothing anomalous about a chair's falling in love with a table. The most that can be conceded is that some inferences become so frequent and commonplace that rather than having to make them over and over again, people keep a record of their outcome....Doctors generally cure patients rather than the converse; professors generally lecture students rather than the converse; waiters generally serve customers rather than the converse.(pp236-238).

Even if we accept that some inferences are so common that we keep a record of their outcome, there are still a number of assertions for which we would have to make inferences to real or possible worlds. However, a model of semantics based on inferences to real or possible worlds is not acceptable because there are infinitely many possible worlds, and infinitely many inferences might have to be made. What Johnson-Laird argues is that if we accept his theory of mental models (see Chapter three) then the solution to the problem of there being infinitely many possible worlds is that <u>a mental model is a single representative sample from the set of models satisfying the assertion</u>. Johnson-Laird stresses that the notion of a <u>representative sample</u> does NOT imply that a set of models satisfying the context is constructed and then a sample is selected from them. On the contrary, comprehension normally leads to the construction of just one single model which satisfies an assertion. If subsequent assertion shows that this particular model is incorrect, then recursive procedures attempt to reconstruct the model so as to satisfy the current set of assertions. The important point is that the significance of an assertion depends on both the mental model and the procedures which evaluate and manipulate it.

With regard to the feature of selectional restriction it seems that Minsky's and Johnson-Laird's theories are opposed. Minsky's frames clearly depend on selectional restriction both on slot level and frame level. Johnson-Laird claims that his notion of a <u>representative sample</u> does NOT imply that a set of models is constructed from which the selection takes place. According to Johnson-Laird only one single model is constructed which satisfy the constraints arising from the linguistic environment around a word. According to Johnson-Laird his theory does not depend on selectional restriction whereas Minsky's theory does. I can not agree with Johnson-Laird to his representative sample not implying selectional restriction. The general notion of 'representative' assumes some measure of selection. The selection may take place on a level where models are not yet constructed, but selectional restriction does take place. The difference between Minsky's theory and Johnson-Laird's theory in terms of selectional restriction is not whether selectional restriction takes place or not, but the structure level on which the selectional restriction takes place. Whereas Minsky's selectional restriction takes place both within and above his frames, Johnson-Laird is merely claiming, so I shall contend, that the selectional restriction in his theory takes place as a precursor to the creation of a mental model.

In terms of selectional restriction the following model of 'best fit' is placed between Minsky's theory of frames and Johnson-Laird's mental models. I want to emphasise that I am NOT attempting a full description or analysis of our linguistic device. Nor am I in any way trying to create a semantic model. I am only interested in one single feature of our linguistic device, namely that of the selectional restriction wich takes place as a result of the interaction between context and words. If, as I shall assume, selectional restriction in some form takes place during the cognitive processing of text strings, the concepts of information theory, with regard to selection, would apply, and we should be able to establish the presence of such selectional procedures by measuring the transfer of entropy into information caused by this selection.

A theory of 'best fit'.

We have in this and previous chapters been introduced to a number of linguistic/semantic theories and have examined more closely those that are most relevant to the research presented in this thesis. We have been made aware of the shortcomings of some of the theories and the pitfalls of others. We found that the major deficiencies of present linguistic/semantic models are their inability to account for self-expression and subjectivity of language, their inability to account for the interaction between referents and context, and the failure to describe the relationship between mental language and the real or possible world.

In the following I shall describe the theory of 'best fit'. This theory is based on what I have called a <u>minimum reference unit</u> (MRU). When our linguistic device encounters a word in a text string, the word's MRU is mobilised. The minimum reference unit differs from Minsky's frames in three ways:

1. <u>The extension of an MRU is flexible.</u>

   We must imagine an MRU as a dynamic entity, contracting and expanding in complex and little understood ways.

   Although the internal of a Minsky frame is easily changed in the sense that a number of slots are filled to match a specific linguistic environment, the frame itself is not changeable. If a best match can not be found by means of 're-slotting', the frame is discarded. In the theory of 'best fit', on the contrary, the MRU is not discarded if a best match can not be found. Instead, the MRU is revised in its entirety by recursive processes until it <u>fits</u> into its specific linguistic environment. Only this level of flexibility can account for the full interaction between referents and context.

2. <u>An MRU has no internal strategy.</u>

MRUs do not contain a strategy in the sense that an inference shall provide a predictable referent. An MRU is a probabilistic/heuristic unit which changes its program after each inference involving the unit. If MRUs are controlled by fixed strategies - algorithmic programs - it is entirely externally, from other MRUs or from supervisory functions. Only this level of adaptability can provide for the necessary flexibility of constraint of referents.

3. <u>An MRU functions as an n-dimensional probability space.</u>

The MRU, as I envisage it, is an entity (neurological or otherwise) in which each of a number of referents, resulting from earlier inferences, are represented by a bond, the strength of which is probability weighted according to - amongst other factors - how frequent that referent has been the result of former inferences. The bonds of an MRU are thus vectors in an n-dimensional probability space. The size of 'n' I shall return to on the following page, but some of the parameters would depend on e.g. how long ago a particular referent was the result of an inference, the impact from other (grammatical) units, the impact from the context etc., in short, a number of forces from the full linguistic environment.

I mentioned above that time is probably an important factor. If a specific inference has just been made there should be a very high probability that the resulting referent is re-selected. If 'plane' has just meant 'aeroplane' in a text string, we expect it to mean 'aeroplane' again if we meet 'plane' within a short space of time - or short length of text string. Accepting that time is one important parameter in the n-dimensional probability space would thus account for the feature of extension of context. The constancy of referent over some minimum period of time, or length of text string, means, in information theoretical terms, that the structure of the MRU, which provided the referent, has increased for as long as that referent is constant. We could say that the MRU temporarily has 'set', while the referent remains constant, to indicate that the structure within the MRU temporarily has increased. When the constraints on an MRU changes and a particular referent is no longer current, we must imagine that the MRU 'falls back' to its former, less structured, malleable state. I am of course not implying that inferences are made solely according to probability, but there must be significant elements of probability and learning involved, as quoted above (p 193) from Johnson-Laird.

The problem about semantic models based on inferences to real or possible worlds is, as Johnson-Laird also points out, that there are infinitely many possible worlds, and infinitely many inferences may have to be made. Let us consider for a moment how many inferences we would be able to muster for one word, or put another way: What would be the maximum number of bonds our MRU could manage? I am sure that we do not expect astronomical numbers; but would an MRU be able to handle, say, 100 probability weighted vectors?; or only 20? Some research has focused on the ability of humans to assess and grade a sensory continuum (Miller,1956). The experiments dealt with qualities like acidity of solutions, tone pitch and tone volume, and showed, that we can grade a continuum in no more than 7 (+/- 2) different levels. Experiments, which have been done on short span memory, give similar results; we can remember on average a sequence of 7 symbols without the use of special recall techniques. So, realistically the answer, to how big is 'n' above, is: not greater than between 7 to 9, i.e. an MRU would be able to connect to maximally 7 to 9 referents.

Let us return to the four different miniature linguistic environments of sentences (8.1) to (8.4) on page 194 and process them with a view to selectional restriction, first according to Minsky's theory of frames, and next, according to the theory of best fit.

In Minsky's model of semantics, 'tree' would mobilise the frame 'TREE' which would contain numerous empty slots. Some slots would be of the kind: 'shape-slot', 'size-slot', 'colour-slot'. Some slots could be: leaf-slot, 'nests-slot', 'state-of-health-slot'. As each slot is being filled, our linguistic device compares the frame with the specific linguistic environment of 'tree' and selects in each case the slot-qaulifier which gives the whole frame 'TREE' the 'best match' with its linguistic environment. In information theoretical terms there would be considerable information transfer since each selection of the 'best match' slot-qualifier and eventually the final selection of the 'best match' frame would constitute a transformation of entropy into information.

According to the theory of best fit, when we perceive a word like 'tree' our linguistic device mobilises an MRU which contains a number of weak bonds which on their own are too weak to produce a referent. If 'tree' is placed in a linguistic environment, i.e. an environment with intimate interaction between words, each word will mobilise an MRU and some supervisory control contained in the linguistic device will attempt to establish a <u>minimum resistance track</u> through the bonds of all involved MRUs. To account for the intimate interaction between units, such a minimum resistance track must be established instantanously through all MRUs at the same time. The liking of the situation to a pile of index cards poked by a knitting needle i.e. sequentially, would not account for the interaction which we know takes place. We must envisage that the minimum resistance track is established through all MRUs at the same time, i.e. <u>in parallel</u>. The bond nearest the minimum resistance track in each MRU shall 'point' to that units referent (i.e. the probability vector assigned to that bond shall point to that units referent). The feature mentioned above - that each bond would be probability weighted - would still hold, and the chance, that the minimum resistance track would go through a bond, would depend on the probability assigned to that bond (i.e. would depend on the direction and length of the probability vector assigned to that bond).

Practical problems around the theory of best fit.

The principle of restrictive selection outlined above has been the underlying principle throughout the analysis of text strings in the following research. Although I would have liked to carry out my analyses on the relative boldness of verbal text strings rather than on written text strings with their reflected structures and gloss-up, this has proved impossible. The linguistic environment of verbal text strings is so complex and difficult to handle, that I have had to limit my research to books and, in the case of children, self-contained short stories.

The benefit of using books or self-contained short stories as a data base is that each of this kind of material can be considered to provide a small 'language universe' of its own. A semantical enclave in which the whole linguistic environment is contained in the text itself, unlike the case of real life communication, where a whole range of uncontrollable parameters add to the linguistic environment. In a self-contained book we may consider to be present all the constraint-imposers necessary to reproduce the author's semantical enclave, his intension, around us - or within us. May be 'language universe' is a rather ambitious term when 'possible world' would do, but by terming it 'language universe', I feel, that I preserve the idea of uniqueness of what any author - albeit with different skill - tries to convey: the idea of uniqueness and subjectivity which Lyons rightly holds in such high regard.

Let us imagine, that we are reading a particular text string, and let us simplify for the sake of comprehension. First of all, we want to analyse continuous text strings, so I shall start by assuming, that some of the words in the string have been read (some of the MRUs have produced a referent) and a linguistic environment is beginning to emerge. This is how I see SOME of the cognitive processing involved in reading a continous text string according to the theory of best fit: We have read enough to have created a linguistic environment inside us. We read on, and when a new word arrives in the text string, another MRU is ready to be constrained by the linguistic environment. What happens INTERNALLY, in the MRU, is that the referent pointed to by the highest probability bond will be checked by the linguistic device to establish if it conforms with the external constraints (the linguistic environment constituted by the text string). If it does not conform with the external constraints, the referent pointed to by the second highest probability bond will be checked and so on until the referent pointed to by the lowest probability bond has been checked. If none of the referents pointed to by the vectors of the MRU have been found suitable, i.e. if no best fit has been found, the linguistic device will insert the necessary referent somewhere near the MRU and point to it with a very short probability vector from a new bond inside the MRU. If a best fit has been found, we can go on taking the following words in. Every time our MRU has suggested a referent, this would be followed by external checking (analysis by synthesis as suggested by Liberman (Liberman, Mattingly and Turvey, 1972), external /internal refusal, internal suggestion of another referent, another external checking and so on, back an fro between the MRU and the internal or external linguistic environments untill the best fit has been found. The intake of one single word at a time should not be taken too litterally. It is well known, that a skilled reader often scans unconsciously ahead of the word his attention is focused on. But simulating a reading technique, which reads one word at a time, is at least not unrealistic.

If you at this point can remember any of the information theory which opened this paper, you may recall, that gaining information had to do with structuring. We could increase the information in a system by increasing the structure in a sub-system. But this is exactly what happens during perception of textstrings in a model like the theory of best fit. When a new word is encountered, the MRU of this word is mobilised and if a best fit has been established, the structure of this MRU increases momentarily, or as long as the constraints from the linguistic environment remain stable. But according to the theory of information, the increase in the structure of the MRU constitutes an increase in information. But from that must also follow, that every time a new word is constrained and a best fit has been found, there must be a gain in information. It does not make sense to assume, that new words would not be constrained (a best fit not found), because this would mean, that the reader did not process the text. We can therefore take for granted, that provided the text string being analysed makes sense, then a new word's arrival in such a string implies a gain in information. What I have tried to establish in my research is whether there is a specific pattern of information pulses arising from the processes of selectional restriction and best fit, a super-structure which does not rely on a syntax grammar, but on a 'grammar' of information pulses.

Generally, a word is only new the first time it is encountered in the text string being analysed. However, whereas this is obvious in computer operational terms, in cognitive terms, such a view is far too simplistic. The semantic content of a word is a dynamic entity. We often forget this, because the fact, that we pronounce and spell a word the same way time and time again, belies the dynamic nature of what this word may refer to, and attaches to our language processing an illusion of concreteness.

In cognitive terms the semantic content of the same word in two linguistic settings is really only the same if the two linguistic environments are identical in every semantical detail, and that is unlikely. We do not use language the way we use mathematics or logic; if we did, very little information would be transferred. The languages of mathematics and logic are languages with a very high redundancy. Accordingly, what little information can be gained appears as re-arrangements of well defined units or 'words' which do not change their content when they are restructured or re-arranged. Natural language is very different in that the information unit, be it on the word level or semem sevel, gets its meaning from its environment at the same time - and to the same extent - as the environment becomes meaningful through the use of a particular referent.

Even though we can say with some justification that a word is more likely to transfer information first time it is encountered in a text string than when it is repeated, this does indeed depend on how much the semantic content of the word has changed from the first time it is encountered to the second or following times that its 'best fit' has been established. I envisage that the 'best fit' of a word remains relatively unchanged for some time - or some length of text string. The problem is establishing this length of string. If we are too exact in our assessment of the change of semantic content we render our analysis unworkable since the semantic content of most words is never entirely the same. If we are too 'loose', we render our analysis useless. I shall later suggest a method of establishing the length of the string - the REFERENCE FIELD - within which the semantic content, the 'best fit', of a word is defined as being 'constant'. In this case however, it will be done on a pragmatic basis, for the purpose of a well defined Fourier transformation ONLY. The question is then whether we are any better off defining the reference field in this way, but as I shall explain later, I think we are - at least marginally.

There is another important point; that of quantity of information transferred per new word i.e. per each new best fit. On page 198 and 199 we dealt briefly with the suggestion that the maximum number of referents, an MRU is able to point to, is around eight. As suggested elsewhere these referents are attached to the MRU through bonds which are probability weighted.

For the sake of explaining, let us say, that the MRU of a fairly concrete word like 'tree' contains four bonds representing four different referents of 'tree' and the attached probabilites: 0.4, 0.3, 0.2 and 0.1. Since the bonds are probability weighted the sum of the probabilities is of course 1.0. If the referent pointed to by the bond with the highest probability of 0.4 is selected as the best fit, the information transferred, as explained in Chapter 1, is $I = -\log(p)$ i.e. $I = -\log(0.4) = 1.32$ bit. If the referent to be selected as a best fit was the one pointed to by the bond with the lowest probability of 0.1 the information transferred would be $I = -\log(0.1) = 3.32$. As we recall, the less likely the selection, the higher the transfer of information. By the same token, if the best fit to be selected is the 'standard' referent of a word, the information transfer is not as great as if the referent to be selected represents the more unlikely case.

If we take another kind of word, an abstract like 'love', which, judging from variety, must number thousands and thousands of possible referents, the limitations of our perception still limits the number of bonds in the MRU 'love' to around eight. I shall not hazard to guess what these eight most common referents of 'love' are, suffice to say, the probability weighting of the bonds in <u>your</u> MRU 'love' would probably be quite different from those of <u>mine</u>, since the MRU represents our own subjective linguistic experience. The fascinating thing about the notion of MRU is that the rarer the occurrence, the higher the information transfer: Let us assume that we can generally agree to what is the most common referent of 'love' and let us say that the bond in the MRU 'love' pointing to this referent has a probability weighting of, say, 0.5 (because it is a very general token of 'love'). Let us further say that six of the other bonds in the MRU represent referents less common, but still quite 'acceptable' (in whatever terms) and say they each have a weighting of 0.08. The last referent picked as the best fit to a linguistic environment, however, turns out to be rather unheard of in terms of 'love' and gets the weighting 0.01 (because there are maximum 8 bonds, and 0.01 left until all probabilities add up to 1.0). In terms of information, the different best fits would transfer: 'the ordinary' = 1.0 bit, 'the acceptable' = 3.6 bit and the 'not so acceptable' = 6.6 bit! I leave it to you to judge what people would rather talk about!

It would be desirable if we could measure exactly the transfer of information for each best fit as it is selected during the computerised reading of text strings later in this thesis, but it is not possible. However, what I am interested in are only the pulses of information not their amplitude. Fortunately their are versions of the fourier transform which are independent of the amplitude, so this is not going to become a problem. For simplicity we could therefore say that a best fit transfers information of the value one or zero depending on whether the word is new or a repeat.

For the moment being, I shall asign to each RECOGNISED word the value 0 bit and to each NEW word a positive value of information equal to 1 bit. Furthermore, I shall for future purposes use the following terms: A word is in "I-mode" first time it is encountered in the text string which is being analysed, and in "O-mode" if it has been encountered before in the text string in question. Accordingly, first time a word is being read and is in "I-mode" it will transfer a positive amount of information. If the word reappears in the textstring, and thus is in "O-mode", zero bit of information is being transferred.

Secondly, whether a word is new or a repeat is a question of whether it is repeated within its REFERENCE FIELD. As touched upon above, it is possible to envisage - at least theoretically - a length of text string within which the semantic content of a word is unchanged. This length of text string I shall call the word's reference field and when we judge whether a word is in I-mode or O-mode, it is only with reference to this field - not the entire text string from word one. If the word is repeated within this reference field, the word will not have changed its semantic content and shall count as an O-mode. If the word is repeated outwith its reference field, the semantic content of the word has changed enough to justify that it counts as a new word, an I-mode. I shall enlarge on this in the second half of this chapter.

I have assumed above, that all words in I-mode will transfer a pulse of information. However, some words like the small words "and","the" and "for" and numerals like "two", "three" and "a dozen" do not so easily lend themselves to the same best fit selection as may more likely candidates like nouns and adjectives. The semantical content of such words is so entwined with the words they relate to, that their own semantical content is negligible. It is questionable whether such words can be given a semantical content on their own. In a way, they seem to be passive parts of the linguistic environment, sections which constrain, but are not themselves constrained. Nevertheless, even if such words do not immediately fit the bill, I assume that they somehow do contribute to the information transfer, for which reason they will be analysed and treated like all other words in the text strings.

The 'one word - one role' concept of language processing has its roots in the simplistic idea that the linguistic device orderly generates or decodes text strings one word at a time with minimum regard as to what precedes or succedes each unit. Or to put it another way, according to this view, text strings are processed serially. However, from the examples of this chapter, and indeed from every day observations, it is obvious, that the basis of language processing can not be only serial, but must be parallel as well.

When the end result of the language generating process is a text string, this text string is by its very nature serial ie, the units of information are arranged serially. However, this is only the case on the superficial representative level. The process which generated the text string can not possibly be serial since, as we have seen above, the text string on the semantic level is produced or analysed in conjunction with its environment - its neighbouring semantical units, its syntax and its grammar.

As to whether the linguistic process of generating or decoding text strings is parallel AND serial or only parallel, the question is only academic, since a serial process can be seen as a special case of parallel processing, namely the case N = 1, where N is the number of parallel channels. As to how many parallel channels our linguistic device is able to handle, one can only guess. If we look at simple channels - channels with no wait stages, which only process one semantic unit at a time - and we assume - equally simplistically - that the process is a one level process, then a SPOKEN, GRAMMATICALLY COHERENT AND SEMANTICALLY MEANINGFUL sentence would require as many channels as there were semantic units in the sentence. However, it is equally possible, and much more probable, that our channels have wait stages, and that the processing is multi-level. If this is the case, then there are two possibilities: either each grammatical class constitutes one channel, or each channel can take on different grammatical functions. The latter would be the more economical in terms of number of channels, the former would be the more economical in terms of speed.

Personally, I see the stem diagrams of the functional analysis, like the one in figure 2.5 (page 30) as representing such a kind of parallel processing. If it is indeed possible for our linguistic device to process one level at a time, and reprogram each channel according to which grammatical function it is going to proces, then we may never need more than three channels (plus some intermediate store units, plus the hard wiring of the grammatical function of these channels, plus the firm wiring of the exceptions to the hard wired grammatical functions). If on the other hand, for the sake of speed, each grammatical function constitutes one channel, then we would need one channel per grammatical class (plus intermediate store units, plus firm wiring of the exceptions to the hard wired processing through each grammatical channel.

Wherever our speculations may take us, one thing is certain: the reality of the human language processing is far more complex than we are able to anticipate, and the above considerations, as to the nature of this processing, are only tentative excursions into the realms of the possible - as opposed to the probable.

So much said, it does appear from my research, that our linguistic device is able to handle a great number, may be as many as over a hundred, of parallel channels at any given time.

In the second half of this chapter we shall move the emphasis from the theoretical aspects of the model of best fit to the practical proplems arising from the application of this model to the stucture analysis of text strings by a computer program.

THE PRACTICAL IMPLEMENTATION OF THE MODEL OF 'BEST FIT'.

In the second half of this chapter I shall enlarge further on the model of 'best fit' developed in the last chapter and show how this model can be employed in practical terms in the automatic reading of text strings.

As you may recall from the beginning of this chapter, I introduced a new terminology: 'I-mode' was the state of a word first time it was encountered in a text string, 'O-mode' was the state of a repeated word. I furthermore decided, that the state of a word, I-mode or O-mode, should be determined not by reference to the whole string preceding the word in question, but by reference to some shorter string, the exact length of which we have yet to determine.

You may recall too, that we looked at the impulses of information transferred each time a word is in I-mode, and we illustrated this transfer by filling in an information array with ones or zeroes according to whether the word was in I-mode or in O-mode. The main obstacle against our accepting the checking of incoming words against all the preceding words in the string to establish if a word is in I-mode or O-mode (an approach which I shall call the 'straight forward approach') was, that by doing so, we would get an information array with an increasing ratio of zeroes and very few 'ones', which again would infer, that after some reading, there would be little or no information transferred. In the case of a book containing say, 10,000 words, if we stuck to the straight forward approach, there would be few - if any - new words arriving in the text string towards the end of the book.

This state of affairs is clearly at odds with our common-sense knowledge about what happens while we read a book. Although some items of literature can be pretty trying, we know from experience that generally the transfer of information does not drop to virtually nil after the reading of even several thousand words. We normally feel that we get more and more out of a book as we read on; not less and less.

As our common-sense notion of reading is that the information transfer is fairly constant during the reading of whatever length of text string, we would expect the information array of ones and zeroes to mirror this fact by the ratio between the ones and the zeroes being equally fairly constant.

Another obstacle to the 'straight forward approach' was the fact, that words are only vehicles of information - not the information itself. A word has an outer form, which can be the way it is spelled, but much more important than this outer form is its substance, i.e. the meanings or the connotations which are evoked in us by the outer form of the word. To take account of only the form and not the substance is to miss the essential, but also the most complex, feature of our linguistic behaviour. Ideally, when we analyse text strings; we are not interested in the words per se, what we really want to know is whether the content of each word, its meaning, has changed. So if we want to count proper O-modes and I-modes in a text string, we would ideally check preceding semems - not words - for repeats.

This however, demands cognitive skills which we can not employ in our automatic reading of text strings. We are confined to compare forms, and forms only.

However, a couple of times in the past we have touched on the idea, that although the semantic content of a word changes as its environment - its linguistic surroundings - changes, it is not conceivable that this content, the meaning of the word, should not be fairly constant over a certain minimum length of text string. I state 'not conceivable' because in all (other) intellectual processes our brain depends on some degree of generalisation of the environment (words included) to carry out these processes.

As implied above, the concept of a reference field is a concept closely related to each individual word. Each individual word has its own length of text string over which its semantic content stays fairly constant. The semantic content of some static abstracts like numerals would be constant over a considerable length of text string, whereas dynamic abstracts like 'love' and 'hate' would be constant over relatively short lengths of string.

This minimum length of text string, during which the semantic content of a word - the word's 'best fit' - is fairly constant, I have called the 'reference field' of that particular word. The exact length of this reference field is however as difficult to establish as the semantic content of the word itself. For the purpose of this present research I shall only assume with regard to the length of reference field of a word, that any reference field shorter than the whole of the string preceding the word in question is more realistic than a reference field stretching from word one to the word in question.

To illustrate what I mean I shal draw on a text string from Bertrand Russell's "History of Western Philosophy" (8.5).

> PHILOSOPHY, AS I SHALL UNDERSTAND THE WORD, IS SOMETHING INTERMEDIATE BETWEEN THEOLOGY AND SCIENCE. LIKE THEOLOGY IT CONSISTS OF SPECULATIONS ON MATTERS AS TO WHICH DEFINITE KNOWLEDGE HAS, SO FAR, BEEN UNASCERTAINABLE, BUT LIKE SCIENCE, IT APPEALS TO HUMAN REASON RATHER THAN TO AUTHORITY, WHETHER THAT OF TRADITION OR THAT OF REVELATION. ALL DEFINITE KNOWLEDGE, SO I SHOULD CONTEND, BELONGS TO SCIENCE; ALL DOGMA AS TO WHAT SURPASSES DEFINITE KNOWLEDGE BELONGS TO THEOLOGY. BUT BETWEEN THEOLOGY AND SCIENCE THERE IS A NO MAN'S LAND, EXPOSED TO ATTACK FROM BOTH SIDES; THIS NO MAN'S LAND IS PHILOSOPHY.

Text string 8.5

In text string 8.5 we see in praxis many of the features of the theory of 'best fit'. The huge, loosely defined concept 'philosophy' is introduced with the first word, and the rest of the text string is basically an exercise in finding 'best fit' for this concept. For good measure we get the 'best fit' of science and theology trown in as well. However, The important point here is, that if we have to decide if the last word in 8.5 'philosophy'(2), is the same as the first word in 8.5 'philosophy'(1), the straight forward approach says that the last word is an O-mode since it has been in the string before, whereas a more realistic approach would state, that the whole point of the text string 8.5 is to 'mould' - to modify - 'philosophy'(1) into 'philosophy'(2). Because of this, 'philosophy'(2) has become a subset of 'philosophy'(1), and thus - because of the smaller number of choises in this subset compared to the initial set - some information must have been transferred. For this reason, 'philosophy'(2) can not be said to be in O-mode, but must be in I-mode even though it is spelled the same way as 'philosophy'(1) and is placed in the same text string.

The question is: at which point of the string did 'philosophy'(1) change into 'philosophy'(2)?. Let us look at where the text string modifies the concept 'philosophy'(1) as we read on. To make it easier to refer to the individual words in text string 8.5 I have reprinted the string with each word numbered successively from word one (text string 8.6). For the sake of clarity I have removed all punctuation. It still seems a bit messy, but let us try:

1.PHILOSOPHY 2.as 3.I 4.shall 5.understand 6.the 7.word 8.IS 9.SOMETHING 10.INTERMEDIATE 11.BETWEEN 12.THEOLOGY 13.AND 14.SCIENCE 15.like 16.theology 17.IT 18.CONSISTS 19.OF 20.SPECULATIONS 21.ON 22.MATTERS 23.AS 24.TO 25.WHICH 26.DEFINITE 27.KNOWLEDGE 28.HAS 29.SO 30.FAR 31.BEEN 32.UNASCERTAINABLE 33.but 34.like 35.science 36.IT 37.APPEALS 38.TO 39.HUMAN 40.REASON 41.RATHER 42.THAN 43.TO 44.AUTHORITY 45.WHETHER 46.THAT 47.OF 48.TRADITION 49.OR 50.THAT 51.OF 52.REVELATION 53.all 54.definite 55.knowledge 56.so 57.I 58.should 59.contend 60.belongs 61.to 62.science 63.all 64.dogma 65.as 66.to 67.what 68.surpasses 69.definite 70.knowledge 71.belongs 72.to 73.theology 74.but 75.BETWEEN 76.THEOLOGY 77.AND 78.SCIENCE 79.THERE 80.IS 81.A 82.NO 83.MANS 84.LAND 85.EXPOSED 86.TO 87.ATTACK 88.FROM 89.BOTH 90.SIDES 91.THIS 92.NO 93.MANS 94.LAND 95.IS 96.PHILOSOPHY

Figure 8.6 Textstring 8.5, words numbered successively.

Referring to text string 8.6, It seems to me, that 'philosophy'(1) is being modified 4 times. The first time is from word number 8 to word number 14 (incl.). The second time is from word number 17 to word number 32 (incl.). Third time is from word number 36 to 52 (incl.). The last modification is really a repeat of the first modification (with extentions) and stretches from number 75 to the last word 'philosophy'(2).

I have emphasised the modifying segments of string by keeping them in capital writing. The segments in small letters are mostly modifiers to the modifiers we are dealing with now, but we shall leave these, since the matter is complex enough as it is.

To return to the object of establishing how long is the reference field of 'philosophy'(2) we can with some justification say that this field stretches from 'philosophy'(2), which is word number

96, back to word number 52 which was the last point where 'philosophy' was modified. The semantic content of 'philosophy'(2) has therefore been constant between word number 52 and number 96. 'Philosophy'(2)'s reference field is thus 96 minus 52 = 44 words long.

So to get some approximation to reality we could instruct INFOR to only check 44 places back in the string while it was reading. This would work fine; 'philosophy'(2) would register as an I-mode and the automatic reading would have been semantically sound - with regard to word number 96, that is. All the other words in the string has probably got reference fields which differ in length, not only from the reference field of word number 96, but from the reference field of each other. To put it boldly: there are probably as many different lengths of reference field as there are different words, and we can not possibly predict or make any general rule for how long each reference field is going to be. We can not even predict how long the reference field is going to be next time the word 'philosophy' has been used.

Accordingly we will eventually have to settle for an approach which is practical and approximate rather than ideal and exact. As stated before, we can can not without considerable cognitive involvment assess the reference field of each word. Our employment of a computer to carry out the practical aspects of reading and checking text strings against a reference field must be based on a GENERAL REFERENCE FIELD i.e. the same length of reference field for all the words in the text string, rather than an INDIVIDUAL REFERENCE FIELD based on the cognitive awareness of the stability of the semantic content of each individual word.

This approach - although less than ideal - is however a sounder one than the straight forward approach attempted earlier, and although not even an attempt to simulate the cognitive coding/decoding of text strings, it is nevertheless an approximation.

A problem, closely related to the problem we have been dealing with here, is the falling ratio of 0's over 1's in the information array as explained in chapter 8 and again at the beginning of this chapter. As we fill in the information array according to the straight forward approach, the fact, that we check each incoming word against an ever increasing number of words, means that the chance of getting a new word in the text string becomes increasingly remote. Accordingly the 0's in the information array become more and more frequent even though we have established, that realistically the ratio of 0's over 1's should stay pretty constant whatever the length of text string.

So how can we change INFOR's reading of a text string to satisfy this expectation. We can not just add I-modes ad libitum to make up for the fast increasing number of O-modes, and the reading of a text string must, as mentioned earlier, begin and end somewhere. However, as soon as we start reading, the number of I-modes start falling exponentially until, after a few hundred words, the information array A is being filled with mainly zeros as a symptom of less and less information being transferred.

Let us just suppose we aggreed to a reference field of 1 or 2 words. This would mean, that an incoming word would only be checked against the last or the second last word before it. Shurely this would mean that nearly all of the incoming words would be judged to be 'new' to the string and therefore in I-mode. This would of course not bring us any nearer to a solution except for the fact, that we have now established the conditions for two opposite extremes: 1) if we check each incoming word against a reference field which stretches from the first word to the incoming word we get an ever increasing number of zeroes in the information array. 2) if we check each incoming word against a reference field of only one or two words we get an ever increasing number of 1's in the information array. But from this must follow, that somewhere in between these two extremes - a reference field of 1 and a reference field as long as from the beginning of the string to the word being read and checked - there must be a length of reference field which would keep the ratio of 1's to 0's constant whatever the length of the string we read.

But from this follows too, that it is not so much a question of which length of reference field we settle for, as the fact that we do settle for a CONSTANT reference field, since by checking each incoming word against a COSTANT number of words, we have also ensured the constancy of the probability that the word will be recognised.

To illustrate the reading of a text string with a general reference field I have made a numerical representation of a text string in figure 8.7 and shall explain how the analysis takes place.

Reference field of w12

w1 w2 w3 w4 w5 w6 w7 w8 w9 w10 w11 w12 w13 w14 w15 w16 w17 w18 w19 w20 w21 w22 w23 w24 w25 w26

Reference field of w11 Reference field of w25

Figure 8.7 Numerical representation of the analysis of a text string of 26 words with a reference field of 10

Figure 8.7 represents a text string of 26 words, w1 is the first word and w26 is of course the last word. Let us decide to read this string with a reference field of say, 10 words.

As explained, if the reference field is 10, it means, that we check each incoming word against the 10 preceding words in the string. Thus, if we want to analyse string 8.7 for I-modes and O-modes it means, that we can not start at word 1, since that would give us no reference field at all. The first word we can analyse with a reference field of 10 is of course word number 11, since this would be the first word to have 10 preceding words. So let us start filling in our information array IA with 1's or 0's according to whether the incoming words are I-modes or O-modes.

So we start INFOR off by informing it to read from word number 11 and check against a reference field of 10. INFOR now reads word number 11 and checks it against each of the words number 1 to number 10 to see if word 11 is a repeat or a new word with regard to its reference field i.e. with regard to any of the words number 1 to 10. If word number 11 is spelled differently from word number 1 the program will check it against word number 2. If it is also different from word 2, INFOR will check it against word 3 and so on. As long as word 11 is not similar to a word in the reference field, INFOR will check the next successive word up till and including word 10. If the last word in the reference field , i.e. word 10, too is different from word 11, word 11 will register as an I-mode and the eleventh place in IA will be set to 1.

Having checked word 11 against all the words in the reference field, INFOR established in our example, that word 11 was in I-mode. INFOR now moves its analysis to the next word in the text string. This is word number 12, and it too will be checked against the ten words preceding this word i.e. w12 will be checked against w11, w10, w9.... and so on down to w2. Because the reference field is constant (=10) it has moved 1 word forward as the word being analysed has moved 1 word forward. Let us say that INFOR finds word 4 similar to the word being analysed (w12). INFOR now sets place 12 in IA to zero and moves its analysis to word number 13. The reference field is now constituted by word number 3 to word number 12, and word number 13 will now be checked against each of the words w3, w4, w5, ... and up to w12 to establish if w13 is in I-mode or O-mode. Whatever mode word 13 is, the 13th place in IA will be set to the appropriate digit (1 or 0) and INFOR moves on to analyse word 14 and check it against the 10 words in its reference field, which is now made up of the words w4, w5, w6,......w13.

And so on; each time a new word is being analysed, the reference field has moved one word forward, and the word which was the last to be analysed has itself become a member of the next words reference field. Of course, if we decide to start our analysis with another word, say number 25, the reference field (RF=10) would now stretch from word 15 to word 24, but everything else would work as before.

Summing up, the reading of say a string of 100 successive words with a reference field of 10 would mean the successive checking of 100 words against each of the words in a reference field stretching 10 words behind all the time.

Let us assume that we have decided on a fixed reference field of some particular length. Let us now look at what would happen to the ratio of 0's over 1's if we increased or decreased this reference field.

By increasing the reference field we would increase the number of words against which each incomming word is being checked, and consequently increase the probability that the word would be registered as an O-mode. This would give us a constant - but INCREASED - ratio of 0's over 1's.

If we on the other hand decreased the length of the reference field, we would decrease the number of words aginst which the same incoming word is being checked, and consequently decrease the probability that the word would be registered as an O-mode. This would give us a constant, but DECREASED, ratio of 0's over 1's. Apparently, it is entirely up to us to decide how big we want this ratio to be.

So, by sheer use of logic we have now established, that somewhere in between using a reference field longer than 1 word, but shorter than the length of the full text string, INFOR is bound to find a more or less similar number of I-modes and O-modes and fill the information array with a more or less equal number of 1's and 0's. Whatever the length of the string, we can always adjust the reference field so that the chance of a word being read by INFOR has an equal chance of becoming an I-mode or an O-mode.

Before we can analyse text strings however, we have to decide how far back we want this reference field to stretch. It is one thing, that we have established, that by introducing a constant reference field, we have also introduced a constant ratio of 0's over 1's. It is another matter to decide exactly how long this reference field must stretch back. Since we have established, that there is a close link between the length of the reference field and the resulting constant ratio of 0's and 1's, I suggest, that first we decide on the size of the ratio of 0's and 1's and then we establish which reference field would yield this ratio.

There are good reasons for wanting the number of I-modes in the final information array to be equal to the number of O-modes, ie a ratio of new words to repeated words equal to 1:1.

The first reason is that a level of redundancy of this size - 50% of the words recognised by the computer or guessed by a human reader - would be in agreemment with the levels of redundancy in communication established experimentally by Shannon and others.

The second reason is that of sensitivity of method of analysis. Just like a pair of scales are most sensitive when they are in balance, so does a array of ones and zeros give the best indication of the balance between the two set of digits if the ratio between them is 1:1. I shall prove this in chapter 11, when we are fully ready to apply Fourier analysis to text strings.

The program FINDRF which I shall be examining in chapter 10 has been written so as to establish - by means of a binary iteration technique - the length of reference field which yields a ratio of I-modes and O-modes equal to 1:1.

We have now seen how our accept of a reference field in the suggested "best fit" linguistic model accommodates the common-sense notion that the information transfer stays fairly constant whatever the length of text string i.e. a constant ratio of I-modes over O-modes and we have achieved our two main objects:

1) A computer simulation of the reading of a continuous text string according to the suggested model of "best fit" and

2) an information array which is a fairly constant representation of the information transfer during this reading.

This information array, this series of zeros and ones reflecting the transfer of information is going to be the focus of our attention from now on. What particularly interests me is the possibility that these zeros and ones in the information array constitute patterns.

In the next chapter I shall introduce you to the various programs used in this research, amongst them two different INFOR's representing two different approaches to Fourier transformation.

CHAPTER 9.

PROGRAMS IMPLEMENTING THE METHODS OF CHAPTER 8.

In this chapter I shall describe the different programs used in the present research, in particular the two versions of INFOR, which have been the principal tools in this present analysis of structures in text strings, and finally I shall provide one example of a complete read-out of all intermediate data of the calculations of one of the INFOR versions.

As mentioned earlier, the programs are developed for use on a micro computer. The language is Pascal/M which is the Pascal dialect written by the American software firm Sorcim. The reason for using this particular version is solely, that when I began developing these programs some years ago, Pascal/M was the only Pascal compiler available for micro computers. This version of Pascal is in my opinion no worse and no better than other versions around at the moment. It has - like all commercially available Pascal versions - quite a few extensions to the original Pascal version by Jensen and Wirth (Jensen and Wirth, 1975). On the other hand, to support the portability of all the programs, I have whenever possible avoided procedures not defined by Jensen and Wirth. This should make it easy to implement these on any machine - big or small - which supports Pascal.

To clarify what I mean when I in the following use the terms 'window' and 'reference field' I shall make a graphic representation of the terms (Fig.9.1) and explain.

1ST REFERENCE FIELD WINDOW

w1 w2 w3 .....w21 w22 w23 w24 w25.....w30 w31 w32 w33 w34 w35 w36 w37 w38 w39 w40..........w62 w63 w64 w65

Figure 9.1 Numerical representation of a text string, 65 words long

Let us say that the text string w1 to w65 in figure 10.1 is going to be analysed by INFOR and that we are particularly interested in the information transfer in that segment of the string which runs from word number 31 (w31) to word number 65 (w65). This is the length of text string we want to assess I-modes and O-modes in, and this segment of the string is therefore the WINDOW. The window thus extends the 35 words from w31 to w65 (incl). As explained in chapter 9, INFOR now creates an information array IA with as many places as there are words in the window and for each word, starting from w31, INFOR will check this word against the words in the reference field. Let us say that window w31 to w65 is going to be read with a reference field of 10. From what we have seen in chapter 8, this means, that the first word in the window (w31) will be checked against the 10 words preceding this word (w31), that is, w31 will be checked against w21, w22, w23 or an O-mode, the first place in the information array is set to 1 or 0.

INFOR will now move to the next word in the window which is w32 and check this word against the reference field of 10 words, which too has moved one word along. Word number 32 (w32) will be checked against w22, w23, w24,.....,w30, w31. If w32 is an I-mode the second place in IA will be set to 1 otherwise to 0. And so on, each word in the window and finishing by the last word in the window (w65) which will be checked against the 10 words preceding it; the reference field always extending backwards from the word in the window which is being analysed.

In the hope that this explanation will prove helpfull, I shall now turn to the explanation of the programs which implement the theory and methods of last chapter.

Program FINDRF.

It would be natural first to take a look at the program FINDRF (Page 220) since before we can apply INFOR to any text string, we must know the general reference field with which INFOR is going to read the string. The program FINDRF, as the name suggests, does just that.

The procedures READWORD, COMPAREWORD and MOVEONE are the same as in the two versions of INFOR and shall be dealt with more closely when these programs are being examined in a short while.

Let us examine the other procedures in FINDRF. After we have decided which particular measuring window of a particular text string we want INFOR to analyse, we let FINDRF read the text string with the same window. On the basis of this window, FINDRF calculates the ratio of I-modes and O-modes after several consecutive readings with reference fields of varying length. When the program finds the reference field which gives the ratio 1:1 between I-modes and O-modes, the program stops and gives a read out of the window and the length of the reference field.

The varying lengths of the reference fields used by FINDRF to establish the 1:1 field are naturally not a question of trial and error - that would take too long. Normally, the initial reference field tried by FINDRF is the length from the start of the string to the start of the window. This was the procedure in my first version of FINDRF, but this meant, that if I wanted to analyse a window starting at say word nr 501 then FINDRF would automatically use a reference field of 500 words in its first attempt. A reference field of 500 words is however unrealistically long, and so I waisted much time while FINDRF realised the hopelesness of its doings and eventually settled for a much shorter reference field. The length of the first reference field used by FINDRF is in this version of the program initialised by the operator with his answer to the question in line 155. I have found that this synthesis between an 'educated' guess and FINDRF's binary search mentioned below, is the fastest way of establishing the final reference field.

After FINDRF has established whether the ratio between I-modes and O-modes is greater than or less than 1 after the first run, the search for the reference field with a ratio equal to 1 is taken over by the binary search routine (Line 163 to line 201).

This routine will normally establish the final reference field within 4 to 5 attempts. There are however a couple of provisions for the possibility that this does fails. The first one - and quite common with short strings like some of the childrens text samples used in this research - that the string is shorter than its necessary reference field (Line 169 to line 182). The second reason, why FINDRF may fail, is that the ratio between I-modes and O-modes is not exactly 1. In this case FINDRF moves the whole window 3 words to the left and starts all over again.

Program INFOR25TIMESERIES.

When FINDRF has established the proper reference field, we can then analyse the structure of the text string with INFOR. As mentioned above, I have had to make two slightly different versions of this program. The two versions of INFOR represent two different ways of applying Fourier analysis to a signal. The need for two different approaches reflects the basically two different kinds of signal: binary or analog. I think the simplest way of explaining INFOR to you is to deal fully with the first INFOR I developed - the version which analyses only binary signals - and then after the full tour through this version, look at those procedures in the later version - the version which analyses analog signals - and explain the changes. Only a couple of procedures are different in the two versions.

INFOR is build around a short main program - 63 lines - with 12 modules (procedures) which can be called in when necessary. Including the procedures, which take up the major part of the program, the program is 401 lines long. The main program begins in line 338 and ends with line 401.

The text samples used as data have on all occasions been disk files i.e. the textstrings to be analysed first had to be written on to a memory disk. The first word of the text string is the label, and INFOR will extract this information before the reading of the words begins.

The easiest way to look at the program is to take it step by step and follow the dataflow. Assuming that we have loaded and started the program we go to the start of the main program in line 338. The first two lines are reset and clear screen. Line 341 is a reminder that the number number of words in the text string to be analysed is limited to 750. Next line is a pause procedure which leaves the above information on the screen for 2 seconds. Line 343 define the letters and numbers allowed in the textstrings to be analysed. Line 344 sets the boolean variable "MORE" equal to false. If we run INFOR several times with different variables, "MORE" is changed to true and controls that the heading is only printed once on the printer output.

The next control variable is "HAM" in line 345. "HAM" is short for "Hamming" which is a smoothing procedure employed later on in the program. "HAM" is set to false because the program is going to ask us later if we want smoothing of the power spectrum. If we at that point do want smoothing, HAM is changed to true. As a general rule, no smoothing has been used in the majority of analysis. Only when we have made 'multiple run' analysis (see later) has the graphs been smoothed slightly to give a more even surface.

The first two procedure calls, line 346 and 347, refer to the procedures named in the calls. BOOKIN (line 28) initiates the input file and BOOKOUT (line 51) initiates the output file. The third procedure call INITIATE refers us to the procedure which first initiates the variable WIDTH OF ANALYSING WINDOW AFTER AOUTOCOR which is the number of frequencies in the Fourier transform, next, initiates the beginning and end of the analysing window, and finally asks for the value of RF and number of runs. RF is the reference field as we defined it in chapter 8, and we would have found the value of this field by exposing the text string to the program 'FINDRF" (page 204) using the same parameters for begining and end of window. "Number of runs" is a provision for up to 25 consecutive runs with the window moved STEP number of words to the right before each new run. The multiple run provision gives up to 25 successive power spectra of the same text string with the window moved - normally - 8 words to the right after each run. These 25 spectra represent 25 'scans' of a moving window and are arranged in a 3-dimensional coordinate system to give a topological surface which clearly shows the changes of spectral features over a 200 word text string (25 runs moved 8 words each time = 200).

With the procedure body INITIATE exhausted, the main program takes over. STEP is set to 0, which means, that the window will be stationary, and (line 350) if NOR (number of runs) is greater than 1 ie if we want more than one run, the main program asks for another value of STEP, and (line 354) whether we want to smoothe with a "Hamming window". If this is the case, we are asked for the weighting of this window.

The procedure body of HAMMING is at line 304. To understand what this procedure does, let us look at a series of data: A1, A2, A3, A4, A5, ...An. The Hamming smoothing procedure will at any point of this series exchange one value with an average, calculated from part of the original value and part of the two neighbour values. Say that the Hamming window is at the value A3 in our series above and let us say that we have settled for a weighting of 0.60. The procedure then takes 60% of the value of A3 and adds to this 20% of each of the values of the neigbours A2 and A4. This becomes the new value of A3. The window then moves to the next value, A4 and calculates the weighted average between this value and the two neighbours A3 and A5 in the same way, and substitutes A4 with this weighted average.

I have arranged the parameters in such a way that the answer to 'weighting?' is the amount with which we want the neighbour values to contribute to the weighted average. Thus, if we answer 0.40, each of the two neighbour points will contribute with 0.20 of their value to the weighted average, whereas an answer of 0.20 would imply that each of the two neigbour points would contribute with 0.10 of their value.

However, a Hamming window used on a Fourier transformation is like "a woolf in sheep's clothes". By this I mean, that the smoothed power spectra resulting from a 50% weighted Hamming window do indeed look seducively nice and smoothe, but in fact, many of the significant peaks have gone. As a rule I have only used smoothing on the three-dimensional graphs and on these graphs I have used a contribution from each neighbour of only 0.12, as this level of weighting smoothes the topological surface without changing its features dramatically.

We will continue with the main program. After the input file has been opened (line 363) the procedure READWORD is called with the parameter N taking the value from 1 to 1+FIN+NOR*STEP. The latter value is the finishing point of the window after INFOR has run NOR runs, and the window has moved STEP words each time. Of course we do not want INFOR to read the textstring from the disk file more than once even though we are moving the window each time, since this is a particular time consuming process, so INFOR reads the maximum necessary text string once only and stores it in the work memory for re-reading.

Not much need to be said about READWORD. It is a straight forward read file procedure which will ignore all characters except those defined in the set of LETTERS i.e. capital letters and numbers only. A word is defined as a number of permitted characters between 2 separators. Accepted separators are: space, end of line and end of file..

The words are stored in the array WORD which is a two-dimensional array with outer boundaries of 1:751 and 1:20. Accordingly this array will store 751 words, which each are not longer than 20 letters. Words longer than 20 letters will be truncated. The array WORD will contain all the words of the string which therefore must not be longer than 712 words. The first word of the string is stored in WORD[1] place 1 to 20, the second word is stored in WORD[2] place 1 to 20 and so forth. When all the words have been read, the main program calls procedure MOVEONE, which moves to LABL the word stored in WORD[1] as this constitutes the label of the string as mentioned above. Finally MOVEONE moves the rest of the words one place forward.

With the required length of text string stored in WORD, all the places in the information array TRANSA are set to 1 (line 372) and the procedure COMPAREWORD is called with the parameters TRANSA and N which will take the value from beginning of the window to the end of the window. For any value of N, COMPAREWORD compares WORD[N] with all the preceding words in the text string as far back as the reference field stretches. Let us say, that we stated to the procedure INITIATE, that our window should begin with word number 401 and end with word number 700 and let us say, that our reference field is 200. COMPAREWORD(TRANSA,401) will then compare word number 401 to all preceding words starting from word number 201 (401 minus reference field) and ending with word number 400. If COMPAREWORD finds a word similar to WORD[401] the value of TRANSA[401] is set to zero. By consecutive calls of COMPAREWORD with N rising from 401 to 700 each incoming word will be compared to all the words of a reference field which remains a constant 200 words stretched out behind the word being checked. When a word is recognised, the place in the information array with the same number as the recognised word is set to zero. A place in the information array with the same number as a word which was not recognised, remains equal to one.

When COMPAREWORD has finished the checking of each word against the word's reference field, TRANSA will contain a succession of zeros and ones, a one on the place of the words which were not recognised, and a zero for each word which was recognised. After this array which is numbered according to the window eg 401 to 700 is now renumbered from 1 to the length of the window (in this case: 300) and the length of the array is attributed to the parameter REAL-TIME.

The array TRANSA is now of the form

TRANSA[1:...]:=10110001011110001101........

and as there are 20 digits, the window resulting in this array must have been 20 words long. To change this series of pulses into a time series it will have to be transformed into a series of distances between the pulses constituted by the ones.

Procedure PULSE (line 167) is such a pulse detector and if we adhere to the example above PULSE will transform TRANSA to the time series

TRANSB[1:10] := (1)2142111412

I have put a paranthesis around the first timing in TRANSB since it is not a genuine distance between two pulses, only between the start of the signal and the first pulse. As it is not immediately obvious how TRANSA transforms into TRANSB I shall explain how it is done. Figure 9.2 is a graphic representation of how the train of pulses in TRANSA is being translated into the time series TRANSB.

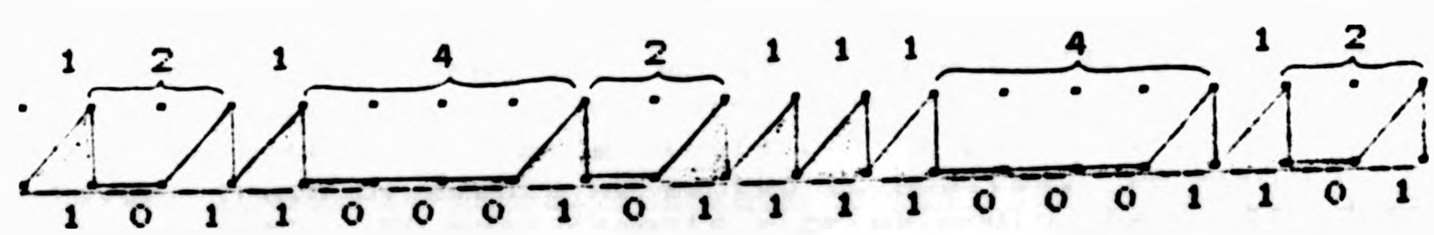

Figure 9.2 The transformation of TRANSA to TRANSB in the procedure PULSE.

The important thing to understand is that the distance between the pulses are measured between the top of the pulses where these become infinitively narrow. Understanding this, it becomes clear enough how TRANSA transforms into TRANSB.

The time series TRANSB however is still not suitable for Fourier analysis: it consists of the timing of eleven peaks taken over the course of 20 time units (word-time units). What we need is a formula which could calculate the value of the signal in each of the 20 time unit points on the basis of interpolation between the eleven known timings. This is what the procedure SINX does. It is able to convert a number of time samples into an equidistant time series. Let us say, more generally, that we have measured the time between M number of events spanned over a total of N seconds. SINX is able to expand the M values into a time series with N equally spaced values. The procedure does this by putting the M samples on polar form and expand this polar series while smoothing and interpolating. The equidistant time series resulting from this procedure is stored in TRANSA which is now empty. Whatever the size of the time series, SINX will transform it into an equidistant time series of the same size as the measuring window.

To recapitulate: Let the measuring window be 200 words long. Let us further assume that after the analysis of I-modes and O-modes, COMPAREWORD has produced a time series with 100 samples of timing, some indicating long distances between the 'ones' in TRANSA, some indicating just one (word) time unit between them. SINX is able to restore this 100 point time series of higly different spacing into an equidistant time series of the same length as the original measuring window, i.e. 200 samples. The equidistant time series resulting from SINX is stored in TRANSA which is now empty.

The main program now calls procedure AUTOCOR with the parameters TRANSA, TRANSB, REALTIME and SAMPLES. TRANSA contains the equidistant timeseries. TRANSB will contain the autocovariance function after this procedure, REALTIME is the length of the measuring window and WIDTH is the so called 'lag' of the autocovariance weighting window which must be the same size as the number of sample points entering the Fourier transform. I shall spend some time explaining the purpose of the autocovariance function.

AUTOCOR serves really two purposes:

Firstly, the autocovariance function 'can change the number of values entering this function into another number of values on exit from this function'. Say, that we want a 50 point power spectrum. If we want a 50 point spectrum from the Fourier transform used in this program, we would have to 'feed' it with 50 values from our time domain. This again means, that every time we wanted to make a Fourier analysis of the pattern, structure or whatever train of events we wanted to analyse, we would have to obtain exactly 50 measurements - or we would have to discard whatever number of measurements greater than 50. This would certainly be possible in many cases, but more often than not, we would want many more measurements than 50 included in our analysis to increase the significance of our results, since as we shall see later, the significance of the results from the Fourier analysis is a function of the number of measurements in the time domain divided by the number of points in the frequency spectrum.

This is where the autocovariance function becomes a great help, since if we have say, 217 measurements of the train of events we want to analyse, but have decided on a 50 point spectrum, we can 'feed' all 217 measurements into the autocovariance function, set the 'lag' of this function to 50 (see below), and out comes (most of) the information from the 217 measurements condensed into 50 values which we can now transform into a spectrum of 50 points. I write 'most of' the information, since some information like phase shift is lost. However, this is not going to have any impact on our search for structures.

Secondly, when we are working with time series, the Fourier transform of such series becomes particularly simple, even simpler than the Fast Fourier Transform, if we autocorrelate this time series, since all we need to do to obtain the power spectrum is to apply the simple so called cosine transform (the procedure

PSPEC. line 283). This procedure on its own is much faster than 'The Fast Fourier Transform' mentioned earlier, but since we would have to precede any Forier transform of a time series with a slow procedure like SINX to get an equidistant time series, nothing is gained.

As stated in chapter 7, when we dealt with the folding of the frequency spectrum, it is not possible to get higher frequencies in the frequency spectrum than half the sampling frequency. This means, that because our particular sampling was done once per word = 1/1, our highest frequency in the frequency spectrum is not going to be greater than 1/2 = 0.5. If we want a resolution in this spectrum of 0.01 it means, that we shall need 50 points. That has a bearing on the autocovariance function since we must settle for a maximum lag of 50 in this case. I shall explain what this means.

Although I have no intention of sidestepping into making this a course in statistics, I shall try - very briefly - to account for what is going on in an autocovariance analysis. You may vaguely remember the "standard deviation" from an early introduction to basic statistics and you may even remember, that this deviation was the difference between a set of data of a sample and the mean of this sample. Variance is the square of the standard deviation. If you look at equation (9.3) below you will see, that the last part {Y(j)-Y(mean)}*{Y(j+k)-Y(mean)} is really just a glorified standard deviation squared, except for the ...+k in the second last subscribt. This k is the above mentioned lag, and I shall try to describe the function of this.

Let us say that we have an ordered set of data (eg a time series) Y(1),Y(2),Y(3),......,Y(99),Y(100). To make an autocovariance function out of this set of data we decide on the size of the "lag". For the reasons stated above, we want a maximum lag of 50. Bearing in mind, that during the first "run" through the series, k takes the value 1, during the second "run" the value 2 and so on up to 50, we then calculate the following according to (9.1): Y(1)-Y(mean) and multiply this with Y(1+1)-Y(mean). Let us call this variance S(1). We are still in the first "run" and k remains at the value 1 whereas j takes successive values of 1,2,3,4... up to 100 - k. For each value of j we calculate the product of each variance (Y and Y+lag) up to 100 - the lag. In this way we get successive products of variance S(1),S(2),S(3)... up to S(99)=(100-k). For each "run" of a different value of k, we sum these variance products and multiply them whith the factor 1/(100-k). In the end we have the so called autocovariance function which, if the lag is 50, will consist of 50 elements, one for each value of k.

The following formula is the base of procedure AUTOCOR:

$$R\ (k) = \frac{1}{N-K} \sum_{j=1}^{N-K} z_j . z_{j+k} = \frac{1}{N-K} \sum_{j=1}^{N-K} (Y_j - Y_{Mean})\ (Y_{j+k} - Y_{Mean}) \qquad (9.3)$$

in which
N = number of elements in time series emerging from SINX.
k = lag in autocovariance function (k=1,2,3,4...,WIDTH).
j = number of element in time series (j=1,2,3,4....,N).
Y = element (IN) of time series.
R = element (OUT) of autocovariance function.

The elements resulting from the autocovariance function are stored in the array OUT[O:WIDTH] in line 277. One last point: In line 261 and 276 an integer has been changed to a real number. This has been done because the integer in both cases were going to be squared in the following lines and thereby would have exceeded the highest integer value my microcomputer could cope with.

Procedure PSPEC. (Line 265).

This procedure calculates the power density spectrum of a time series by Fourier transformation of the autocovariance function as calculated by AUTOCOR. The following formula was used

$$S \quad (m) = \frac{\Delta t}{100} \{ R \quad (0) + 2 \sum_{k=1}^{m-1} R \quad (k) \,.\, \cos \frac{\pi k m}{M} + R \quad (M) \cos (\pi m) \} \qquad (9.4)$$

where

S(m) = power of the m'th frequency.
R(k) = k'th autocovariance element.
t = sample interval.
m = element of frequency spectrum (m=1,2,3,.....,WIDTH).
k = element of autocovariance function (k=1,2,3,.....WIDTH).
M = maximum frequency.

As a guideline, if you want to go through the principle of calculating the power spectrum according to this formula, note, that this time it is m which is kept constant during each run, while k takes the values 1,2,3,......,WITH-1, WIDTH.

Enough has been said about the smoothing procedure HAMMING above, so there is only the procedure FILEOUT left to look at. This procedure quite simply channels the smoothed or not smoothed data comming from PSPEC to the disk file with initial information about the name of the string, the start and end of the measuring window, the length of the reference field, the number of runs and the size of STEP, which, as you may remember, is the number of words, the window is moved after each consecutive run.

Finally (Line 387 to line 390), if the counter (j in line 390) of the actual number of performed runs is less than the final number of runs, then the window is moved STEP words to the right and INFOR repeats the analysis with the window in the new position. This means, that if INFOR has made 25 consecutive analysis' then the outfile contains the spectral powers for 25 consecutive spectra, ie. if the number of frequency points in each spectrum is 32 then the outfile will contain 25 times 32+1 points (The extra point is the DC value or the value in the frequency point zero. These values are arranged in such a way, that the first 33 values constitute the first spectrum, the next 33 values constitute the second spectrum and so forth. These values will be stored on a memory disk and later fed to the program PLOT25, which we shall have a look at later.

Program INFOR25FFT.

With this, I hope, adequate explanation of the first version of

INFOR (Program INFOR25TIMESERIES) I shall turn to the second version (Program INFOR25FFT). The need for another version reflects a need for a more graded analysis of the information transfer from a text string. The first version of INFOR is in accordance with the basic view of the model of 'best fit' that when we read a text string there are only 2 states of information: zero and one. But is it realistic to assume, that eg. the word "and" in I-mode, transfers just as much information (namely 1) as does a word like "war" in I-mode? Our common sense says not.

So, to accommodate a more graded approach to information transfer from text strings, the second version (Program INFOR25FFT) which is able to transform analog signals, was developed. While still within the model of "best fit" we are however now able to analyse an information array , the values of which do not have to be zero or one, but can take any (positive) value.

We have now got two Fourier transforms. The first one - the Cosine Transform - which we used in INFOR-TIMESERIES, and the second one - the Fast Fourier Transform - which we are going to use in the second version of INFOR - appropriately called INFOR-FFT.

It is important to understand the basic difference between the Cosine Transform and the Fast Fourier Transform. The first transform - the one which is used to analyse a time series - can only transform a signal based on distances between events eg. distances between two peaks or between the 'ones' of our information array. This transform - the Cosine Transform - depends on the pulses of events being very narrow, and does thus not provide for different shapes of pulse, like square or triangle pulses; nor does it provide for different amplitude of the pulses.

The Fast Fourier Transform on the other hand does not impose such restrictions on our analysis. The amplitude of the signal as well as the shape of its pulses have become part of the analysis and have an impact on the power spectrum. This is important - often essential - in some kinds of analysis, but does on the other hand have its disadvantages: One is, that if the signal is made up of square pulses, as the case is in our application of the transforms, the power peaks in the high frequency part of the spectrum reflect the 'squareness' of the pulses as explained in chapter 7, rather than the presence of a basic periodicity. In such cases one would try to use the Cosine Transform instead to reduce the 'noise' in the high part of the spectrum, but in the cases where the amplitude of the signal MUST be taken into account, one would have to use the Fast Fourier Transform and accept the 'disfiguration' or 'noise' in the high frequency part of the power spectrum.

We are primarily going to use the FFT for the analysis of analog signals - signals with a variation of amplitudes. Although, in a sense, the use of the FFT on binary signals - signals with just two different levels like 1 and 0 - is 'over-kill', we shall try too to apply the FFT to our 'old' 1 and 0 signals. The advantage, of doing so, is that we can check our results, we can compare the power spectrum we get from the Cosine Transform with the one we get from an analysis of the same text string made by the FFT. Apart from some differences in the high frequency part, the two spectra should be pretty similar. Figure 12.1 in chapter 12 shows, that this is indeed the case.

One problem regarding the FFT is that it can only transform a number of samples if the number is a power of two, ie. it can transform a sample of 32 or 64 or 128 values and so on, and the transform will contain two in the next lower power spectral points. This means, that if we provide 32 measurements to the FFT, we only get a 16 point spectrum. A 64 point function leaves us with 32 spectral point etc. This has proved a restriction in the anlysis of childrens short text strings, because I have found, that the minimum number of frequency points needed to give the necessary resolution in a power spectrum, is 32. This does not pose a problem with the Cosine Transform since this transform only needs a 32 point window to give a 32 point spectrum, whereas using the FFT, one needs a 64 point window to get a 32 point spectrum. This does not give much room for a reference field as well as a measuring window, when the text string is short, may be of less than 100 words.

Initially I only knew of the FFT analysis and found it hopelessly restrictive to work with, as my main object (then) was to analyse childrens text strings only. From most of these text strings I could get only 16 point spectra, and virtually no sta-tistical significance. My later encounter with the time series transform - and some considerable adaptation of this method to my purpose - provided me with a means of analysing these shorter strings. Later, when I realised how far more flexible time series trans-formation is, it became my main tool, until the need to analyse different amplitudes - the more graded view of information trans-fer mentioned above - made it necessary to return to the FFT analysis.

We shall now turn to another problem. That of 'stationarity'. That a function is stationary means, that a possible periodicity in the function does not change with time. However, it is almost inherent in our concept of life, that biological functions are not perfectly stationary even though over a shorter period of time they may exhibit some measure of stationarity and periodici-ty. To find periodicity in a function which is not perfectly stationary is thus a balance between using a window which is long enough for a periodicity to establish itself, and not so long that this periodicity becomes unstationary. It is even quite feasable, that the different periodicities in a function may have different stationarity as well. That this is indeed the case with the output from our 'linguistic device' I shall demonstrate in the features on the topological surface on the graphs from the multiple - scanning - runs in the next chapter.

But let us now turn to INFOR25FFT (Page 231). The first (with regard to data flow) difference between this version of INFOR and the former, is found in the main program at line 288, where the program asks whether we want to change from binary to analog coding. If this is the case - and I shall not enlarge further on the opposite possibility - the boolean variable CODE is changed to true. The text strings which were used for analog coding were of the form printed in the appendix to chapter 12. The first character in the words which I wanted to give a higher rating in I-modes were a number, normally an '8' as explained in chapters 8 and 9.

If we have chosen the program to read in analog mode, the procedure COMPAREWORD (Line 108), on encountering a word in I-mode, checks the first character of the word, and if this character is a number, this number will be transferred to the information array. If the first character is not a number, the usual '1' will be transferred to the information array. This means of course, that any coded word in I-mode in the text string will transfer to the information array the value we have put in front of the word, and that the information array, instead of being an array of only zeroes and ones, as before, now is an array of zeroes, ones and some higher values - namely the values we have chosen to put in front of some words as a token of a higher information transfer taking place.

There is a provision for choosing the value of the 'pulse' (Line 299). This was made so that I could choose the amplitude of the signal with regard to the non-encoded I-modes, but it has in all the results presented in this paper been set to '1' and is therefore no different from setting the information array to '1' before the start of the analysis done in the first version of INFOR (INFOR25TIMESERIES, line 372).

The next procedure which is different is the Fourier Transform itself, the FFT. I shall not enter into an extensive examination of this procedure as it is rather complex. Suffice to say, that it is a two-dimensional transform, which is able to analyse the real as well as the imaginary part of a function. As we use it to analyse only real functions, the imaginary parameter of the procedure is set to zero (Line 332).

As you can see from the procedure calls before and after FFT, the number of points changes from 64 to 32 as explained above.

Like the case was in the first version of INFOR, there is also in this version the option of having the data from the power spectrum smoothed by a Hamming window. Like before, this option was only used to smoothe the date during the multiple scanning runs, never in the single runs. The option in this version of INFOR for multiple scanning runs i.e. 25 consecutive analysis with the window moved STEP number of words each time, is exactly the same as in the first version and the explanation shall not be repeated. With this, we have in fact concluded the examination of both versions of INFOR.

Program PLOT25.

To transform the series of spectral points from either of the two versions of INFOR into a power spectrum, the program PLOT25 (Page 237) was written. This program is, as the name implies, a plotting routine. As my ambition all along has been to demonstrate the dynamic structures in text strings, both versions of INFOR provide for 25 consecutive runs - a scanning - of a text string with the window moved a few words to the right each time. PLOT25 provides of course for the eventual plotting of those 25 consecutive spectra, and, by means of a hidden line routine, creates a topological surface within a 3-axis system where the parameters are: LN power (y-axis), frequency (x-axis) and length of text string or 'time' (z-axis).

PLOT25 provides for the plotting of both single power spectra and multiple runs by always first plotting a single power spectrum. If the data comming in to PLOT25 are from a single run, this first graph is the final power spectrum (Figure 9.5). If the data fed to PLOT25 are from a multiple run, the first graph will become an averaged spectrum of the 25 spectra, and the heading will change to 'AVERAGED SPECTRUM' (Figure 9.6). In this case, as shown in figure 9.6, the three-dimensional surface will be plotted after the average power spectrum has been plotted.

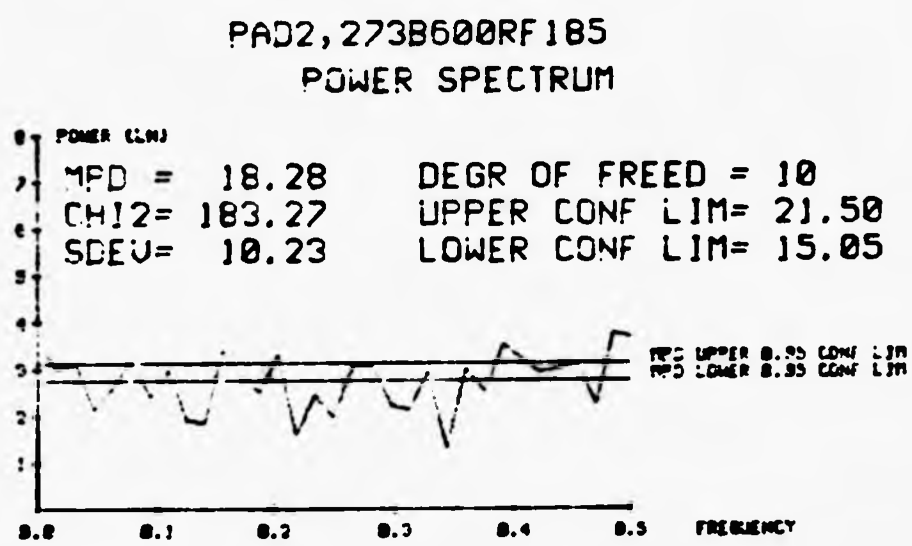

Figure 9.5 Power spectrum of PADDINGTON/2. window 273 to 600.

But let us focus first on single power spectra. These are FIXED WINDOW analysis as opposed to the multiple run analysis with the moving window we have just been talking about. Figure 9.5 shows a typical spectrum. It is the 32 point power spectrum of the text string PADDINGTON 2. from word number 273 to word number 600, with a reference field of 185 words. The Y-axis, is the logarithm (ln e) to the power in each spectral point, the X-axis is equidistant and gives the frequency, with the lower frequencies to the left and higher frequencies to the right. The point furthest to the right (F = 0.5) represents the highest resolution we will be able to get (2 words) when we sample at the frequency of 1 word at a time. This means, that the spectrum will not be able to tell us about structures between less than two words. Fourtunate-ly this has no bearing on our analysis, since we do not consider it possible to anticipate structures between less than two words anyway. As we move to the left on the X-axis, the change in frequency represents bindings between more and more words. F=0.2 thus represents periodicity or structures stretching over 5 words while F=0.1 represents periodicity or structures stretching over 10 words etc. The point furthest to the left of the X-axis (F=0.0) represents the DC power as explained in chapter 7.

I shall leave further considerations regarding the spectrum until the next chapter when we are going to analyse all the text samples in this way. Suffice only to explain the statistics procedure.

MPD stands for 'Mean Power Density' and is the mean of the power of all 33 spectral points (32 points + F=0.0). The mean power density is calculated in procedure FINDMPDS (line 86). CHI2 stands for chi square and is chosen as the best measure of variance since there are considerable variations between the mean power of all the individual spectra. Chi square remedies this by being a 'normalised' measure of variance i.e. a variance divided by a mean. Chi square and the standard deviation SDEV are calculated in procedure STAT (line 115). The standard deviation is needed for the calculation of the 0.95 upper and lower confidence limit. For this purpose we need the number of degrees of freedom as well. As stated earlier, the number of degrees of freedom is found as the length of the window divided by the number of frequency points in the spectrum.

The confidence limits are calculated in procedure LIMITS (line 300) and the necessary T values come from the T table in function TEATABLE (line 134). The single power spectrum is plotted by procedure MPDPLOT (line 312). The statistical information is printed and the upper and lower confidence limits drawn by procedure PLOTSTAT in line 364.

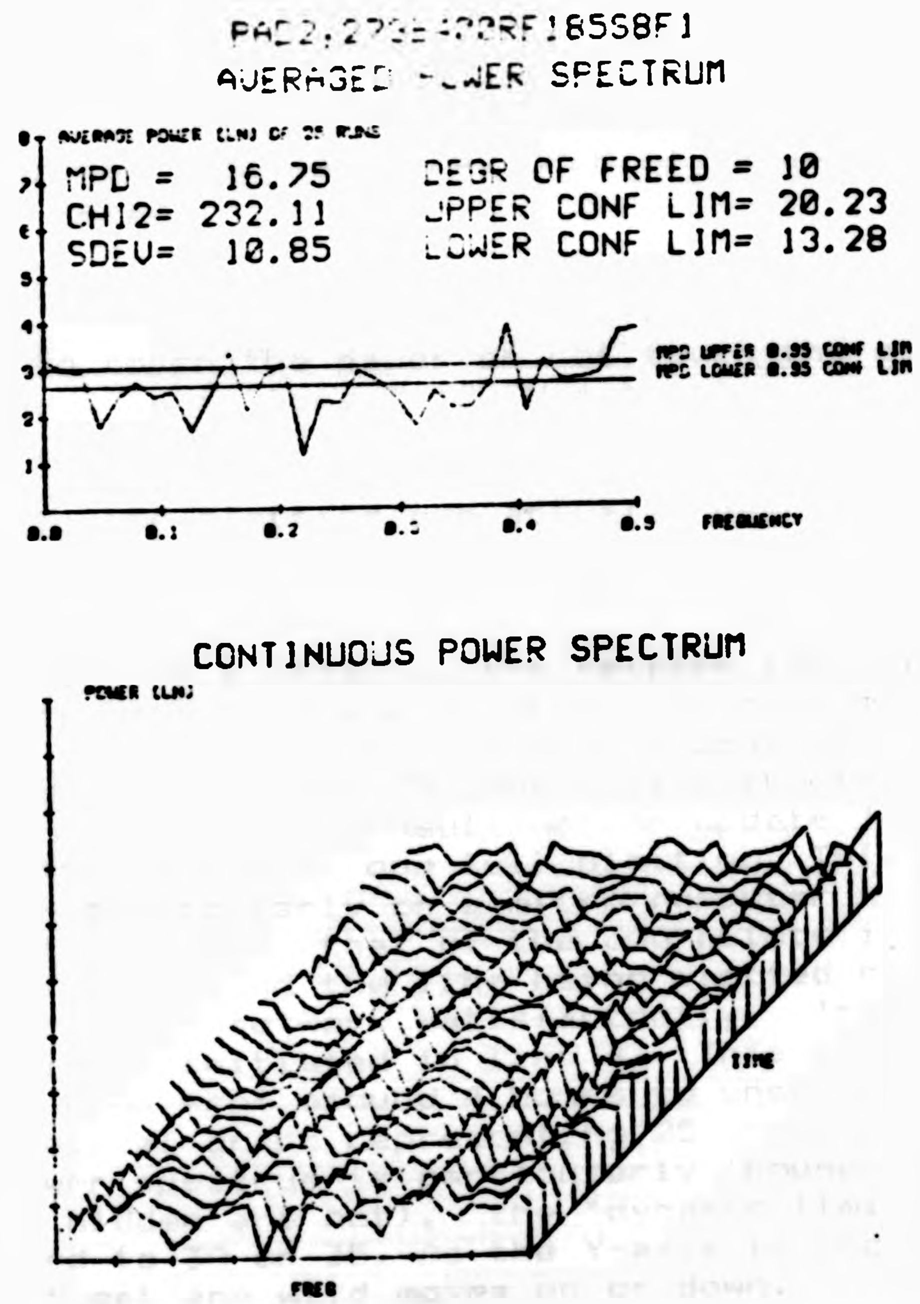

Figure 9.6 Multiple power spectra of PADDINGTON/2.

In spite of the time consuming exercise of writing the three-dimensional plotting algorithm, this particular aspect of PLOT25 can be said to be of minor importance, since it was only used a few times in my research. For this reason, I shall not enter into lengthy explanations about this part of the program, only explain a couple of the less obvious routines.

The most complex (and time consuming) algorithm is the hidden line routine made up of the two procedures SHADOW (Line 241) and MINALFA (Line 263). The first procedure is a shadow mask consisting of a two-dimensional boolean array OPEN, 8 plotting points wide and 300 plotting points high, the initial value for all members of this array being set to 'true'. This shadow mask works as a map of the lines which have been drawn and is continually being updated.

The three-dimensional surface is plotted vertically from left to right, all 25 spectra at the same time. While the surface is being plotted, the procedure EXPAND divides each area between two frequency points into a number of sub-zones, and MINALFA calculates the path - through these sub-zones - of each line connecting two frequency points.

As each value in the shadow mask OPEN refers to a point in the sub-zones between two frequency points, the calculated path between two frequency points can be represented by a path in the two-dimensional boolean array OPEN of values being changed from 'true' to 'false'.

At any point within an area covered by the 8 by 300 points of the shadow mask OPEN, this mask (reference map) directs the plotting pen to touch the paper or not touch the paper according to whether the area is 'open' (OPEN = true) i.e. no lines have been drawn here so far, or 'not open' (OPEN = false) i.e. another line was drawn here and the next line must then be hidden (not drawn). Consequently the plotting pen actually describes the moves of all lines - hidden or not - but lifts from the paper when the line is hidden, and returns to the paper when the line is visible.

Each time we have plotted a line between two frequency points, we must update the shadow mask OPEN. As this mask consists of 8 times 300 points, and each spectrum consists of 32+1 frequency points, and as there are 25 consecutive spectra, we can calculate that we would have to consult and/or update 1,980,000 reference points in the course of one full plotting. This is of course time consuming - particularly on a micro computer - so from experience I have established, that of the 300 points in the Y-direction only 25 points around the line being plotted need to be consulted for the routine to work satisfactorily. This is the so called 'dynamic limit' initiated in line 4. This has brought the plotting time down from around 4 hours to under half an hour for a full topological graph representing 25 consecutive runs by INFOR. If the power spectrum is particularly 'bouncy' (some lines that should be hidden are not), the 'dynamic limit' in line 4 should be increased to 30 or 35. As the Y-axis is logarithmic, we should however not get any wild moves up or down.

Program INFORNORMALISED.

The two versions of INFOR we have dealt with in the past - INFOR TIMESERIES and INFOR FFT - give absolute measures of power in each frequency point, and the mean power density is an absolute measure of the amount of structure in each text string. The size of MPD varies widely between the different text samples, and although no connection between the size of MPD and other factors has been established, it is a worthwile exercise comparing the different text strings in this respect.

In the last part of my research - the grammatical coding - it was necessary to change the calculation of the power spectra slightly. In the analysis of grammatical coding we code the same text string in different ways and want to compare the spectrum derived from each change of coding. To make it possible to superimpose one spectrum onto another spectrum to evaluate relative change, the spectra were 'normalised'. This simply means, that the power in each frequency point is divided by the highest power of any of the frequency points. In this way the maximum power of any power spectrum will be 1 and all other values will be 1 or less. This makes it easier to compare relative movements, but is paid for by the loss of the above mentioned information. (Now it becomes clear, that the reason, we had to use a logarithmic Y-axis in connection with the two versions of INFOR, was that we could not prevent the big fluctuations in the power spectra by normalising after the AUTOCOR procedure, since there would then have been no point in calculating and comparing mean power densities).

INFORNORMALISED caters for this particular provision. Apart from the power being normalised, it is just like a one-run INFOR FFT. INFORNORMALISED is made for the sole purpose of grammatical coding (see chapter 12) and evaluation of relative changes between power spectra. Even though the primary purpose of INFORNORMALISED is to provide qualitative rather than quantitative comparison between different power spectra, Mean Power Density and Variance is provided never the less (on the power print-outs) and 95% confidence limits are shown on the spectra.

Program PLOTNORMALISED.

PLOTNORMALISED plots the data emerging from INFORNORMALISED's analysis of the grammatically coded text string. The program provides for the plotting of two graphs in the same co-ordinate system. Normally the two graphs would be the spectra of the grammatically coded and the non-coded version of the same text string. This makes comparison between the two spectra easy. As it is evident from the explanation above, the Y axis does not need to be logarithmic any longer.

With PLOTNORMALISED we have finished the examination of the programs which make power spectral analysis of text strings possible. However, as I thought it might be of some help in the understanding of how INFOR TIMESERIES works, I have included two pages which show the intermediate values between each procedure of INFOR during the calculation of the power spectrum of figure 9.5.

In the next chapter we shall optimise some of the parameters of these programs: number of frequency points in the spectra, window width and reference field, and in chapter 11 we shall make use of these programs to evaluate quantity and quality of structure in text strings - and at the same time get a look into the linguistic device.

PROGRAM CODE

INDEX:

```
PROGRAM FINDRF(TEXTIN);
LABEL 1,2,3;
CONST
    MAXWORDLEN=20;
    NUMBOFWORD=801;
TYPE
    WORDINDEX=1;MAXWORDLEN;
    TEXTINDEX=0;NUMBOFWORD;
    WORDTYPE=PACKED ARRAY[TEXTINDEX.WORDINDEX] OF CHAR;
    TRANSFTYPE=ARRAY[TEXTINDEX] OF REAL;
VAR
    WORD:WORDTYPE;
    LABL:PACKED ARRAY[WORDINDEX] OF CHAR;
    TRANLA:TRANSFTYPE;
    N,N1.N2.RF,START.FIN:INTEGER;
    RATIO:REAL;
    CH:CHAR;
    FIRST:BOOLEAN;
    TEXTIN:TEXT;
    LETTERS:SET OF CHAR;
    F:INTERACTIVE;

PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
     BLANK=' ';
VAR
     N.CHARCOUNT:INTEGER;
     CH:CHAR;
BEGIN

      FOR N:=1 TO MAXWORDLEN DO WORD[L.N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
          WHILE NOT EOLN(TEXTIN) DO
          BEGIN
              READ(TEXTIN.CH);
              IF CH=BLANK THEN GOTO 2;
              IF EOLN(TEXTIN) THEN
              BEGIN
                  WORD[L.CHARCOUNT]:=CH;
                  GOTO 2;
              END;
              IF CH IN LETTERS THEN
              BEGIN
                  WORD[L.CHARCOUNT]:=CH;
                  CHARCOUNT:=CHARCOUNT+1;
                  IF CHARCOUNT>MAXWORDLEN THEN
                  BEGIN
                      WHILE CH<>BLANK DO
                      READ(TEXTIN,CH);
                      CHARCOUNT:=1;
                  END;
                  GOTO 1;
              END;
          END;
          READLN(TEXTIN);
      END;
      IF EOF(TEXTIN) THEN
      BEGIN
          CONACT(0);
          WRITE('EOF AT WORD NR:'.L);
```

```
          HALT;
       END;
  2:   IF WORD[L,1]=BLANK THEN
       BEGIN
          CHARCOUNT:=1;
          GOTO 1;
       END;
  END;

  PROCEDURE MOVEONE;
  VAR
      N,M:INTEGER;
  BEGIN
      FOR N:=1 TO 20 DO
      LABL[N]:=WORD[1,N];

      FOR N:=2 TO FIN+1 DO
      WORD[N-1]:=WORD[N];
  END;


  PROCEDURE COMPAREWORD(VAR INFARRAY:TRANSFTYPE;
                                RIGHTEDGE:INTEGER);
  LABEL 1;
  VAR
      LEFTEDGE,K:INTEGER;
  BEGIN
      LEFTEDGE:=RIGHTEDGE-RF;
      K:=0;
      REPEAT
          IF WORD[LEFTEDGE+K]=WORD[RIGHTEDGE] THEN
          BEGIN
              INFARRAY[RIGHTEDGE]:=0;
              GOTO 1;
          END;
          K:=K+1;
      UNTIL K=RF;
  1:END;

  PROCEDURE FINDRATIO(VAR NEW:TRANSFTYPE;
                           N,M:INTEGER);
  VAR
      NIL,ONE,L:INTEGER;
  BEGIN
      ONE:=1; NIL:=1;
      FOR L:=N TO M DO
      IF ROUND(NEW[L])=0
      THEN NIL:=NIL+1
      ELSE ONE:=ONE+1;
      RATIO:=NIL/ONE;
  END;

  PROCEDURE BOOKIN;
  VAR
      NAME:STRING;
  BEGIN
      CONACT(0);
      WRITELN('NAME OF INPUT FILE:');
      READLN(NAME);
      {$I- I/O OFF}
      RESET(TEXTIN,NAME);
      WHILE IORESULT<>0 DO
      BEGIN
          WRITELN('FILE NOT FOUND, TRY AGAIN');
          READLN(NAME);
          RESET(TEXTIN,NAME);
```

```
          END;
    END;



    BEGIN--MAIN PROGRAM
          RESET(F,'CONSOLE:');
          LETTERS:=['0':'9','A':'Z'];
    3:    BOOKIN;
          FIRST:=TRUE;
          CONACT(0);
          WRITELN('PRESENT LIMITATION: 800 WORDS');
          WRITELN;
    1:    WRITELN('WINDOW TO START WITH WORD NR:');
          READLN(F,START);
          WRITELN('WINDOW TO END WITH WORD NR:');
          READLN(F,FIN);
          N:=FIN-START+1;
          IF ODD(N) THEN
          BEGIN
               WRITELN;
               WRITELN('ONE END OF WINDOW MUST BE EVEN, THE OTHER ODD');
               WRITELN;
               GOTO 1;
          END;
          WRITELN('INITIAL RF: ');
          READLN(F,RF);
          IF FIRST THEN
          BEGIN
               FOR N:=1 TO FIN+1 DO READWORD(N);
               MOVEONE;
               FIRST:=FALSE;
          END;
    2:    N1:=TRUNC(LN(RF)/LN(2));
          REPEAT
               WRITE('RF = ',RF:3);
               FOR N:=START TO FIN DO TRANLA[N]:=1;
               FOR N:=START TO FIN DO COMPAREWORD(TRANLA,N);
               FINDRATIO(TRANLA,START,FIN);
               IF (RF=START-1) AND (RATIO<1) THEN
               BEGIN
                    WRITELN; WRITELN;
                    WRITELN('******** REFERENCE FIELD TOO SHORT ********')
                    WRITELN('DO YOU WANT TO CONTINUE WITH THIS FILE? (Y/N)
                    READ(F,CH);
                    WRITELN;
                    IF CH = 'Y' THEN GOTO 1
                    ELSE
                    BEGIN
                         CLOSE(TEXTIN);
                         GOTO 3;
                    END;
               END;
               WRITELN('    RATIO = ',RATIO:3:2);
               N1:=N1-1;
               N2:=ROUND(EXP(N1*LN(2)));
               IF RATIO > 1.0 THEN RF:=RF-N2
               ELSE IF RATIO < 1.0 THEN RF:=RF+N2;
          UNTIL (RATIO = 1) OR (N1 < 0);
          IF RATIO <> 1 THEN
          BEGIN
               WRITELN('DO YOU WANT WINDOW MOVED? (Y/N)');
               READ(F,CH);
               IF CH = 'Y' THEN
               BEGIN
                    START:=START-3;
```

```
                FIN:=FIN-3;
                CONACT(0);
                WRITELN('WINDOW MOVED 3 STEPS TO THE LEFT');
                GOTO 2;
            END;
        END;
        IF RATIO=1 THEN
        BEGIN
            CONACT(0);
            FOR N:=1 TO 20 DO WRITE(LABL[N]);
            WRITELN;
            WRITELN('START:'.START:4.'    FIN:',FIN:4);
            WRITELN('REFERENCE FIELD:',RF:4);
        END;
        WRITELN; WRITELN;
        WRITELN('ANOTHER RUN? (Y/N)');
        READ(F.CH);
        IF CH='Y' THEN
        BEGIN
            CLOSE(TEXTIN);
            GOTO 3;
        END;
    END.
```

```
PROGRAM INFOR25TIMESERIES(TEXTIN,TEXTOUT);
LABEL 1;
CONST
    MAXWORDLEN=20;
    NUMBOFWORD=751;
TYPE
    WORDINDEX=1:MAXWORDLEN;
    TEXTINDEX=0:NUMBOFWORD;
    WORDTYPE=PACKED ARRAY[TEXTINDEX,WORDINDEX] OF CHAR;
    TRANSFTYPE=ARRAY[TEXTINDEX] OF REAL;
VAR
    WORD:WORDTYPE;
    LABL:PACKED ARRAY[WORDINDEX] OF CHAR;
    TRANSA,TRANSB:TRANSFTYPE;
    J,N,M,RF,START,FIN,NOR,STEP,SAMPLES,
    TRANSINT,REALTIME,WIDTH:INTEGER;
    TGEM,MPD,WEIGHT:REAL;
    F:INTERACTIVE;
    HAM,MORE:BOOLEAN;
    CH:CHAR;
    NAMEIN,NAMEOUT:STRING;
    TEXTIN,TEXTOUT:TEXT;
    LETTERS:SET OF CHAR;
    NUMBERS:SET OF CHAR;
PROCEDURE BOOKIN(VAR NAME:STRING);
BEGIN
     CONACT(0);
     IF MORE THEN
     BEGIN
          WRITELN(NAMEIN,' WAS LAST FILE IN');
          WRITELN(NAMEOUT,' WAS LAST FILE OUT');
          WRITELN;WRITELN;
     END;
     WRITELN('NAME OF INPUT FILE:');
     READLN(F,NAME);
     {$I- I/O OFF}
     RESET(TEXTIN,NAME);
     WHILE IORESULT<>0 DO
     BEGIN
          WRITELN('FILE NOT FOUND, TRY AGAIN');
          READLN(F,NAME);
          RESET(TEXTIN,NAME);
     END;
END;
PROCEDURE BOOKOUT(VAR NAME:STRING);
BEGIN
          WRITELN('NAME OF OUTPUT FILE:');
          READLN(F,NAME);
          {$I- I/O OFF}
          RESET(TEXTOUT,NAME);
          CLOSE(TEXTOUT,PURGE);
          REWRITE(TEXTOUT,NAME);
END;
PROCEDURE INITIATE;
```

```
VAR
     CH:CHAR;
BEGIN
     CONACT(0); WRITELN(NAMEIN,' IS FILE IN');
     WRITELN(NAMEOUT,' IS FILE OUT');
     WRITELN;
     WRITELN('WIDTH OF ANALYSING WINDOW AFTER AUTOCOR: ');
     READLN(F,WIDTH);
     WRITELN('WINDOW TO START WITH WORD NR:');
     READLN(F,START);
     WRITELN('WINDOW TO END WITH WORD NR:');
     READLN(F,FIN);
     WRITELN('RF:');
     READLN(F,RF);
     WRITELN('NUMBER OF RUNS: ');
     READLN(F,NOR);
END;



PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
     BLANK=' ';
VAR
     N,CHARCOUNT:INTEGER;
     CH:CHAR;
BEGIN

      FOR N:=1 TO MAXWORDLEN DO WORD[L,N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
           WHILE NOT EOLN(TEXTIN) DO
           BEGIN
                READ(TEXTIN,CH);
                IF CH=BLANK THEN GOTO 2;
                IF EOLN(TEXTIN) THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     GOTO 2;
                END;
                IF CH IN LETTERS THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     CHARCOUNT:=CHARCOUNT+1;
                     IF CHARCOUNT>MAXWORDLEN THEN
                     BEGIN
                          WHILE CH<>BLANK DO
                          READ(TEXTIN,CH);
                          CHARCOUNT:=1;
                     END;
                     GOTO 1;
                END;
           END;
           READLN(TEXTIN);
      END;
      IF EOF(TEXTIN) THEN
      BEGIN
           CONACT(0);
           WRITE('EOF AT WORD NR:',L);
           HALT;
      END;
```

```
2:    IF WORD[L,1]=BLANK THEN
      BEGIN
           CHARCOUNT:=1;
           GOTO 1;
      END;
END;



PROCEDURE MOVEONE;
VAR
     N,M:INTEGER;
BEGIN
     FOR N:=1 TO MAXWORDLEN DO
     LABL[N]:=WORD[1,N];
     FOR N:=2 TO FIN+1 DO
     WORD[N-1]:=WORD[N];
END;



PROCEDURE COMPAREWORD(VAR INFARRAY:TRANSFTYPE;
                          RIGHTEDGE:INTEGER);
VAR
     LEFTEDGE,K:INTEGER;
BEGIN
     LEFTEDGE:= RIGHTEDGE-RF;
     K:=0;
     REPEAT
          IF WORD[LEFTEDGE+K]=WORD[RIGHTEDGE] THEN
          BEGIN
               INFARRAY[RIGHTEDGE]:=0;
               EXIT(COMPAREWORD);
          END;
          K:=K+1;
      UNTIL K = RF;
END;



PROCEDURE PULSE(VAR TRANSF,INF:TRANSFTYPE;
                    NI:INTEGER;
                VAR NO:INTEGER);
VAR
     K,N,M,STEP:INTEGER;
BEGIN
     K:=0; N:=1;
     REPEAT
          STEP:=1;
          WHILE TRANSF[N+STEP] < 0.5 DO STEP:=STEP+1;
          K:=K+1;
          N:=N+STEP;
          INF[K]:=STEP;
     UNTIL N+STEP > NI;
     NO:=K;
END;



PROCEDURE SINX(VAR NEWF,OUT:TRANSFTYPE;
                   NI,NO:INTEGER);
LABEL 1,2,3,4;
VAR
```

```
     SIX,IND:ARRAY[-100:NUMBOFWORD] OF REAL;
     IST,I,N,K,IV,KU,LIMITS:INTEGER;
     DELT,PI,RSI,VX,XS,ST,TSV,STS:REAL;
BEGIN
     TGEM:=0;
     FOR I:=1 TO NI DO TGEM:=TGEM+NEWF[I];
     TGEM:=TGEM/NI;
     STS:=-40; ST:=STS; PI:=4*ARCTAN(1);
     IST:=ROUND(ST/TGEM);
     FOR I:=IST TO -1 DO
     BEGIN
          IND[I+1]:=TGEM;
          IND[NI-I]:=TGEM;
     END;
     IND[IST]:=0;
     FOR I:=1 TO NI DO IND[I]:=NEWF[I];
     FOR I:=IST TO (NI-IST) DO
     BEGIN
          ST:=ST+IND[I];
          SIX[I]:=SIN(PI*ST);
     END;
     I:=IST; ST:=STS;
     FOR K:=1 TO NO DO
     BEGIN
          KU:=0; RSI:=0;
 1:       DELT:=ST-K;
          IF DELT< -40 THEN GOTO 2
          ELSE
          BEGIN
               IF KU=1 THEN GOTO 3
               ELSE
               BEGIN
                    TSV:=ST;
                     KU:=1;
                     IV:=I;
               END;
 3:            VX:=PI*DELT;
               IF VX=0 THEN
               BEGIN
                    IF ODD(K) THEN XS:= -1
                    ELSE XS:=1;
               END
               ELSE XS:=SIX[I]/VX;
               RSI:=RSI+XS;
 2:            I:=I+1;
               IF I>(NI-IST) THEN GOTO 4;
               ST:= ST+IND[I];
               IF DELT < 40 THEN GOTO 1;
          END;
 4:       IF ODD(K) THEN RSI:=(-1)*RSI;
          OUT[K]:=(RSI*TGEM);
          I:=IV;
          ST:=TSV;
     END;
END;--SINX



PROCEDURE AUTOCOR(VAR NEWB,OUT:TRANSFTYPE;
                          NI,NO:INTEGER);
VAR
     I,K,J,N:INTEGER;
     X,H,SX,SX1,SY,XY,TOL:REAL;
```

```
BEGIN
     SX:=0; SX1:=0;
     FOR N:=1 TO NI DO
     BEGIN
          X:=NEWB[N];
          SX:=SX+X;
          SX1:=SX1+X*X;
     END;
     H:=NI; --INTEGER MOVED TO REAL
     TOL:=SX1/H-SX*SX/(H*H);
     OUT[0]:=TOL;
     N:=NI;
     K:=1;
     SY:=SX;
     FOR J:=1 TO NO DO
     BEGIN
          SX:=SX-NEWB[N];
          SY:=SY-NEWB[K];
          N:=N-1;
          K:=K+1;
          XY:=0;
          FOR I:=1 TO N DO
          XY:=XY+NEWB[I]*NEWB[I+J];
          H:=N; --INTEGER MOVED TO REAL--
          OUT[J]:=XY/H-SX*SY/(H*H);
     END;
END;--AUTOCOR



PROCEDURE PSPEC(VAR OUT:TRANSFTYPE;
                           NI:INTEGER);
VAR
     NEWB:ARRAY[0:128] OF REAL;
     INT,I,J:INTEGER;
     PI,STORE:REAL;
BEGIN
     PI:=4*ARCTAN(1);
     FOR I:=0 TO NI DO NEWB[I]:=OUT[I];
     FOR I:=0 TO NI DO
     BEGIN
          STORE:=0;
          FOR J:=1 TO NI-1 DO
          STORE:=STORE+NEWB[J]*COS(J*I*PI/NI);
          OUT[I]:=NEWB[0]+2*STORE+NEWB[NI]*COS(I*PI);
          OUT[I]:=17*ABS(OUT[I]);
     END;
END;--PSPEC



PROCEDURE HAMMING(VAR INOUT:TRANSFTYPE; NS:INTEGER;
                                                WEIGHT:REAL);
VAR
     WORK:TRANSFTYPE;
     I:INTEGER;
     H,M,L:REAL;
BEGIN
     H:=1-WEIGHT; M:=WEIGHT; L:=H/2;
     WORK[0]:=H*INOUT[0]+M*INOUT[1];
     FOR I:=1 TO NS-1 DO
     WORK[I]:=L*INOUT[I-1]+H*INOUT[I]+L*INOUT[I+1];
     WORK[NS]:=H*INOUT[NS]+M*INOUT[NS-1];
```

```
     FOR I:=0 TO NS DO INOUT[I]:=WORK[I];
END;



PROCEDURE FILEOUT(VAR OUT:TRANSFTYPE; K:INTEGER);
VAR N:INTEGER;
BEGIN
     IF J=0 THEN
     BEGIN
          FOR N:=1 TO 4 DO IF LABL[N]<>' ' THEN
          WRITE(TEXTOUT,LABL[N]);
          WRITE(TEXTOUT,',',START);
          WRITE(TEXTOUT,'B');
          WRITE(TEXTOUT,FIN,'RF',RF,'S',STEP,'F',1,' ');
          WRITE(TEXTOUT,WIDTH,' ',NOR,' ');
     END;
     FOR N:=0 TO K DO WRITE(TEXTOUT,OUT[N],' ');
END;



BEGIN--MAIN PROGRAM
     RESET(F,'CONSOLE:');
     CONACT(0);
     WRITELN('PRESENT LIMITATION IS 750 WORDS');
     FOR N:=1 TO 6000 DO; CONACT(0);
     LETTERS:=[',','0':'9','A':'Z'];
     NUMBERS:=['0':'9']; MORE:=FALSE;
1:   HAM:=FALSE;
     BOOKIN(NAMEIN);
     BOOKOUT(NAMEOUT);
     INITIATE;
     STEP:=0;
     IF NOR > 1 THEN
     BEGIN
          WRITELN('EVERY N WORD: ');
          READLN(F,STEP);
          WRITELN('DO YOU WANT TO SMOOTHE WITH A HAMMING WINDOW? (Y
          READLN(F,CH);
          IF CH = 'Y' THEN
          BEGIN
               HAM:=TRUE;
               WRITELN('WEIGHTING ? (EVEN NUMBER BETWEEN 0.2 AND 0.9
               READLN(F,WEIGHT);
          END;
     END;
     RESET(TEXTIN);
     FOR N:=1 TO FIN+NOR*STEP+1 DO READWORD(N);
     MOVEONE;
     J:=0;
     REPEAT
          CONACT(0);
          WRITELN('FILE IN: ',NAMEIN);
          WRITELN('FILE OUT: ',NAMEOUT);
          N:=J+1; WRITELN('RUN NUMBER: ',N);
          FOR N:=0 TO FIN DO TRANSA[N]:=1;
          FOR N:=START TO FIN DO COMPAREWORD(TRANSA,N);
          M:=0;
          FOR N:=START TO FIN DO
          BEGIN
               M:=M+1;
               TRANSA[M]:=TRANSA[N];
```

```
          END;
          REALTIME:=M;
          PULSE(TRANSA,TRANSB,REALTIME,SAMPLES);
          SINX(TRANSB,TRANSA,SAMPLES,REALTIME);
          AUTOCOR(TRANSA,TRANSB,REALTIME,WIDTH);
          PSPEC(TRANSB,WIDTH);
          IF HAM THEN HAMMING(TRANSB,WIDTH,WEIGHT);
          FILEOUT(TRANSB,WIDTH);
          START:=START+STEP;
          FIN:=FIN+STEP;
          J:=J+1;
     UNTIL J=NOR;
     CLOSE(TEXTOUT);
     WRITE(CHR(7));
     WRITELN('ANOTHER RUN? (Y/N)');
     READ(F,CH);
     IF CH='Y' THEN
     BEGIN
          MORE:=TRUE;
          CLOSE(TEXTIN);
          GOTO 1;
     END;
END.
```

```
PROGRAM INFOR25FFT(TEXTIN,TEXTOUT);
CONST
    MAXWORDLEN=20;
    NUMBOFWORD=801;
    SHORT=200;
TYPE
    WORDINDEX=1:MAXWORDLEN;
    TEXTINDEX=0:NUMBOFWORD;
    SHORTINDEX=0:SHORT;
    WORDTYPE=PACKED ARRAY[TEXTINDEX,WORDINDEX] OF CHAR;
    TRANSFTYPE=ARRAY[TEXTINDEX] OF REAL;
    SHORTTYPE=ARRAY[SHORTINDEX] OF REAL;
VAR
    WORD:WORDTYPE;
    LABL:ARRAY[WORDINDEX] OF CHAR;
    TRANSA,TRANSB:SHORTTYPE;
    TRANLA:TRANSFTYPE;
    J,N,M,RF,START,FIN,NOR,STEP,
    TRANSINT,REALTIME,PULSE:INTEGER;
    MPD:REAL;
    HAMCH,CH:CHAR;
    F:INTERACTIVE;
    CODE:BOOLEAN;
    TEXTIN,TEXTOUT:TEXT;
    LETTERS:SET OF CHAR;
    NUMBERS:SET OF CHAR;


PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
     BLANK=' ';
VAR
     N,CHARCOUNT:INTEGER;
     CH:CHAR;
BEGIN
      FOR N:=1 TO MAXWORDLEN DO WORD[L,N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
           WHILE NOT EOLN(TEXTIN) DO
           BEGIN
                READ(TEXTIN,CH);
                IF CH=BLANK THEN GOTO 2;
                IF EOLN(TEXTIN) THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     GOTO 2;
                END;
                IF CH IN LETTERS THEN
                BEGIN
                     WORD[L,CHARCOUNT]:=CH;
                     CHARCOUNT:=CHARCOUNT+1;
                     IF CHARCOUNT>MAXWORDLEN THEN
                     BEGIN
                          WHILE CH<>BLANK DO
                          READ(TEXTIN,CH);
                          CHARCOUNT:=1;
                     END;
                     GOTO 1;
                END;
           END;
           READLN(TEXTIN);
```

```
      END;
      IF EOF(TEXTIN) THEN
      BEGIN
           CONACT(O);
           WRITE('EOF AT WORD NR:',L);
           HALT;
      END;
2:    IF WORD[L,1]=BLANK THEN
      BEGIN
           CHARCOUNT:=1;
           GOTO 1;
      END;
END;


PROCEDURE BOOKIN;
VAR
     NAME:STRING;
BEGIN
     CONACT(O);
     WRITELN('NAME OF INPUT FILE:');
     READLN(NAME);
     {$I- I/O OFF}
     RESET(TEXTIN,NAME);
     WHILE IORESULT<>O DO
     BEGIN
          WRITELN('FILE NOT FOUND, TRY AGAIN');
          READLN(NAME);
          RESET(TEXTIN,NAME);
     END;
END;


PROCEDURE MOVEONE;
VAR
     N,M:INTEGER;
BEGIN
     FOR N:=1 TO 20 DO
     LABL[N]:=WORD[1,N];
     FOR N:=2 TO FIN+1 DO
     WORD[N-1]:=WORD[N];
END;


PROCEDURE COMPAREWORD(VAR INFARRAY:TRANSFTYPE;
                          RIGHTEDGE:INTEGER);
LABEL 1;
VAR
     LEFTEDGE,K:INTEGER;
BEGIN
     LEFTEDGE:=RIGHTEDGE-RF;
     K:=O;
     REPEAT
          IF WORD[LEFTEDGE+K]=WORD[RIGHTEDGE] THEN
          BEGIN
               INFARRAY[RIGHTEDGE]:=O;
               GOTO 1;
          END;
          K:=K+1;
     UNTIL K=RF;
     IF CODE THEN
          IF WORD[RIGHTEDGE,1] IN NUMBERS THEN
          INFARRAY[RIGHTEDGE]:=ORD(WORD[RIGHTEDGE,1])-48;
```

```
1:END;


PROCEDURE AUTOCOR(VAR INN:TRANSFTYPE;
                  VAR OUT:SHORTTYPE;
                      NI,NO:INTEGER);
VAR
     I,K,J,N:INTEGER;
     X,H,SX,SX1,SY,XY,TOL:REAL;
BEGIN
     SX:=0; SX1:=0;
     FOR N:=1 TO NI DO
     BEGIN
          X:=INN[N];
          SX:=SX+X;
          SX1:=SX1+X*X;
     END;
     H:=NI; --INTEGER MOVED TO REAL
     TOL:=SX1/H-SX*SX/(H*H);
     OUT[0]:=TOL;
     N:=NI;
     K:=1;
     SY:=SX;
     FOR J:=1 TO NO DO
     BEGIN
          SX:=SX-INN[N];
          SY:=SY-INN[K];
          N:=N-1;
          K:=K+1;
          XY:=0;
          FOR I:=1 TO N DO
          XY:=XY+INN[I]*INN[I+J];
          H:=N; --INTEGER MOVED TO REAL--
          OUT[J]:=XY/H-SX*SY/(H*H);
     END;
END;--AUTOCOR


PROCEDURE FFT(VAR XREAL,XIMAG:SHORTTYPE;
                  NUMBER,NU:INTEGER);
LABEL 1;
VAR
     IM,N2,NU1,I,K,L:INTEGER;
     TREAL,TIMAG,P,ARG,CO,SI:REAL;

FUNCTION BITREV(J,NU:INTEGER):INTEGER;
VAR
     I,J1,J2,K:INTEGER;
BEGIN
     J1:=J;
     K:=0;
     FOR I:=1 TO NU DO
     BEGIN
          J2:=J1 DIV 2;
          K:=K*2+(J1-2*J2);
          J1:=J2;
     END;
     BITREV:=K;
END;--BITREV
BEGIN
     MPD:=0;
     N2:=NUMBER DIV 2;
     NU1:=NU-1;
```

```
     K:=0;
     FOR L:=1 TO NU DO
     BEGIN
1:        FOR I:=1 TO N2 DO
          BEGIN
               IM:=K DIV ROUND(EXP(NU1*LN(2)));
               P:=BITREV(IM,NU);
               ARG:=6.2832*P/NUMBER;
               CO:=COS(ARG);
               SI:=SIN(ARG);
               TREAL:=XREAL[K+N2]*CO+XIMAG[K+N2]*SI;
               TIMAG:=XIMAG[K+N2]*CO-XREAL[K+N2]*SI;
               XREAL[K+N2]:=XREAL[K]-TREAL;
               XIMAG[K+N2]:=XIMAG[K]-TIMAG;
               XREAL[K]:=XREAL[K]+TREAL;
               XIMAG[K]:=XIMAG[K]+TIMAG;
               K:=K+1;
          END;
          K:=K+N2;
          IF K < NUMBER THEN GOTO 1;
          K:=0;
          NU1:=NU1-1;
          N2:=N2 DIV 2;
     END;
     K:=0;
     REPEAT
          I:=BITREV(K,NU);
          IF I > K THEN
          BEGIN
               TREAL:=XREAL[K];
               TIMAG:=XIMAG[K];
               XREAL[K]:=XREAL[I];
               XIMAG[K]:=XIMAG[I];
               XREAL[I]:=TREAL;
               XIMAG[I]:=TIMAG;
          END;
          K:=K+1;
     UNTIL K=NUMBER;
     K:=NUMBER DIV 2;
     FOR L:=0 TO K DO
     XREAL[L]:=17*SQRT(SQR(XREAL[L])+SQR(XIMAG[L]));
END;


PROCEDURE HAMMING(VAR INOUT:SHORTTYPE; NS:INTEGER);
VAR
     WORK:SHORTTYPE;
     I:INTEGER;
BEGIN
     WORK[0]:=0.74*INOUT[0]+0.26*INOUT[1];
     FOR I:=1 TO NS-1 DO
     WORK[I]:=0.13*INOUT[I-1]+0.74*INOUT[I]+0.13*INOUT[I+1];
     WORK[NS]:=0.74*INOUT[NS]+0.26*INOUT[NS-1];
     FOR I:=0 TO NS DO INOUT[I]:=WORK[I];
END;


PROCEDURE FILEOUT(VAR OUT:SHORTTYPE; K:INTEGER);
VAR N:INTEGER;
BEGIN
     IF J=0 THEN
     BEGIN
          N:=1;
```

```
        REPEAT
            WRITE(TEXTOUT,LABL[N]);
            N:=N+1;
        UNTIL LABL[N]=' ';
        WRITE(TEXTOUT,',',START);
        IF CODE THEN WRITE(TEXTOUT,'A') ELSE
        WRITE(TEXTOUT,'B');
        WRITE(TEXTOUT,FIN,'RF',RF,'S',STEP,'P',PULSE,' ');
    END;
    FOR N:=0 TO K DO WRITE(TEXTOUT,OUT[N],' ');
END;


PROCEDURE BOOKOUT;
VAR
    NAME:STRING;
BEGIN
    CONACT(0);
    WRITELN('NAME OF OUTPUT FILE:');
    READLN(NAME);
    {$I- I/O OFF}
    RESET(TEXTOUT,NAME);
    CLOSE(TEXTOUT,PURGE);
    REWRITE(TEXTOUT,NAME);
END;


BEGIN--MAIN PROGRAM
RESET(F,'CONSOLE:');
LETTERS:=[',','0':'9','A':'Z'];
NUMBERS:=['0':'9'];
CODE:=FALSE;
BOOKIN;
BOOKOUT;
CONACT(0);
WRITELN('THE CODING OF I-MODES IN THE PRESENT STATE');
WRITELN('IS BINARY. DO YOU WANT ANALOG CODING? (Y/N)');
READ(F,CH);
CONACT(0);
IF CH='Y' THEN
BEGIN
    WRITELN('CODING CHANGED TO ANALOG');
    CODE:=TRUE;
    END
ELSE
WRITELN('CODING REMAINS BINARY');
WRITELN('PULSE SIZE: ');
READLN(F,PULSE);
WRITELN;
WRITELN('SMOOTHING WITH A 13% HAMMING WINDOW? (Y/N):');
READ(F,HAMCH);
WRITELN;
WRITELN('WINDOW TO START WITH WORD NR:');
READLN(F,START);
WRITELN('WINDOW TO END WITH WORD NR:');
READLN(F,FIN);
WRITELN('RF:');
READLN(F,RF);
WRITELN('EVERY N WORD: ');
READLN(F,STEP);
WRITELN('NUMBER OF RUNS: ');
READLN(F,NOR);
RESET(TEXTIN);
```

```
FOR N:=1 TO FIN+NOR*STEP+1 DO READWORD(N);
MOVEONE;
J:=0;
REPEAT
     CONACT(0);
     N:=J+1; WRITELN('RUN NUMBER: ',N);
     FOR N:=0 TO FIN DO TRANLA[N]:=PULSE;
     FOR N:=START TO FIN DO COMPAREWORD(TRANLA,N);
     M:=0;
     FOR N:=START TO FIN DO
     BEGIN
          M:=M+1;
          TRANLA[M]:=TRANLA[N];
     END;
     TRANLA[0]:=0; REALTIME:=M;
     AUTOCOR(TRANLA,TRANSA,REALTIME,64);
     FOR N:=0 TO REALTIME DO TRANSB[N]:=0;
     FFT(TRANSA,TRANSB,64,6);
     IF HAMCH='Y' THEN
     HAMMING(TRANSA,32);
     FILEOUT(TRANSA,32);
     START:=START+STEP;
     FIN:=FIN+STEP;
     J:=J+1;
UNTIL J=NOR;
END.
```

```
PROGRAM PLOT25(PLOTIN,P);
LABEL 1,2,3,4;
CONST
   LIMIT=25;   -- PLUS/MINUS DYNAMIC LIMIT OF SHADOW MASK
TYPE
   FREQINDEX=0:128;
   RUNINDEX=0:25;
   POWERTYPE=ARRAY[RUNINDEX,FREQINDEX] OF REAL;
   SHADOWTYPE=PACKED ARRAY[0:8,0:300] OF BOOLEAN;
VAR
   POWER:POWERTYPE;
   OPEN:SHADOWTYPE;
   MPDFREQ:ARRAY[FREQINDEX] OF REAL;
   LABL:ARRAY[1:30] OF CHAR;
   START,FIN,NRUNS,FREQ,STEP,STEPX,STEPY,SUMFREQ,NR,
   DEGREE,CROSSFACTOR,FR,MIN,MAX:INTEGER;
   SDEV,CHISQUARE,ALFA,MPDSTAT,UPLIMIT,LOLIMIT:REAL;
   CH:CHAR;
   IA:INTERACTIVE;
   PLOTIN,P:TEXT;
PROCEDURE BOOKIN;
VAR
    NAME:STRING;
BEGIN
    CONACT(0);
    WRITELN('NAME OF INPUT FILE:');
    READLN(NAME);
    {$I- I/O OFF}
    RESET(PLOTIN,NAME);
    WHILE IORESULT<>0 DO
    BEGIN
        WRITELN('FILE NOT FOUND, TRY AGAIN');
        READLN(NAME);
        RESET(PLOTIN,NAME);
    END;
END;
PROCEDURE BOOKOUT;
VAR
    N:INTEGER;
    NAME:STRING;
BEGIN
    REWRITE(P,'PRINTER:');
    WRITELN(P,'A');
    WRITELN(P,CHR(18));
    FOR N:=1 TO 2000 DO;
END;
PROCEDURE ASKWINDOW;
BEGIN
    WRITELN;
    WRITELN('START:');
    READLN(START);
    WRITELN('FIN:');
    READLN(FIN);
END;
```

```
PROCEDURE READFILE(VAR POW:POWERTYPE);
VAR
     NR,FR:INTEGER;
     CH:CHAR;
BEGIN
     FOR NR:=1 TO 30 DO LABL[NR]:=' ';
     NR:=1;
     REPEAT
          READ(PLOTIN,CH);
          LABL[NR]:=CH;
          NR:=NR+1;
     UNTIL CH=' ';
     READ(PLOTIN,FREQ); READ(PLOTIN,NRUNS);
     SUMFREQ:= FREQ + NRUNS;
     FOR NR:=1 TO NRUNS DO
     FOR FR:=0 TO SUMFREQ DO
     POW[NR,FR]:=0;
     FOR NR:=1 TO NRUNS DO
     FOR FR:=0 TO FREQ DO
     READ(PLOTIN,POW[NR,FR]);
END;


PROCEDURE FINDMPDS(VAR POW:POWERTYPE);
VAR
     NR,FR:INTEGER;
BEGIN
     MPDSTAT:=0;
     FOR FR:=0 TO FREQ DO MPDFREQ[FR]:=0;
     FOR NR:=1 TO NRUNS DO
     FOR FR:=0 TO FREQ DO
     MPDFREQ[FR]:=MPDFREQ[FR]+POW[NR,FR];
     FOR FR:=0 TO FREQ DO MPDFREQ[FR]:=MPDFREQ[FR]/NRUNS;
     FOR FR:=0 TO FREQ DO MPDSTAT:=MPDSTAT+MPDFREQ[FR];
     MPDSTAT:=MPDSTAT/FREQ;
END;


PROCEDURE EXPO(VAR POW:POWERTYPE);
VAR
  NR,FR:INTEGER;
BEGIN
     FOR NR:=1 TO NRUNS DO
     FOR FR:=0 TO FREQ DO
     BEGIN
          IF POW[NR,FR] < 1 THEN POW[NR,FR]:=1;
          POW[NR,FR]:=LN(POW[NR,FR]);
     END;
END;



PROCEDURE STAT;
VAR
     FR:INTEGER;
     CHIVAR,SVAR,MEAN,DEV:REAL;
BEGIN
     MEAN:=0; CHIVAR:=0; SVAR:=0;
     FOR FR:=0 TO FREQ DO MEAN:=MEAN+MPDFREQ[FR];
     MEAN:=MEAN/(FREQ+1); -- NUMBER OF POINTS = FREQ+1
     FOR FR:=0 TO FREQ DO
     BEGIN
          DEV:=MPDFREQ[FR]-MEAN;
```

```
            SVAR:=SVAR+DEV*DEV;
            CHIVAR:=CHIVAR+MPDFREQ[FR]*MPDFREQ[FR]/MEAN;
        END;
        SDEV:=SQRT(SVAR/FREQ); --NUMBER OF POINTS = FREQ+1
        CHISQUARE:=CHIVAR-MEAN*(FREQ+1);
END;


FUNCTION TEATABLE(D:INTEGER):REAL;
BEGIN
        CASE D OF
        1:TEATABLE:=6.314; 2:TEATABLE:=2.920; 3:TEATABLE:=2.353;
        4:TEATABLE:=2.132; 5:TEATABLE:=2.015; 6:TEATABLE:=1.943;
        7:TEATABLE:=1.895; 8:TEATABLE:=1.860; 9:TEATABLE:=1.833;
        10:TEATABLE:=1.812; 11:TEATABLE:=1.796; 12:TEATABLE:=1.782;
        13:TEATABLE:=1.771; 14:TEATABLE:=1.761; 15:TEATABLE:=1.753;
        16:TEATABLE:=1.746; 17:TEATABLE:=1.740; 18:TEATABLE:=1.734;
        19:TEATABLE:=1.729; 20:TEATABLE:=1.725; 21:TEATABLE:=1.721;
        22:TEATABLE:=1.717; 23:TEATABLE:=1.714; 24:TEATABLE:=1.711;
        25:TEATABLE:=1.708; 26:TEATABLE:=1.706; 27:TEATABLE:=1.703;
        28:TEATABLE:=1.701; 29:TEATABLE:=1.699; 30:TEATABLE:=1.697;
        END;
END;


PROCEDURE MAKEZAXIS(VAR POW:POWERTYPE);
VAR
        NR,FR:INTEGER;
BEGIN
        FOR NR:=1 TO NRUNS DO
        FOR FR:=FREQ DOWNTO 0 DO
        POW[NR,FR+NR-1]:=POW[NR,FR];
END;


PROCEDURE NEGMASK(VAR POW:POWERTYPE);
VAR
        NR,FR,LIMES:INTEGER;
BEGIN
        LIMES:=FREQ+1;
        FOR NR:=1 TO NRUNS DO
        BEGIN
            FOR FR:=LIMES TO SUMFREQ DO
            POW[NR,FR]:=-100;
            LIMES:=LIMES+1;
        END;
END;


PROCEDURE EXPAND(VAR POW:POWERTYPE);--MAKES STEP SUBINTERVALS
VAR
        NR,FR:INTEGER;
BEGIN
        FOR NR:=1 TO NRUNS DO
        FOR FR:=0 TO SUMFREQ DO
        POW[NR,FR]:= CROSSFACTOR*POW[NR,FR];
END;


PROCEDURE PERSPECTIVE(VAR POW:POWERTYPE);
VAR
        NR,FR:INTEGER;
BEGIN
```

```
    FOR NR:=1 TO NRUNS DO
    FOR FR:=0 TO SUMFREQ DO
    POW[NR,FR]:=POW[NR,FR]+CROSSFACTOR*(NR-1);
END;


PROCEDURE AXIS;
VAR
    X,Y,N,DIST:INTEGER;
    F:REAL;
BEGIN
    WRITELN(P,'S0');
    WRITELN(P,'M0,-400');
    WRITELN(P,'I');
    DIST:=FREQ;
    IF DIST > 32 THEN DIST:=32;
    WRITELN(P,'X1,',DIST,',8');
    Y:=(NRUNS-1)*STEP; X:=Y;
    WRITELN(P,'J',X,',',Y);
    WRITELN(P,'R',(-X DIV 2)+15,',',-Y DIV 2);
    WRITELN(P,'PTIME');
    WRITELN(P,'H');
    WRITELN(P,'M',4*DIST,',-20');
    WRITELN(P,'PFREQ');
    WRITELN(P,'H');
    WRITELN(P,'X0,30,10');
    WRITELN(P,'M80,315');
    WRITELN(P,'S1');
    WRITELN(P,'PCONTINUOUS POWER SPECTRUM');
    WRITELN(P,'S0');
    WRITELN(P,'M15,300');
    WRITELN(P,'P POWER (LN)');
    WRITELN(P,'H');
END;


PROCEDURE PLOT(CH:CHAR; X,Y:INTEGER);
BEGIN
    WRITELN(P,CH,X,',',Y)
END;


PROCEDURE INITPOS(VAR POW:POWERTYPE;
                      NR,FR:INTEGER);
VAR X,Y:INTEGER;
    CH:CHAR;
BEGIN
    CH:='M'; X:=FR*STEP; Y:=ROUND(POW[NR,FR]);
    PLOT(CH,X,Y);
END;


PROCEDURE SHADOW(VAR POW:POWERTYPE;
                 VAR OPEN:SHADOWTYPE;
                     NR,FR:INTEGER;
                     ALFA:REAL);
VAR XX,X,Y,N:INTEGER;
BEGIN
    FOR XX:=1 TO STEP DO
    BEGIN
        Y:=ROUND(ALFA*XX+POW[NR,FR]);
        X:=XX+FR*STEP;
        IF OPEN[XX,Y] THEN
```

```
            CH:='D' ELSE CH:='M';
            PLOT(CH,X,Y);
            FOR N:=MIN TO Y DO
            BEGIN
                 IF N<0 THEN N:=0;
                 OPEN[XX,N]:=FALSE;
            END;
       END;
  END;


  PROCEDURE MINALFA(VAR POW:POWERTYPE;
                              NR,FR:INTEGER;
                          VAR MIN,MAX:INTEGER;
                          VAR ALFA:REAL);
  BEGIN
       IF POW[NR,FR]<POWER[NR,FR+1] THEN
       MIN:=ROUND(POW[NR,FR])-LIMIT ELSE
       MIN:=ROUND(POW[NR,FR+1])-LIMIT;
       IF POW[NR,FR]>POW[NR,FR+1] THEN
       MAX:=ROUND(POW[NR,FR]+LIMIT) ELSE
       MAX:=ROUND(POW[NR,FR+1]+LIMIT);
       ALFA:=(POW[NR,FR+1]-POW[NR,FR])/STEP;
  END;


  PROCEDURE ZERO(VAR OPEN:SHADOWTYPE;
                     MAX:INTEGER);
  VAR M,N:INTEGER;
  BEGIN
       FOR M:=0 TO MAX DO
       FOR N:=0 TO STEP DO
       OPEN[N,M]:=TRUE;
  END;


  PROCEDURE STOP(NR,FR:INTEGER);
  VAR
       X,Y:INTEGER;
       CH:CHAR;
  BEGIN
       X:=STEP*FR;
       Y:=(NR-1)*CROSSFACTOR;
       CH:='D';
       PLOT(CH,X,Y);
  END;


  PROCEDURE LIMITS;
  VAR
       B:REAL;

  BEGIN
       B:=SDEV/SQRT(FREQ);
       DEGREE:=ROUND((FIN-START+1)/FREQ);
       UPLIMIT:=MPDSTAT+B*TEATABLE(DEGREE);
       LOLIMIT:=MPDSTAT-B*TEATABLE(DEGREE);
  END;


  PROCEDURE MPDPLOT;
  VAR
       Y,N:INTEGER;
```

```
BEGIN
    STEPX:=ROUND(320/FREQ);
    STEPY:= 25;
    WRITELN(P,'S0');
    WRITELN(P,'M10,-400');
    WRITELN(P,'I');
    WRITELN(P,'X1,64,5');
    WRITELN(P,'H');
    WRITELN(P,'M-8,-15');
    FOR N:=0 TO 5 DO
    BEGIN
        WRITELN(P,'P0.',N);
        WRITELN(P,'R46,0');
    END;
    WRITELN(P,'R-20,0');
    WRITELN(P,'PFREQUENCY');
    WRITELN(P,'H');
    WRITELN(P,'X0,25,8');
    WRITELN(P,'M-10,-4');
    WRITELN(P,'I');
    FOR N:=1 TO 8 DO
    BEGIN
        Y:=N*25;
        WRITELN(P,'M0,',Y);
        WRITELN(P,'P',N);
    END;
    WRITELN(P,'M115,250');
    WRITELN(P,'S1');
    FOR N:=1 TO 30 DO
    WRITELN(P,'P',LABL[N]);
    WRITELN(P,'M95,225');
    IF NRUNS=1 THEN
    WRITELN(P,'P      POWER SPECTRUM') ELSE
    WRITELN(P,'P AVERAGED POWER SPECTRUM');
    WRITELN(P,'S0');
    WRITELN(P,'M15,200');
    IF NRUNS=1 THEN WRITELN(P,'P POWER (LN)') ELSE
    WRITELN(P,'P AVERAGE POWER (LN) OF ',NRUNS,' RUNS');
    WRITELN(P,'M10,4');
    WRITELN(P,'I');
    FOR N:=0 TO FREQ DO
    BEGIN
        IF MPDFREQ[N] < 1 THEN
        Y:=0 ELSE Y:=ROUND(STEPY*LN(MPDFREQ[N]));
        WRITELN(P,'D',N*STEPX,',',Y);
    END;
END;


PROCEDURE PLOTSTAT;
VAR
    PLOTVARX,PLOTVARY:INTEGER;
BEGIN
    WRITELN(P,'M15,170');
    WRITELN(P,'S1');
    WRITELN(P,'PMPD = ');
    IF MPDSTAT < 10.0 THEN WRITELN(P,'P ');
    WRITELN(P,'P',MPDSTAT:5:2);
    WRITELN(P,'P    DEGR OF FREED = ',DEGREE:2);
    WRITELN(P,'M15,150');
    WRITELN(P,'PCHI2=');
    IF CHISQUARE < 100.0 THEN WRITELN(P,'P ');
    WRITELN(P,'P',CHISQUARE:3:2);
```

```
     WRITELN(P,'P    UPPER CONF LIM=',UPLIMIT:4:2);
     WRITELN(P,'M15,130');
     WRITELN(P,'PSDEV= ');
     IF SDEV < 10.0 THEN WRITELN(P,'P ');
     WRITELN(P,'P',SDEV:5:2);
     WRITELN(P,'P    LOWER CONF LIM=',LOLIMIT:4:2);
     PLOTVARX:=STEPX*FREQ;
     PLOTVARY:=ROUND(STEPY*LN(UPLIMIT));
     WRITELN(P,'M0,',PLOTVARY);
     WRITELN(P,'D',PLOTVARX,',',PLOTVARY);
     WRITELN(P,'S0');
     WRITELN(P,'P  MPD UPPER 0.95 CONF LIM');
     PLOTVARY:=ROUND(STEPY*LN(LOLIMIT));
     WRITELN(P,'M0,',PLOTVARY);
     WRITELN(P,'D',PLOTVARX,',',PLOTVARY);
     WRITELN(P,'P  MPD LOWER 0.95 CONF LIM');
     WRITELN(P,'H');
END;


BEGIN--MAIN PROGRAM
     RESET(IA,'CONSOLE:');
3:   CONACT(0);
     BOOKIN;
     BOOKOUT;
     ASKWINDOW;
     READFILE(POWER);
     FINDMPDS(POWER);
     STAT;
     LIMITS;
     EXPO(POWER);
     MPDPLOT;
     PLOTSTAT;
     IF NRUNS = 1 THEN GOTO 4;
     STEP:=8;                          --STEP SETS WIDTH OF GRAPH
     IF FREQ > 32 THEN STEP:=256 DIV FREQ;
     CROSSFACTOR:=STEP;     --CROSSFACTOR SETS HIGHT OF GRAPH
     MAKEZAXIS(POWER);
     NEGMASK(POWER);
     EXPAND(POWER);
     PERSPECTIVE(POWER);
     AXIS;
     MAX:=0;
     FOR FR:=0 TO SUMFREQ DO
     BEGIN
          ZERO(OPEN,MAX);
          FOR NR:=1 TO FR+1 DO
          BEGIN
               IF NR>NRUNS THEN GOTO 2;
               IF POWER[NR,FR+1]<0 THEN
               IF POWER[NR,FR]>0 THEN
               BEGIN
                    INITPOS(POWER,NR,FR);
                    STOP(NR,FR);
                    GOTO 1;
               END;
               IF POWER[NR,FR]<0 THEN GOTO 1;
               MINALFA(POWER,NR,FR,MIN,MAX,ALFA);
               INITPOS(POWER,NR,FR);
               SHADOW(POWER,OPEN,NR,FR,ALFA);
1:        END;
2:   END;
4:   WRITELN('DO YOU WANT ANOTHER RUN? (Y/N)');
```

```
     READ(IA,CH);
     IF CH='Y' THEN
     BEGIN
          CLOSE(PLOTIN);
          GOTO 3;
     END;
END.
```

```
PROGRAM INFORNORMALISED(TEXTIN,TEXTOUT);
CONST
   MAXWORDLEN=20;
   NUMBOFWORD=701;
   FREQ=64;
   TWOFREQ=128;
   POWERTWO=7;
TYPE
   WORDINDEX=1:MAXWORDLEN;
   TEXTINDEX=0:NUMBOFWORD;
   WORDTYPE=PACKED ARRAY[TEXTINDEX,WORDINDEX] OF CHAR;
   TRANSFTYPE=ARRAY[TEXTINDEX] OF REAL;
VAR
   WORD:WORDTYPE;
   LABL:PACKED ARRAY[WORDINDEX] OF CHAR;
   TRANSA,TRANSB:TRANSFTYPE;
   N,RF,START,FIN,SAMPLES,REALTIME:INTEGER;
   F:INTERACTIVE;
   HAM,CODE:BOOLEAN;
   CH:CHAR;
   TEXTIN,TEXTOUT:TEXT;
   LETTERS:SET OF CHAR;
   NUMBERS:SET OF CHAR;


PROCEDURE INITIATE;
BEGIN
    WRITELN('THE CODING OF I-MODES IN THE PRESENT STATE');
    WRITELN('IS BINARY. DO YOU WANT ANALOG CODING? (Y/N)');
    READ(F,CH);
    CONACT(0);
    IF CH='Y' THEN
    BEGIN
        WRITELN('CODING CHANGED TO ANALOG');
        CODE:=TRUE;
        END
    ELSE
    WRITELN('CODING REMAINS BINARY');WRITELN;
    WRITELN('WINDOW TO START WITH WORD NR:');
    READLN(F,START);
    WRITELN('WINDOW TO END WITH WORD NR:');
    READLN(F,FIN);
    WRITELN('RF:');
    READLN(F,RF);
END;


PROCEDURE BOOKIN;
VAR
    NAME:STRING;
BEGIN
    CONACT(0);
    WRITELN('NAME OF INPUT FILE:');
    READLN(NAME);
    {$I- I/O OFF}
    RESET(TEXTIN,NAME);
    WHILE IORESULT<>0 DO
    BEGIN
        WRITELN('FILE NOT FOUND, TRY AGAIN');
        READLN(NAME);
        RESET(TEXTIN,NAME);
    END;
END;
```

```


PROCEDURE BOOKOUT;
VAR
    NAME:STRING;
BEGIN
        CONACT(O);
        WRITELN('NAME OF OUTPUT FILE:');
        READLN(NAME);
        {$I- I/O OFF}
        RESET(TEXTOUT,NAME);
        CLOSE(TEXTOUT,PURGE);
        REWRITE(TEXTOUT,NAME);
END;


PROCEDURE READWORD(L:INTEGER);
LABEL 1,2;
CONST
    BLANK=' ';
VAR
    N,CHARCOUNT:INTEGER;
    CH:CHAR;
BEGIN
      FOR N:=1 TO MAXWORDLEN DO WORD[L,N]:=BLANK;
      CHARCOUNT:=1;
1:    WHILE NOT EOF(TEXTIN) DO
      BEGIN
          WHILE NOT EOLN(TEXTIN) DO
          BEGIN
              READ(TEXTIN,CH);
              IF CH=BLANK THEN GOTO 2;
              IF EOLN(TEXTIN) THEN
              BEGIN
                  WORD[L,CHARCOUNT]:=CH;
                  GOTO 2;
              END;
              IF CH IN LETTERS THEN
              BEGIN
                  WORD[L,CHARCOUNT]:=CH;
                  CHARCOUNT:=CHARCOUNT+1;
                  IF CHARCOUNT>MAXWORDLEN THEN
                  BEGIN
                      WHILE CH<>BLANK DO
                      READ(TEXTIN,CH);
                      CHARCOUNT:=1;
                  END;
                  GOTO 1;
              END;
          END;
          READLN(TEXTIN);
      END;
      IF EOF(TEXTIN) THEN
      BEGIN
          CONACT(O);
          WRITE('EOF AT WORD NR:',L);
          HALT;
      END;
2:    IF WORD[L,1]=BLANK THEN
      BEGIN
          CHARCOUNT:=1;
          GOTO 1;
      END;
```

```
END;


PROCEDURE MOVEONE;
VAR
     N,M:INTEGER;
BEGIN
     FOR N:=1 TO MAXWORDLEN DO
     LABL[N]:=WORD[1,N];
     FOR N:=2 TO FIN+1 DO
     WORD[N-1]:=WORD[N];
END;


FUNCTION NEWWORD(RE,RFF:INTEGER):INTEGER;
VAR LE:INTEGER;
BEGIN
     NEWWORD:=1;
     FOR LE:=RE-RFF TO RE-1 DO
     IF WORD[RE]=WORD[LE] THEN
     BEGIN
          NEWWORD:=0;
          EXIT(NEWWORD);
     END;
     IF CODE
     THEN IF WORD[RE,1] IN NUMBERS
     THEN NEWWORD:=ORD(WORD[RE,1])-48;
END;


PROCEDURE DCEQU(VAR INOUT:TRANSFTYPE; NI:INTEGER);
VAR
     I:INTEGER;
     MEAN,SUM:REAL;
BEGIN
     SUM:=0;
     FOR I:=1 TO NI DO
     SUM:=SUM+INOUT[I];
     MEAN:=SUM/NI;
     FOR I:=1 TO NI DO
     INOUT[I]:=INOUT[I]-MEAN;
END;


PROCEDURE AUTOCOR(VAR NEWB,OUT:TRANSFTYPE;
                                  NI,NO:INTEGER);
VAR
     I,K,J,N:INTEGER;
     X,H,SX,SX1,SY,XY,TOL:REAL;
BEGIN
     SX:=0; SX1:=0;
     FOR N:=1 TO NI DO
     BEGIN
          X:=NEWB[N];
          SX:=SX+X;
          SX1:=SX1+X*X;
     END;
     H:=NI; --INTEGER MOVED TO REAL
     TOL:=SX1/H-SX*SX/(H*H);
     OUT[0]:=TOL;
     N:=NI;
     K:=1;
     SY:=SX;
```

```
     FOR J:=1 TO NO DO
     BEGIN
          SX:=SX-NEWB[N];
          SY:=SY-NEWB[K];
          N:=N-1;
          K:=K+1;
          XY:=0;
          FOR I:=1 TO N DO
          XY:=XY+NEWB[I]*NEWB[I+J];
          H:=N; --INTEGER MOVED TO REAL--
          OUT[J]:=XY/H-SX*SY/(H*H);
     END;
END;--AUTOCOR


PROCEDURE NORMALISE(VAR OUT:TRANSFTYPE;
                        NI:INTEGER);
VAR
     N:INTEGER;
     MAX:REAL;
BEGIN
     MAX:=0;
     FOR N:=0 TO NI DO IF MAX < OUT[N]
     THEN MAX:=OUT[N];
     FOR N:=0 TO NI DO
     OUT[N]:=OUT[N]/MAX;
END;


PROCEDURE FFT(VAR XREAL,XIMAG:TRANSFTYPE;
                  NUMBER,NU:INTEGER);
LABEL 1;
VAR
     IM,N2,NU1,I,K,L:INTEGER;
     TREAL,TIMAG,P,ARG,CO,SI:REAL;

FUNCTION BITREV(J,NU:INTEGER):INTEGER;
VAR
     I,J1,J2,K:INTEGER;
BEGIN
     J1:=J;
     K:=0;
     FOR I:=1 TO NU DO
     BEGIN
          J2:=J1 DIV 2;
          K:=K*2+(J1-2*J2);
          J1:=J2;
     END;
     BITREV:=K;
END;--BITREV
BEGIN
     N2:=NUMBER DIV 2;
     NU1:=NU-1;
     K:=0;
     FOR L:=1 TO NU DO
     BEGIN
 1:       FOR I:=1 TO N2 DO
          BEGIN
               IM:=K DIV ROUND(EXP(NU1*LN(2)));
               P:=BITREV(IM,NU);
               ARG:=6.2832*P/NUMBER;
               CO:=COS(ARG);
               SI:=SIN(ARG);
```

```
                TREAL:=XREAL[K+N2]*CO+XIMAG[K+N2]*SI;
                TIMAG:=XIMAG[K+N2]*CO-XREAL[K+N2]*SI;
                XREAL[K+N2]:=XREAL[K]-TREAL;
                XIMAG[K+N2]:=XIMAG[K]-TIMAG;
                XREAL[K]:=XREAL[K]+TREAL;
                XIMAG[K]:=XIMAG[K]+TIMAG;
                K:=K+1;
          END;
          K:=K+N2;
          IF K < NUMBER THEN GOTO 1;
          K:=0;
          NU1:=NU1-1;
          N2:=N2 DIV 2;
     END;
     K:=0;
     REPEAT
          I:=BITREV(K,NU);
          IF I > K THEN
          BEGIN
               TREAL:=XREAL[K];
               TIMAG:=XIMAG[K];
               XREAL[K]:=XREAL[I];
               XIMAG[K]:=XIMAG[I];
               XREAL[I]:=TREAL;
               XIMAG[I]:=TIMAG;
          END;
          K:=K+1;
     UNTIL K=NUMBER;
     K:=NUMBER;-- DIV 2;
     FOR L:=0 TO K DO
     XREAL[L]:=0.944929*17*SQRT(SQR(XREAL[L])+SQR(XIMAG[L]));
END; --FACTOR 0.944929 ADJUSTS FFT TO TIMESERIES


PROCEDURE HAMMING(VAR INOUT:TRANSFTYPE; NS:INTEGER;
                                              WEIGHT:REAL);

VAR
     WORK:TRANSFTYPE;
     I:INTEGER;
     H,M,L:REAL;
BEGIN
     H:=1-WEIGHT; M:=WEIGHT; L:=H/2;
     WORK[0]:=H*INOUT[0]+M*INOUT[1];
     FOR I:=1 TO NS-1 DO
     WORK[I]:=L*INOUT[I-1]+H*INOUT[I]+L*INOUT[I+1];
     WORK[NS]:=H*INOUT[NS]+M*INOUT[NS-1];
     FOR I:=0 TO NS DO INOUT[I]:=WORK[I];
END;


PROCEDURE FILEOUT(VAR OUT:TRANSFTYPE; K:INTEGER);
VAR N:INTEGER;
BEGIN
     FOR N:=1 TO 4 DO
     WRITE(TEXTOUT,LABL[N]);
     WRITE(TEXTOUT,',',START);
     IF CODE THEN WRITE(TEXTOUT,'A') ELSE
     WRITE(TEXTOUT,'B');
     WRITE(TEXTOUT,FIN,'RF',RF,' ');
     WRITE(TEXTOUT,K,' 1 ');
     FOR N:=0 TO K DO WRITE(TEXTOUT,OUT[N],' ');
END;
```

```
BEGIN--MAIN PROGRAM
     RESET(F,'CONSOLE:');
     LETTERS:=[',','0':'9','A':'Z'];
     NUMBERS:=['0':'9'];
     CODE:=FALSE; HAM:=FALSE;
     WRITELN('This program samples 128 values for FFT  and is');
     WRITELN('not suitable for windows of less than 400 words');
     WRITELN;
     BOOKIN;
     BOOKOUT;
     CONACT(O);
     INITIATE;
     RESET(TEXTIN);
     WRITELN('DO YOU WANT TO SMOOTHE WITH A HAMMING WINDOW? (Y/N)');
     READ(F,CH);
     IF CH='Y' THEN HAM:=TRUE;
     FOR N:=1 TO FIN+1 DO READWORD(N);
     MOVEONE;
     FOR N:=START TO FIN DO TRANSA[N]:=NEWWORD(N,RF);
     REALTIME:=0;
     FOR N:=START TO FIN DO
     BEGIN
          REALTIME:=REALTIME+1;
          TRANSA[REALTIME]:=TRANSA[N];
     END;
     FOR N:=1 TO REALTIME DO
     BEGIN
          WRITE(ROUND(TRANSA[N]));
          IF N MOD 50 = 0 THEN WRITELN;
     END;
     DCEQU(TRANSA,REALTIME);
     AUTOCOR(TRANSA,TRANSB,REALTIME,TWOFREQ);
     NORMALISE(TRANSB,TWOFREQ);
     FOR N:=0 TO TWOFREQ DO TRANSA[N]:=0;
     FFT(TRANSB,TRANSA,TWOFREQ,POWERTWO);
     IF HAM THEN HAMMING(TRANSB,FREQ,0.26);
     FILEOUT(TRANSB,FREQ);
END.
```

```
PROGRAM PLOTNORMALISED(PLOTIN,P);
CONST
   STEPX=5;
   STEPY=3;
TYPE
   FREQINDEX=0:64;
   POWERTYPE=ARRAY[FREQINDEX] OF REAL;
VAR
   POWER2,POWER1:POWERTYPE;
   LABL:ARRAY[1:30] OF CHAR;
   FREQ,NRUNS,NR,FR,N:INTEGER;
   WORDING,NAME,NAME1,NAME2,NAME3:STRING;
   IA:INTERACTIVE;
   PLOTIN,P:TEXT;

PROCEDURE ASK(VAR FILENAME:STRING);
BEGIN
    WRITE(FILENAME);
END;

PROCEDURE REED(VAR FILENAME:STRING);
BEGIN
     FILENAME:='            ';
     READLN(IA,FILENAME);
END;

PROCEDURE BOOKIN(VAR NAME:STRING);
VAR N:INTEGER;
BEGIN
     {$I- I/O OFF}
     RESET(PLOTIN,NAME);
     WHILE IORESULT<>0 DO
     BEGIN
          WRITELN('FILE NOT FOUND, TRY AGAIN');
          READLN(NAME);
          RESET(PLOTIN,NAME);
     END;
END;

PROCEDURE BOOKOUT;
VAR
     N:INTEGER;
BEGIN
     REWRITE(P,'PRINTER:');
     WRITELN(P,'A');
     WRITELN(P,CHR(18));
     FOR N:=1 TO 2000 DO;
END;

PROCEDURE READFILE(VAR POW:POWERTYPE);
VAR
     NR,FR:INTEGER;
     CH:CHAR;
BEGIN
     FOR NR:=1 TO 30 DO LABL[NR]:=' ';
     NR:=1;
     REPEAT
          READ(PLOTIN,CH);
```

```
          LABL[NR]:=CH;
          NR:=NR+1;
      UNTIL CH=' ';
      READ(PLOTIN,FREQ); READ(PLOTIN,NRUNS);
      FOR FR:=0 TO FREQ DO
      READ(PLOTIN,POW[FR]);
END;


PROCEDURE AXIS;
VAR
      Y,N:INTEGER;
BEGIN
      WRITELN(P,'S0');
      WRITELN(P,'M10,-400');
      WRITELN(P,'I');
      WRITELN(P,'X1,64,5');
      WRITELN(P,'H');
      WRITELN(P,'M-8,-15');
      FOR N:=0 TO 5 DO
      BEGIN
           WRITELN(P,'P0.',N);
           WRITELN(P,'R46,0');
      END;
      WRITELN(P,'R-20,0');
      WRITELN(P,'PFREQUENCY');
      WRITELN(P,'H');
      WRITELN(P,'X0,30,6');
      WRITELN(P,'M-10,-4');
      WRITELN(P,'I');
      FOR N:=1 TO 6 DO
      BEGIN
           Y:=N*30;
           WRITELN(P,'M0,',Y);
           WRITELN(P,'P',N);
      END;
      WRITELN(P,'M130,260');
      WRITELN(P,'S1');
      WRITELN(P,'P',NAME1);
      WRITELN(P,'M95,215');
      WRITELN(P,'P    POWER SPECTRUM');
      WRITELN(P,'S0');
      WRITELN(P,'M15,180');
      WRITELN(P,'P POWER * 10');
      WRITELN(P,'M10,4');
      WRITELN(P,'I');
END;


PROCEDURE PLOT(VAR EACHPOW:POWERTYPE;
                   NAME:STRING);
VAR N,Y:INTEGER;
BEGIN
      FOR N:=0 TO FREQ DO
      BEGIN
           IF EACHPOW[N] < 1 THEN
           Y:=0 ELSE Y:=ROUND(STEPY*EACHPOW[N]);
           WRITELN(P,'D',N*STEPX,',',Y);
      END;
      WRITELN(P,'J15,0');
      WRITELN(P,'P ',NAME);
      WRITELN(P,'H');
END;
```

```
BEGIN--MAIN PROGRAM
     RESET(IA,'CONSOLE:');
     CONACT(0);
     WRITELN('HEADING OF GRAPH: ');
     READLN(IA,NAME1);
     WORDING:='NAME OF DATA FILE FOR FULL LINE GRAPH: ';
     ASK(WORDING);
     REED(NAME);
     BOOKIN(NAME);
     READFILE(POWER1);
     CLOSE(PLOTIN);
     WORDING:='NAME OF DATA FILE FOR DOTTED LINE GRAPH: ';
     ASK(WORDING);
     REED(NAME);
     BOOKIN(NAME);
     READFILE(POWER2);
     WRITELN('NAME ON FULL GRAPH: ');
     READLN(IA,NAME2);
     WRITELN('NAME ON DOTTED GRAPH: ');
     READLN(IA,NAME3);
     BOOKOUT;
     AXIS;
     PLOT(POWER1,NAME2);
     WRITELN(P,'L4');
     PLOT(POWER2,NAME3);
END.
```

Intermediate values from Fourier analysis of PAD2,273B600RF185

After COMPAREWORD:

```
1.00 0.00 1.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00
1.00 0.00 1.00 1.00 0.00 1.00 0.00 0.00 0.00 0.00
0.00 1.00 1.00 0.00 1.00 1.00 1.00 1.00 0.00 1.00
0.00 0.00 0.00 1.00 0.00 1.00 0.00 1.00 0.00 0.00
1.00 0.00 0.00 1.00 0.00 0.00 0.00 1.00 0.00 1.00
1.00 1.00 1.00 1.00 1.00 1.00 0.00 0.00 1.00 1.00
1.00 0.00 1.00 0.00 0.00 1.00 1.00 0.00 0.00 0.00
1.00 1.00 1.00 0.00 0.00 0.00 1.00 0.00 0.00 0.00
0.00 1.00 0.00 1.00 0.00 1.00 1.00 1.00 0.00 1.00
0.00 1.00 0.00 0.00 0.00 0.00 1.00 0.00 0.00 1.00
0.00 1.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 1.00
0.00 1.00 1.00 0.00 0.00 1.00 0.00 1.00 0.00 1.00
1.00 0.00 1.00 0.00 0.00 0.00 1.00 1.00 0.00 1.00
0.00 1.00 0.00 1.00 0.00 0.00 0.00 1.00 0.00 1.00
1.00 0.00 1.00 0.00 1.00 1.00 1.00 1.00 0.00 0.00
0.00 1.00 1.00 0.00 0.00 0.00 0.00 1.00 0.00 1.00
1.00 1.00 0.00 0.00 1.00 1.00 0.00 1.00 0.00 1.00
1.00 1.00 1.00 1.00 0.00 1.00 1.00 1.00 1.00 1.00
1.00 1.00 1.00 0.00 1.00 1.00 1.00 1.00 1.00 1.00
0.00 1.00 0.00 1.00 0.00 1.00 1.00 1.00 0.00 0.00
1.00 1.00 1.00 1.00 0.00 1.00 0.00 1.00 0.00 1.00
0.00 1.00 0.00 0.00 1.00 1.00 0.00 1.00 0.00 0.00
0.00 1.00 0.00 1.00 0.00 1.00 0.00 1.00 1.00 0.00
0.00 1.00 0.00 1.00 0.00 1.00 0.00 0.00 1.00 1.00
1.00 1.00 1.00 1.00 1.00 1.00 0.00 0.00 1.00 1.00
1.00 1.00 1.00 1.00 1.00 0.00 1.00 0.00 0.00 0.00
0.00 0.00 1.00 0.00 1.00 0.00 0.00 0.00 0.00 1.00
0.00 0.00 0.00 1.00 0.00 0.00 1.00 0.00 0.00 1.00
1.00 1.00 0.00 1.00 0.00 0.00 0.00 0.00 1.00 0.00
0.00 1.00 0.00 0.00 0.00 1.00 0.00 0.00 1.00 1.00
1.00 1.00 0.00 0.00 0.00 1.00 1.00 1.00 0.00 0.00
1.00 0.00 0.00 0.00 0.00 0.00 0.00 1.00 0.00 1.00
1.00 0.00 0.00 1.00 1.00 1.00 0.00 0.00
```

After PULSE:

```
0.00
2.00 5.00 3.00 2.00 1.00 2.00 6.00 1.00 2.00 1.00
1.00 1.00 2.00 4.00 2.00 2.00 3.00 3.00 4.00 2.00
1.00 1.00 1.00 1.00 1.00 1.00 3.00 1.00 1.00 2.00
3.00 1.00 4.00 1.00 1.00 4.00 5.00 2.00 2.00 1.00
1.00 2.00 2.00 5.00 3.00 2.00 6.00 2.00 2.00 1.00
3.00 2.00 2.00 1.00 2.00 4.00 1.00 2.00 2.00 2.00
4.00 2.00 1.00 2.00 2.00 1.00 1.00 1.00 4.00 1.00
5.00 2.00 1.00 1.00 3.00 1.00 2.00 2.00 1.00 1.00
1.00 1.00 2.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00
2.00 1.00 1.00 1.00 1.00 1.00 2.00 2.00 2.00 1.00
1.00 3.00 1.00 1.00 1.00 2.00 2.00 2.00 2.00 3.00
1.00 2.00 4.00 2.00 2.00 2.00 1.00 3.00 2.00 2.00
3.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 3.00 1.00
1.00 1.00 1.00 1.00 1.00 2.00 6.00 2.00 5.00 4.00
3.00 3.00 1.00 1.00 2.00 5.00 3.00 4.00 3.00 1.00
1.00 1.00 4.00 1.00 1.00 3.00 7.00 2.00 1.00 3.00
1.00 1.00 5.00
```

After SINX:

```
 1.00
 1.83 0.01 2.33-1.41 1.21-1.22 1.97 0.73-0.11 0.89
 1.66-0.16 3.54-0.21 1.73 0.79 0.06-0.25 0.36-0.48
 1.17 2.30 1.04 0.34 2.96 1.15 3.03 0.09 1.52 0.88
 0.11-0.51 1.54 0.78 1.02 1.20 0.58 1.83-1.03 1.63
 1.14-0.59 1.37 1.18-0.27-0.08 1.10 1.28 0.34 2.79
 1.46 2.50 1.60 2.37 1.79 1.53-0.94 1.61 1.70 2.62
 0.49 1.07 1.39-0.60 1.09 2.45 0.87-0.15-0.11 0.90
 2.36 1.98 1.25-0.47 0.19 0.68 1.91-1.16 1.10-1.24
 2.15 0.24 1.52 0.71 1.01 2.02 2.49 0.46 1.27 0.94
 0.84 1.50-0.58 0.36-0.38 1.11 1.64-1.08 1.90 0.54
 1.16 1.23-0.30 0.02 0.20-0.50 1.51 0.81 0.98 1.28
 0.38 2.79 0.84-0.45 1.36 1.03 0.71 1.58 0.02 3.29
 0.09 1.37 1.17-0.36 0.17 0.49 3.04 0.12 1.53 0.73
 1.13 1.08 0.77 1.54-0.52 0.13 0.88 1.57 0.00 3.33
 0.02 1.50 0.90 0.66 2.56 1.62 2.51 0.79-0.03-0.22
 0.99 2.38 1.07-0.49 0.50-0.69 1.64 0.79 0.83 2.26
 2.12 1.11-0.40 0.88 2.75 0.40 1.22 1.06 0.60 2.47
 1.83 2.04 2.25 0.86 0.66 2.51 1.72 2.21 1.88 2.14
 1.86 2.30 0.90 0.51 2.74 1.38 2.66 1.29 3.00 0.07
 1.62 0.59 1.23 0.99 0.73 2.34 2.07 1.11-0.38 0.91
 2.59 1.40 2.91 0.14 1.58 0.62 1.27 0.86 1.05 1.11
 0.74 1.60-0.69 1.08 2.59 0.52 1.11 1.23-0.22-0.25
 1.33 0.93 0.90 1.27 0.61 1.59 0.10 3.03 0.60-0.27
 1.21 1.14 0.66 1.57 0.22 2.17-1.34 1.84 1.61 2.49
 1.56 2.43 1.63 2.38 1.78 1.54-0.95 1.57 1.81 2.34
 1.65 2.43 1.52 2.73 0.36 1.25 1.19-0.29 0.06 0.13
-0.36 1.30 1.10 0.59 1.84-0.97 0.85-0.94 1.76 0.82
 0.07-0.39 1.30 1.29-0.58 1.22 1.50-0.88 1.53 1.77
 2.57 0.51 1.08 1.38-0.51 0.36-0.41 1.18 1.50-0.89
 1.61 0.97-0.12-0.21 1.11 1.48-0.76 1.31 2.13 1.94
 2.22 1.05-0.31 0.05 0.73 2.55 1.72 1.58-1.01 1.72
 0.92-0.13 0.00-0.01 0.05-0.22 1.09 1.39 0.15 3.12
 0.38 0.12 0.55 2.77 1.47 1.84-1.19 1.19
```

After AUTOCOR:

```
 1.04
-0.09 0.15-0.05 0.06 0.04 0.05 0.01 0.06-0.12 0.12
 0.04 0.09-0.01 0.04 0.01-0.02-0.10 0.09 0.01 0.03
-0.05-0.04-0.07-0.02 0.16 0.03 0.03 0.01 0.02 0.02
 0.09-0.14
```

After PSPEC and FILEOUT

```
 36.1
 20.3   22.5    8.3   13.1   23.7   11.2   19.3    6.5    6.2   30.3
 16.5   12.1   26.3    4.7   11.5    7.0   21.6   22.1    9.1    8.3
 18.7    3.6   19.7   12.7   33.5   24.3   18.5   19.7   23.1    9.5
 43.1   39.9
```

CHAPTER 10.

THE OPTIMAL: SIZE OF REFERENCE FIELD, NUMBER OF FREQUENCY POINTS IN POWER SPECTRUM, AND WINDOW WIDTH.

OPTIMAL SIZE OF REFERENCE FIELD.

In chapter 8, I explained that the reason we want a reference field which yields a ratio I-modes/O-modes of 1:1 is partly that a series of a balanced number of ones and zeros gives a more sensitive analysis of periodicity, and partly that this would compare to the redundancy level in normal text strings.

On the following pages I shall substantiate the first part of this claim by showing the spectral analysis of a text string with varying lengths of reference field (Figure 10.1 to 10.5).

First, the normal reference field with the ratio 1:1 of I-modes and O-modes of a text string (C114, from word 265 to word 364) was established with the program FINDRF. The reference field was found to be 144. The spectrum from the analysis of C114 with this reference field is the one shown in figure 10.3.

The length of reference field (RF = 144) was then multiplied by 0.50, 0.75, 1.25 and 1.50 respectively, and the same string (C114, from word 265 to word 364) was analysed against these four reference fields, two of which were progressively shorter (by 0.5 and 0.75), two of which were progressively longer (by 1.25 and 1.5), than the normal reference field.

The shorter than normal fields (144 multiplied by 0.5 and 0.75 respectively) would yield more I-modes than O-modes in the information array than the normal reference field, because fewer words

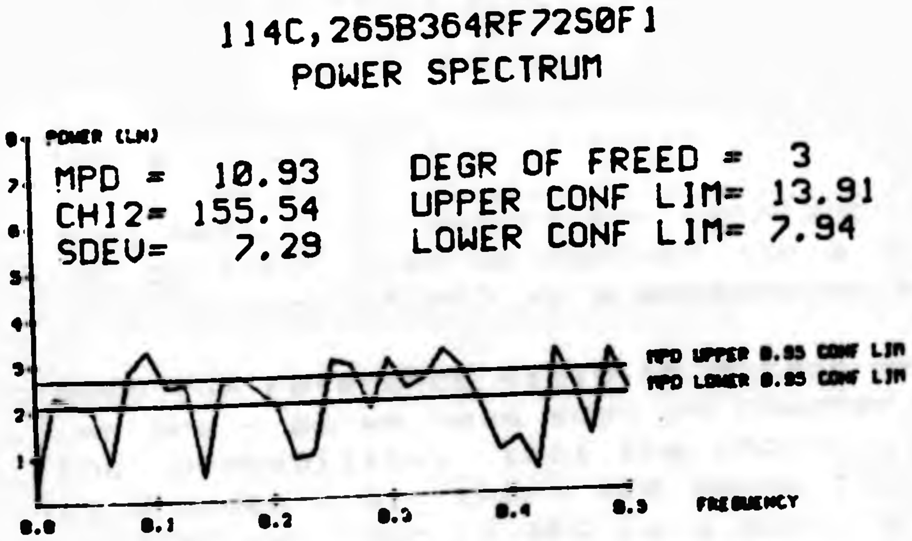

Figure 10.1 Reference field reduced by 50%

114C,265B364RF108S0F1
POWER SPECTRUM

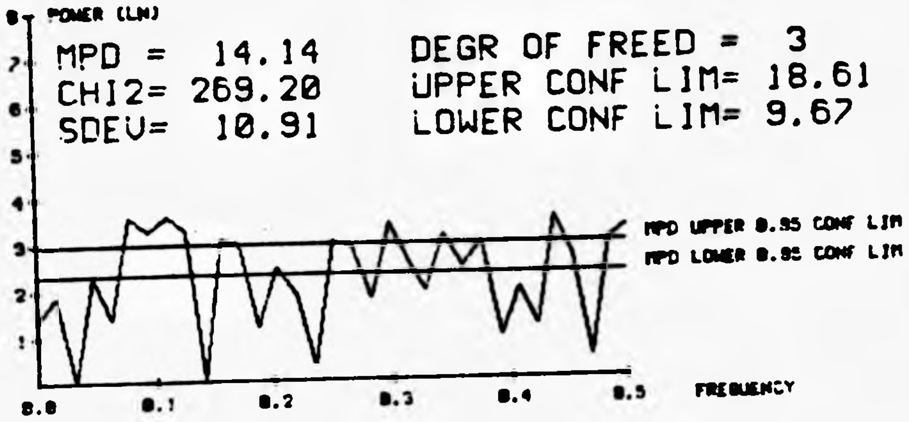

Figure 10.2 Reference field reduced by 25%

in string C114 between word 265 and 364 will be recognised. The longer than normal reference fields (144 multiplied by 1.25 and 1.5 respectively) will yield fewer I-modes than O-modes because, with a longer reference field, more words will be recognised.

With these lengths of reference field ranging from 0.50 to 1.50 of the value RF = 144 as established by FINDRF, I hope to demonstrate, that the reference field established by FINDRF (the 1:1 field) is indeed the optimal one, the one with the greatest sensitivity i.e. the one with the greatest measure of variance.

Looking at figures 10.1 to 10.5, the first thing that strikes the attentative observer is that as the reference field increases, so does the Mean Power Density. As the reference field increases by 50%, the Mean Power Density has increased by around 25%. As the reference field is decreased by 50%, the Mean Power Density has decreased by around 45%. We furthermore observe, that the variance, both the normalised chi square and the not normalised standard deviation, increases as the reference field increases - until the reference field is the one established by FINDRF i.e the field with an equal number of I-modes and O-modes. When the reference field is increased still higher, the variance falls again.

The actual values of the power densities from all the spectra can be found in the appendix to this chapter.

As we have just seen, increasing the reference field increased the mean power density. Let us reflect for a moment on how this ties up with our concept of MPD as a measure of structure:

When we increase the reference field in excess of the established 1:1 field, we are - as we have seen in chapter 8 - effectively increasing the probability, that the incoming words will be registered as O-modes i.e. there are going to be more zeros in the information array. But if MPD is a measure of structure and MPD raises with increased numbers of repeats, then - if we want to think of MPD in terms of structure - we must accept, that an

114C,265B364RF144S0F1
POWER SPECTRUM

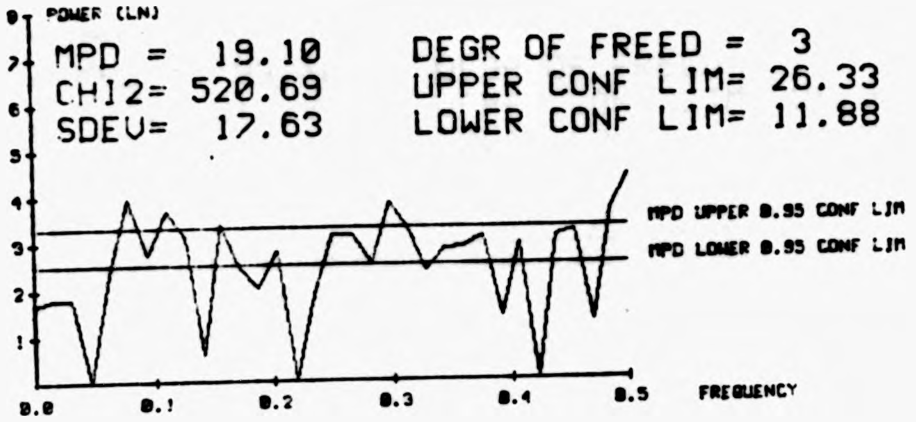

Figure 10.3 Reference field not altered.

114C,265B364RF180S0F1
POWER SPECTRUM

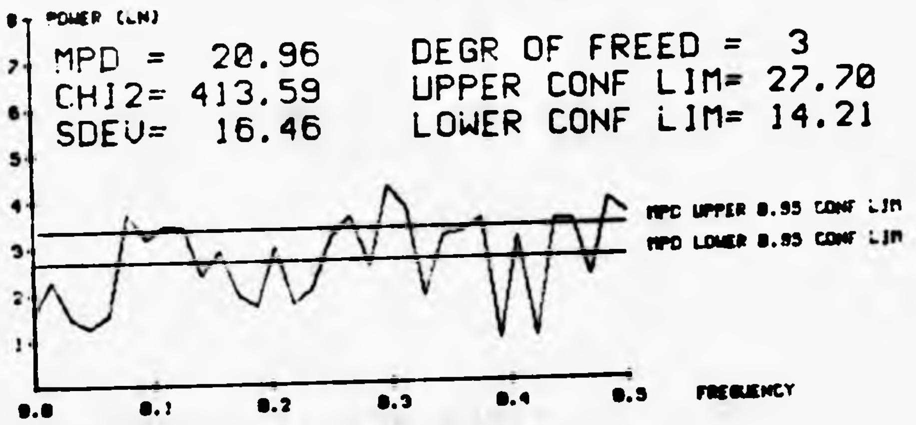

Figure 10.4 Reference field increased by 25%

increased number of repeated words is equivalent to increased structure.

But how does that comply with our common sense view of structure? A good way to judge this situation is to carry it to extremes. Let us imagine. that more and more words become repeats. At one point we will have substituted all 'ones' for zeros. This kind of information array however, reflects an analysis of a text string where all incoming words are repeats; but a text string, where all the words are repeats of a number of initial words, is indeed coherent with our common sense notion of structure, at least compared to the other extreme: a text string where all the words are different.

The clash between the change in MPD and our intuitive notion of 'structure', arises because we think of structure as something 'nice and ordered', but 20 different words repeating themselves 5 times is 'structure' compared to 100 different words.

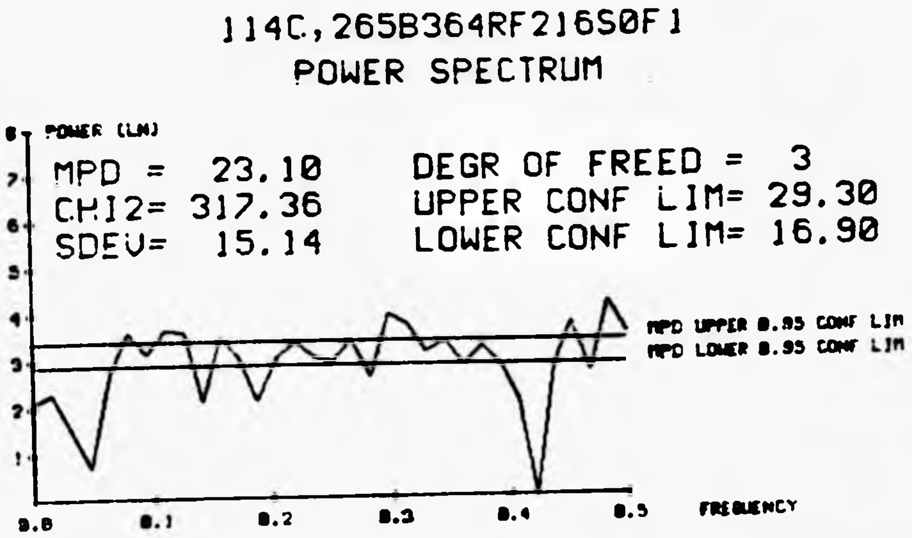

Figure 10.5 Reference field increased by 50%

Another interesting point, arising from the analysis with different reference fields above, is the amount of power at the zero point of the spectrum (F=0.0). You may remember, that the amount of power in F=0.0 is the amount of DC power in the initial function before it is transformed to the frequency domain. When we start substituting 'new' words with 'old' words in a text string, like we did above, we are in information theoretical terms just adding a constant to the signal (adding DC power to the signal). That this is indeed the case can be seen on the level of the Y-axis intercept on the spectra in figures 10.1 to 10.5. The higher the increase in the reference field, the higher the power in F=0.0

As you may recall from the different functions and their Fourier transforms in chapter 7, the addition of a constant to a function would after Fourier transformation show up in F=0.0, the Y-axis intercept, as a value equal to the constant which was added.

Having established that the reference field which yields an equal number of D-mode and I-modes is indeed optimal with regard to sensitivity, we now turn to two other parameters. Those of window width and number of frequency points in the power spectrum.

NUMBER OF FREQUENCY POINTS IN THE POWER SPECTRUM.

The next important question is how many frequency points we want in our spectra (apart from point zero). A simplistic approach would demand as high a resolution as possible, that is, demand as many points as possible. Unfortunately, it is not this easy.

A number of different factors have to be taken into consideration like: the length of the text sample being analysed, the required level of statistical significance, the length of the measuring window, the length of the reference field of this window, the stationarity of the structures in the text string, which Fourier transform we use (time series or FFT), to name but a few. All

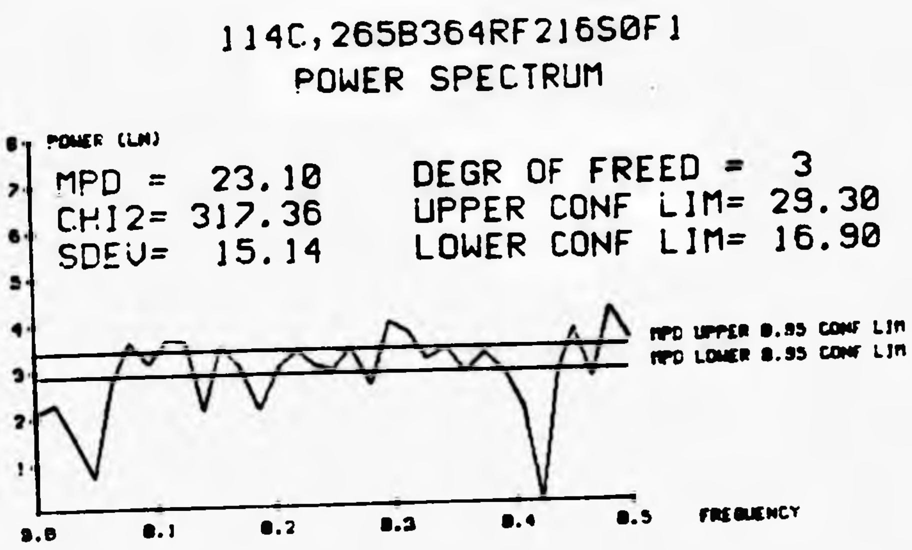

Figure 10.5 Reference field increased by 50%

Another interesting point, arising from the analysis with different reference fields above, is the amount of power at the zero point of the spectrum (F=0.0). You may remember, that the amount of power in F=0.0 is the amount of DC power in the initial function before it is transformed to the frequency domain. When we start substituting 'new' words with 'old' words in a text string, like we did above, we are in information theoretical terms just adding a constant to the signal (adding DC power to the signal). That this is indeed the case can be seen on the level of the Y-axis intercept on the spectra in figures 10.1 to 10.5. The higher the increase in the reference field, the higher the power in F=0.0

As you may recall from the different functions and their Fourier transforms in chapter 7, the addition of a constant to a function would after Fourier transformation show up in F=0.0, the Y-axis intercept, as a value equal to the constant which was added.

Having established that the reference field which yields an equal number of O-mode and I-modes is indeed optimal with regard to sensitivity, we now turn to two other parameters. Those of window width and number of frequency points in the power spectrum.

NUMBER OF FREQUENCY POINTS IN THE POWER SPECTRUM.

The next important question is how many frequency points we want in our spectra (apart from point zero). A simplistic approach would demand as high a resolution as possible, that is, demand as many points as possible. Unfortunately, it is not this easy.

A number of different factors have to be taken into consideration like: the length of the text sample being analysed, the required level of statistical significance, the length of the measuring window, the length of the reference field of this window, the stationarity of the structures in the text string, which Fourier transform we use (time series or FFT), to name but a few. All these parameters are closely interrelated, and it is difficult to evaluate any of them in isolation.

When we are dealing with the analysis of childrens text strings, the obvious limitation is the lack of words. However, If we want a resolution of say, 100 frequency points, then AUTOCOR must be 'fed' with more than 100 points to produce a 'lag' of 100. Even though AUTOCOR would function with just 102 points in this case, it reveals the repetitive features best if it is 'fed' with at least double as many points as the wanted 'lag'. This is particularly important because the method of simulating information transfer from text strings, as presented in this thesis, is necessarily both crude and limited.

But if we want 200 points put in to AUTOCOR, then it means, that our measuring window must be 200 words wide. Not only is this an impossible demand on a text string which is say 150 words long, but even if the string was 210 words long, there still would not be room for a reference field.

Another reason for keeping both number of frequency points and window width down has to do with computing time. Double as many frequency points and double the window width, and may be an increased reference field because of the wider window, means that for some computer procedures the time factor increases with the power of two rather than just a factor of two. Particularly on a micro computer this is a crucial point.

From experience, I have established that a 32 point spectrum represents the minimum resolution acceptable for our purpose. Even if we use the less demanding (in terms of length of string) time series transform, this resolution demands a window of at least 64 words because, as explained above, the AUTOCOR is most sensitive if we feed it with at least twice as many observations as we want spectral points.

If, instead of the time series transform, we use the FFT, the necessary minimum window suddenly raises to 128 words. As explained in chapter 7, the FFT yields only half as many frequency points as the number of observations before the tranformation. To produce a spectrum with 32 frequency points, the FFT thus needs 64 observations. But to produce 64 observations, AUTOCOR must have a 'lag' of 64. As before, AUTOCOR works best if it is fed with at least twice the number of observations as the wanted 'lag'. With a 'lag' of 64 we have to produce at least 128 initial observations.

Obviously, if we want to analyse the younger childrens text strings with a spectrum of 32 frequency points, the use of the FFT is out of the question, its demands become impossible to satisfy. For this reason, as explained before, the TIME SERIES TRANSFORM HAS BEEN THE MAIN TRANSFORM THORUGHOUT THIS RESEARCH, both for the analysis of childrens and adults' text strings where the signal levels were binary; zero and one. The FFT was used only in chapter 12 for the analysis of grammatical categories because the signals in this case are analog (three levels): zero, one and eight. In all these cases the analysis was of course carried out on strings which were sufficiently long.

The relationship between the number of frequency points in the spectrum and the statistical significance of the power in each of these parameters are closely interrelated, and it is difficult to evaluate any of them in isolation.

When we are dealing with the analysis of childrens text strings, the obvious limitation is the lack of words. However, If we want a resolution of say, 100 frequency points, then AUTOCOR must be 'fed' with more than 100 points to produce a 'lag' of 100. Even though AUTOCOR would function with just 102 points in this case, it reveals the repetitive features best if it is 'fed' with at least double as many points as the wanted 'lag'. This is particularly important because the method of simulating information transfer from text strings, as presented in this thesis, is necessarily both crude and limited.

But if we want 200 points put in to AUTOCOR, then it means, that our measuring window must be 200 words wide. Not only is this an impossible demand on a text string which is say 150 words long, but even if the string was 210 words long, there still would not be room for a reference field.

Another reason for keeping both number of frequency points and window width down has to do with computing time. Double as many frequency points and double the window width, and may be an increased reference field because of the wider window, means that for some computer procedures the time factor increases with the power of two rather than just a factor of two. Particularly on a micro computer this is a crucial point.

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Obviously, if we want to analyse the younger childrens text strings with a spectrum of 32 frequency points, the use of the FFT is out of the question, its demands become impossible to satisfy. For this reason, as explained before, the TIME SERIES TRANSFORM HAS BEEN THE MAIN TRANSFORM THORUGHOUT THIS RESEARCH, both for the analysis of childrens and adults' text strings where the signal levels were binary: zero and one. The FFT was used only in chapter 12 for the analysis of grammatical categories because the signals in this case are analog (three levels): zero, one and eight. In all these cases the analysis was of course carried out on strings which were sufficiently long.

The relationship between the number of frequency points in the spectrum and the statistical significance of the power in each of these frequency points, I shall explain in the following.

OPTIMAL SIZE OF THE MEASURING WINDOW.

With regard to the size of the window we are again in the position of having to make compromises. There are at least three factors which we have to concider when we decide the size of the window.

The first problem is that of statistical significance. The level of significance is related to the number of degrees of freedom. The rule in power spectral analysis is, that the number of degrees of freedom is determined by the width of the window divided by the number of frequency points in the spectrum, i.e. if our window is 64 words wide and our spectrum has got 32 frequency points, the number of degrees of freedom is 64/32 = 2.

The second and third problem are reciprocally related and are those of low-frequency sensitivity and of stationarity. If the text string is not prohibitively short, we would be inclined to have a very wide window to get as high a confidence level as possible. However, if we do that, we may quench a periodicity which is not very stationary. On the other hand, if we try to counter this by making the window smaller, we may not pick up weak low-frequency structures.

To evaluate the impact of the window size on the factors mentioned above i.e. stationarity and low-frequency sensitivity , a number of power spectra were obtained by INFOR of the same text string with different sizes window. Power spectra were made from windows of 50, 100, 200, 300, and 400 words respectively. Because of the distinct possibility, that structures in childrens text strings are substantially different from those of adult text strings, for example with regard to stationarity, the analysis was carried out on a string written by an adult as well as on a string written by a child.

Comparing the spectra of different window widths in tables 10.6 to 10.10, the effect of the width of the measuring window on the sensitivity of the spectrum can clearly be seen. With regard to the sensitivity to long frequency structures, you can observe the increasing sensitivity in the low-frequency part of the spectrum as the window length increases. With a window width of 50 words (table 10.6) the power at f=0.016 is 27.9, well below the 95% confidence limit of 40.1. With a window width of 100 words (table 10.7) the power in f=0.016 has risen to 29.0, but is still not significant. Only with a window width between 100 and 200 (table 10.8) has the power in f=0.016 risen above the upper 95% confidence limit. This is of course partly due to the fact that the level of the upper 95% confidence limit is falling with increasing number of degrees of freedom. But the power level in f=0.016 is still increasing in absolute terms with increasing window width up to 200, after which the power drops, presumably due to lack of stationarity of the structures at this frequency.

At the high-frequency end of the spectrum (f=0.484) the situation is the same. As the window width increases up to between 100 and 200, the power increases from 15.2 at 50 words to 88.2 at 100

FIE1,151B200RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.7								
0.016	27.9	0.031	13.2	0.047	15.7	0.063	21.7	0.078	0.3
0.094	38.6	0.109	5.8	0.125	24.7	0.141	8.6	0.156	11.7
0.172	3.4	0.188	3.6	0.203	1.1	0.219	3.9	0.234	38.5
0.250	62.0	0.266	7.4	0.281	14.8	0.297	9.4	0.313	38.7
0.328	85.4	0.344	8.0	0.359	24.3	0.375	3.3	0.391	51.1
0.406	6.0	0.422	2.2	0.438	23.1	0.453	18.5	0.469	9.3
0.484	15.2	0.500	21.2						

MEAN POWER DENSITY: 19.22
DEGREES OF FREEDOM = 1
CHISQUARE = 601.10
ST.DEVIATION = 19.00
MPD UPPER 0.95 CONF LIMIT = 40.10
MPD LOWER 0.95 CONF LIMIT =-1.67
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 3
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 0
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 3

Table 10.6 Power level in each of 32 frequency points. Spectrum from child's text string. Measuring window: 50 words.

FIE1,151B250RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	14.6								
0.016	29.0	0.031	19.5	0.047	3.2	0.063	27.3	0.078	2.3
0.094	24.8	0.109	0.3	0.125	17.2	0.141	13.1	0.156	15.4
0.172	16.1	0.188	4.5	0.203	9.0	0.219	4.8	0.234	20.2
0.250	36.8	0.266	21.3	0.281	0.1	0.297	21.5	0.313	47.4
0.328	20.0	0.344	9.3	0.359	22.3	0.375	8.3	0.391	50.9
0.406	33.8	0.422	8.4	0.438	18.0	0.453	18.3	0.469	6.2
0.484	88.2	0.500	101.5						

MEAN POWER DENSITY: 22.23
DEGREES OF FREEDOM = 3
CHISQUARE = 726.64
ST.DEVIATION = 22.47
MPD UPPER 0.95 CONF LIMIT = 31.44
MPD LOWER 0.95 CONF LIMIT = 13.03
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

Table 10.7 Power level in each of 32 frequency points. Spectrum from child's text string. Measuring window: 100 words.

FIE1,151B350RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.0								
0.016	37.6	0.031	11.5	0.047	0.4	0.063	11.1	0.078	7.5
0.094	14.7	0.109	6.9	0.125	16.9	0.141	13.6	0.156	14.6
0.172	15.0	0.188	2.3	0.203	17.5	0.219	14.6	0.234	15.0
0.250	26.1	0.266	31.8	0.281	19.5	0.297	13.0	0.313	39.3
0.328	24.8	0.344	6.1	0.359	36.2	0.375	9.4	0.391	16.2
0.406	30.8	0.422	14.4	0.438	21.1	0.453	11.4	0.469	33.9
0.484	43.1	0.500	23.6						

MEAN POWER DENSITY: 18.20
DEGREES OF FREEDOM = 6
CHISQUARE = 225.40
ST.DEVIATION = 11.32
MPD UPPER 0.95 CONF LIMIT = 22.03
MPD LOWER 0.95 CONF LIMIT = 14.37
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

Table 10.8 Power level in each of 32 frequency points. Spectrum from child's text string. Measuring window: 200 words.

FIE1,151B450RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	7.3								
0.016	27.9	0.031	10.1	0.047	10.0	0.063	14.9	0.078	11.3
0.094	10.2	0.109	8.4	0.125	15.2	0.141	13.2	0.156	15.5
0.172	14.8	0.188	5.1	0.203	23.4	0.219	18.0	0.234	13.0
0.250	19.1	0.266	21.7	0.281	17.6	0.297	12.7	0.313	38.4
0.328	15.4	0.344	16.3	0.359	29.7	0.375	6.3	0.391	15.7
0.406	26.6	0.422	22.1	0.438	22.8	0.453	12.3	0.469	22.3
0.484	43.9	0.500	50.3						

MEAN POWER DENSITY: 18.52
DEGREES OF FREEDOM = 9
CHISQUARE = 185.27
ST.DEVIATION = 10.35
MPD UPPER 0.95 CONF LIMIT = 21.82
MPD LOWER 0.95 CONF LIMIT = 15.21
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

Table 10.9 Power level in each of 32 frequency points. Spectrum from child's text string. Measuring window: 300 words.

FIE1,151B550RF76 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	10.8								
0.016	31.0	0.031	8.8	0.047	11.5	0.063	19.9	0.078	12.9
0.094	15.5	0.109	8.9	0.125	11.6	0.141	16.0	0.156	15.2
0.172	14.8	0.188	6.7	0.203	25.5	0.219	13.7	0.234	19.9
0.250	13.8	0.266	26.6	0.281	19.6	0.297	13.7	0.313	33.6
0.328	8.9	0.344	13.5	0.359	18.0	0.375	8.9	0.391	12.4
0.406	28.1	0.422	19.7	0.438	16.6	0.453	14.7	0.469	24.6
0.484	24.3	0.500	33.3						

MEAN POWER DENSITY: 17.35
DEGREES OF FREEDOM = 12
CHISQUARE = 99.82
ST.DEVIATION = 7.36
MPD UPPER 0.95 CONF LIMIT = 19.64
MPD LOWER 0.95 CONF LIMIT = 15.07
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

Table 10.10 Power level in each of 32 frequency points. Spectrum from child's text string. Measuring window: 400 words.

words. At 200 words the power has fallen to 43.1. We can see too how the lack of stationarity causes the power to dissipate from f=0.484 to f=0.469 as the window width is increased over 200 words: With increasing width, f=0.469 shares an increasingly high proportion of the power in f=0.484 (tables 10.6 to 10.10)

The impact on the statistical level of significance of a very short window can clearly be seen in table 10.6 where the window is 50 words long. With a 32 point frequency spectrum we would need a window length of at least 64 words to get 2 degrees of freedom. as explained above. However, as I deliberately have kept the window lower than 64, we have achieved only 1 degree of freedom. The result is, that the lower 95% confidence limit is less than the lowest power level of the spectrum. The result is of course, that our level of significance is unacceptably low and consequently only 3 of the 32 frequency points give significant power levels.

It is clear from tables 10.6 to 10.10, where the number of significant points are given in the bottom line of each table, that already with 2 degrees of freedom, there is a marked increase in the number of significant points: from 3 points (1 degree of freedom) to 17 points (2 degrees of freedom). We can see too, that once we have reached around 6 degrees of freedom, the number of significant points increases only slightly with increasing number of degrees of freedom.

Summing up, we have found, that with a 32 point power spectrum, the minimum window which will give a statistically sound spectrum must be twice the number of frequency points, i.e. 64. We have seen too, that at windows of over 200 words, the lack of stationarity causes the power to drift in both the high and the low frequency bands.

Next, we shall have a look at the same kind of analysis, but this time applied to a text string written by an adult.

1RUS,201B250RF182 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	24.8								
0.016	2.3	0.031	18.5	0.047	0.5	0.063	14.6	0.078	5.3
0.094	18.0	0.109	2.3	0.125	1.7	0.141	1.2	0.156	14.6
0.172	3.9	0.188	21.1	0.203	19.4	0.219	28.7	0.234	36.3
0.250	3.4	0.266	2.1	0.281	34.0	0.297	32.5	0.313	7.3
0.328	10.7	0.344	66.5	0.359	5.5	0.375	27.4	0.391	42.8
0.406	0.3	0.422	24.2	0.438	46.2	0.453	2.2	0.469	38.0
0.484	9.1	0.500	32.7						

MEAN POWER DENSITY: 18.12
DEGREES OF FREEDOM = 1
CHISQUARE = 477.46
ST.DEVIATION = 16.44
MPD UPPER 0.95 CONF LIMIT = 36.19
MPD LOWER 0.95 CONF LIMIT = 0.05
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 0
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 5

Table 10.11 Power level in each of 32 frequency points. Spectrum from adult's text string. Measuring window: 50 words.

1RUS.201B300RF198 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	12.7								
0.016	43.8	0.031	18.2	0.047	10.1	0.063	3.0	0.078	5.6
0.094	6.1	0.109	1.2	0.125	3.1	0.141	2.5	0.156	23.5
0.172	10.0	0.188	10.7	0.203	11.6	0.219	13.7	0.234	39.5
0.250	2.7	0.266	23.8	0.281	0.4	0.297	38.7	0.313	20.4
0.328	18.2	0.344	22.4	0.359	22.3	0.375	27.9	0.391	7.8
0.406	14.7	0.422	10.7	0.438	15.9	0.453	2.6	0.469	10.3
0.484	24.6	0.500	90.3						

MEAN POWER DENSITY: 17.24
DEGREES OF FREEDOM = 3
CHISQUARE = 554.14
ST.DEVIATION = 17.28
MPD UPPER 0.95 CONF LIMIT = 24.32
MPD LOWER 0.95 CONF LIMIT = 10.16
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

Table 10.12 Power level in each of 32 frequency points. Spectrum from adult's text string. Measuring window: 100 words.

1RUS.201B400RF119 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	29.0								
0.016	28.1	0.031	30.2	0.047	19.9	0.063	1.3	0.078	12.5
0.094	11.7	0.109	0.1	0.125	7.4	0.141	14.1	0.156	33.7
0.172	10.2	0.188	13.4	0.203	13.3	0.219	9.5	0.234	34.3
0.250	11.4	0.266	15.0	0.281	10.6	0.297	12.9	0.313	9.3
0.328	21.4	0.344	5.6	0.359	24.0	0.375	17.1	0.391	21.8
0.406	7.4	0.422	31.4	0.438	15.8	0.453	22.2	0.469	24.6
0.484	24.6	0.500	44.5						

MEAN POWER DENSITY: 17.83
DEGREES OF FREEDOM = 6
CHISQUARE = 189.93
ST.DEVIATION = 10.29
MPD UPPER 0.95 CONF LIMIT = 21.31
MPD LOWER 0.95 CONF LIMIT = 14.35
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 29

Table 10.13 Power level in each of 32 frequency points. Spectrum from adult's text string. Measuring window:200 words.

1RUS,201B500RF181 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	35.2								
0.016	28.9	0.031	24.9	0.047	19.0	0.063	3.0	0.078	11.6
0.094	5.3	0.109	9.4	0.125	12.3	0.141	16.0	0.156	28.4
0.172	4.3	0.188	5.2	0.203	10.5	0.219	12.9	0.234	26.5
0.250	8.6	0.266	14.9	0.281	14.3	0.297	15.5	0.313	9.7
0.328	24.4	0.344	14.5	0.359	21.9	0.375	27.6	0.391	26.6
0.406	21.0	0.422	41.2	0.438	16.1	0.453	6.2	0.469	28.6
0.484	5.6	0.500	23.4						

MEAN POWER DENSITY: 17.37
DEGREES OF FREEDOM = 9
CHISQUARE = 173.19
ST.DEVIATION = 9.70
MPD UPPER 0.95 CONF LIMIT = 20.47
MPD LOWER 0.95 CONF LIMIT = 14.28
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

Table 10.14 Power level in each of 32 frequency points. Spectrum from adult's text string. Measuring window: 300 words.

1RUS,201B600RF162 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	29.1								
0.016	23.9	0.031	25.0	0.047	17.2	0.063	13.7	0.078	17.1
0.094	7.2	0.109	8.9	0.125	19.6	0.141	14.0	0.156	20.9
0.172	8.9	0.188	11.1	0.203	10.1	0.219	14.5	0.234	25.8
0.250	10.7	0.266	16.7	0.281	10.4	0.297	16.2	0.313	23.2
0.328	16.7	0.344	15.2	0.359	19.0	0.375	23.5	0.391	20.7
0.406	13.0	0.422	36.1	0.438	15.0	0.453	7.4	0.469	25.3
0.484	7.3	0.500	19.6						

MEAN POWER DENSITY: 17.06
DEGREES OF FREEDOM = 12
CHISQUARE = 89.49
ST.DEVIATION = 6.91
MPD UPPER 0.95 CONF LIMIT = 19.20
MPD LOWER 0.95 CONF LIMIT = 14.91
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

Table 10.15 Power level in each of 32 frequency points. Spectrum from adult's text string. Measuring window: 400 words.

Comparing this last series of 'adult' spectra with the series of 'child' spectra, we note the following points:

Statistical significance.

Here too, the increase from 1 to 2 degrees of freedom sees a marked increase in the number of frequency points rising above the upper 95% confidence limit.

Regarding the optimal window, we find this time, that the number of significant spectral power points rises until the number of degrees of freedom is between 6 and 9. This is not much different from the case of a child's text string where we found that more than 9 degrees of freedom did not increase the number of significant points noticeably. In the case of the adult text string, the number of significant points actually falls slightly when the degree of freedom is higher than between 6 and 9.

Overall power.

For each of the windows of 50, 100, 200, 300 and 400, the Mean Power Density (MPD) of the child's string is higher than that of the adult string. This is different from our findings in an earlier chapter, that childrens text strings had a smaller (but not significantly so) level of structure than adult strings, but as the analysis in this case is carried out on only one string, it does not qualify as an inconsistency. In spite of minor fluctuations both strings show clearly the same tendency to a fall in MPD with an increase in window width. This has two implications: First we must try to reflect on whether this is consistent with our concept of MPD as representative of the concept of structure. I shall return to this point in the next chapter. Secondly, it means that whenever we want to compare power densities, we must be shure. that the spectra are obtained with windows of the same length. This is a parallel to our findings in an earlier chapter, that if we wanted to compare structure (or vocabulary) in different text strings, the strings must be of the same length.

Power in low-frequency band.

In the analysis of the adult string we find the same 'behaviour': increasing sensitivity in the low frequency end of the spectrum with increased window width, and dissipation of power from f=0.016 to f=0.031 if the window is increased above around 200 words.

Although the power level in f=0.016 (adult) is almost zero when the window is only 50 words, already with a window of 100, the power at this frequency is almost twice that of the 95% confidence limit. This is significantly higher than in the case of the child's spectrum, both relatively with respect to the confidence limit, and in absolute terms. With increased window width, the power in f=0.016 decreases. However, a closer study of neighbouring frequencies show, that what happens is that the frequency drifts to the right in the spectrum i.e. the power in f=0.031 and f=0.047 increases as the power in f=0.016 decreases. This is again due to lack of stationarity.

STATIONARITY.

In the initial stages of my research I developed a scanning technique which gives a direct view of the feature of stationarity and its impact on the power spectrum. To give the reader a QUALITATIVE idea of stationarity and other features of the reading of a text string I shall present 6 of these scans. Each scan consists of 25 consequtive spectral analysis of the same text string, but moved 8 words forward between each analysis. Thus, each scan covers 25 times 8 words = 200 words and can be looked at as a continuous picture of what goes on (on our crude level anyway) during the processing of a text string.

The scans are presented in pairs of contrasting features: The text string with the lowest vocabulary next to the text string with the highest vocabulary (figures 10.16 a and b), the text string which gave the lowest value of gradient B next to the text string with the highest gradient B (figures 10.17 a and b) and finally two text strings by Bertrand Russell, one from "The History of Western Philosophy" next to one from his "Childrens' Stories" (figures 10.18 a and b).

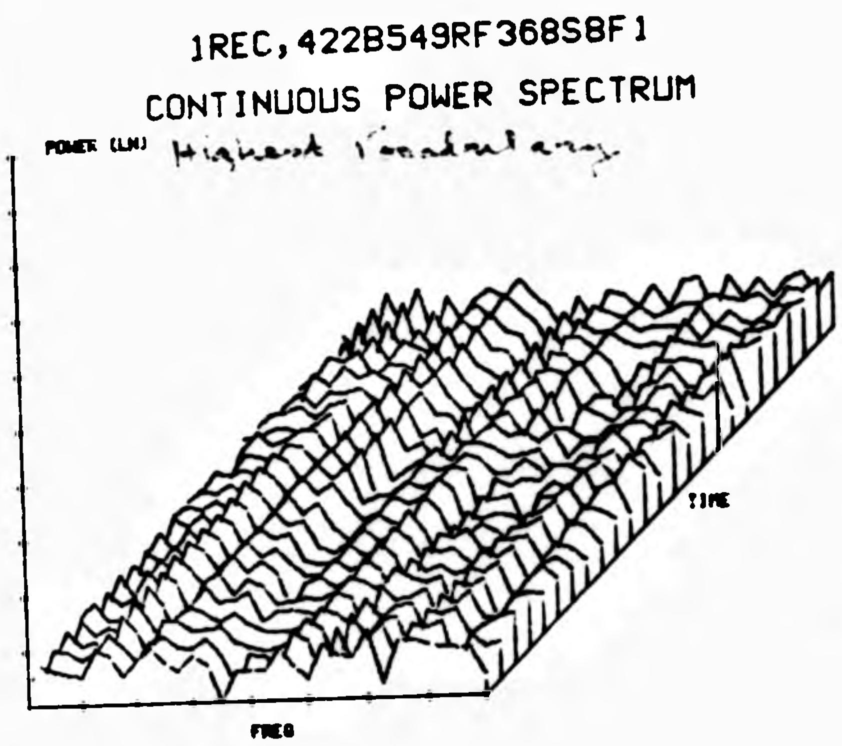

Figure 10.16 a.
Scan of text string with
highest vocabulary

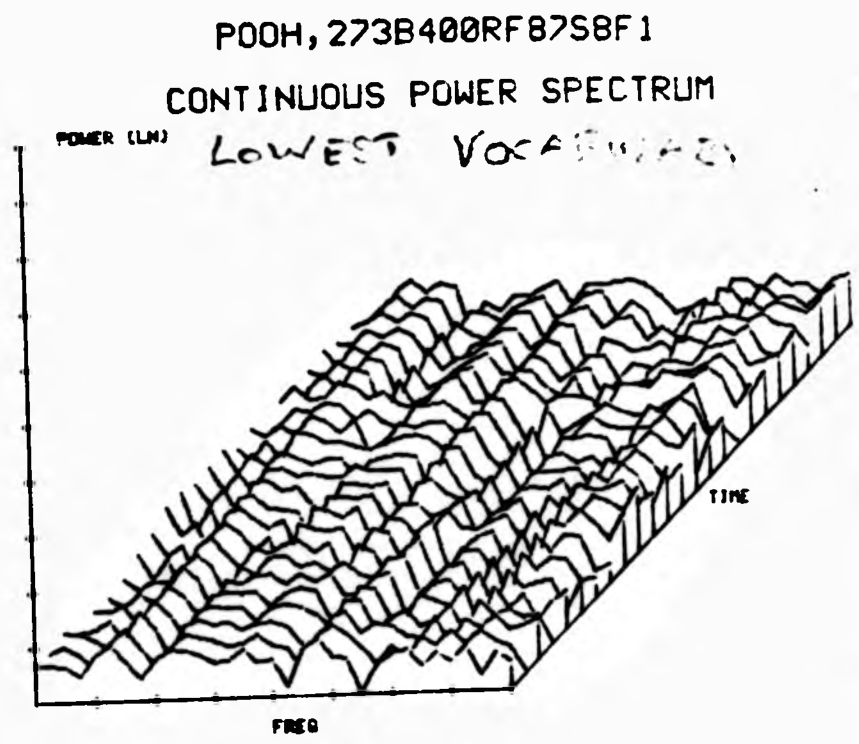

Figure 10.16 b.
Scan of text string with
lowest vocabulary

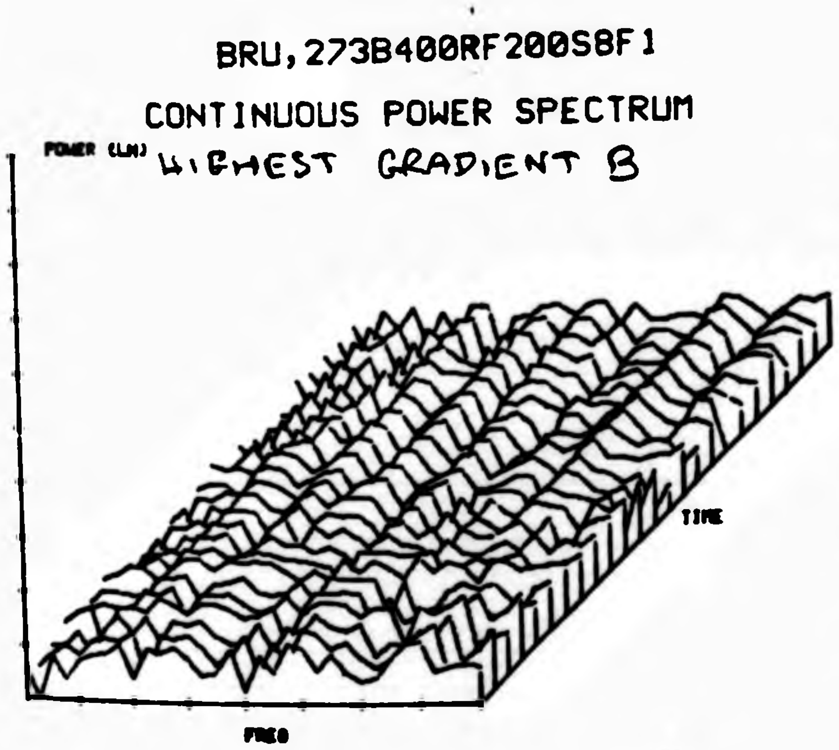

Figure 10.17 a.
Scan of text string with
highest value of B

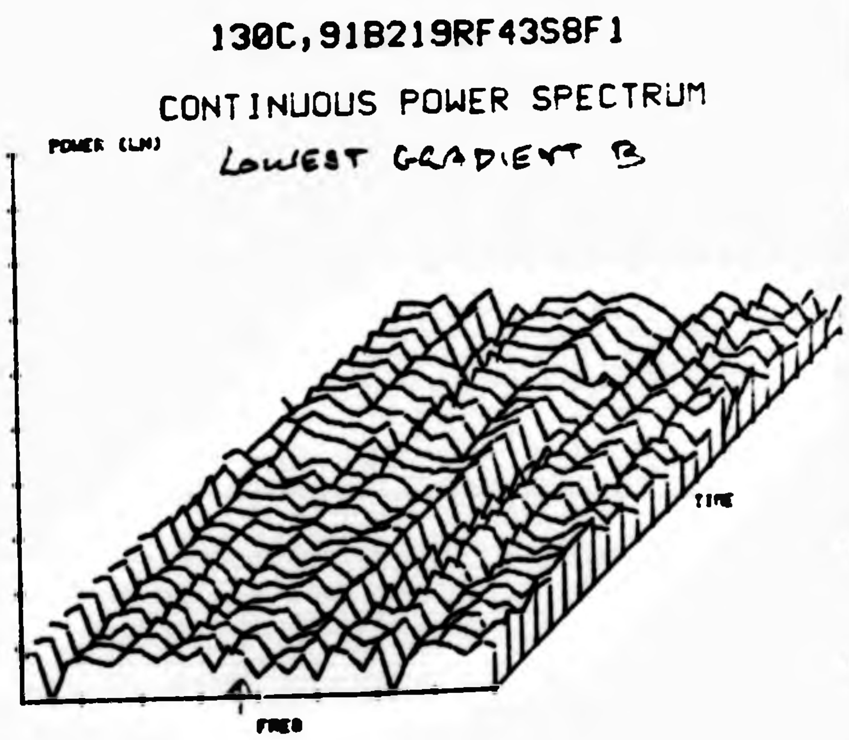

Figure 10.17 b.
Scan of text string with
lowest value of B

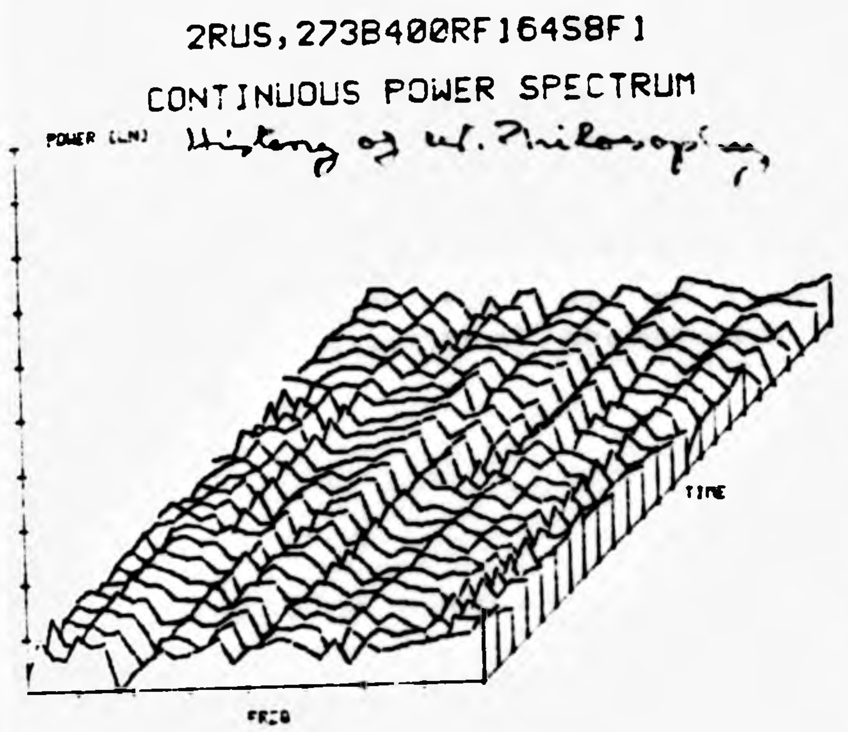

Figure 10.18 a.
Scan of complex text string

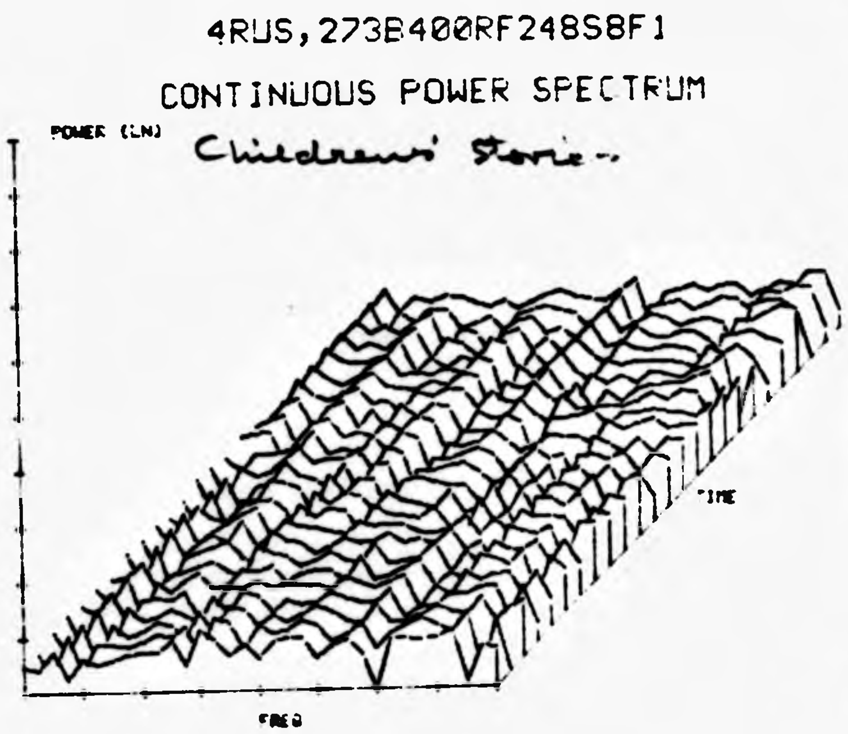

Figure 10.18 b.
Scan of simple text string

The way to judge stationarity on these surfaces is to look at the ridges formed by consecutive peaks of power along the direction of the time axis. Figure 10.16 (a) has some very straight ridges and furrows to the left of the middle of the spectrum. We say that the periodicity at this frequency (around f=0.125 since each division on the frequency axis is 0.0625) is stationary. To the right of the middle (about 5 divisions from the beginning of the axis i.e f=0.31) we have a different situation: beginning at the front, some ridges and furrows can be seen to be moving to the right, so that half the way down the time axis, the peaks have moved to the 6th division (f=0.38). Obviously, around this frequency the periodicity is not stationary.

We can see that on most scans, there is a fair amount of stationarity. Peaks may come and go, but within half of the scan i.e 10 to 15 consecutive spectra or 'runs', the peaks on the whole stay on the same frequency. This means, that if we do not drag our analysis out over more than the span of 10 to 15 runs then we can expect a fair amount of staionarity. As each 'run' spans 8 words, 10 to 15 'runs' would span 80 to 120 words. The conclusion must be that as long as our window is shorter than around 120 words we do not need to worry too much about the influence of lack of staionarity.

This finding compares well with our finding above (tables 10.6 to 10.15) that lack of stationarity is not a problem until the window width is increased to around 200 words.

We can see too, that there is not much difference between the six scans. There is certainly no way in which it would be immediately possible to tell that the surface of figure 10.16 (a) is that of a scan of a text string with a very high vocabulary while figure 10.16 (b) is that of a low vocabulary text string, or that 10.18 (b) is a 'simple' text string while 10.18 (a) is a complex text string written by the same author.

However, I find these scans fascinating in their own right because they all - albeit crudely - depict the power distribution during the processing of the text strings in our linguistic device somewhere on the synthetical/generative or the analytical/perceptual level. And I would like to believe, that some of the ridges and furrows of these topological surfaces do in fact represent control mechanisms of our linguistic device.

SUMMARY OF OPTIMAL PARAMETERS.

1) REFERENCE FIELD: The optimal field is the one which gives a 1:1 ratio of zeroes and ones in the information array.

2) NUMBER OF FREQUENCY POINTS IN POWER SPECTRUM: Minimum 32 points, but if the combination: [length of text string] vs [reference field] allows it, then 64 points.

3) WIDTH OF MEASURING WINDOW: MINIMUM: twice the number of frequency points (2 degrees of freedom). MAXIMUM: 6 to 9 times the number of frequency points (6 to 9 degrees of freedom), but if the window exceeds around 120 - 200 words, lack of stationarity may result at some frequencies.

In the next chapter we shall apply the sum of our findings to all the text samples in chapter 4. This causes some problems with some of the childrens text strings which are too short to give 2 degrees of freedom with a power spectrum of 32 frequency points. However, in spite of their lack of statistical significance I shall present these spectra in the following chapter as well - as a 'special case' - since, even with one degree of freedom, some tendencies might be revealed.

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CHAPTER 11.

POWER SPECTRAL ANALYSIS OF TEXT STRINGS.

Using the very sensitive Fourier analysis we established in chapter 10 the optimal length of the reference field and the optimal number of frequency points in the power spectrum. The width of the measuring window was assessed, both with regard to its impact on the statistical significance and its immunity to lack of stationarity. We established that the lower limit for a 32 frequency point spectrum was a window of 64 words and the upper limit was the window which would give between 6 and 9 degrees of freedom, which for the same 32 point spectrum means a window somewhere between 192 and 288 words. With regard to lack of stationarity, practical experience showed that a window greater than 200 words caused power to be dissipated from one frequency to neighbouring frequencies. In this chapter we shall use these findings to obtain power spectra of those text samples in chapter 4 which are long enough to satisfy these conditions.

A point which I mentioned at the end of chapter 10, but did not enlarge upon, was that from the two lines of analysis of an 'adult' string and a 'child' string in chapter 10, it emerged that the degree of structure was reciprocally related to the width of the window: the shorter the window, the higher the degree of structure - everything else equal (table 10.6 to table 10.15).

Is this consistent with the concept of structure we have used so far? To answer this question, let us look at two sizes of window and let us approach the problem according to the Information Theory and think of the two windows as physical systems. Let us say that one window - system I - contains 64 units (words) and the other window - system II - contains 128 units (words). Let us further agree that the two windows are applied to sections of the same text string no further apart, than we can expect the grammatical structure or bonding between the words in each section to be roughly the same.

IF the units are distributed at random, then by the same token the information in system I (the shorter of the windows) is 6 bit (2 in power 6 equals 64) and in system II (the longer window) the information is 7 bit (2 in power 7 equals 128).

But by the definition of information and redundancy in the Information Theory (chapter 1) then, if system II is the higher on information, then it is the lower on redundancy, or put another way: If system II is the higher on information, then system I is the higher on redundancy and structure. From this follows, that - everything else equal - the shorter window should give a higher measure of structure.

You will probably want to interrupt me here and state, about the argument above, that the whole point of the strings being natural text strings is, that the units are NOT distributed at random, and this is of course true. However, by using the same text string in this mental experiment, we can assume that the distribution of units (words) in the two systems - random or not - is the same.

This has important implications, both for our analysis in the past and for our future search for structures. When compared structure - as well as vocabulary - in chapter 5 by fitting a straight line to the graphical representation of the vocabulary of strings in a double logartihmic coordinate system, we made sure that the text strings were of equal length, and we picked the length of 100 words as a practical compromise. If we had not measured on strings of equal length, the shorter strings would register as having a higher degree of structure - other parameters being equal.

We thus find ourselves in the same difficult situation as when we compared vocabulary of different categories: we can only legitimately compare power spectra if the spectra are based on analysis with the same size window. Now as then, this does not pose any problem when we are dealing with 'adult' strings. But if we want to campare the spectra of 'child' strings with those of 'adult' strings, it means, that either we compare short 'adult' strings with normal length 'child' strings - which is not realistic for the 'adult' strings - or we compare the very few long 'child' strings of chapter 4 with normal size 'adult' strings - which by the same token is not realistic for the 'child' strings.

As stated above, the absolute minimum of the measuring window is 64 and the upper limit is somewhere around 200 words. Within these limits I shall now try to establish if there is an optimal size window. My line of action shall be that of making spectra of as many of the text samples in chapter 4 as possible, first with a measuring window of 64, then with a window of 128 and finally with a window of 256. I have picked these windows because they are powers of 2 within the acceptable upper and lower limits as established in chapter 10. The importance of the window size being a power of two has to do with my use of the FFT to cross-check the results from the time series transform used in these analyses as explained more fully in chapters 7 and 10.

All the 22 adult text strings in chapter 4 are long enough to provide reference field plus a window of 64, 128 and 256 respectively. The problem arises with the childrens text strngs. Of the childrens text samples in chapter 4, 25 of the samples were long enough to provide the necessary reference field PLUS the minimum window of 64 words; 13 samples were long enough to provide reference field plus a window of 128, but only 5 samples were long enough to participate in the analysis with a window of 256.

I shall now make three analyses which differ in the size of the measuring window and the number of participating text strings only. The first analysis is performed with a measuring window of 64 words on 25 child strings and 22 adult strings, the second with a window of 128 words on 13 child strings and 22 adult strings and the last with a window of 256 words on 5 child strings and 22 adult strings. In this way we shall have - of the text samples in chapter 4 - 47 spectra obtained with a 64 word measuring window, 35 spectra obtained with a 128 word window and 27 spectra resulting from an analysis with a 256 word window.

These three groups shall be kept strictly separate. One feature which we, according to the considerations above, would expect these three analyses to confirm, is that the shorter the strings are, the higher the level of structure, i.e. the power spectra resulting from the analyses with a 64 word window should give a higher overall structure than the spectra resulting from the 128 word window, which again should give higher structure levels than the analyses based on a 256 word window

We are now in danger of becoming confused about the terminology since each collection of spectra obtained with windows of 64, 128 and 256 constitute a group, which again can be divided into subgroups: Adults, children, which in turn divide into sub-sub-groups: children = younger children + older children, and adults = scientists + newspapers + childrens books.

For the sake of clarity I shall hereafter call a collection of spectra obtained with one particular window size for a 'window-group', and a group like that of scientists I shall call a category. Thus the 'window-group 64' is the collection of all the spectra obtained with a measuring window of 64 words, and the category 'scientists' is the collection of spectra based on the text samples written by scientists. Thus, the window-group 64 comprises the categories: 'scientists', 'newspapers', 'childrens books', 'young children' and 'old children' each based on text string analyses with a 64 word window. By the same token 'window-group 128' comprises the same categories as 'window-group 64' but the text strings in each category have of course been analysed with a window of 128 words.

Again for reasons of clarity and organisation, all individual spectra have been moved to the appendix to this chapter together with their respective numerical read-outs. Included in this chapter are only the average power spectra from each window-group and the statistical considerations.

The LABEL of the averaged power spectra:

AVR stands of course for 'average'. The next group of letters and numerals are a '10W' and a number. After 10 has been subtracted from this number we have the total of the windows which this average is based on. Thus '10W650' would indicate, that the total number of words which have gone into the making of this average would have been 650 minus 10 words equal to 640 words. If this was an average for one of the categories in the window-group 64, it would indicate, that 10 spectra each based on a window of 64 words had contributed to this average. This may seem complicated, but it has been necessary to do it this way because of the way the average power spectra have been calculated. The averaged spectra are not just simple means of powers in each frequency point, but are WEIGHTED MEANS of the individual spectra:

If we have an averaged power spectrum based on an average of 10 windows and we want to find the average between this spectrum and another average power spectrum based on only two windows, we cannot just add the powers in each frequency point of the two spectra and divide by two. This would give the spectrum based on two windows far more significance than it is entitled to. We must weigh the powers so that the numerical values of the 10 window spectrum count 10/12th of each average and the 2 window average counts 2/12th of the average.

Particularly when we calculate the adult average spectra this becomes important since newspapers have only 5 text samples = 5 windows and scientists have 9 text samples = 9 windows. If we calculated the average power spectrum of these two categories, newspapers and scientists, by simply adding and dividing by 2, the 'average' spectrum obtained in this way would put far too great an emphasis on the features of 'newspaper language'.

As an example, I shall go through the averaging of the adult text strings to explain how this is done: We have three categories of adult writers: 'SCIENTISTS', 'NEWSPAPERS' and 'CHILDRENS' BOOKS'. For each of these three categories we have obtained an average spectrum as seen on the following 8 pages. To compare these three categories with the power spectra based on childrens text strings it would be convenient to create a new average called 'ADULTS'. To calculate this power spectrum called 'ADULTS' I proceed as follows: The average spectrum marked 'SCIENTISTS' is averaged from 9 windows. The average spectrum of 'NEWSPAPERS' is averaged from 5 windows and the average spectrum of 'CHILDRENS BOOKS' is based on 8 windows. This gives a total of 22 windows. To this total the scientists contributed 9 windows and thus the power in each frequency point of the average scientist spectrum should contribute with a factor of 9/22 to the average adult spectrum. As newspapers and childrens books contributed with 5 and 8 windows respectively, the power in each frequency point must for the same reason be multiplied by a factor of 5/22 and 8/22 respectively before they are added to make up one frequency point in the spectrum marked 'ADULTS'.

STATISTICS of the averaged power spectra:

The statistics printed on each power spectrum were explained in chapter 9. but for convenience I shall give a short summary: MPD stands for Mean Power Density and is the sum of the powers in each frequency point divided by the number of points. CHI2 is the usual chi square and is included here because it is a NORMALISED measure of the variance (the variance divided by the mean) and thus does not depend on the size of the MPD. SDEV is the usual standard deviation i.e. the not normalised measure of variance and it is used together with the number of degrees of freedom to calculate the upper and lower 95% confidence limits.

On the following pages I shall present the spectra which are averaged from each of the 5 categories: 'young children', 'old children', 'scientists', 'newspapers' and 'childrens books'. After these spectra I shall present: 1) the average of 'childrens power spectra (weighted average of 'young children' and 'old children' average spectra). 2) the average of 'adults' power spectra (weighted average of 'scientist', 'newspapers' and 'childrens books'). 3) average of all spectra.

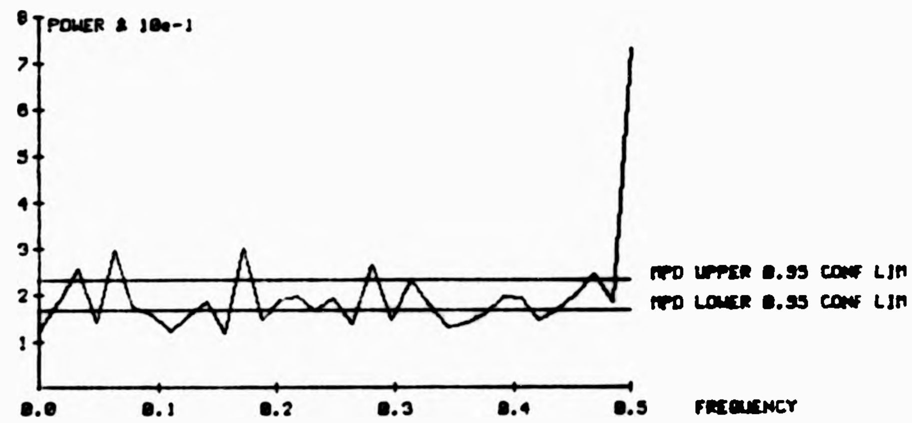
On the basis of the spectra within each of the window-groups 64, 128 and 256, I shall test with the Kruskal-Wallis one-way analysis of variance the following categories against each other: 'young children', 'old children', 'all children', 'scientists', 'newspapers', 'childrens books' and 'adults' to evaluate if the difference between these categories is significant enough to suggest that they are indeed drawn from different populations.

First, the averages for window-group 64 are presented followed by the statistical consideration for this window-group. Next, this approach is repeated for window-group 128 and window-group 256. Lastly I shall compare the findings from each of the three window-groups.

WINDOW-GROUP 64:

AVR,10W850FF:YOUNGCHILD
AVERAGED POWER SPECTRUM

MPD = 19.76 DEGR OF FREED = 26
CHI2= 185.40 UPPER CONF LIM= 22.93
SDEV= 10.70 LOWER CONF LIM= 16.58



AVR,10W850FF:YOUNGCHILD POWER DENSITY IN FREQUENCY POINTS:

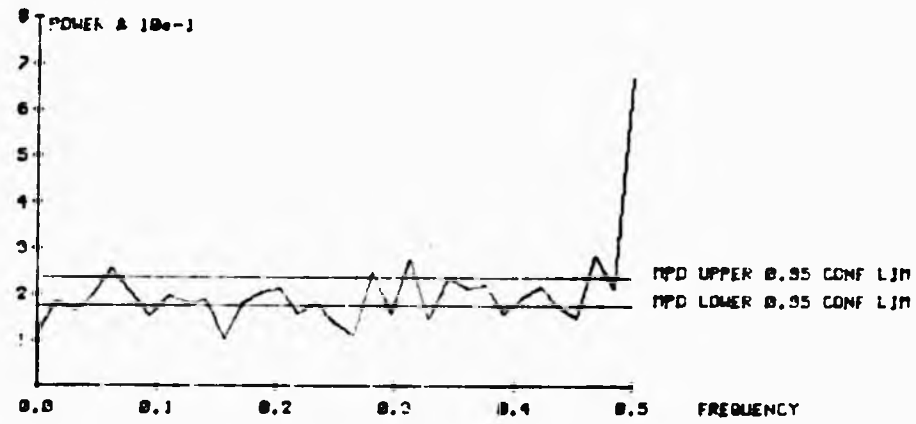
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.1								
0.016	18.5	0.031	25.6	0.047	13.9	0.063	29.8	0.078	17.2
0.094	15.5	0.109	11.9	0.125	15.5	0.141	18.3	0.156	11.8
0.172	30.0	0.188	14.6	0.203	18.6	0.219	19.6	0.234	16.4
0.250	19.1	0.266	13.8	0.281	26.2	0.297	14.4	0.313	23.0
0.328	17.4	0.344	12.8	0.359	14.2	0.375	15.9	0.391	19.8
0.406	19.1	0.422	14.4	0.438	16.6	0.453	19.9	0.469	24.5
0.484	18.5	0.500	73.1						

MEAN POWER DENSITY: 19.76
DEGREES OF FREEDOM = 26
CHISQUARE = 185.40
ST.DEVIATION = 10.70
MPD UPPER 0.95 CONF LIMIT = 22.93
MPD LOWER 0.95 CONF LIMIT = 16.58
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

Figure 11.1 Average Power Spectrum 'Young Children', W = 64.

AVR,10W777FF:OLDCHILD
AVERAGED POWER SPECTRUM

MPD = 20.15   DEGR OF FREED = 24
CHI2= 144.90   UPPER CONF LIM= 23.00
SDEV= 9.55   LOWER CONF LIM= 17.31



AVR.10W777FF:OLDCHILD   POWER DENSITY IN FREQUENCY POINTS:

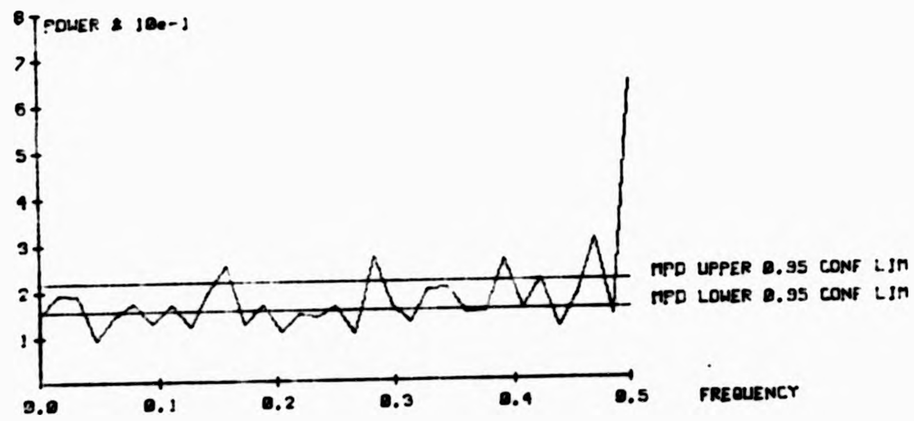
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.0								
0.016	18.5	0.031	16.6	0.047	20.1	0.063	25.4	0.078	20.3
0.094	15.1	0.109	19.8	0.125	18.0	0.141	18.9	0.156	9.8
0.172	17.9	0.188	20.2	0.203	21.2	0.219	15.6	0.234	18.0
0.250	13.6	0.266	10.7	0.281	24.7	0.297	15.7	0.313	27.6
0.328	14.3	0.344	23.7	0.359	21.1	0.375	22.1	0.391	15.7
0.406	19.3	0.422	21.6	0.438	17.1	0.453	15.0	0.469	28.4
0.484	21.0	0.500	67.2						

MEAN POWER DENSITY: 20.15
DEGREES OF FREEDOM = 24
CHISQUARE = 144.90
ST.DEVIATION = 9.55
MPD UPPER 0.95 CONF LIMIT = 23.00
MPD LOWER 0.95 CONF LIMIT = 17.31
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

Figure 11.2 Average Power Spectrum 'Old Children'. W = 64.

AVR,10W585FF:SCIENTISTS
AVERAGED POWER SPECTRUM

MPD = 19.92 DEGR OF FREED = 18
CHI2= 153.36 UPPER CONF LIM= 22.87
SDEV= 9.77 LOWER CONF LIM= 16.97



AVR.10W585FF:SCIENTISTS POWER DENSITY IN FREQUENCY POINTS:

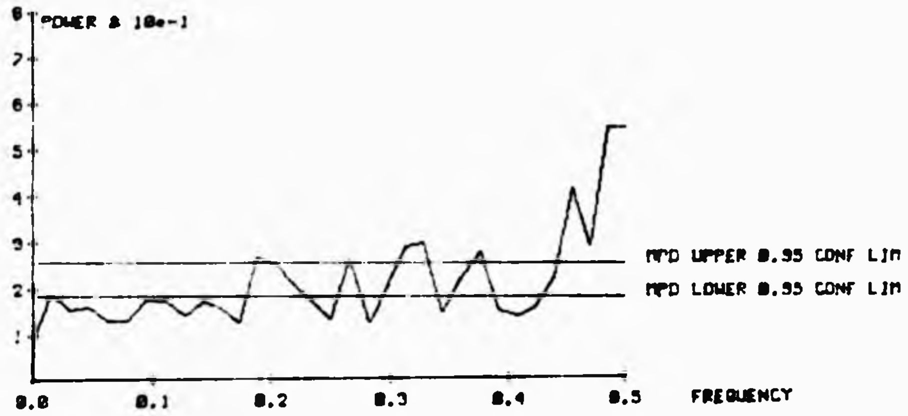
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	16.3								
0.016	20.8	0.031	20.3	0.047	10.6	0.063	15.9	0.078	18.6
0.094	14.3	0.109	18.2	0.125	13.5	0.141	21.1	0.156	26.6
0.172	13.8	0.188	18.4	0.203	12.6	0.219	16.4	0.234	15.5
0.250	18.1	0.266	11.9	0.281	28.8	0.297	17.9	0.313	14.2
0.328	21.7	0.344	22.2	0.359	16.4	0.375	16.8	0.391	27.9
0.406	17.1	0.422	23.6	0.438	13.2	0.453	20.4	0.469	32.3
0.484	15.5	0.500	66.5						

MEAN POWER DENSITY: 19.92
DEGREES OF FREEDOM = 18
CHISQUARE = 153.36
ST.DEVIATION = 9.77
MPD UPPER 0.95 CONF LIMIT = 22.87
MPD LOWER 0.95 CONF LIMIT = 16.97
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

Figure 11.3 Average Power Spectrum 'Scientists', W = 64.

AVR,10W330FF:PAPERS
AVERAGED POWER SPECTRUM

MPD = 21.63　　DEGR OF FREED = 10
CHI2= 182.85　　UPPER CONF LIM= 25.14
SDEV= 11.12　　LOWER CONF LIM= 18.13



AVR,10W330FF:PAPERS　　POWER DENSITY IN FREQUENCY POINTS:

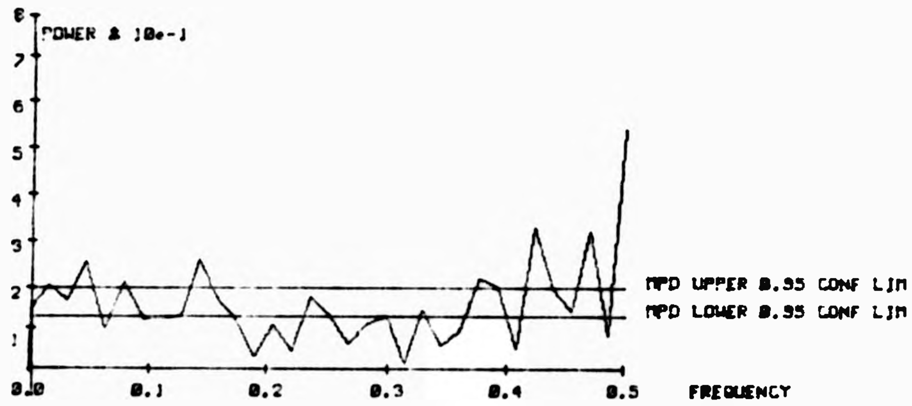
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.6								
0.016	18.7	0.031	15.1	0.047	15.9	0.063	12.8	0.078	12.9
0.094	17.6	0.109	17.2	0.125	14.0	0.141	17.0	0.156	15.8
0.172	12.3	0.188	26.7	0.203	25.1	0.219	20.6	0.234	17.3
0.250	13.2	0.266	26.2	0.281	12.5	0.297	21.2	0.313	29.3
0.328	29.9	0.344	14.6	0.359	22.3	0.375	28.1	0.391	15.0
0.406	13.9	0.422	16.1	0.438	22.4	0.453	42.0	0.469	29.2
0.484	55.2	0.500	55.2						

MEAN POWER DENSITY: 21.63
DEGREES OF FREEDOM = 10
CHISQUARE = 182.85
ST.DEVIATION = 11.12
MPD UPPER 0.95 CONF LIMIT = 25.14
MPD LOWER 0.95 CONF LIMIT = 18.13
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 18
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

Figure 11.4 Average Power Spectrum 'Newspapers', W = 64.

AVR,10W521FF:CHBOOKS
AVERAGED POWER SPECTRUM

MPD = 19.81 DEGR OF FREED = 16
CHI2= 156.12 UPPER CONF LIM= 22.80
SDEV= 9.83 LOWER CONF LIM= 16.82



AVR,10W521FF:CHBOOKS POWER DENSITY IN FREQUENCY POINTS:

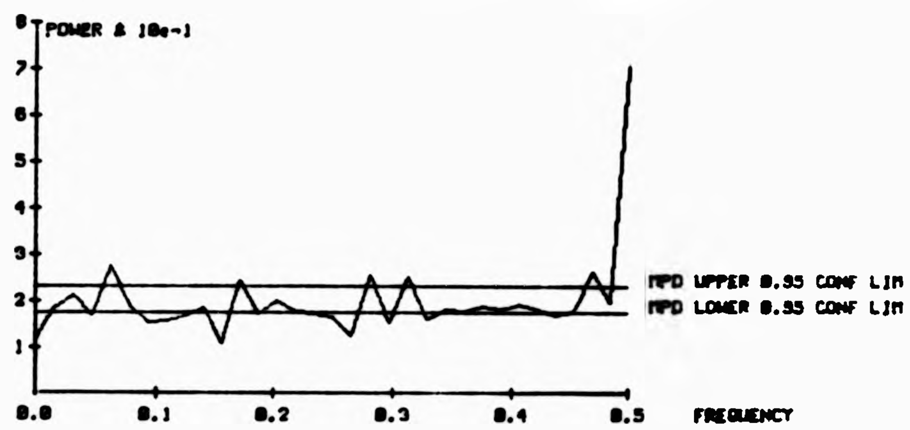
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	19.0								
0.016	23.4	0.031	20.5	0.047	29.0	0.063	14.2	0.078	24.2
0.094	16.5	0.109	16.3	0.125	17.2	0.141	29.3	0.156	20.3
0.172	16.5	0.188	8.4	0.203	15.0	0.219	9.6	0.234	21.3
0.250	17.0	0.266	11.3	0.281	15.7	0.297	17.3	0.313	6.8
0.328	18.4	0.344	10.6	0.359	13.9	0.375	25.2	0.391	23.1
0.406	10.0	0.422	36.6	0.438	22.6	0.453	18.2	0.469	35.8
0.484	12.8	0.500	57.6						

MEAN POWER DENSITY: 19.81
DEGREES OF FREEDOM = 16
CHISQUARE = 156.12
ST.DEVIATION = 9.83
MPD UPPER 0.95 CONF LIMIT = 22.80
MPD LOWER 0.95 CONF LIMIT = 16.82
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

Figure 11.5 Average Power Spectrum 'Childrens' Books', W = 64.

AVR,10W1618FF:CHILDREN
AVERAGED POWER SPECTRUM

MPD = 19.95 DEGR OF FREED = 50
CHI2= 155.29 UPPER CONF LIM= 22.85
SDEV= 9.84 LOWER CONF LIM= 17.04



AVR,10W1618FF:CHILDREN POWER DENSITY IN FREQUENCY POINTS:

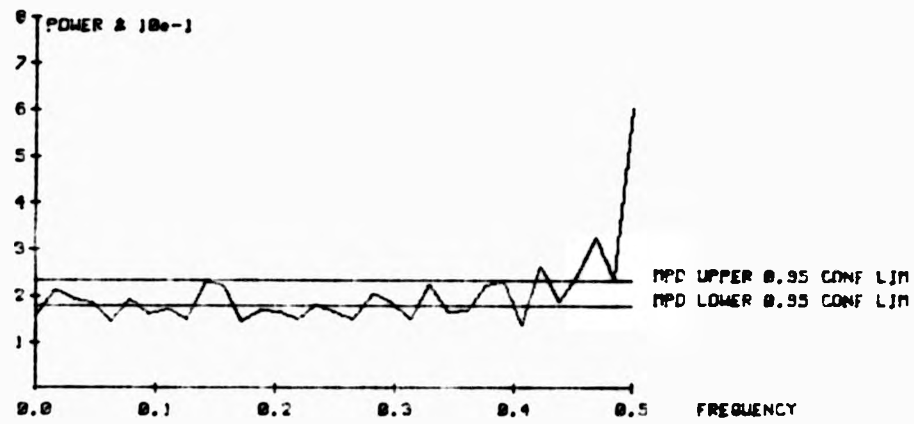
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.6								
0.016	18.5	0.031	21.3	0.047	16.9	0.063	27.7	0.078	18.7
0.094	15.3	0.109	15.7	0.125	16.7	0.141	18.6	0.156	10.9
0.172	24.2	0.188	17.3	0.203	19.8	0.219	17.7	0.234	17.2
0.250	16.5	0.266	12.3	0.281	25.5	0.297	15.0	0.313	25.2
0.328	16.0	0.344	18.0	0.359	17.5	0.375	18.8	0.391	17.9
0.406	19.2	0.422	17.8	0.438	16.8	0.453	17.5	0.469	26.4
0.484	19.7	0.500	70.3						

MEAN POWER DENSITY: 19.95
DEGREES OF FREEDOM = 40
CHISQUARE = 155.29
ST.DEVIATION = 9.84
MPD UPPER 0.95 CONF LIMIT = 22.83
MPD LOWER 0.95 CONF LIMIT = 17.06
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

Figure 11.6 Average Power Spectrum 'All Children', W = 64.

AVR,10W1418FF:ADULTS
AVERAGED POWER SPECTRUM

MPD = 20.27 DEGR OF FREED = 44
CHI2= 110.99 UPPER CONF LIM= 22.75
SDEV= 8.39 LOWER CONF LIM= 17.79



AVR,10W1418FF:ADULTS POWER DENSITY IN FREQUENCY POINTS:

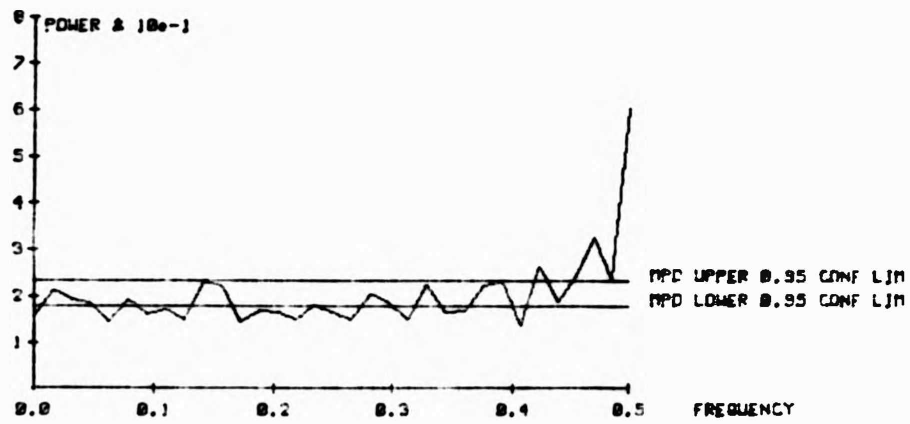
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.5								
0.016	21.3	0.031	19.2	0.047	18.5	0.063	14.6	0.078	19.3
0.094	15.9	0.109	17.3	0.125	15.0	0.141	23.2	0.156	21.8
0.172	14.4	0.188	16.7	0.203	16.3	0.219	14.9	0.234	18.0
0.250	16.6	0.266	14.9	0.281	20.3	0.297	18.4	0.313	15.0
0.328	22.4	0.344	16.3	0.359	16.8	0.375	22.4	0.391	23.2
0.406	13.8	0.422	26.6	0.438	18.7	0.453	24.5	0.469	32.9
0.484	23.6	0.500	60.7						

MEAN POWER DENSITY: 20.27
DEGREES OF FREEDOM = 40
CHISQUARE = 110.99
ST.DEVIATION = 8.39
MPD UPPER 0.95 CONF LIMIT = 22.73
MPD LOWER 0.95 CONF LIMIT = 17.81
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

Figure 11.7 Average Power Spectrum 'All Adults', W = 64.

AVR,10W1418FF:ADULTS
AVERAGED POWER SPECTRUM

MPD = 20.27 DEGR OF FREED = 44
CHI2= 110.99 UPPER CONF LIM= 22.75
SDEV= 8.39 LOWER CONF LIM= 17.79



AVR,10W1418FF:ADULTS POWER DENSITY IN FREQUENCY POINTS:

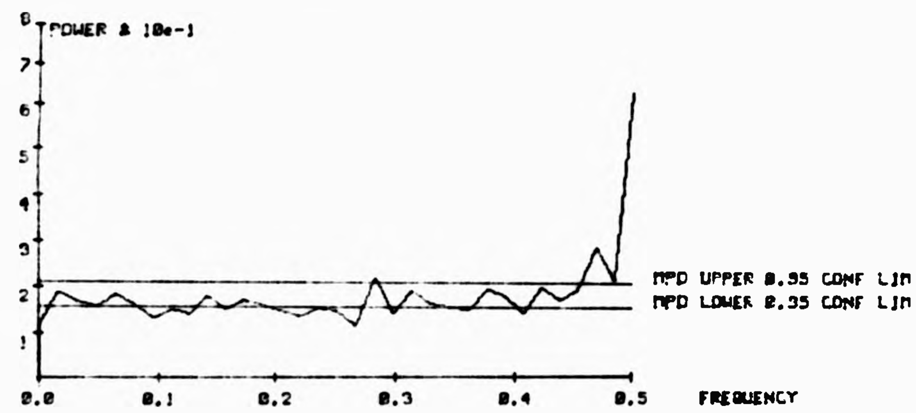
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.5								
0.016	21.3	0.031	19.2	0.047	18.5	0.063	14.6	0.078	19.3
0.094	15.9	0.109	17.3	0.125	15.0	0.141	23.2	0.156	21.8
0.172	14.4	0.188	16.7	0.203	16.3	0.219	14.9	0.234	18.0
0.250	16.6	0.266	14.9	0.281	20.3	0.297	18.4	0.313	15.0
0.328	22.4	0.344	16.3	0.359	16.8	0.375	22.4	0.391	23.2
0.406	13.8	0.422	26.6	0.438	18.7	0.453	24.5	0.469	32.9
0.484	23.6	0.500	60.7						

MEAN POWER DENSITY: 20.27
DEGREES OF FREEDOM = 40
CHISQUARE = 110.99
ST.DEVIATION = 8.39
MPD UPPER 0.95 CONF LIMIT = 22.73
MPD LOWER 0.95 CONF LIMIT = 17.81
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

Figure 11.7 Average Power Spectrum 'All Adults', W = 64.

AVR,10W2699FF:ALL64
AVERAGED POWER SPECTRUM

MPD = 20.11 DEGR OF FREED = 84
CHI2= 118.62 UPPER CONF LIM= 22.81
SDEV= 8.66 LOWER CONF LIM= 17.69



AVR.10W2699FF:ALL64 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	14.1								
0.016	20.7	0.031	18.9	0.047	17.6	0.063	20.3	0.078	18.2
0.094	15.3	0.109	17.1	0.125	15.8	0.141	20.2	0.156	17.0
0.172	19.2	0.188	18.0	0.203	16.9	0.219	15.8	0.234	17.6
0.250	17.0	0.266	13.5	0.281	23.8	0.297	16.6	0.313	21.3
0.328	18.4	0.344	17.6	0.359	17.3	0.375	21.8	0.391	20.0
0.406	16.4	0.422	21.9	0.438	19.3	0.453	21.6	0.469	30.6
0.484	23.4	0.500	65.0						

MEAN POWER DENSITY: 20.11
DEGREES OF FREEDOM = 120
CHISQUARE = 118.62
ST.DEVIATION = 8.66
MPD UPPER 0.95 CONF LIMIT = 22.75
MPD LOWER 0.95 CONF LIMIT = 17.75
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 4
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

Figure 11.8 Average Power Spectrum 'All Window-Group 64'.

Statistical evaluations in window-group 64.

In chapter 10 we found, on the basis of theoretical considerations and on the basis of number of significant spectral points, that if we wanted our spectral analysis to provide a 95% confidence level, this size of window was the minimum necessary.

However, having established a means of analysis which is 95% 'safe' we may still not be able to 'pick up' any particular features from our text strings in chapter 4. In chapter 10 I explained how 'entangled' were the different initial parameters which this method of analysis is based on. The size of the

CATEGORY:	N	MPD	S.D.
young children	13	19.76	2.74
old children	12	20.15	2.42
scientists	9	19.92	3.83
newspapers	5	21.63	1.99
ch.books	8	19.81	1.68
all children	25	19.95	2.77
all adults	22	20.27	2.80

Table 11.9 Number of samples, Mean Power Density and Standard Deviation for each category in window-group 64.

measuring window is not only related to the statistical significance of the power in each frequency point, but is related to the stability of the structures, the so called 'stationarity'. One reason for choosing a very small, but statistically significant, window, was that with a small window we would counteract the lack of stationarity in the overall spectrum. This however, could only be done on the expence of sensitivity, particularly the sensitivity in the low-frequency bands of the spectrum.

Table 11.9 gives the mean of the Mean Power Density for each category of window-group 64. The mean is the simple mean found by adding the MPD's of the individual spectra within each category (see appendix to this chapter).

Confirming our findings of chapter 5 we find here that with progressively younger writers, the MPD decreases: 'adults' have a higher mean MPD than 'older children', which again has a higher MPD than 'younger children', even though the difference is small.

To evaluate the significance of these findings, the distribution of the values of MPD between any two categories was measured with the Kruskal-Wallis one-way analysis of variance. The 'raw' H-values from this test can be found in table 11.10 and gave that no two categories are significantly (95%) different and that, as far as the Mean Power Density is concerned, there is no reason to suggest that the categories in window-group 64 are drawn from different populations. Even between the two categories 'young children' and 'newspapers' which show the greatest difference in MPD, this difference is only significant on a 20% level.

As the H-value for independence between 'younger children' and 'older children' indicates that there is nothing to suggest that these two categories are drawn from different populations, we will have to include the common group 'children' in table 11.10. On the other hand, as we have two fairly big samples of children, it makes sense to continue the distinction between younger and older children as well.

	childy	childo	scient	papers	chbooks
childy	-	0.02	0.13	2.04	0.29
childo		-	0.05	2.03	0.46
children	-	-	0.11	2.43	0.15
scientists			-	0.75	0.15
papers				-	2.59
chbooks					-

Table 11.10 H-values from Kruskal-Wallis one-way test of variance based on analysis of Mean Power Density over 64 words.

The only H-values approaching significance in table 11.10 are the values between newspapers on the one hand and children and childrens books on the other. These values translate into around a 15% significance level, and we can thus conclude, that analysed with a 64 word window, there does not seem to be any significant difference between the amount of overall structure in childrens text strings and adult text strings.

CATEGORY:	N	CHI2	S.D.
young children	13	832.69	560.25
old children	12	643.67	357.59
scientists	9	711.11	398.94
newspapers	5	606.80	242.90
ch.books	8	713.75	536.31
all children	25	741.96	474.19
all adults	22	688.36	412.06

Table 11.11 Number of samples, Variance and Standard Deviation for each category in window-group 64.

Table 11.11 gives the mean of the normalised variance (CHI2) for each category of window-group 64. The mean is the simple mean found by adding the CHI2's from the individual spectra within each category (see appendix to this chapter). As above, the H-value of independence between the two categories 'younger children' and 'older children', although much higher than that of the mean power density above, still does not suggest that these categories are drawn from different populations.

	childv	childo	scient	papers	chbooks
childv	-	1.43	0.19	0.41	1.34
childo		-	0.85	0.01	0.05
children	-	-	0.06	0.09	0.40
scientists			-	0.54	0.33
papers				-	0.00
chbooks					-

Table 11.12 H-values from Kruskal-Wallis one-way test of variance based on analysis of CHI2 over 64 words.

The probability that these values represented populations significantly different from each other were evaluated in the same way as above with the Kruskal-Wallis one-way analysis of variance. The 'raw' H-values from this test can be found in table 11.12 and gave that no two categories are significantly (5%) different and that, based on evaluation of the normalised variance CHI2, there is no reason to suggest that the categories in window-group 64 are drawn from different populations.

As above, the greatest difference is between 'young children' and 'newspapers' , but even so, there is no more than a 50% chance that these two categories are drawn from different populations.

Finally the correlations between age and MPD, and age and CHI2 of the 25 children were measured. The correlation coefficient (MPD) came to -0.00203 and thus shows that there is no correlation between age and structure in this window-group. The correlation coefficient (CHI2) was -0.1033 which is not significant, but for a sample of 12 can be said with some justification to indicate a tendency. Thus, the variance of the distribution of powers in the frequency points of the power spectra tend to be reciprocally related to the age of the writer, indicating that children have less, adults more variation in their spectra.

Although we have found some subtle features with a measuring window of 64 words, none of these features have been significant and none indicated a significant difference in structure between children and adults. This is clearly disappointing.

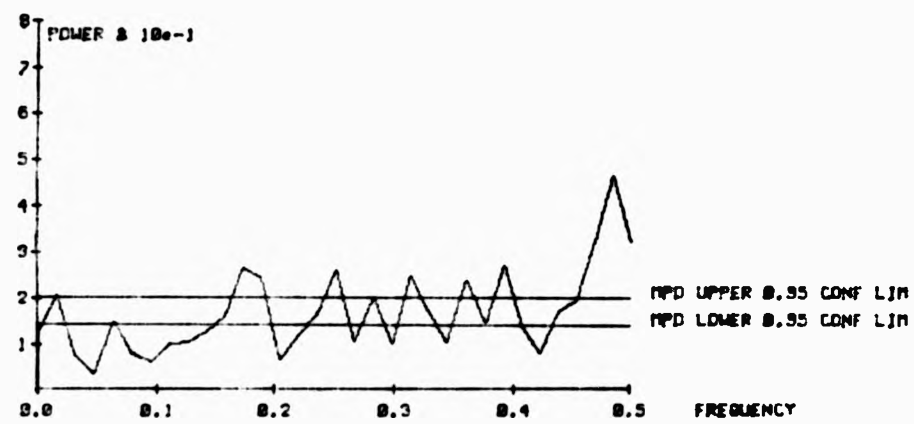
There are at least 2 reasons why this could be so. 1) A measuring window of 64 words is too short or too long. 2) There is no significant difference in the amount of structure in the different categories of text strings in chapter 4, particularly between children and adults.

To evaluate the first possibility, we shall proceed to the next window-group, that of a measuring window of 128 words.

WINDOW-GROUP 128:

AVR,10W393FF:YOUNGCHILD
AVERAGED POWER SPECTRUM

MPD = 18.17 DEGR OF FREED = 12
CHI2= 155.74 UPPER CONF LIM= 21.09
SDEV= 9.40 LOWER CONF LIM= 15.25



AVR,10W393FF:YOUNGCHILD POWER DENSITY IN FREQUENCY POINTS:

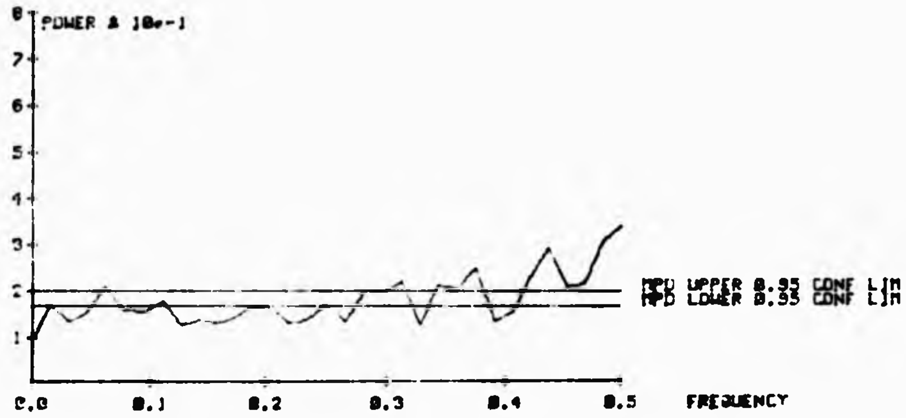
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	13.2								
0.016	21.7	0.031	8.4	0.047	4.5	0.063	16.0	0.078	8.9
0.094	7.2	0.109	11.0	0.125	11.7	0.141	13.9	0.156	17.3
0.172	27.4	0.188	25.1	0.203	7.5	0.219	13.4	0.234	17.7
0.250	27.2	0.266	11.6	0.281	21.2	0.297	11.2	0.313	26.0
0.328	18.3	0.344	11.7	0.359	25.1	0.375	15.5	0.391	28.4
0.406	14.8	0.422	9.1	0.438	18.3	0.453	21.0	0.469	33.5
0.484	48.1	0.500	33.7						

MEAN POWER DENSITY: 18.17
DEGREES OF FREEDOM = 12
CHISQUARE = 155.74
ST.DEVIATION = 9.40
MPD UPPER 0.95 CONF LIMIT = 21.09
MPD LOWER 0.95 CONF LIMIT = 15.25
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

Figure 11.13 Average Power Spectrum 'Young Children', W = 128.

AVR,10W1291FF:OLDERCHILD
AVERAGED POWER SPECTRUM

MPD = 18.02 DEGR OF FREED = 40
CHI2= 57.49 UPPER CONF LIM= 19.70
SDEV= 5.69 LOWER CONF LIM= 16.34



AVR,10W1291FF:OLDERCHILD POWER DENSITY IN FREQUENCY POINTS:

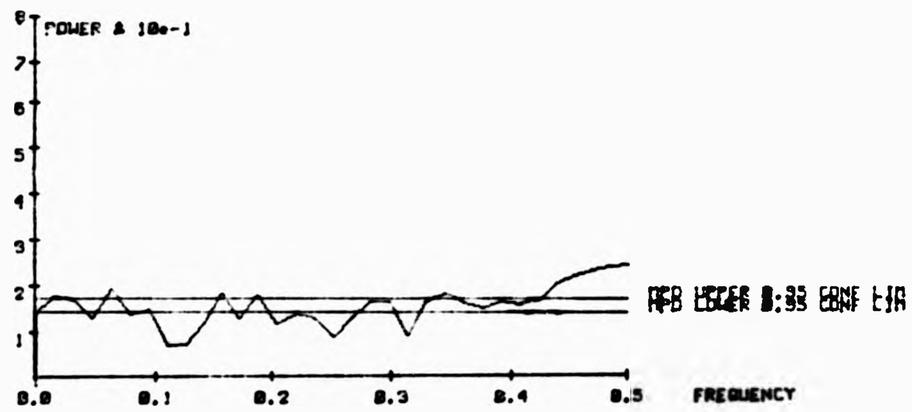
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.4								
0.016	16.8	0.031	13.1	0.047	15.1	0.063	20.8	0.078	15.5
0.094	15.3	0.109	17.6	0.125	12.6	0.141	13.7	0.156	12.8
0.172	13.9	0.188	16.4	0.203	16.5	0.219	12.9	0.234	13.5
0.250	16.7	0.266	13.2	0.281	20.1	0.297	19.9	0.313	22.1
0.328	12.2	0.344	21.2	0.359	20.3	0.375	24.6	0.391	13.1
0.406	15.8	0.422	23.3	0.438	29.1	0.453	20.9	0.469	21.5
0.484	30.9	0.500	33.9						

MEAN POWER DENSITY: 18.02
DEGREES OF FREEDOM = 40
CHISQUARE = 57.49
ST.DEVIATION = 5.69
MPD UPPER 0.95 CONF LIMIT = 19.69
MPD LOWER 0.95 CONF LIMIT = 16.35
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

Figure 11.14 Average Power Spectrum 'Old Children', W = 128.

AVR,10W1161FF:SCIENTISTS
AVERAGED POWER SPECTRUM

MPD = 17.77 DEGR OF FREED = 36
CHI2= 36.64 UPPER CONF LIM= 19.10
SDEV= 4.51 LOWER CONF LIM= 16.43



AVR,10W1161FF:SCIENTISTS POWER DENSITY IN FREQUENCY POINTS:

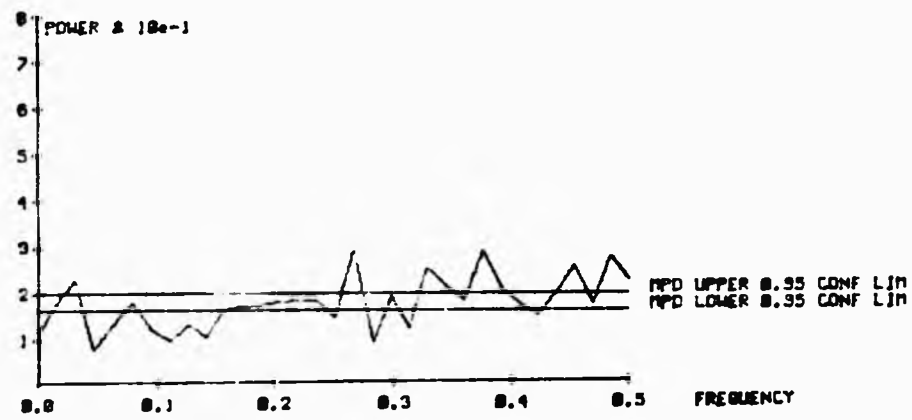
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.9								
0.016	19.7	0.031	18.7	0.047	15.0	0.063	21.3	0.078	15.6
0.094	16.9	0.109	8.9	0.125	9.3	0.141	13.9	0.156	20.4
0.172	14.7	0.188	20.0	0.203	13.5	0.219	16.0	0.234	14.9
0.250	10.9	0.266	15.4	0.281	18.8	0.297	18.6	0.313	11.2
0.328	18.9	0.344	20.6	0.359	18.2	0.375	17.1	0.391	18.9
0.406	17.9	0.422	18.8	0.438	22.9	0.453	24.5	0.469	25.7
0.484	26.5	0.500	26.8						

MEAN POWER DENSITY: 17.77
DEGREES OF FREEDOM = 40
CHISQUARE = 36.64
ST.DEVIATION = 4.51
MPD UPPER 0.95 CONF LIMIT = 19.09
MPD LOWER 0.95 CONF LIMIT = 16.44
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

Figure 11.15 Average Power Spectrum 'Scientists', W = 128.

AVR,10W649FF:PAPERS
AVERAGED POWER SPECTRUM

MPD = 17.89 DEGR OF FREED = 20
CHI2= 57.78 UPPER CONF LIM= 19.60
SDEV= 5.68 LOWER CONF LIM= 16.19



AVR,10W649FF:PAPERS POWER DENSITY IN FREQUENCY POINTS:

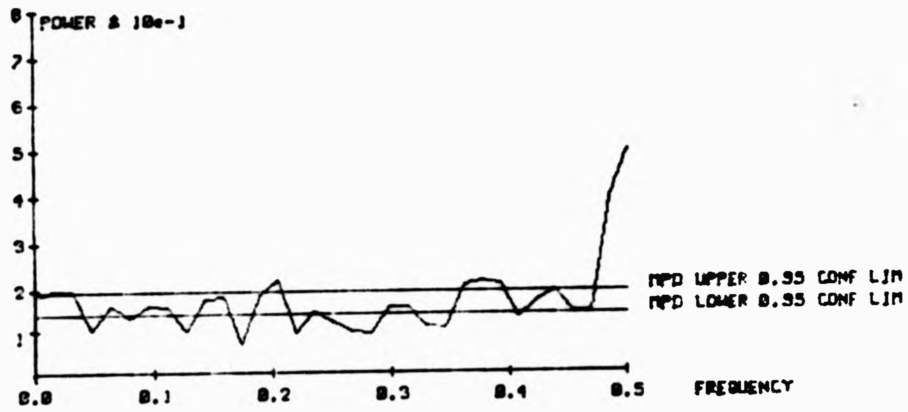
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.3								
0.016	17.9	0.031	22.8	0.047	7.7	0.063	13.2	0.078	17.9
0.094	12.1	0.109	9.6	0.125	13.3	0.141	10.3	0.156	16.5
0.172	17.0	0.188	17.5	0.203	18.3	0.219	18.8	0.234	18.8
0.250	15.0	0.266	29.1	0.281	9.0	0.297	19.1	0.313	12.4
0.328	25.6	0.344	21.5	0.359	18.4	0.375	29.2	0.391	20.7
0.406	17.8	0.422	15.2	0.438	20.2	0.453	26.1	0.469	17.6
0.484	27.8	0.500	22.7						

MEAN POWER DENSITY: 17.89
DEGREES OF FREEDOM = 20
CHISQUARE = 57.78
ST.DEVIATION = 5.68
MPD UPPER 0.95 CONF LIMIT = 19.60
MPD LOWER 0.95 CONF LIMIT = 16.19
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

Figure 11.16 Average Power Spectrum 'Newspapers', W = 128.

AVR,10W1033FF:CHBOOKS
AVERAGED POWER SPECTRUM

MPD = 19.55	DEGR OF FREED = 32
CHI2= 108.78	UPPER CONF LIM= 21.96
SDEV= 8.15	LOWER CONF LIM= 17.14



AVR,10W1033FF:CHBOOKS POWER DENSITY IN FREQUENCY POINTS:

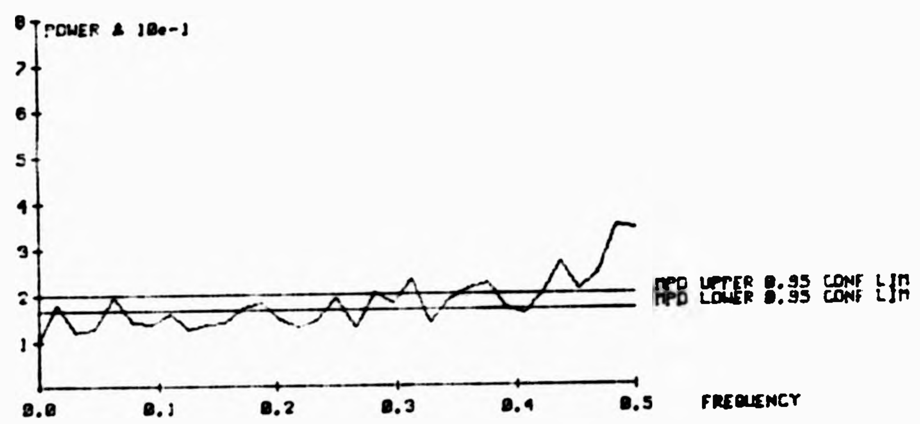
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	20.0								
0.016	21.4	0.031	21.7	0.047	12.9	0.063	18.3	0.078	15.6
0.094	18.4	0.109	17.8	0.125	12.7	0.141	20.1	0.156	20.6
0.172	9.9	0.188	20.8	0.203	24.0	0.219	12.5	0.234	17.3
0.250	14.6	0.266	12.9	0.281	12.6	0.297	18.2	0.313	18.5
0.328	13.9	0.344	13.8	0.359	23.2	0.375	24.0	0.391	23.2
0.406	15.9	0.422	19.5	0.438	21.8	0.453	17.2	0.469	17.1
0.484	42.0	0.500	52.2						

MEAN POWER DENSITY: 19.55
DEGREES OF FREEDOM = 30
CHISQUARE = 108.78
ST.DEVIATION = 8.15
MPD UPPER 0.95 CONF LIMIT = 21.96
MPD LOWER 0.95 CONF LIMIT = 17.14
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

Figure 11.17 Average Power Spectrum 'Childrens' Books', W = 128.

AVR,10W1675FF:CHILDREN
AVERAGED POWER SPECTRUM

MPD = 18.05   DEGR OF FREED = 52
CHI2= 59.10   UPPER CONF LIM= 19.76
SDEV= 5.77   LOWER CONF LIM= 16.35



AVR,10W1675FF:CHILDREN   POWER DENSITY IN FREQUENCY POINTS:

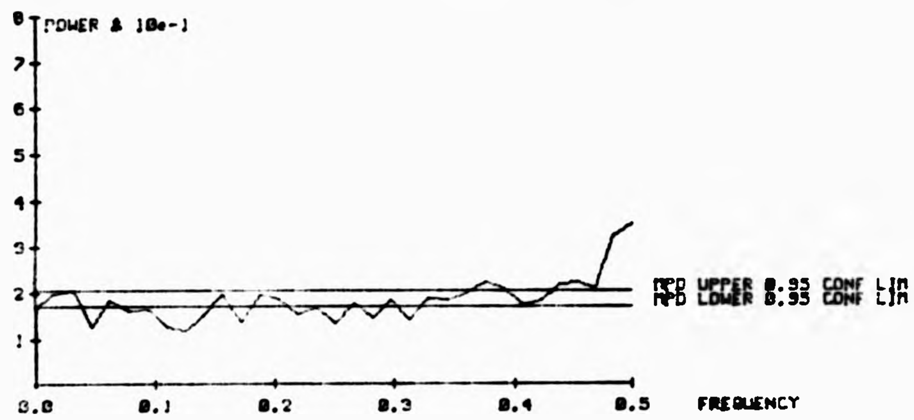
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	10.3								
0.016	17.9	0.031	12.0	0.047	12.6	0.063	19.7	0.078	14.0
0.094	13.4	0.109	16.1	0.125	12.4	0.141	13.7	0.156	13.8
0.172	17.0	0.188	18.4	0.203	14.4	0.219	13.0	0.234	14.5
0.250	19.1	0.266	12.9	0.281	20.3	0.297	17.9	0.313	23.0
0.328	13.6	0.344	19.0	0.359	21.4	0.375	22.5	0.391	16.6
0.406	15.6	0.422	20.0	0.438	26.6	0.453	20.9	0.469	24.3
0.484	34.9	0.500	33.9						

MEAN POWER DENSITY: 18.05
DEGREES OF FREEDOM = 60
CHISQUARE = 59.10
ST.DEVIATION = 5.77
MPD UPPER 0.95 CONF LIMIT = 19.73
MPD LOWER 0.95 CONF LIMIT = 16.37
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

Figure 11.18 Average Power Spectrum 'All Children'. W = 128.

AVR,10W2825FF:ADULTS
AVERAGED POWER SPECTRUM

MPD = 18.44 DEGR OF FREED = 88
CHI2= 42.71 UPPER CONF LIM= 19.91
SDEV= 4.96 LOWER CONF LIM= 16.98



AVR,10W2825FF:ADULTS POWER DENSITY IN FREQUENCY POINTS:

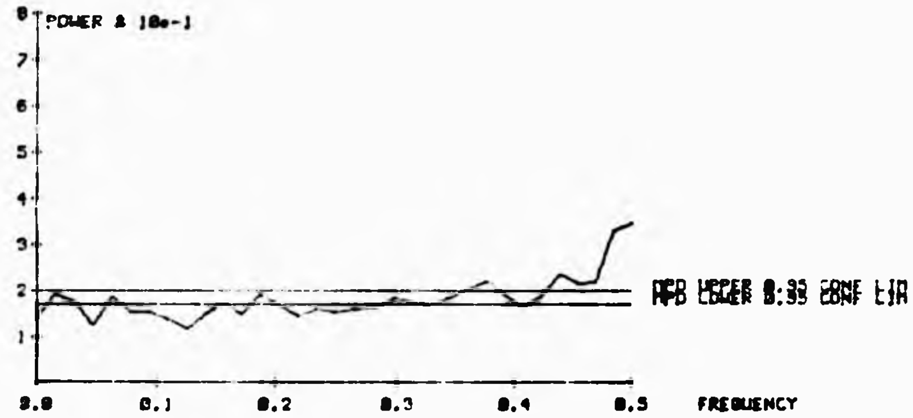
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	16.3								
0.016	19.9	0.031	20.7	0.047	12.6	0.063	18.4	0.078	16.1
0.094	16.4	0.109	12.3	0.125	11.4	0.141	15.3	0.156	19.6
0.172	13.5	0.188	19.7	0.203	18.4	0.219	15.4	0.234	16.7
0.250	13.2	0.266	17.6	0.281	14.3	0.297	18.6	0.313	14.2
0.328	18.6	0.344	18.3	0.359	20.1	0.375	22.4	0.391	20.9
0.406	17.1	0.422	18.2	0.438	21.9	0.453	22.2	0.469	20.7
0.484	32.4	0.500	35.1						

MEAN POWER DENSITY: 18.44
DEGREES OF FREEDOM = 120
CHISQUARE = 42.71
ST.DEVIATION = 4.96
MPD UPPER 0.95 CONF LIMIT = 19.87
MPD LOWER 0.95 CONF LIMIT = 17.01
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

Figure 11.19 Average Power Spectrum 'All Adults', W = 128.

AVR,10W4491FF:ALL128
AVERAGED POWER SPECTRUM

MPD = 18.30   DEGR OF FREED = 140
CHI2= 42.53   UPPER CONF LIM= 19.75
SDEV= 4.93   LOWER CONF LIM= 16.84



AVR,10W4491FF:ALL128   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	14.1								
0.016	19.2	0.031	17.5	0.047	12.6	0.063	18.9	0.078	15.[illegible]
0.094	15.3	0.109	13.7	0.125	11.8	0.141	14.8	0.156	17.4
0.172	14.8	0.188	19.2	0.203	16.9	0.219	14.5	0.234	15.[illegible]
0.250	15.4	0.266	15.8	0.281	16.5	0.297	18.3	0.313	17.5
0.328	16.8	0.344	18.6	0.359	20.6	0.375	22.4	0.391	19.3
0.406	16.6	0.422	18.9	0.438	23.7	0.453	21.7	0.469	22.[illegible]
0.484	33.3	0.500	34.7						

MEAN POWER DENSITY: 18.30
DEGREES OF FREEDOM = 120
CHISQUARE = 42.53
ST.DEVIATION = 4.93
MPD UPPER 0.95 CONF LIMIT = 19.72
MPD LOWER 0.95 CONF LIMIT = 16.87
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

Figure 11.20 Average Power Spectrum 'All Window-Group 128'.

Statistical evaluations in window-group 128.

Table 11.21 gives the mean of the Mean Power Density (MPD) for each category of window-group 128. The mean is the simple mean of the MPD's of the individual spectra within each category. (Individual spectra can be found in the appendix to this chapter).

CATEGORY:	N	MPD	S.D.
young children	3	18.17	1.09
old children	10	18.02	1.31
scientists	9	17.77	1.11
newspapers	5	17.89	1.61
ch.books	8	19.55	1.10
all children	13	18.05	1.22
all adults	22	18.44	1.45

Table 11.21 Number of samples, Mean Power Density and Standard Deviation for each category in window-group 128.

With regard to the category of 'young children' in this window-group, it must be pointed out, that it is questionable how representative this category of text strings is since the three text strings in this category are in fact written by the same child, albeit at different ages. To evaluate if these two categories do in fact qualify as two independent populations, they were tested with the Kruskal-Wallis one-way analysis of variance and it was found that there was no indication of independence between the two categories. For this reason, I have combined the two groups into one: 'children'.

We again find, that the mean power density of children as a whole is slightly less than that of adults. However, if we check the two categories 'children' vs 'adults' with the Kruskal-Wallis one-way analysis of variance, we find, that the difference is not significant. The greatest difference in MPD (table 11.21) is between 'scientists' (lowest at 17.77) and 'childrens books' (highest at 19.55). If we check these two categories against each other for independence with the Kruskal-Wallis test, we find that there is a 99% chance that these two categories are drawn from different populations. The difference between the four categories 'children', 'scientists', 'newspapers' and 'childrens books' was evaluated with the same test and established on a 5% significance level, that these 4 categories are drawn from different populations. Finally, any one category was checked against all other categories for difference in MPD. The 'raw' H-values of this test and their 'translation' into levels of significance is given in table 11.22 (a) and 11.22 (b).

The figures in tables 11.22 (a) and (b) are sligtly more encouraging than the results in window-group 64. It is however surprising, that only the language in childrens books seems to stand out significantly with regard to overall structure.

	children	scientists	papers	chbooks
children	–	0.11	0.00	6.42
scientists		–	0.04	7.79
papers			–	2.59
chbooks				–

Table 11.22 (a) Kruskal-Wallis test of difference between categories in Mean Power Density over 128 words

	children	scientists	papers	chbooks
children	–	ns	ns	2%
scientists		–	ns	1%
papers			–	ns
chbooks				–

Table 11.22 (b) Significance of test in table 11.22 (a).

It is interesting to see, that there is no significant difference between the various categories of adult writers writing for adults. The significant differences emerge only when adult writers write for children.

Nor is there any significant difference between the overall structure in childrens text strings and that of adult text strings when the adult strings have adult target.

It is important to remember, that these results emerge from a method of analysis which not only is experimental, but ostensibly crude. I am surprised however, that this analysis does not pick up differences between the overall structure in childrens language and adult language, where I should have thought that the difference was most obvious. The Kruskal-Wallis test established that the hypothesis that 'children' and 'adults' are drawn from different populations on the basis of the distribution of MPD within each category can only be established on a 30% significance level. This is clearly not significant and must reflect either that this method of analysis is too crude to pick up the difference in overall structure between adult and child language, or - as was suggested in window-group 64 - that there is not any structural difference to be picked up.

The same analysis was then carried out on the basis of the normalised variance CHI2. Table 11.23 gives the mean values for each category.

As the case was above, the difference between the means of CHI2 between categories was evaluated with the Kruskall-Wallis one-way analysis of variance. The 4 categories 'children', 'scientists', 'newspapers' and 'childrens books' were tested as a whole and gave that the hypothesis that that they are drawn from different populations could be established on a 0.5% significance level. For the two categories 'adults' and 'children' the significance level was 0.07% - altogether rather more encouraging than the results of the analysis of MPD.

CATEGORY:	N	CHI2	S.D.
young children	3	331.63	78.94
old children	10	226.83	32.01
scientists	9	369.11	97.38
newspapers	5	310.40	103.09
ch.books	8	463.63	175.79
all children	13	241.85	72.44
all adults	22	390.14	140.35

Table 11.23 Number of Samples, CHI2 and Standard Deviation for each category in window-group 128.

With regard to the category of 'young children' in this window-group, I must again point out, that it is questionable how representative this category of text strings is since the three text strings in this category are written by the same child - albeit at different ages. When we evaluated the independence between the categories 'young children and 'old children' with regard to MPD above, we had already established, that the two categories were not significantly independent of each other with regard to this parameter (Table 11.21). Combining the two categories into one in the same way with regard to the present evaluation of CHI2 is not as straight forward, since by applying The Kruskal-Wallis test to the two categories 'young children' and 'old children' with regard to CHI2 we find, that the indepence between the two categories is just on the verge of being significant (5%). This accounts for the additional category 'children' in tables 11.24 (a) and (b).

	childy	childo	scient	papers	chbooks
childy	-	3.77	0.42	0.02	1.04
childo		-	9.83	3.24	12.00
children			8.64	2.34	10.63
scientists			-	0.64	1.45
papers				-	3.36
chbooks					-

Table 11.24 (a) Kruskal-Wallis test of difference between categories in CHI2 over 128 words.

	childy	childo	scient	papers	chbooks
childy	-	5%	ns	ns	ns
childo		-	0.2%	ns (7%)	0.08%
children			0.5%	ns (15%)	0.1%
scientists			-	ns	ns
papers				-	ns (6%)
chbooks					-

Table 11.24 (b) Significance of test in table 11.24 (a).

This time we find that the combination of the two groups of children into one has been paid for by a decrease in significance. However, as seen in table 11.24 (b), where the independence between any two categories was significant before the combination of the two age groups of children into one, even though the significance has decreased, the independence is still better than the 5% level of significance.

On the basis of CHI2 the hypothesis that children and adults were drawn from different populations was established on a 0.07% significance level, and as we would have expected, there is considerable difference between the categories 'scientists' and 'children' as well. Furthermore, the power spectra of (older) children are significantly less varied than those of other categories with newspapers as a borderline case. On the whole it seems like the normalised variance CHI2 is a better measure of different features in text strings than the Mean Power Density.

We again find - with regard to CHI2 - that there is significant difference between 'older children' and 'childrens books', whereas no such difference between 'younger children' and 'childrens books' was found. This is probably a reflection of the target audience of the books for children being the younger age group. On the whole - both with regard to overall structure in text strings and with regard to the variance in the power spectrum - the text strings written by adults for children stand out as different from everything else. Almost as if high structure and high variance were the result of the adult writers attempt to 'pretend'.

The correlation between the age of the children on the one hand, and MPD and CHI2 on the other was measured. The correlation coefficient (MPD) is 0.030 indicating no correlation. The correlation (CHI2) is -0.3803, which for a sample of 13 gives that a reciprocal relationship between age and CHI2 has been established on between a 5% and a 10% significance level (one tailed). Thus, the tendency we found in window-group 64 - although still only a 'tendency' - we have found again here: The more competent the writer, the more variation in the spectrum resulting from the Fourier analysis of the text string.

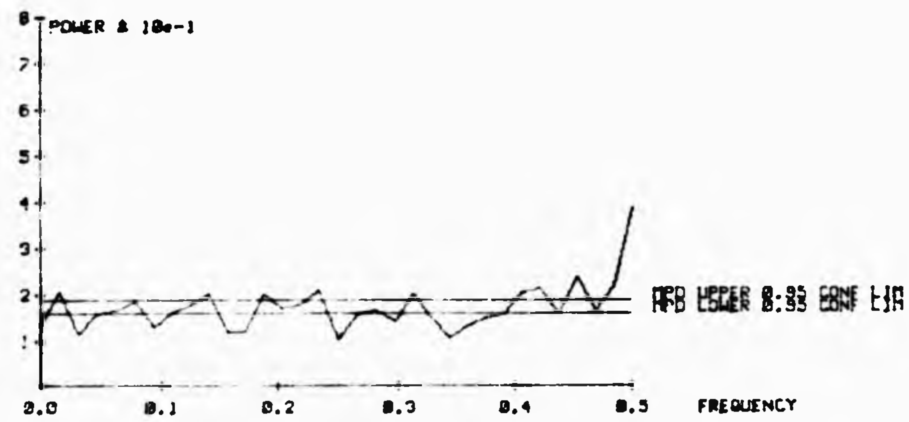
If we can accept that the two groups of children, with regard to variance (CHI2) are really just one group - and the lack of difference as measured with the Kruskal-Wallis test does not suggest that we should not do so - it will be easier to establish a simple relationship between variance (CHI2) and our intuitive perception of linguistic ability of each category as stated in table 11.23. We then have that children have the lowest variance, followed by newspapers and scientists in increasing order of variance. It is debatable whether the high variance scored by the text strings in books written by adults for children fit into this intuitive ladder of linguistic ability, but the fact is, that the highest variance is found in the power spectra based on childrens books, which brings us back to the 'irregularity' of the text strings in childrens books.

After the next basic analysis - that of window group 256 - I shall return to window group 128 and look at 1) distribution of run length before and after permutation, 2) reference fields and 3) power in the high frequency band of the power spectra.

WINDOW-GROUP 256:

AVR,10W1289FF:CHILDREN
AVERAGED POWER SPECTRUM

MPD = 17.04   DEGR OF FREED = 40
CHI2= 51.84   UPPER CONF LIM= 18.59
SDEV= 5.25   LOWER CONF LIM= 15.49



AVR,10W1289FF:CHILDREN   POWER DENSITY IN FREQUENCY POINTS:

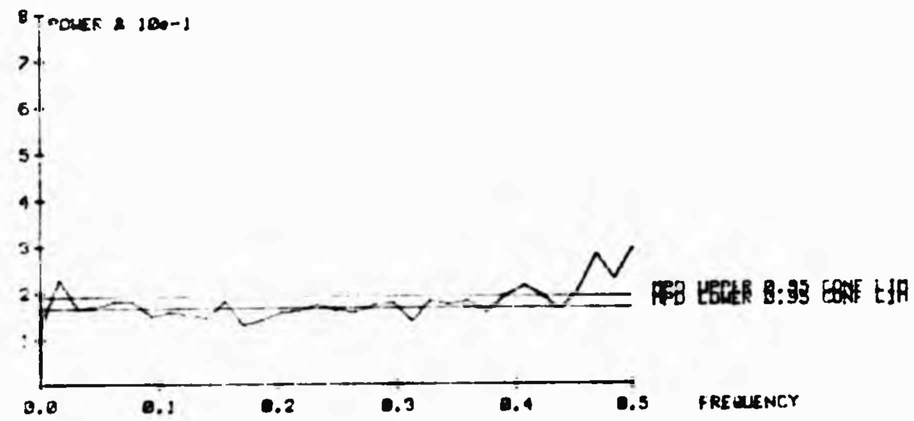
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	13.4								
0.016	20.4	0.031	11.4	0.047	15.5	0.063	16.4	0.078	18.5
0.094	12.6	0.109	15.9	0.125	17.4	0.141	19.9	0.156	11.6
0.172	11.4	0.188	19.9	0.203	16.7	0.219	17.7	0.234	20.7
0.250	9.9	0.266	15.7	0.281	16.4	0.297	14.1	0.313	20.0
0.328	14.8	0.344	10.5	0.359	13.2	0.375	14.7	0.391	15.5
0.406	20.5	0.422	21.4	0.438	15.6	0.453	23.5	0.469	16.5
0.484	21.8	0.500	38.7						

MEAN POWER DENSITY: 17.04
DEGREES OF FREEDOM = 40
CHISQUARE = 51.84
ST.DEVIATION = 5.25
MPD UPPER 0.95 CONF LIMIT = 18.58
MPD LOWER 0.95 CONF LIMIT = 15.50
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

Figure 11.25 Average Power Spectrum 'Children', W = 256.

AVR,10W2313FF:SCIENTISTS
AVERAGED POWER SPECTRUM

MPD = 17.64 DEGR OF FREED = 72
CHI2= 26.05 UPPER CONF LIM= 18.76
SDEV= 3.79 LOWER CONF LIM= 16.52



AVR.10W2313FF:SCIENTISTS POWER DENSITY IN FREQUENCY POINTS:

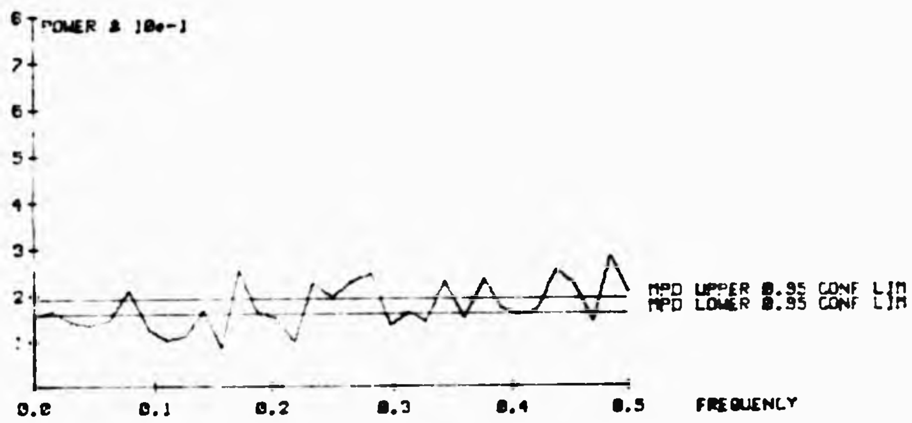
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.8								
0.016	22.9	0.031	16.6	0.047	16.6	0.063	17.9	0.078	18.2
0.094	14.7	0.109	15.5	0.125	15.1	0.141	14.4	0.156	17.9
0.172	13.0	0.188	13.9	0.203	15.5	0.219	16.1	0.234	17.1
0.250	16.0	0.266	15.5	0.281	17.2	0.297	17.6	0.313	13.4
0.328	18.1	0.344	17.3	0.359	18.1	0.375	15.7	0.391	19.1
0.406	21.2	0.422	19.1	0.438	16.1	0.453	20.0	0.469	28.1
0.484	22.9	0.500	29.1						

MEAN POWER DENSITY: 17.64
DEGREES OF FREEDOM = 60
CHISQUARE = 26.05
ST.DEVIATION = 3.79
MPD UPPER 0.95 CONF LIMIT = 18.74
MPD LOWER 0.95 CONF LIMIT = 16.53
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

Figure 11.26 Average Power Spectrum 'Scientists', W = 256.

AVR,10W1289FF:PAPERS
AVERAGED POWER SPECTRUM

MPD =	17.21	DEGR OF FREED =	40
CHI2=	46.99	UPPER CONF LIM=	18.69
SDEV=	5.03	LOWER CONF LIM=	15.72



AVR,10W1289FF:PAPERS   POWER DENSITY IN FREQUENCY POINTS:

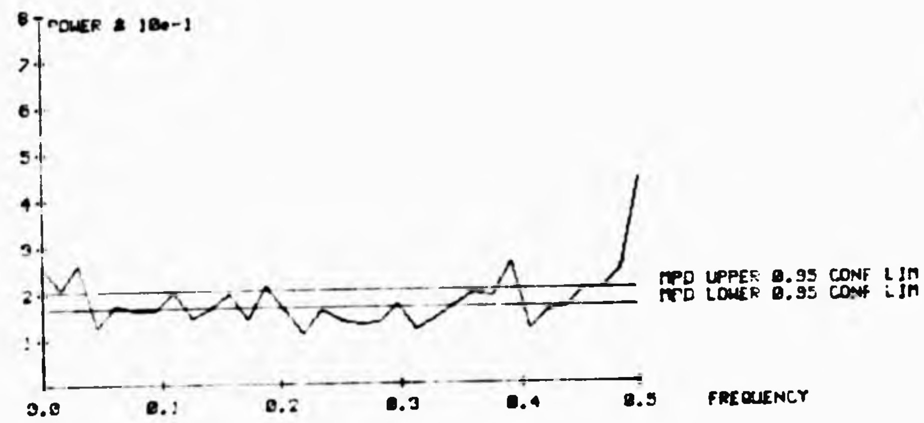
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.2								
0.016	16.3	0.031	14.1	0.047	13.1	0.063	14.5	0.078	20.6
0.094	12.4	0.109	10.0	0.125	11.0	0.141	16.5	0.156	8.3
0.172	25.0	0.188	15.8	0.203	14.6	0.219	9.6	0.234	22.4
0.250	19.2	0.266	22.7	0.281	24.2	0.297	13.2	0.313	15.9
0.328	14.0	0.344	22.6	0.359	14.6	0.375	23.3	0.391	16.6
0.406	15.6	0.422	16.5	0.438	25.1	0.453	22.1	0.469	14.2
0.484	28.1	0.500	20.2						

MEAN POWER DENSITY: 17.21
DEGREES OF FREEDOM = 40
CHISQUARE = 46.99
ST.DEVIATION = 5.03
MPD UPPER 0.95 CONF LIMIT = 18.68
MPD LOWER 0.95 CONF LIMIT = 15.74
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

Figure 11.27 Average Power Spectrum 'Newspapers', W = 256.

AVR,10W2057FF:CHBOOKS
AVERAGED POWER SPECTRUM

MPD = 18.13   DEGR OF FREED = 64
CHI2= 69.26   UPPER CONF LIM= 19.
SDEV= 6.26   LOWER CONF LIM= 16.2



AVR,10W2057FF:CHBOOKS   POWER DENSITY IN FREQUENCY POINTS:

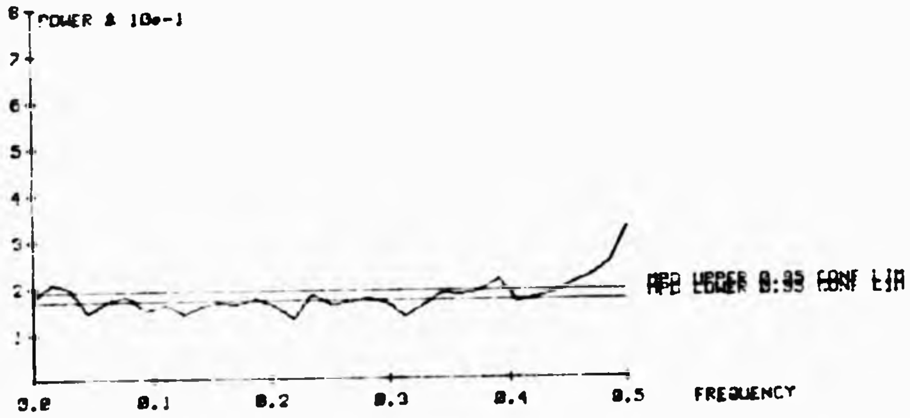
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	26.1								
0.016	20.7	0.031	25.9	0.047	12.5	0.063	17.3	0.078	15.8
0.094	15.9	0.109	19.9	0.125	14.6	0.141	16.3	0.156	19.5
0.172	14.0	0.188	21.3	0.203	15.9	0.219	10.9	0.234	15.9
0.250	13.6	0.266	12.9	0.281	13.1	0.297	17.1	0.313	11.6
0.328	13.9	0.344	16.9	0.359	19.5	0.375	18.9	0.391	25.9
0.406	11.5	0.422	15.8	0.438	16.2	0.453	20.3	0.469	20.3
0.484	24.3	0.500	44.1						

MEAN POWER DENSITY: 18.13
DEGREES OF FREEDOM = 60
CHISQUARE = 69.26
ST.DEVIATION = 6.26
MPD UPPER 0.95 CONF LIMIT = 19.95
MPD LOWER 0.95 CONF LIMIT = 16.30
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

Figure 11.28 Average Power Spectrum 'Childrens' Books', W = 256.

AVR,10W5641FF:ADULTS
AVERAGED POWER SPECTRUM

MPD = 17.72 DEGR OF FREED = 176
CHI2= 24.22 UPPER CONF LIM= 18.80
SDEV= 3.66 LOWER CONF LIM= 16.64



AVR.10W5641FF:ADULTS POWER DENSITY IN FREQUENCY POINTS:

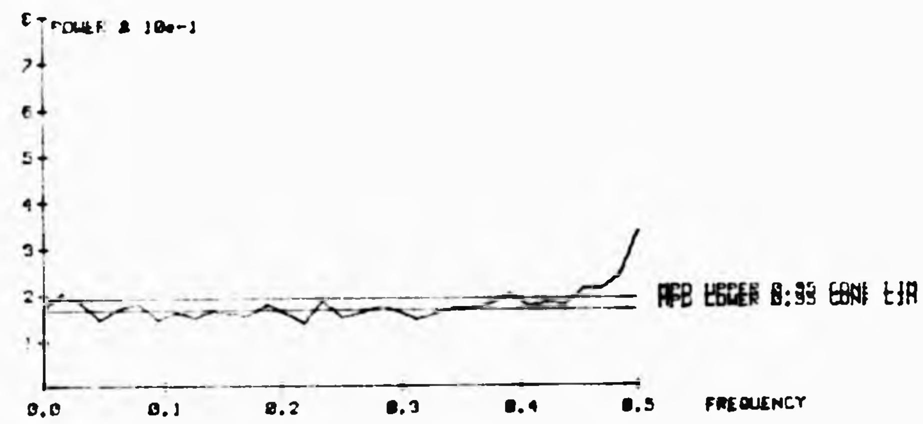
FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER
0.000	17.8								
0.016	20.6	0.031	19.4	0.047	14.3	0.063	16.9	0.078	17.9
0.094	14.6	0.109	15.8	0.125	14.0	0.141	15.6	0.156	16.3
0.172	16.1	0.188	17.0	0.203	15.4	0.219	12.7	0.234	17.9
0.250	15.9	0.266	16.2	0.281	17.3	0.297	16.4	0.313	13.3
0.328	15.6	0.344	18.4	0.359	17.8	0.375	18.6	0.391	21.0
0.406	16.4	0.422	17.3	0.438	18.2	0.453	20.6	0.469	22.1
0.484	24.6	0.500	32.5						

MEAN POWER DENSITY: 17.72
DEGREES OF FREEDOM: > 120
CHISQUARE = 24.22
ST.DEVIATION = 3.66
MPD UPPER 0.95 CONF LIMIT = 18.77
MPD LOWER 0.95 CONF LIMIT = 16.67
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

Figure 11.29 Average Power Spectrum 'All Adults', W = 256.

AVR,10W6921FF:ALL256
AVERAGED POWER SPECTRUM

MPD = 17.59 DEGR OF FREED = 216
CHI2= 24.60 UPPER CONF LIM= 18.68
SDEV= 3.68 LOWER CONF LIM= 16.51



AVR.10W6921FF:ALL256 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	17.0								
0.016	20.6	0.031	17.9	0.047	14.5	0.063	16.8	0.078	18.0
0.094	14.3	0.109	15.9	0.125	14.6	0.141	16.4	0.156	15.4
0.172	15.2	0.188	17.6	0.203	15.7	0.219	13.7	0.234	18.4
0.250	14.8	0.266	16.1	0.281	17.1	0.297	16.0	0.313	14.6
0.328	15.5	0.344	16.9	0.359	17.0	0.375	17.9	0.391	20.0
0.406	17.2	0.422	18.1	0.438	17.7	0.453	21.1	0.469	21.0
0.484	24.1	0.500	33.7						

MEAN POWER DENSITY: 17.59
DEGREES OF FREEDOM: > 120
CHISQUARE = 24.60
ST.DEVIATION = 3.68
MPD UPPER 0.95 CONF LIMIT = 18.64
MPD LOWER 0.95 CONF LIMIT = 16.54
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

Figure 11.30 Average Power Spectrum 'All Window-Group 256'.

Statistical evaluations in window-group 256.

Table 11.30 gives the mean of the Mean Power Density (MPD) for each category of window-group 256. The mean is the simple mean of the MPD's of the individual spectra within each category. (Individual spectra can be found in the appendix to this chapter). As the measuring window has been increased yet again, there are now so few children left - 2 'young' and 3 'old' - that it would not be statistically sound to keep them as two separate categories. Thus, in this window-group there are only 4 categories: 'children', 'scientists', 'newspapers' and 'childrens books'.

CATEGORY:	N	MPD	S.D.
children	5	17.04	0.74
scientists	9	17.64	1.34
newspapers	5	17.21	0.85
ch.books	8	18.13	1.71
all adults	22	17.72	1.39

Table 11.30 Number of samples, Mean Power Density and Standard Deviation for each category in Window-Group 256.

We again find, that the mean power density of children as a whole is slightly less than that of adults. However, if we check the two categories 'children' vs 'adults' with the Kruskal-Wallis one-way analysis of variance, we find, that the difference is not significant. The greatest difference in MPD (table 11.30) is between 'children' (lowest at 17.04) and 'childrens books' (highest at 18.13). If we evaluate the difference between these two categories with the Kruskal-Wallis test, we find that the hypothesis that that these two categories are drawn from different populations cannot be established on a better than 40% significance level. The difference between the four categories 'children', 'scientists', 'newspapers' and 'childrens books' was evaluated with the same test and showed, in fact, that the hypothesis that the 4 groups are drawn from the SAME population can be established on a 25% significance level.

This is not very encouraging. We have apparently reached a state of 'over-kill', a state where the measuring window is so long, that stationarity has become a serious problem. As the 'raw' H-values of this test and their 'translation' into levels of significance (tables 11.31 (a) and (b)) show, it was not possible to establish any significant level of difference between any two categories in this window-group.

	children	scientists	papers	chbooks
children	-	0.45	0.10	0.77
scientists		-	0.45	0.33
papers			-	0.54
chbooks				-

Table 11.31 (a) Kruskal-Wallis test of difference between categories in MPD over 256 words

	children	scientists	papers	chbooks
children	-	ns	ns	ns
scientists		-	ns	ns
papers			-	ns
chbooks				-

Table 11.31 (b) Significance of test in table 11.31 (b).

In spite of this size window's overall failure to 'pick up' significant features of the individual categories, there is one interesting difference between table 11.31 (a) of window-group 128 and table 11.22 (a) of this window-group: the H-value of difference between the two categories 'scientists' and 'newspapers'. With the longer measuring window, the H-value has - while still translating into insignificance - in fact increased considerably, from 0.04 to 0.45. So may be there are, after all, features in the adult text strings which are being picked up by the longer window. However, on the whole, the findings of window-group 256 have been somewhat in-conclusive with regard to the levels of MPD.

With regard to the levels of CHI2, the evaluation of difference between the four categories turns out to be equally feature-less. Table 11.32 gives the mean of the normalised variance (CHI2) of each category of window-group 256. As before. the mean is the simple mean of the CHI2's of the individual spectra within each category. (Individual spectra can be found in the appendix to this chapter).

CATEGORY:	N	CHI2	S.D.
children	5	182.00	106.70
scientists	9	156.67	41.16
newspapers	5	196.60	54.98
ch.books	8	245.37	134.28
all adults	22	198.00	93.91

Table 11.32 Number of samples, CHI2 and Standard Deviation for each category in Window-Group 256.

As was the case in window-group 64 and window-group 128, each category has been tested against the other categories with the Kruskal-Wallis test. The 'raw' H-values of this test and their

	children	scientists	papers	chbooks
children	-	0.04	1.58	0.34
scientists		-	2.35	1.33
papers			-	0.02
chbooks				-

Table 11.33 (a) Kruskal-Wallis test of difference between categories in CHI2 over 256 words.

	children	scientists	papers	chbooks
children	-	ns	ns	ns
scientists		-	ns	ns
papers			-	ns
chbooks				-

Table 11.33 (b) Significance of test in table 11.33 (a).

'translation' into levels of significance (tables 11.33 (a) and (b)) show, that in no case was there reason to suggest, that the four categories had been drawn from different populations. The probability, that the four categories 'children', 'scientists', 'newspapers' and 'childrens books' are drawn from different populations was in fact 50%.

This concludes the basic evaluation of the three sizes of measuring window. With regard to the application of Fourier analysis to the measurement of structure and varians in text strings we have found that a window of 128 words offers the best compromise between sensitivity and lack of stationarity. In the following I shall extend our application of WINDOW-GROUP 128 and: 1) measure the difference in Mean Power Density (MPD) and Variance (CHI2) before and after permutation of the text strings, 2) assess the distribution of run lengths before and after permutation. both analyses being similar to the analyses carried out in chapter 5 when we used a much simpler method to assess structure. 3) assess if the length of reference field of the different categories of writers is significantly different. 4) analyse more closely the distribution of power in the high-frequency end of the spectra resulting from the Fourier analysis with the 128 word long measuring window.

Finally, as a last measure of comparability between the simple statistical approach of Chapter 5 and the present fourier analyses. I shall obtain correlations between the values of A, B and VOC on the one hand, and MPD, CHI2 and RF on the other for all 34 text strings of window-group 128.

MEAN POWER DENSITY BEFORE AND AFTER PERMUTATION IN WINDOW-GROUP 128.

In chapter 5 it was argued that if intercept A and gradient B were in some ways related to sequential structure, we would expect the value of these parameters to change if the analysis was applied to the same text string before and after permutation of the string, and we saw, that not only was this the case with a high degree of significance, the direction of the change - from low A and high B before permutation to high A and low B after permutation - was equally significant.

Assuming that the Mean Power Density resulting from the Fourier analysis is related to sequential structure as were intercept A and gradient B in the simple statistical analysis in chapter 5, we shall follow the same line of analysis in the Fourier analysis of all the text strings in window-group 128 and examine if the permutation of each string leads to a significant change in the level of MPD of the power spectra.

To this end MPD was obtained from the power spectrum of each of the strings in window-group 128 before and after the string was permutated. The individual data can be found in the appendix to this chapter. The mean values of each category are presented in table 11.34.

CATEGORY:	MPD (nat)	MPD (perm)	MPD delta.
children	18.23	17.83	-0.40
scientists	17.77	17.84	0.07
newspapers	17.89	16.82	-1.08
ch.books	19.55	17.74	-1.81
all samples	18.37	17.66	-0.71

Table 11.34 Mean values of MPD before and after permutation for each category in Window-Group 128.

We see here, as we saw in chapter 5, that the category with the minimum value - that of scientists - moves in the opposite direction of that expected. Again, 'childrens books' gives the highest difference.

CATEGORY	N	T	Z	confidence level
children	12	43.5	0.35	36%
scientists	9	20.5	0.24	40%
newspapers	5	3.0	1.21	11%
ch.books	8	5.0	1.82	4%
all samples	34	202.5	1.62	5.3%

Table 11.35 Results of Wilcoxon test of change in MPD before and after permutation within each category and for all the samples together.

As before, the size and direction of change of MPD, before and after permutation within each category, were measured with the Wilcoxon test and gave the results stated in table 11.35.

Clearly, the change in sequential structure, as picked up by the Fourier analysis, is not as significant as that found with our simple statistical method in chapter 5 where the overall change caused by permutation of the string was confirmed on a better than 0.01% level for intercept A and on a better than 0.03% level for gradient B.

Whether one wants to consider as significant the 5.3% level of confirmation stated in table 11.35 is, superficially at least, a question of temperament. However, it must be remembered, that in chapter 5 we measured the change over 550 to 600 words per sample and even if we had only 27 samples there, as opposed to the present 34 samples of window-group 128, it can easily be calculated that the change found in the analysis in chapter 5 was based on a total of 15950 words, while, in the present case of window-group 128, the measurement is based on a total of only 4352 words i.e. almost a quarter of the size of the sample total in chapter 5. My reason for measuring the effect of permutation over 550 to 600 words in chapter 5 was that I had found that the effect was very small measured over strings of less than 300 words. However, this particular analysis is part of a number of comparative analyses for window-group 128 and for this reason we can not increase the length of the strings. But as we know that the effect is only 0.3% from reaching the 5% significance level and, added to that, that the effect is accumulative, it is safe to assume that spectra derived from permutated text strings do indeed on the whole show a significantly lower Mean Power Density than the spectra based on natural text strings even though the difference is low, only around 4% for text strings of 128 words.

As the term Mean Power Density indicates, this is an over all measure of the power in the power spectrum. However, the reason for employing Fourier analysis was that we wanted more than just the single measure of structure obtained by the simple graph-fitting algorithm in chapter 5; we wanted to assess the distribution of structures of different length - or to put it another way: We wanted to measure the power density at different frequencies. The next obvious step along this line of thinking would therefore be to delve in to the distribution of power in the different parts of the power spectra obtained with the Fourier analysis. However, to follow the line of action taken in chapter 5, I shall first 1) evaluate another parameter which seems to be equally - or more - affected by the permutation of the text strings than does the MPD, namely that of the Variance CHI2, 2) examine the correlation between these parameters and the run lengths in the 128 word long measuring window.

VARIANCE BEFORE AND AFTER PERMUTATION IN WINDOW-GROUP 128.

Still following the line of analysis of chapter 5 we shall examine the effect on the VARIANCE of the permutation of the text strings. We have several times in the past seen that the permutation of a text string causes the amount of structure to decrease. We were therefore able to predict the direction of the change in MEAN POWER DENSITY following the permutation of the text strings. This meant, that the necessary test for significance was that of the less stringent one-tailed test. However, we can not possibly have any intuitive idea of which way the VARIANCE will move when the sequential structure is broken down. This means, our demands for significance will be more difficult to meet since, in this case, we must compete against the greater demands of the two-tailed test for significance. Otherwise the method was as above: The value of CHI2 was obtained from the power spectrum of each of the strings in window-group 128 before and after the string was permutated and the difference and direction was tested with the Wilcoxon test. The individual data can be found in the appendix to this chapter. The mean values of each category are given in table 11.36.

CATEGORY:	CHI2 (nat)	CHI2 (perm)	CHI2 delta.
children	260.66	319.88	59.22
scientists	369.74	335.60	-34.14
newspapers	311.04	282.67	-28.36
ch.books	463.92	305.63	-158.29
all samples	344.77	315.21	-29.55

Table 11.36 Mean values of CHI2 before and after permutation for each category in Window-Group 128.

Table 11.36 shows that as the strings are permutated - as the sequential structure is broken - the variance generally decreases. However, here too, the direction of move for the category with the minimum value is opposite to the general trend: Whereas the variance of 'scientists', 'newspapers' and 'childrens books' decreases as the sequential structure is broken, the variance of 'children' increases.

The size and direction of change of CHI2, before and after permutation within each category, were measured with the Wilcoxon test and gave the results stated in table 11.37.

CATEGORY	N	T	Z	confidence level
children	12	16	1.80	7.1%
scientists	9	15	0.89	3.7%
newspapers	5	5	0.67	5.0%
ch.books	8	5	1.82	6.9%
all samples	34	257	0.69	4.9%

Table 11.37 Results of Wilcoxon test of change in CHI2 before and after permutation within each category and for all the samples together.

The overall impression of Table 11.37 is that of a much higher general level of significance than that of the effect on the Mean Power Density in table 11.35. Not only have two of the categories reached the 5% significance level, but even the two categories, which have not, are quite close, and the overall result - 'all samples' - shows clearly that the power spectra derived from natural text strings have a higher variance than text strings which have been permutated.

One can only speculate at what causes the variance of the power spectrum to fall when the sequential structure is broken. My thesis - as I have expressed it on several occasions - is that the power spectrum of a text string is an - albeit crude - graphic representation of (some of) the generator and control mechanisms in the linguistic device which generated the text string. I can envisage two principally different functions of the linguistic device which would be clearly visible in a power spectrum: That of EMISSION and that of ABSORBTION. Both features are clearly visible on most of the spectra, the emission being represented by the peaks and the absorbtion 'lines' being represented by the fall in the power to zero - the troughs reaching the base line - in the spectra. In this connection it must be pointed out, that the DC level was not subtracted from the transformed function before the spectrum was plotted. Had it been, the fall to zero of the power in parts of the spectrum would hardly have been surprising!

Looking at the power spectra as emission spectra containing absorbtion lines, the fall in variance caused by permutation becomes obvious rather than mysterious. The question is: What causes the features of emission and absorbtion in the power spectra. We must here try to envisage the linguistic device as representing at least two basic mechanisms: 1) One - or several - generator function(s). This would account for the emission spectra. 2) One (or several) control function(s) or 'filter' function(s). This would account for the absorbtion lines. The idea, that we generate language and that the generated product filters through one or several controling barriers (lexical controls?) seems intuitively right and is neither astonishing nor, may be, important, but is emphasised here because these mechanisms could account for the features found in our analysis.

DISTRIBUTION OF RUNS BEFORE
AND AFTER PERMUTATION.

Again following the line of action in chapter 5, the distribution of runs in the 128 word window was measured before and after permutation of the 34 text strings.

In chapter 5 we found, much to our surprise, that the permutation of a text string caused an increase in run length rather than the expected decrease. One feature which was important in the analysis in chapter 5 was the, usually, long run of 1's in the beginning of each string, a feature caused, of course, by the number of 'new' words which a text string is bound to begin with.

In the present Fourier analysis, where we compare each word in the measuring window with a number of words in the reference field, the information array does not normally begin with a succession of 1's. As you will recall, the primary function of the reference field was to give a balance between 1's and 0's in the information array. There is thus no point in assessing - as we did in chapter 5 - the length of the first run of 1's.

For all 34 text strings in window-group 128, the distribution of run lengths before and after permutation was obtained in much the same way as we did it in chapter 5, except of course, for the fact, that this time the strings were analysed with a reference field. All the graphs and data can be found in the appendix to this chapter. The mean number of runs for each category is given in table 11.38.

CATEGORY:	mean number of runs before perm.	after perm.	delta
children	32.83	32.17	0.66
scientists	33.67	32.78	0.89
newspapers	34.80	32.00	2.80
ch.books	32.63	31.50	1.13

Table 11.38 Mean number of runs before and after permutation for each category in Window-Group 128.

Mean NUMBER of runs easily translates into mean LENGTH of runs. Knowing that the measuring window is 128 words wide, we simply divide the length of window with the relevant mean number of runs. Table 11.39 gives the mean length of runs for the different categories.

CATEGORY:	mean length of runs before perm.	after perm.	delta
children	3.90	3.98	0.08
scientists	3.80	3.90	0.10
newspapers	3.68	4.00	0.32
ch.books	3.92	4.06	0.14

Table 11.39 Mean length of runs before and after permutation for each category in Window-Group 128.

Table 11.39 shows that the analysis with a reference field yields the same result: the permutation of a text string increases the run length. Here, as in chapter 5, we find that 'newspapers' has the shortest run length of all categories followed by 'scientists' with 'children' and 'childrens books' as the text strings with the longest run lengths. That 'newpapers' have the shortest run length of all text strings - i.e. that runs of 'new' words are more freqently interrupted by 'old' words - probably contributes to this kind of text being more pallatable. We saw earlier that newspapers, contrary to common belief, have a higher vocabulary than any of the other text samples. That these kind of text strings are still able to sport the shortest run length supports my frequent suggestions, in the past, that these strings far from being rudimentary are in fact very clever, very reflected, constructions.

The change in size and direction of run lengths was measured with the Wilcoxon test and gave that for all the text strings as a whole, the change is confirmed on a 4.7% significance level. This is - although significant - again less significant than the changes in run length found in chapter 5 using the simple graph fitting algorithm, but again we must remember, that the measurements in window-group 128 are based on only a quarter of the sample size used in chapter 5.

REFERENCE FIELDS.

The final analysis, before we turn to the distribution of power in the power spectra, is that of the length of reference field within each category. All along my research I was aware of the relatively long computing time needed to analyse adult strings as compared to childrens strings of similar length. The reason is that childrens strings generally have shorter reference fields than do adult strings. To get a more exact measure of this difference, the mean length of reference field was calculated for each category and the difference measured with the Kruskal-Wallis test. The mean length of reference field for each category are given in table 11.40.

Category	Mean length of reference field	s.d.
Children	85.50	22.24
Scientists	154.78	60.78
Newspapers	220.40	101.07
Ch.books	142.25	56.98

Table 11.40 Mean length of reference field for each category in window-group 128.

Table 11.40 gives the values one would intuitively have expected with newspapers well above all other strings followed by scientists, childrens books and, with the shortest reference field, children. This is somewhat better - in developmental terms - than the results shown in table 5.19 (a) regarding vocabulary in chapter 5 where childrens books fared better than scientists.

Table 11.41 (a) gives the values when each category was tested against each other category with the Kruskal-Wallis test for difference with regard to length of reference field.

	children	scientists	papers	chbooks
children	-	8.50	7.83	6.50
scientists		-	1.60	0.06
papers			-	1.38
chbooks				-

Table 11.41 (a) Kruskal-Wallis test for difference between categories in window-group 128.

This translates into the significance levels of table 11.41 (b).

	children	scientists	papers	chbooks
children	-	1%	1%	2%
scientists		-	ns	ns
papers			-	ns
chbooks				-

Table 11.41 (b) Significance of test in table 11.41 (a).

Comparing table 11.41 (b) with table 5.19 (c) in chapter 5 it would appear, that length of reference field is an altogether better measure than vocabulary in terms of developmental factors since, with regard to length of reference field, there is a clear cut difference between children and all adult categories, while there is no significant difference between any of the adult categories. It is interesting to see too, that where one would expect a slightly smaller difference - between children and childrens books - the significance level is indeed 2% rather than the 1% for children/scientists and children/papers. No such clear distinction could be found with regard to vocabulary. The overall level of significance in table 11.41 (b) is interesting too, since still with only about a quarter of the sample size of chapter 5, the difference is confirmed on about the same significance level as in chapter 5. In fact, when children as a whole were measured against adults as a whole the difference was confirmed on a 0.1% significance level with regard to length of reference field. In spite of the much smaller samples used here, this is exactly the same level of significance found in chapter 5 with regard to vocabulary. This must mean, that the length of reference field is a MUCH better measure of developmental features than is vocabulary.

DISTRIBUTION OF POWER IN THE POWER SPECTRA.

The motivation for adapting Fourier analysis to our search for structures in text strings was partly that it is a very sensitive method and partly that it gives much more information about the structures found in the data base.

The main benefit of power spectrum analysis is that we are able to measure what size of structures are present in the data base.

By the nature of a spectrum and its division into frequencies we are able to see directly the frequencies of the main periodicities present in the data base. If one particular feature is repeated every 4 words in the text string we would find, as explained earlier, a peak in the power spectrum at F = 0.25. Likewise, periodicities of 2, 3, 5, or 10 would give peaks at F=0.5, F=0.33, F=0.2 and F=0.1 respectively. Thus the frequencies in the power spectrum refer to periodicities - or bindings - of different length, and we have just seen that the integers 2, 3, 4, 5 etc correspond to the frequencies 0.5, 0.33, 0.25 and 0.1 respectively.

One feature, which we must adjust ourselves to, is the fact, that the resolution in the spectrum is greater in the high-frequency end of the spectrum (the 0.5 end to the right) than in the low-frequency end to the left. I can best explain this by referring to the axis on one of the spectra in this chapter. A periodicity which stretches over, say, 2 words in the text string, would give a peak at F=0.5 in the power spectrum as we have just seen. The next higher integer (3 words) periodicity would come out as a peak at F=0.33. The difference is of course 0.17, which is almost two divisions in the higher right part of the spectrum. But if we look at frequencies in the lower left part of the spectrum and measure the difference in frequency between a periodicity of say 10 words which would give a peak at F=0.1 and 11 words which would give a peak at F=0.09 we see that in this end of the spectrum the difference between 2 adjacent integers (10 and 11) translates into a difference in frequency of only 0.01 which is only one tenth of a division.

Because of the much higher resolution in the high-frequency end of the spectrum, we will be able to measure a given periodicity with greater accuracy. Say we have a peak at F=0.25. We could with some conviction claim that this peak refers to a periodicity of 4 words: not 3 words - because that would have given a peak at F=0.33; not 5 words - because that would have given a peak at F=0.20, both positions on the axis well separated from the position of F=0.25. But if the peak was in the low-frequency end, say at F=0.1, it would be impossible to find out if this peak referred to a periodicity of 9 words, 10 words or 11 words.

Of the possibilites, which the present use of Fourier analysis has opened up, I find that of looking into the linguistic device by far the most fascinating. As we have seen in an earlier chapter, Fourier analysis applies to 'black box' problematic. Until now, we have managed to access only the sequential structure of a text string, and have yet to move from the caracteristics of the output of the linguistic device into the device itself.

A frequency which is the reciprocal of an integer i.e. refers to an integer periodicity like F=0.5 (integer: 2), F=0.33 (integer: 3), F=0.25 (integer: 4) etc. I shall in the following call an 'Integer Refer Frequency' or IRF for short. Because of the discontinuous integer nature of our text strings (there are only whole words in our text strings, no fractions) it is important that we distinguish between the powers in the IRF's and the power found in between. The reason for this is that the power found IN the IRF's refers to the sequential structure i.e. the periodicity arising from the 1' and O's in the information array being linked together in combinations of two's, three's, four's etc. to mention the simplest combinations, whereas the power in BETWEEN the

IRF's, power which does not refer to periodicities based on simple combinations of integers, represents sub-sequential information, information which the Fourier analysis has been able to extract, because of its ability to dissolve a sum-frequency into basic frequencies.

According to the above, the greatest distance between two IRF's, on the spectrum axis, is in the right, high frequency part of the spectrum, between F=0.33 and F=0.50 which of course represents that piece of the axis which refer to combinations of between 2 and 3 words. However, we know that there are no bindings in the text strings which are longer than two units (words), but shorter than 3 units (words) because we only analyse whole units (words). Consequently, we know that a power peak in this part of the spectrum is either an arte-fact or refers to a basic periodicity picked out by the Fourier analysis from the sum of periodicities constituted by the multitude of combinations of 1's and 0's in the information array.

In this part of the spectrum, between F=0.33 and F=0.50, most of the spectra of all three window-groups have two or three power peaks, not counting eventual peaks at the IRF's 0.33 and 0.50 themselves. (It is easier to find the different maxima and minima on the power read-outs of the spectra in the appendix to this chapter than to try to judge the positions of the peaks in the spectra themselves).

As it can be seen on the power read-outs, the intermediate steps between F=0.33 and F=0.50 in a 32 point spectrum are the ten frequencies:

.344 .359 .375 .391 .406 .422 .438 .453 .469 .484

To the left we would have F=0.33 and to the right F=0.50. Over these 10 frequencies I have determined - where possible - the position of maxima. As it turned out, most spectra had three maxima in this part of the high-frequency band.

These three power peaks, which I have for convenience called alpha, beta and gamma, did roughly look like they were positioned with alpha to the right around F=0.453, beta in the middle around F=0.422 and gamma to the left at around F=0.375. A closer analysis proved however, that the position was different for the different window-groups, and within the same window-group, the position depended as well on whether it was a child spectrum or an adult spectrum.

For the ten frequency steps in the band between IRF(3) and IRF(2) the number and size of ALL significant maxima found at each step was measured and the hypothesis that they were - as a group - significantly higher than the upper 95% confidence limit was tested with the Wilcoxon test.

This indicated that - within each window-group - peaks do indeed occur at three significant positions in the band between IRF(3) and IRF(2). Table 11.42 gives the significance levels of each position of the three window-groups 64, 128 and 256 for adults and for children. Some of the peak positions are not associated directly with one of the ten frequency steps above - e.g. the peak beta (see table 11.42) confirmed on a 0.1% significance level in adult window-group 128 positioned BETWEEN F=0.406 and

F=0.422. This is due to the analysis being carried out on half steps by interpolation rather than just on the ten frequency steps as stipulated above.

ADULTS

freq:	.359	.375	.391	.406	.422	.438	.453	.469	.484	.500
64			.2%		1%			.2%		
128		.01%			.1%		.02%			
256			.06%		.15%			.03%		
			γ		β			α		

Table 11.42 Significance level for each peak in the 0.33 to 0.55 frequency band for windows of 64, 128 and 256 words. Adults' text strings.

CHILDREN

freq:	.359	.375	.391	.406	.422	.438	.453	.469	.484	.500
64			4%			.4%		.4%		
128		.3%					3%		.2%	
256				4%			3%		ns	
			γ				β		α	

Table 11.43 Significance level for each peak in the 0.33 to 0.55 frequency band for windows of 64, 128 and 256 words. Childrens' text strings.

We have seen before, that a window of 128 words was the best compromise between sensitivity and lack of stationarity. It is thus not surprising, that in table 11.42 the significance level is highest for window-group 128. Because of this, I would expect the position of the three peaks alpha, beta and gamma stated under window 128 in table 11.42 to reflect the real position for adults' text strings rather than those stated under windows 64 and 256.

This feature is reflected again in table 11.43 which too shows a higher level of significance in window-group 128 than in the other two window-groups. Thus, the positions of peaks alpha, beta and gamma for childrens text strings are probably those stated in window-group 128 rather than in window-groups 64 or 256.

Another feature of table 11.43, the COMPARATIVELY low significance levels in childrens window-group 256 as compared to the significance levels for adult window-group 256 (table 11.42), would suggest that childrens text strings are less stationary than those of adults.

As mentioned earlier, the peaks alpha, beta and gamma may indeed represent sub-generator functions of our linguistic device. On the other hand, going back to the initial explanation of Fourier analysis in chapter 7, you may recall, that when we Fourier transformed 'square' functions - as opposed to smooth functions - 'spurious' peaks appeared in the high-frequency band of the power spectrum.

To assess if these peaks alpha, beta and gamma, and their positions - however significant they are - are the result of 'squareness' or whether they are indeed ripples created by sub-generator functions of our lingusitic device, the analysis above was carried out again after the strings had been permutated and the differences were measured with the Wilcoxon test. Tables 11.44 and 11.45 give the level of significance of the difference between the peaks of natural text and the peaks of permutated text. The analyses were carried out on text strings of window-group 128 only. First for adults, next for children.

peak	frequency	T	Z	significance level
'alpha'	0.453	127	0.02	49%
'beta'	0.422	87	0.99	16%
'gamma'	0.375	77	1.61	5.4%

Table 11.44 Significance of change to peaks in 0.33 to 0.50 band when text strings are permutated. Adult, W=128

peak	frequency	T	Z	significance level
'alpha'	0.484	15	1.88	2.9%
'beta'	0.438	38	0.08	38%
'gamma'	0.375	35	0.31	38%

Table 11.45 Significance of change to peaks in 0.33 to 0.50 band when text strings are permutated. Children, W=128

It thus appears, that the last two analyses have dismissed, right away, peaks alpha and beta of adult text strings and peaks beta and gamma of childrens text strings. This is not to say, that our original findings were not significant, only that two of the three peaks from both adults' and childrens' spectra are, most probably, high-frequency peaks resulting from 'squareness' in the initial information array.

Left are the two peaks around F=0.375 (adults) and around F=0.484 (children). It is again a question of temperament if one wants to accept as significant the 5.4% significance level of the adult peak at F=0.375. I am inclined to do so, partly because one of the peaks in the childrens spectra proved significant. but mostly because I carried the positioning of the individual maxima out very critically during the test: If there was the slightest doubt about whether a maximum was indeed a maximum or just power which had dissipated from an adjacent frequency, the frequency point in question would not be included. This 'maximum demand' approach did undoubtedly leave out some maxima which a less critical approach would have included. Given this knowledge, I think it is fair to tip the balance in favour of accepting the 5.4% as significant.

Consequently. we are no longer talking about a number of peaks in the 0.33 to 0.50 band. only about two - or may be only one peak: It may be that the linguistic sub-generator function which is represented by the peak at F=0.484 in childrens spectra is of the same nature as the peak at F=0.375 in adults' spectra and that the move from a higher frequency in childrens spectra towards a lower frequency in adults' spectra is a developmental feature. However. this is sheer speculation. The two peaks may just as well represent two distinctly different sub-generator functions.

The same line of action could have been taken with regard to the minima of all the spectra. In this way we would possibly have found sub-control functions or sub-filter functions instead of sub-generator functions.

THE CORRELATION BETWEEN A. B. AND VOC OF THE STATISTICAL ANALYSIS AND MPD. CHI2. AND RF OF THE FOURIER ANALYSIS.

Finally. I shall compare the results from the two different approaches to text structure analysis presented in this thesis. that of the relatively simple statistical methods of Chapter 5 and that of the fourier analysis presented in the latter half of the thesis. The most important values from the statistical approach were: the intercept A, the gradient B and the vocabulary VOC. The most important parameters resulting from the fourier analysis were: the mean power density MPD. the variance CHI2 and the reference field RF. To establish the correlation between the parameters in question, A, B and VOC were found for each of the text strings used in window group 128 and compared with MPD. CHI2 and RF for the same strings within each of the groups: children (N=12). scientists (N=9). newspapers (N=5), children's books (N=8). and for all strings (N=34).

First. each of the 12 samples of children's stories, used in the analyses in window group 128, were analysed by the graph fitting program VOCOUT (see Chapters 5 and 6) to establish intercept A, gradient B and vocabulary VOC. In each case A, B and VOC were measured over the same 128 words used in the fourier analysis of window group 128 to find the mean power density MPD, the variance CHI2 and the reference field RF. Secondly, the correlation between each of the groups A, B and VOC were measured against each of the groups MPD, CHI2 and RF. The result can be found in table 11.46 (a) and the significance level for a sample of 12 can be found in table 11.46 (b).

CHILDREN (N=12)	MPD	CHI2	RF
A	-0.6269	0.0051	-0.4494
B	0.4867	0.1055	0.7194
VOC	0.0079	0.2774	0.8949

Table 11.46(a) Coefficients of Correlation between A, B, VOC and MPD, CHI2, RF for children's text strings.

CHILDREN (N=12)	MPD	CHI2	RF
A	2.5%	ns	ns
B	ns	ns	0.5%
VOC	ns	ns	0.05%

Table 11.46(b) Significance levels (one-tailed) of Coefficients of Correlation in table 11.46 (a).

As we recall from Chapters 5 and 6, the intercept A was inversely, and the gradient B directly, related to the structure of a text string. We would therefore expect a negative coefficient of correlation between the mean power density MPD - itself a measure of structure - and A, while we would expect the coefficient between the correlation of MPD and B to be positive. Consequently, the one-tailed significance levels apply. Likewise, we know from earlier measurements that the reference field RF is directly related to the vocabulary VOC, so also here the one tailed level apply.

The following tables give the results of the same measurements applied to the text samples written by scientists (Table 11.47), newspapers (11.48), children's books (11.49) and the correlation between A, B, VOC and MPD, CHI2, RF for all the samples involved in window group 128 (N=34).

SCIENTISTS (N=9)	MPD	CHI2	RF
A	0.1271	-0.0983	0.0819
B	-0.1730	-0.1066	0.1483
VOC	-0.1491	-0.4061	0.6796

Table 11.47(a) Coefficients of Correlation between A, B, VOC and MPD, CHI2, RF for scientists' text strings.

SCIENTISTS (N=9)	MPD	CHI2	RF
A	ns	ns	ns
B	ns	ns	ns
VOC	ns	ns	2.5%

Table 11.47(b) Significance levels of Coefficients of Correlation in table 11.47 (a).

PAPERS (N=5)	MPD	CHI2	RF
A	0.3966	0.5611	0.1096
B	-0.7695	-0.2895	0.3649
VOC	-0.6577	-0.1548	0.9224

Table 11.48(a) Coefficients of Correlation between A, B, VOC and MPD, CHI2, RF for newspapers.

PAPERS (N=5)	MPD	CHI2	RF
A	ns	ns	ns
B	ns	ns	ns
VOC	ns	ns	2.5%

Table 11.48(b) Significance levels of Coefficients of Correlation in table 11.48 (a).

CHILDRENS' BOOKS (N=9)	MPD	CHI2	RF
A	-0.4430	-0.1076	0.1315
B	0.3224	0.1738	0.1779
VOC	-0.1671	-0.1464	0.6457

Table 11.49(a) Coefficients of Correlation between A, B, VOC and MPD, CHI2, RF for children's books.

CHILDRENS' BOOKS (N=9)	MPD	CHI2	RF
A	ns	ns	ns
B	ns	ns	ns
VOC	ns	ns	5%

Table 11.49(b) Significance levels of Coefficients of Correlation in table 11.49 (a).

ALL SAMPLES (N=34)	MPD	CHI2	RF
A	-0.2406	-0.0771	0.3132
B	0.1369	0.2234	0.5018
VOC	-0.1071	0.1834	0.5250

Table 11.50(a) Coefficients of Correlation between A, B, VOC and MPD, CHI2, RF for all samples of w = 128.

ALL SAMPLES (N=34)	MPD	CHI2	RF
A	6%	ns	ns
B	ns	ns	0.5%
VOC	ns	ns	0.5%

Table 11.50(b) Significance levels of Coefficients of Correlation in table 11.50 (a).

DISCUSSION OF ANALYSES IN THIS CHAPTER.

After the text strings were analysed with three different size windows: 64 words, 128 words and 256 words respectively, it was found that a window of 128 words gave the highest significance with regard to the ability of the analysis to distinguish between different catgories of writers. Presumably, the lack of periodicity in strings longer than around 200 words, would account for the failure of window-group 256 to pick up significant features found by window-group 128. Likewise, window-group 64 failed to pick up significant features due to lack of sensitivity.

It was found too, that whatever the window size, both Mean Power Density and Variance were higher for the more skilled - or older - writers. Adults showed persistently higher MPD and CHI2 than children, whatever the window size. This difference however, was not significant with regard to MPD, but was highly significant with regard to CHI2.

The difference between the 'sensitivity' of MPD and CHI2 to characteristics of the text strings was demonstrated again when MPD and CHI2 were measured before and after permutation of the text strings. Even though both MPD and CHI2 decreased with permutation of the strings, the difference with regard to CHI2 was more significant than that of MPD.

The size of reference field established for each string in the window-group 128 turned out to be a highly significant measure of developmental features of the text strings. 'Children' showed significant differences to all adult categories. This is a far clearer picture than that yielded by the measure of vocabulary in chapter 5.

The hypothesis, that there are significant peaks positioned at frequencies common to all the spectra of all the window-groups was evaluated. Even though the exact positions differed slightly between window-groups and between adult spectra and child spectra, three positions of peaks common to all the text strings were established with a high degree of significance in the high-frequency band between F=0.33 and F=0.50.

Further analysis of the impact of permutation on these peaks made it probable however, that only a peak at F=0.484 in childrens text strings and a peak at F=0.375 in adults' text strings did indeed constitute a feature which, with some justification, can be seen as a graphical representation of a sub-generator function of the human linguistic device.

Finally, for window-group 128, the values of intercept A, gradient B and vocabulary VOC were established with the program VOCOUT and compared to the mean power density MPD, the variance CHI2 and the reference field RF found with the Fourier analysis program INFOR for the same text samples. The correlations and levels of significance can be found in tables 11.46 to 11.50.

Where these measurements of correlation are significant they reaffirm our expectations: Vocabulary and reference field are highly correlated because a long reference field is the result of a high vocabulary. The high negative correlation which we would have expected between A and MPD is only found in children's text strings (Table 11.46), and - less significant - in the analysis of all the samples together (Table 11.50). We found in Chapter 5 that A was inversely, and B directly related to structure. We would thus expect to find a high positive correlation between B and MPD. This is obviously not the case. Only in children's text strings (Table 11.46) is there any indication of such a relationship and even there it is not significant. In Table 11.50 (All samples) there is no indication that B is inversely related to MPD - or related at all for that matter. However, in the same table it appears that there is a very significant relationship between B and the reference field of a text string. It thus appears, as it has appeared before (Page 140), that B is more sensitive to vocabulary than to structure. On the whole, the comparability between the two methods, the relatively simple statistical analysis and the Fourier analysis, as expressed in the low levels of significance in tables 11.46 to 11.50, is disappointing. However, a number of factors make these results quite understandable.

First of all, we have seen in the past that the measurements of structure, by the simple statistical methods employed in Chapter 5, needed more than 300 words to become significant. If the values of A and B are measured over 128 words, as in this case, I would not expect the results to carry much weight, except perhaps for children's text strings, where a string of 128 words is much more typical of general language behaviour of the individual and much closer to exhaustion of vocabulary. Possibly for this reason we find the highest level of correlation between A and MPD in children's text strings (Table 11.46). It is, on the whole, clear that the more untypical a text string of 128 words is from the real life language behaviour, the less correlation we find between the values of MPD and A for that group, culminationg with the group of newspapers which shows a positive correlation between A and MPD. We recall, that newspapers had, by far, the highest vocabulary and sequential structure.

Apart from the low sensitivity of the statistical analysis to strings under 300 words, to further understand the lack of correlation in tables 11.46 to 11.50 it is important to recall (Pages 144 to 150) that the concept of structure, as seen by the simple statistical analyses, was not as straight forward as one could have hoped. In some strings the sequential structure was kept lower than that of a random text string and the structure increased when we permutated the string. In other strings the structure was higher than that of a random string and the structure decreased with permutation.

In view of the sometimes more significant results of the simple statistical method used in Chapter 5, does this mean that the Fourier analysis of text strings is merely redundant?

This could well have been the case if it was not for the fact that in two important aspects the Fourier analysis provides us with more information than does the simple statistical method: 1) With the Fourier analysis we not only get the level of structure, but a picture of the distribution of this structure: 2) With the Fourier analysis we get a measure of the variance CHI2, which in my opinion is just as valuable as the measure of structure because I see it as a measure of the filter functions and generator functions of our linguistic device. As a matter of fact, the variance CHI2 is the only parameter of the four A, B, MFD and CHI2 to show a clear and significant correlation with linguistic development (pages 297 to 299).

So the answer to the question raised above is clearly that the Fourier analysis of text strings is far from superfluous. It obviously needs further development, but already at the present level it has provided us with several thought provoking results.

On the whole the analyses in this chapter have - I hope - substantiated my claim that the use of Fourier analysis - even in its present crude form - on the output from our linguistic device, is not only feasable, but indeed opens up new venues to our understanding of internal language processing. One such venue is presented in the next - and last - chapter, where I shall give an example of how Fourier analysis may be used to expose grammatical generator and filter functions in our linguistic device.

CHAPTER 12.

GRAMMATICAL CODING, A PILOT STUDY.

In this chapter I shall demonstrate how the theory and methods developed in the second half of this thesis - from chapter 7 onwards - can be applied to grammatical categories. This opens up a whole new field of possibilities, of which only a few examples shall be given in this chapter. The scope is considerable and the full evaluation of this application of Fourier analysis would in itself provide enough material for an additional thesis.

We have, up to this point of time, used the Fourier analysis only in the shape of the time series transform called INFOR25TIMESERIES. This transform was adequate for the simple evaluation of Mean Power Density - or mean structure - which we have performed so far. However, it did suffer from the serious limitation of only being able to analyse BINARY series, e.g. series of zeroes and ones, a limitation which made it a poor approximation of our linguistic device.

If we instead use a Fourier transform which can handle more than two energy levels we would presumably get a more realistic simulation of the processes which take place in our linguistic device. The version of the Fast Fourier Transform, the INFOR25FFT presented in chapter 9, is such a Fourier transform. This version can handle ANALOG signals, and it is this transform which we shall be using for the analysis of grammatical categories presented in this chapter.

For this particular piece of research, I wanted to increase the resolution of the spectrum to 64 frequency points. This would mean a serious loss of significance, so I have increased the windows to 400 words. This leaves us with a significance of 400/64 = around 6 degrees of freedom. This kind of analysis was carried out with the special version of INFOR25FFT called INFOR-NORMALISED. Please refer to chapter 9 for an account of the slight difference bewteen these two programs.

As I shall hope to demonstrate features which are common to very different litterary styles, I picked the files PAD2 and RUSS1 for this analysis because of their great stylistic difference, so as to get as 'unfavourable' a data base as possible.

ALIGNMENT.

To preserve the continuity in the research presented in this thesis we would want - before we turn to the use of the FFT and analog coding - to check, that the spectra obtained by this method are basically the same as the spectra arrived at by the time series transform and the binary coding which we have been using up till now.

So to assess the difference between the 'old' spectra obtained in the usual binary way with the INFOR25TIMESERIES, and the 'new' spectra arrived at with the Fast Fourier Transform and analog coding, we shall superimpose a 'new' spectrum on an 'old' spectrum to assess the difference.

Figure 12.1 is the result of such an alignment. First PAD2 was anaysed in the 'usual' binary way and the data transformed with the time series transform INFOR25TIMESERIES. Next, the same text string was analysed and again coded binary, but this time the data were transformed with the Fast Fourier Transform INFORNORMALISED. Thirdly, the two spectra were plotted in the same coordinate system.

The only major difference is in f=0.5. This difference arises, as I have explained in chapter 7, from the difference in the shape of the pulse between the binary and the analog signal:

When we analyse the text string with INFOR25TIMESERIES the information array consists of only zeroes and ones and the binary signal thus obtained is transformed as a series of infinitely narrow peaks. When on the other hand we analyse the text string with INFORNORMALISED (The Fast Fourier Transform) the information array - even if we have coded the I-modes binary - is being transformed as a train of square pulses. The 'corners' of these square pulses transform into power in the high frequency end of the power spectrum.

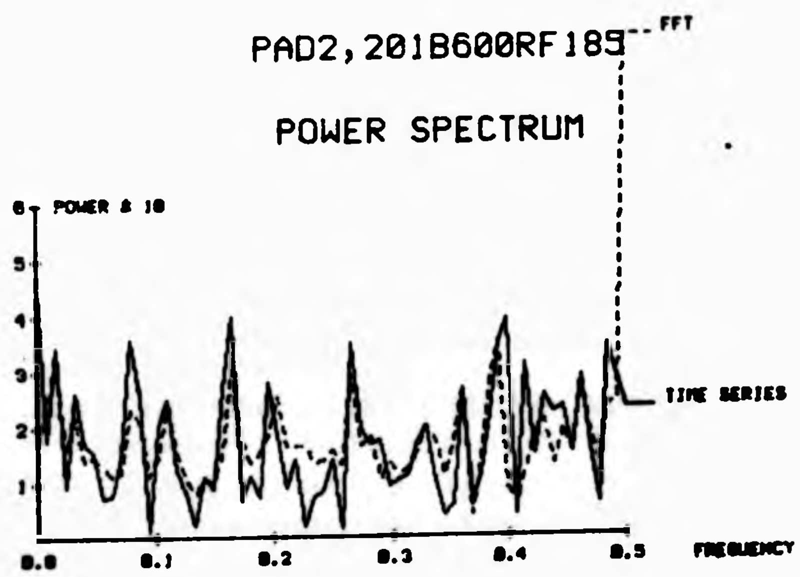


Figure 12.1 Alignment of spectra from time series and FFT.

If we disregard the power values obtained in f=0.5 we can thus apparently continue our research with the FFT as if 'nothing has changed', and it is with this Fourier transform we shall do the remaining analysis in this chapter because it gives us the possibility of analog coding.

For reasons of clarity I have smoothed the spectra, obtained by INFORNORMALISED, with a 10% Hamming Window as explained in chapter 9. The impact of such a smoothing can be seen in figure 12.2 where the smoothed FFT spectrum has been superimposed on the 'raw' FFT spectrum. The spectrum in figure 12.2 is the same as the FFT in figure 12.1. The two spectra in figure 12.2 are marked NO WEIGHTING (RAW) and NO WEIGHTING (SMOOTHED) respectively. The 'NO WEIGHTING' means that the coding of the I-modes was 1 as in the usual binary coding.

ANALYSIS OF TEXT STRINGS WITH GRAMMATICAL CODING.

In chapter 7, during the examination of Fourier analysis, and again in chapter 9, during the examination of INFOR25FFT, I explained how the need for a program which could Fourier-transform ANALOG signals arose from the realisation, that the BINARY coding of I-modes and O-modes is too crude a simulation of the processes which take place in our linguistic device. So to make our coding more graded, we want to rank some words higher than others. There are two problems here. The first one is: what values shall we attribute to the different ranks?. The second is: How do we do the ranking?

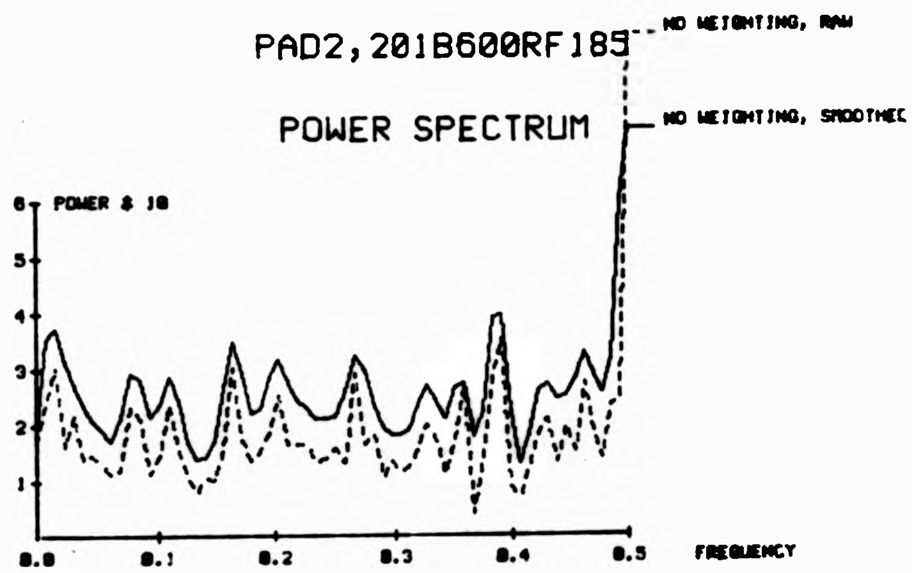


Fig. 12.2 Spectrum before and after smoothing.

The first problem is the simplest to solve. I have decided, that considering the human limitation in judging a sensory continuum (see page 193) I shall stick to the findings presented there, that we are able to judge on average 7 plus minus 2 different sensory levels. If we take 8 as being near enough to the average, then we have got a nice round value in Information Theory terms since 8 is equal to 3 bit. In Information Theory terms there are then 4 integer levels of information transfer: 0,1,2 and 3. Not that I believe for one moment: a) that it is possible to imagine that the same word would have the same information value in different contexts, and b) that the information transfer would only take integer values. But to make it as simple as possible - and still plausible - we shall pretend just that.

The second problem is more difficult. To rank the words in a string realistically is not possible, because, at this stage, we simply do not know the function and coding of our linguistic device. However, we would expect some grammatical categories to have a greater information content than others. But do verbs transfer a greater amount of information than do nouns? After all, the verbs is the category which connect the other categories in an action. Or are the nouns, pronouns and proper nouns more information rich since they are the agents, and we can not have the action without the agents? It is simply impossible to assess with any measure of confidence. So, I have refrained from suggesting such a ranking procedure, which would be nothing more than an adventure into the realms of speculation.

Instead I shall be analysing the problem from a slightly different angle. This shall not be an attempt to simulate real life information transfer. Rather is it an attempt to look into the 'black box' of our linguistic device. We have already seen two examples of Fourier analysis being used in the analysis of such a 'black box' (chapter 7) and came to realise that the power spectra resulting from the Fourier transformation revealed periodicities, and that in the case of the biological 'black box' (the heart beat signal), these periodicities could be interpreted as biological sub-control systems.

My thesis is now, that if we pick a grammatical category (eg. verbs) and code any word in the text string belonging to this grammatical category with a higher transfer value in I-modes than the rest of the words, we might get one or more significant peak/s in the power spectrum and may or may not interpret it as a graphic representation of the specific sub-control system for this particular grammatical category.

Say we code all verbs in a text string in a way which transfers the value '8' (3 bit) to the information array every time a VERB is being read in I-mode. Say furthermore, that all other I-modes than verbs transfer only the value '1' as usual, and the O-modes (verbs or not) transfer the value '0' as usual. This marks each appearance of a verb in I-mode with a pulse of 8 (3 bit) in the information array and should according to my theory result in a signal (an information array) with more information about the specific verb control mechanism in our linguistic device than about any other controls. We could then try to code words of another grammatical category and see if we got peaks in a different part of the spectrum. Finally we could repeat the experiment on different text strings and see if there are inter-human similarities. The initial results from this research are presented on the following pages.

Three grammatical categories common to sentence analysis: nouns, subjects and verbs were coded in turn, and each time the resulting spectrum was superimposed on the uncoded (no weighting) spectrum from the same string for comparison. The coding and analysis was done on two very different files, RUS1 and PAD2. The coded text strings as well as the numerical power in each frequency point of the spectra and all statistics can be found in the appendix to this chapter.

NOUN WEIGHTING.

Figures 12.3 (a) and (b) are the spectra resulting from the coding of NOUNS in text strings from PAD2 and RUS1 respectively. In each case, the spectrum resulting from the weighting of the nouns has been superimposed on the spectrum resulting from the text version where the nouns were treated no differently from any other I-modes or O-modes in the text string i.e. in the NOUN-weighted text string, all nouns have been given the weight 8, other I-modes have been given the weight 1 and the O-modes have been given the weight zero as usual. In the un-weighted text string, the nouns have not been given special weighting, i.e.

they have been treated like any other I-modes and O-modes and been weighted 1 (I-modes) or zero (O-modes).

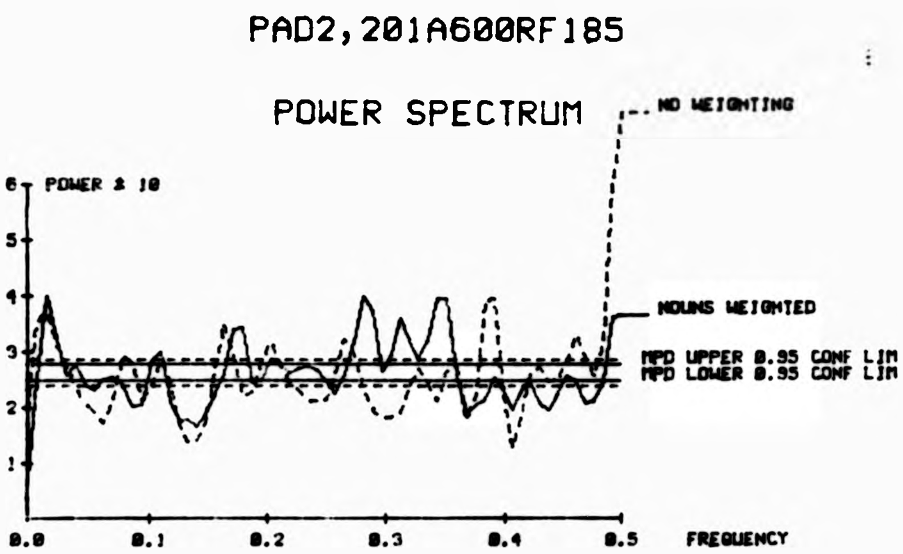


Figure 12.3(a) Nouns weighted
and unweighted in PAD2

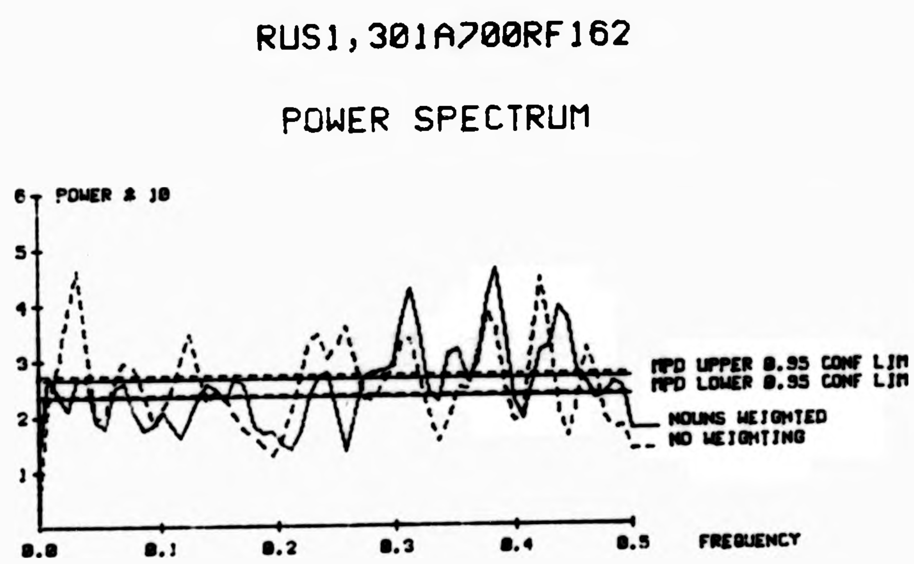


Figure 12.3(b) Nouns weighted
and unweighted in RUSS1

In the weighted spectrum of both files PAD2 and RUS1 the weighting of the nouns have given rise to three peaks between f=0.3 and f=0.4. As we saw in chapter 7 and as explained above, such peaks in the power spectrum may reflect sub-control systems in the generation of the signal being analysed, in this case a text string, and although it borders on speculation, it is feasable that the three peaks seen in the NOUN-weighted spectrum of both files might be the tell-tale of a common NOUN-generating sub-function in our linguistic device.

If it is the case that the three peaks appearing in both spectra between f=0.3 and f=0.4 are indeed specific to a NOUN generating mechanism, we would expect another grammatical category to give rise to another, but equally specific feature somewhere else in the spectrum, and we would also expect such a feature to appear in the spectra from both PAD2 and RUS1.

To examine if such grammar-specific features could be established further, the analysis was repeated first with verbs weighted and later with subjects of sentences weighted.

VERB WEIGHTING.

Figures 12.4 (a) and (b) are the spectra resulting from the coding of VERBS in text strings from PAD2 and RUS1 respectively. In each case, the spectrum resulting from the weighting of the verbs has been superimposed on the spectrum resulting from the

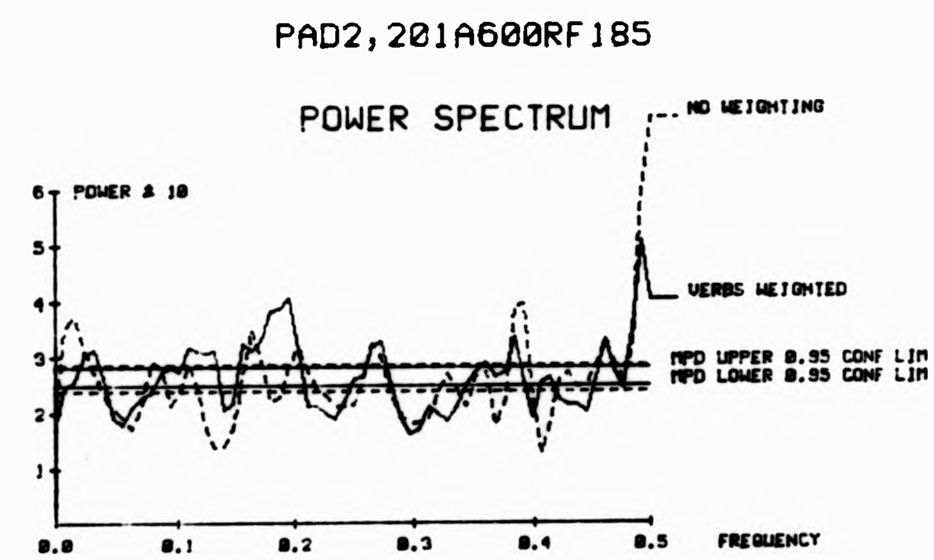


Figure 12.4(a) Verbs weighted and unweighted in PAD2

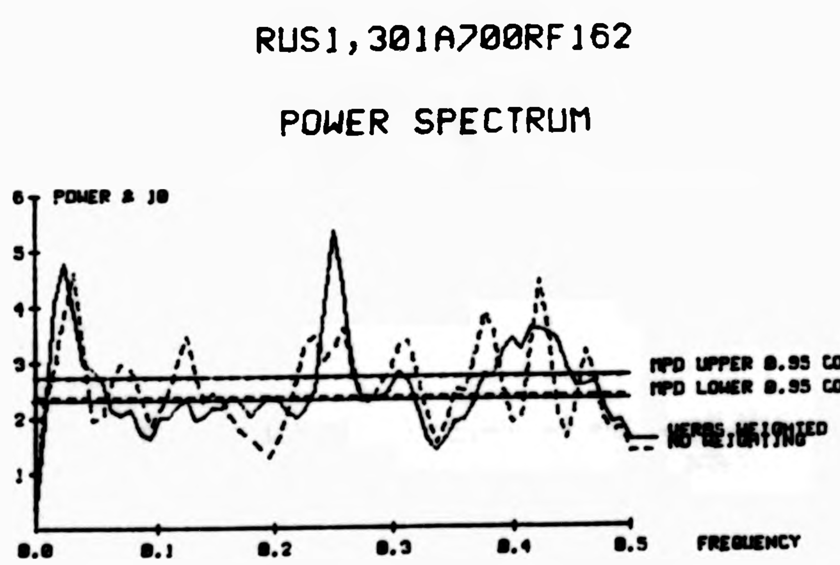


Figure 12.4(b) Verbs weighted and unweighted in RUSS1

text version where the verbs were treated no differently from any other I-modes or O-modes in the text string i.e. in the VERB-weighted text string, all verbs have been given the weight 8, other I-modes have been given the weight 1 and the O-modes have been given the weight zero as usual. In the un-weighted text string, the verbs have not been given special weighting, i.e. they have been treated like any other I-modes and O-modes and been weighted 1 (I-modes) or zero (O-modes).

If we look at figure 12.4 (a) we find that the most prominent difference between the two spectra - the VERB-weighted and the un-weighted from PAD2 is a peak arising around f=0.2 of the VERB-weighted spectrum. Looking at the spectra in figure 12.4 (b) from RUS1 we find that the most prominent feature is that of a peak in the middle of the spectrum (around f=0.25) of the VERB-weighted spectrum.

This would again indicate, that some structures are common to the VERB-weighted versions of the two files, however different the text style of the two files. This lends credit to my suggestion, that we are indeed looking at the telltales of some of the sub-generator mechanisms of our linguistic device.

WEIGHTING OF SENTENCE SUBJECTS.

Finally, the same analysis was carried out with the sentence subjects weighted and unweighted respectively. Figures 12.5(a) and 12.5(b)

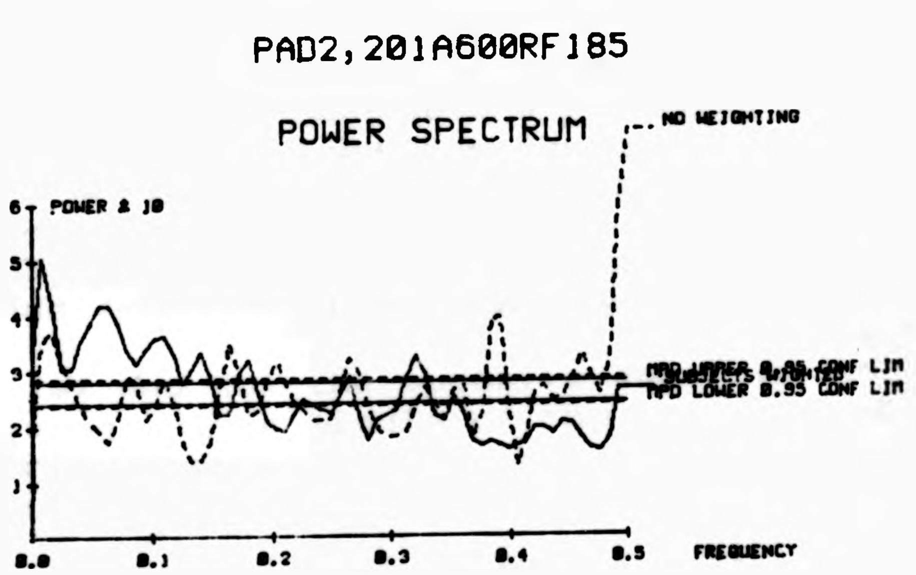


Fig. 12.5(a) Subjects weighted and unweighted in PAD2

show the SUBJECT-weighted and unweighted spectra of PAD2 and RUS1 respectively. The weighting of subjects in a text string seems to give rise to 3 or 4 peaks in the low-frequency part of the spectrum. This is clearly the case for both PAD2 and RUS1.

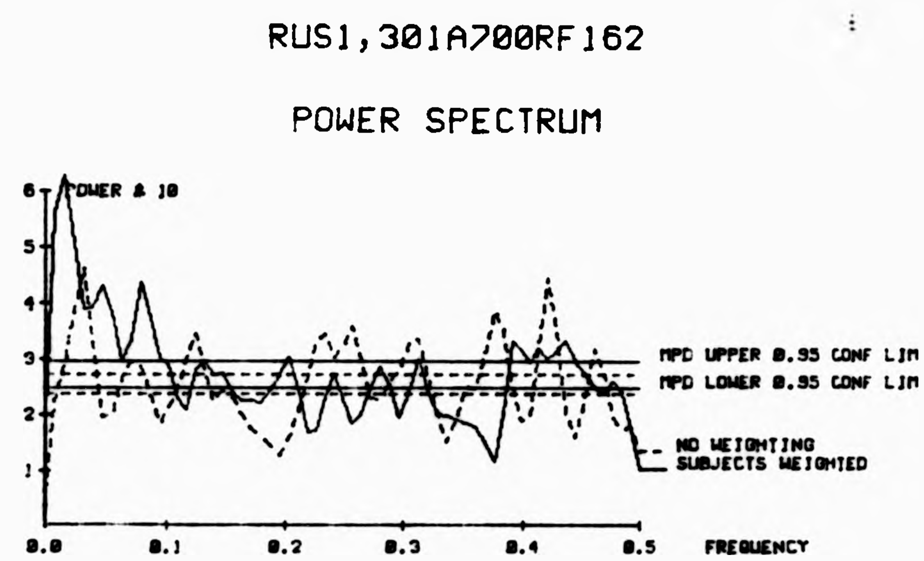


Fig. 12.5(b) Subjects weighted and unweighted in RUSS1

DISCUSSION OF THE ABOVE ANALYSIS..

It is interesting to look at the spectra resulting from grammatical coding in terms of emission and absorbtion features. The peaks arising in different spectra, at very much the same position for the same grammatical cathegory, may well be telltales of sub-generator functions as explained in chapter 11. Functions which are specific to each grammatical cathegory.

Because of the fluctuation in the spectra arising from lack of stationarity in the data base before the Fourier transformation, it is difficult to assess whether the prominent peaks in the weighted spectra above (figures 12.3 to 12.5) do indeed rise from an already existing peak or a trough in the un-weighted spectra. In figure 12.3 (a) and (b) it could look like the three peaks between f=0.3 and f=0.4 arise from already existing peaks.

In figure 12.4 (a) and (b) the opposite seems to be the case. The single peak arising in the middle of the spectrum from both files seems to rise from a feature which could be a minimum between two maxima or it could be a cut-off maximum.

If the findings here do indeed reflect factual structures, then clearly, there are structures much further towards the low end of the spectrum, than we had anticipated. The longest structures reflected in these two last spectra are of a periodicity of around 60 to 120 words. It is difficult to anticipate, that our linguistic device should be so far ranging, when our natural sentence length is about an order of magnitude smaller.

On the other hand, looking at such structural lengths in terms of words may be misleading. Producing, or listening to, 100 words in real time does not take more than around 20 seconds, and it is clear, that we are able to, and indeed do, anticipate both the synthesis of our own strings and the analysis of other peoples' text strings over this length of time.

The other peaks in the low frequency part of the spectrum, which emerged when we weighted the subjects, reflect structural lengths of 18 (f=0.55), 10 (f=0.102) and 7 (f=0.141). It is far easier to accept, that this kind of length could have something to do whith the linguistic device's synthesis and control of outgoing text strings.

Clearly, this last application of Fourier analysis opens up a whole new field of possibilities and with it a great need for further research. As I emphasised, at the beginning of this last chapter, the presentation of my initial research in this use of Fourier analysis is only meant to be an introduction to this field of possibilities. The amount of research needed to establish whether the findings in this chapter are factual or incidental would demand the space and time of another doctoral thesis.

CHAPTER 13.

CONCLUSION.

1. AIM OF THE STUDY.

The aim of this study has been to evaluate information transfer and structures in text strings.

1.1 'information' and 'structure' are here taken in the information theoretical sense. For this reason this thesis begins with an introduction to Information Theory with particular emphasis on the concepts of information and structure originating from this theory (chapter 1). Another two chapters give an account of the use of Information Theory in linguistics (chapter 2) and linguistic models relevant to the present approach (chapter 3).

1.2 Although the data base of the present study has been in the form of written text strings, it is emphasised, that the meaning of 'text string' is the one usually accepted in linguistics i.e. not restricted to written communication.

2. METHODS.

To achieve the aim set out above, two principally different methods of analysis were used; the first - a relatively simple statistical approach (chapters 5 and 6) - based on the established static concept of vocabulary, the second - a pattern evaluation technique by Fourier analysis (chapters 9 to 12) - based on a concept of more dynamic cognitive word processing developed in this thesis (chapter 8).

2.1 The first method is based on my discovery that the vocabulary in a natural text string decreases exponentially with increasing length of string.

2.1.1 This relationship between length of text string and exponential 'decay' of vocabulary means that any natural text string can be represented graphically in a double-logarithmic coordinate system with great accuracy by a straight line of which only two parameters are needed to position the line: The intercept A and the gradient B.

2.2 The second method was developed after some considerations as to how the concept of sememes could be accommodated in a simplistic computer model of cognitive language processing.

2.2.1 No attempt was made to simulate genuine sememe recognition. A much more rudimentary, but - given the present level of computing power and knowledge - more realistic approach, the 'model of best fit' described in chapter 8, was chosen.

2.2.1.1 The 'model of best fit' is based on the concept of sememes in as much as it recognises that a word may have several different connotations and that the connotation which best fits into the context of the word will be chosen by our perception as the 'meaning' of the word.

2.2.1.2 Instead of trying to incorporate in a computer model the choise of the 'best fit' from a number of connotations, the choise of 'best fit' is seen in terms of length of text string.

2.2.1.2.1 Given a word AAA in a text string

'KKK BBB AAA LLL MMM.......TTT DDD AAA FFF'

where AAA appears twice. It is reasonable to suggest that the identity between sememe AAA(1'st appearance) and sememe AAA(2'nd appearance) depends on the length of text string between the two appearances.

2.2.1.2.2 If AAA(1'st appearance) is very close to AAA(2'nd appearance) the sememes AAA(1) and AAA(2) would probably be identical, in which case the second appearance of AAA would not transfer any new information to the linguistic device.

2.2.1.2.3 At the reappearance of AAA after a great number of different words it is reasonable to suggest that sememe AAA(2) has changed from sememe AAA(1) and that therefore sememe AAA(2) would transfer information to the linguistic device.

2.2.1.2.4 The information transfer from a text string can now be seen in terms of length of text string bewteen reappearances of words rather than cognitive choise between sememes.

2.2.1.2.5 Thus, a word in a text string appearing for the first time would transfer information to the linguistic device.

2.2.1.2.6 Within a given length of text string the word reappearing would not transfer any information to the linguistic device because the sememe of the word would be the same.

2.2.1.2.7 After a given length of text string the word reappearing would again transfer information to the linguistic device because its sememe is considered to have changed.

2.2.1.2.8 This length of text string, the so called 'reference field', was chosen so that the number of words in a text string which transfer information is identical to the number of words which do not transfer information. The reasons for this choise are explained in chapters 8 and 10.

2.2.1.2.9 A glossary accommodating the features above was established: An 'I-mode' refers to a word first time it appears within the reference field. Subsequent reappearances are called 'O-modes'.

2.2.1.2.10 Accordingly, the reference field is that length of string which results in the transfer of a steady ratio 1:1 of I-modes and O-modes to the 'linguistic device'.

2.2.1.2.11 An I-mode is defined as transferring a positive amount of information to the 'linguistic device'. An O-mode transfers zero bit of information. The shortcomings of this approach are discussed in chapters 8 and 9.

2.3 Within the second approach, that of Fourier analysis, two principally different methods of Fourier analysis were developed: that of timeseries analysis and that of direct pattern evaluation using the Fast Fourier Transform (chapters 7 and 9).

2.3.1 Because of the lesser demand of the timeseries transform to the length of the text strings, the timeseries analysis was used in all the analyses except for the analog coding in chapter 12 where the Fast Fourier Transform was used.

2.3.2 The purpose of developing two different methods was basically that of my wanting to compare the results when the two different transforms were applied to the same text strings. The spectra from the different transforms of the same text strings were almost identical except for the frequency F=0.50. The difference has been accounted for in chapter 12, where an example is shown of a spectrum from a timeseries transform superimposed on the spectrum of the same text string resulting from the direct pattern evaluation algorithm based on the Fast Fourier Transform.

3. DATA BASE - SAMPLING AND CLASSIFICATION.

The data base of 60 text samples is divided into two main groups. That of childrens text samples (N=42) and that of adults' text samples (N=18).

3.1 Childrens text samples: The 42 samples were written specifically for this study by kind cooperation of two primary schools in Central Region in Scotland. The age of the children ranges from 6 to 14 years. In some of the analyses, the children have been divided into a younger age group (6-9 years) and an older age group (10-14 years).

3.1.1 Of the childrens text samples a total of 1900 words were used in the analysis in chapter 5. Of the 42 text samples written by children only 25 were long enough to be analysed by Fourier analysis in chapter 11. These 25 samples accounted for a total of 1600 words with 13 samples (832 words) written by the 6 to 9 year old, and 12 samples (768 words) written by the age group 10 to 14 year.

3.2 Adults' text samples: The 22 text samples written by adults were taken from books and newspapers to cover as wide a range of styles as possible. Each text sample was 600 words long. The categories were: Scientists (9 samples), newspapers (5 samples) and books written for children (8 samples). The total number of words of the adult text strings were 13200. Of this total all were used in the analysis in chapter 5 while around 6000 words formed the data base of the Fourier analysis in chapters 11 and 12.

4. RESULTS OF ANALYSES.

As explained under 2. METHODS, the analyses fall in two parts. In chapter 5 the method is based on fairly simple statistics and a graph fitting algorithm, while in chapters 11 and 12 the method is that of Fourier analysis. Common to the two approaches is the evaluation of structures before and after permutation of the text strings. In chapter 5 three different kinds of structure, present in text strings, were examined: 'distributive', 'sequential' and 'content' structure, and it was suggested that the structure measured by any of the methods used in this study is mainly that of sequential structure. It was argued too, that only the sequential structure is affected by the permutation of a text string. Consequently, the difference in the amount of structure, before and after a text string has been permutated, as established in all the analyses of this study, is a measure of the change in sequential structure.

4.1 Analyses of text strings based on simple statistical methods (chapter 5):

4.1.1 The numerical values of intercept A and gradient B were established with a graph fitting algorithm for all the 42 text samples of this study. High vocbulary gave low values of A and high values of B. If A and B are related to early linguistic development, we would have expected to see a difference in the values of A and B of younger children as compared to those of older children. This however, did not seem to be the case. A and B were not significantly correlated with age. Tables 5.17 and 5.18 confirmed that the two categories 'younger children' and 'older children' do not seem to be drawn from different populations with regard to A and B. Consequently we would assume that A and B are either not related to linguistic development or are related to developments which take place later on in life i.e. during or after adolescence. The difference between children as a whole and adults as a whole, as measured with the Kruskal-Wallis test seemed to confirm the latter view; the difference in the features between the childrens and adults' language as represented by A or B was confirmed on a better than 5% (A) and better than 1% (B) level, thus suggesting, that the parameters A and B are related to linguistic developments which take place sometimes between the age of the child writers and the adult writers. So much said, tables 5.18 (a) and (b) do show, that even if there are no significant differences between the two categories 'younger children' and 'older children' per se, these two categories tested against the different adult categories, gave that the 'younger children' consistently showed greater difference to the adult categories than the 'older children' with regard to the gradient B, whereas the opposite was the case with regard to the intercept A (tables 5.17 (a) and (b)).

4.1.2. Not unexpectedly it was found that vocabulary is a significant developmental feature of text strings, but only just! Children measured against adults gave that the difference is confirmed on a better than 0.1% level. However, when the children were divided into 2 categories: the younger (6 to 9 years, n=13) and the older (10-14 years, n=12) it was found that when each category was tested against the adults (n=22), the difference between the younger category and the adults was confirmed on a better than 0.01% level, while the difference between the older children and the adults did not quite make it to the 5% level. This is interesting, since it means, that the strings written by the age group 10-14 are not significantly different from the adult text strings with regard to vocabulary. Contrary to common belief, the text strings from newspapers came out as having the highest vocbulary of all the samples in this research. It was even the case, that the more dubious the litterary quality, the higher the vocabulary.

4.1.3. Each of the 42 text strings were then permutated and the parameters A and B measured as before. All movements were tested with the Wilcoxon matched-pairs signed-rank test which established, on a better than 1% significance level, that the overall movement of A and B, after the permutation of the strings, was towards higher values of A and lower values of B i.e. the straight lines representing the text strings generally tilted clockwise in the double-logarithmic coordinate system as a result of the permutation of the string. As the permutation of a text string breaks up the sequential structure rather than the distributive or the content structure, and as the permutation of a string causes A to increase and B to decrease, it was concluded that intercept A is invertedly related, and gradient B directly related to sequential structure.

4.1.4. The analysis showed that newspapers had the lowest A mean values (A=1.20) followed by childrens books (A=1.35) and scientists (A=1.55); children had the highest A value (A=1.57). This suggests that text strings from newspapers have the highest degree of sequential structure while childrens text strings have the lowest degree of sequential structure, and indicates that a greater amount of internal sequential manipulation of text strings takes place during the writing of newspapers and childrens books, than during the writing of scientists' and childrens text strings.

4.1.5. The values found for the gradient B suggested the same distribution of sequential structure in the text samples: B values for children were the lowest (B=0.79) i.e. lowest amount of sequential structure, while B values for newspapers were the highest (B=0.90) again suggesting that newspapers have the highest degree of sequential structure, and confirming that a greater amount of internal sentence manipulation goes on during the writing of newspapers and childrens books than during the writing of the other categories of text strings in this study.

4.1.6. The mean length of runs of 'new' words was measured in the text strings for the different categories. Children had the longest runs followed by childrens books, scientists and finally newspapers which had the shortest run lengths.

4.1.7. It was established that the mean length of runs increased whith the permutation of a text string suggesting that in natural text the sequential structure keeps the run length 'artificially' short.

4.1.8. It was established too, that there was a positive correlation (confirmed on a better than 1% significance level) between the difference in run lengths before and after permutation, and the corresponding differences in the values of A and B.

4.1.9. The high vocabulary of newspaper text strings, combined with the high level of sequential structure found in these strings, suggests that much more sequential manipulation goes on in the mind of the writers of the 'popular' press than in the minds of the writers of the 'serious' press, and certainly more than this category of journalists normally gets credit for.

4.1.10. The fact that the text strings of the popular press combined the highest vocabulary with the shortest run length confirms that even if these strings superficially exhibit litterary incompetence, they are - in a sense - a highly specialised and sophisticated form of writing.

4.2. Analysis of text strings based on Fourier analysis (Power spectral analysis, chapters 10 to 12):

4.2.1. Through practical trials, the optimal size of 3 of the parameters of the power spectral analysis: Reference field, number of frequency points, and width of mesuring window, were established (chapter 10).

4.2.1.1. Reference field: It was shown that the optimal field is the one which gives a 1:1 ratio of zeroes and ones in the information transfer array.

4.2.1.2. Number of frequency points in power spectrum: Minimum 32 points, but if the combination: (length of text string) vs (reference field) allows it, then 64 points.

4.2.1.3. Width of measuring window: Minimum: Twice the number of frequency points (2 degrees of freedom). Maximum: 6 to 9 times the number of frequency points (6 to 9 degrees of freedom), but if the window exceeds around 120 - 200 words, there may be lack of stationarity at some frequencies.

4.2.2. After the text strings were analysed with three different size windows: 64 words, 128 words and 256 words respectively, it was found that a window of 128 words gave the highest significance with regard to the ability of the analysis to distinguish between different catgories of writers. Presumably, the lack of periodicity in strings longer than around 200 words, would account for the failure of window-group 256 to pick up significant features found by window-group 128. Likewise, window-group 64 failed to pick up significant features due to lack of sensitivity (chapter 11).

4.2.3. It was found too, that whatever the window size, both Mean Power Density (MPD) and Variance (CHI2) of the power spectra were higher for the more skilled - or older - writers. Adults showed persistently higher MPD and CHI2 than children, whatever the window size. This difference however, was not significant with regard to MPD, but was highly significant with regard to CHI2 (better than 1% significance level).

4.2.4. The difference between the 'sensitivity' of MPD and CHI2 to the characteristics of the text strings was demonstrated again when MPD and CHI2 were measured before and after permutation of the text strings. Even though both MPD and CHI2 decreased with permutation of the strings, only the difference with regard to CHI2 was significant (better than a 5% significance level).

4.2.5. The size of reference field established for each string in the window-group 128 turned out to be a highly significant measure of developmental features of the text strings. 'Children' showed significant differences to all adult categories. This was a far clearer and more reliable picture than that yielded by the measure of vocabulary in chapter 5.

4.2.6. Two significant features present in all the power spectra in this study are those of 'emission' and 'absorbtion', graphically represented by the peaks and the troughs respectively in the spectra.

4.2.6.1 It is suggested that the peaks in the power spectra, being emission features, represent subgenerator functions of the 'lingusitic device' while the troughs, being absorbtion features, represent sub-control, filter or lexical functions.

4.2.6.2. The view that the peaks and troughs in the spectra are indeed the graphical representations of sub-generator and sub-control functions of the 'linguistic device' is supported by the fact that the variance of the spectra decreased significantly with the permutation of the text strings.

4.2.7. The hypothesis, that some peaks in the power spectra are positioned at frequencies common to all the spectra of all the window-groups was evaluated. Even though the exact positions differed slightly between window-groups and between adult spectra and child spectra, three positions of peaks common to all the text strings were established with a high degree of significance in the high-frequency band between F=0.33 and F=0.50.

4.2.8. Further analysis of the impact of permutation on these peaks made it probable however, that only a peak at F=0.484 in childrens text strings and a peak at F=0.375 in adults' text strings did indeed constitute a feature which, with some justification, can be seen as a graphical representation of a sub-generator function of the human linguistic device.

4.2.9. To evaluate the hypothesis under 4.2.6.1., two text strings, of very different style, were coded so that a 3 bit pulse was transferred to the information array every time a noun was encountered in the text strings, and the resulting spectra were superimposed on the normal spectra where nouns had not been given special weighting (chapter 12).

4.2.9.1. In the two spectra based on the two different text strings, wich had been noun-weighted, three peaks appeared in the high-frequency band of both spectra (around F=0.3), suggesting that some generative and control principles were common to the two different text strings.

4.2.9.2. The same weighting was then given to verbs and sentence subjects respectively in the two text strings. The weighting of verbs gave rise to a peak in the frequency band around F=0.2 in both spectra, while the weighting of sentence subjects gave rise to 4 peaks in the low-frequency band of the two spectra, again suggesting that identical, but grammar specific, sub-generator and sub-filter (lexical) functions were involved in the generation of the two different text strings.

5. LIMITATIONS AND FURTHER DEVELOPMENT.

The limitations of the present approach have been emphasised throughout this study. The task of analysing cognitive information transfer is overwhelming and, as I have stated before, I have not attempted anything like a full description of cognitive language processing.

What I have done is 1) to point out that one very important feature of language perception - the sememe evaluation of our linguistic device - probably is a function, amongst others, of the length of text string between near-identical sememes, and 2) incorporated this feature in a model which lends itself to the very sensitive analysis of Fourier analysis.

That the length of text string between near-identical sememes is just one of presumably myriads of factors involved in the sememe evaluation which goes on in our linguistic device means that only a fraction of the structure present in text strings will be picked up by this analysis. As such this method is both crude and simplistic: not because it is simple in itself - I am sure you did not get that impression - but because it only deals with one particular feature of the overwhelming complexity of natural language.

So much said, the results of this study do suggest that in spite of all the incompleteness of the 'model of best fit', the power sectral analyses do indeed pick up some of the structures which we know must be present in natural text strings.

The 'model of best fit' could be improved in two ways:

1) The first obvious limitation of the model is the inflexibility of the reference field. It is not terribly realistic that all words in a text string should have the same reference field. As touched upon in chapter 8, the sememes of numerals, prepositions and small words like 'and', 'or' etc. are relatively stable over long strings of text i.e. should have long reference fields, while huge, vaguely defined concepts with highly unstable sememes like 'love' should have rather shorter reference fields.

2) The second obvious limitation of the 'model of best fit' is the fact that we have attributed one of only four levels of information transfer: 0, 1, 2, and 3 bit. It has been explained in chapter 8 that resent research suggests that the human sensory continuum can only bee divided into 8 (3 bit) distinct levels. This is the reason for our maximum transfer of information being set to 3 bit. There is however no reason why the amount of transferred information should be an integer. Most words in I-mode would probably transfer between 1 and 2 bit of information when their 'best fit' was established, while numerals and prepositions would transfer less information, say between 0 and 1 bit. Only the big and vague concepts like 'love', 'clever', 'God' etc. would have enough sememe variety to transfer between 2 and 3 bit of information when their 'best fit' was established by the linguistic device.

Since both limitations are a function of 'sememe stabilty', both limitations could be remedied by the inclusion of a wordlist where each word could be looked up by the program and attributed a weighting according to some predetermined scale of 'sememe stability'.

However, given that the analyses presented in this study have been a contionuous struggle against the lack of computing power at my disposal, I have not contemplated the addition of such an extensive lexicon to my program.

It is my hope that someone who reads this study shall find it interesting and convincing - or challenging - enough to continue the development of the 'model of best fit' and improve the analyses and with them the 'mapping' of the linguistic device.

APPENDIX TO CHAPTER 5.

OUTPUT FROM VOCOUT(100)

Index

```
b:c62.txt:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 34
AT WORD NR: 60     VOCABULARY: 38
AT WORD NR: 70     VOCABULARY: 41
AT WORD NR: 80     VOCABULARY: 43
AT WORD NR: 90     VOCABULARY: 48
AT WORD NR: 100    VOCABULARY: 53

F(x) =  2.13611e0 * X TO THE  6.98960e-1 POWER
COEFFICIENT OF CORRELATION = 0.9944
STANDARD ERROR OF ESTIMATE = 0.0580


B:C70.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 34
AT WORD NR: 60     VOCABULARY: 38
AT WORD NR: 70     VOCABULARY: 40
AT WORD NR: 80     VOCABULARY: 45
AT WORD NR: 90     VOCABULARY: 48
AT WORD NR: 100    VOCABULARY: 51

F(x) =  1.99414e0 * X TO THE  7.12844e-1 POWER
COEFFICIENT OF CORRELATION = 0.9967
STANDARD ERROR OF ESTIMATE = 0.0452


B:C71.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 22
AT WORD NR: 40     VOCABULARY: 28
AT WORD NR: 50     VOCABULARY: 32
AT WORD NR: 60     VOCABULARY: 38
AT WORD NR: 70     VOCABULARY: 42
AT WORD NR: 80     VOCABULARY: 46
AT WORD NR: 90     VOCABULARY: 47
AT WORD NR: 100    VOCABULARY: 50

F(x) =  1.66378e0 * X TO THE  7.53572e-1 POWER
COEFFICIENT OF CORRELATION = 0.9974
STANDARD ERROR OF ESTIMATE = 0.0425
```

```
B:C73.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 22
AT WORD NR: 40     VOCABULARY: 26
AT WORD NR: 50     VOCABULARY: 32
AT WORD NR: 60     VOCABULARY: 34
AT WORD NR: 70     VOCABULARY: 39
AT WORD NR: 80     VOCABULARY: 40
AT WORD NR: 90     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 47

F(x) =  1.90879e0 * X TO THE  7.03120e-1 POWER
COEFFICIENT OF CORRELATION = 0.9961
STANDARD ERROR OF ESTIMATE = 0.0486


B:C77.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 22
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 60     VOCABULARY: 43
AT WORD NR: 70     VOCABULARY: 47
AT WORD NR: 80     VOCABULARY: 51
AT WORD NR: 90     VOCABULARY: 56
AT WORD NR: 100    VOCABULARY: 61

F(x) =  1.48464e0 * X TO THE  8.09649e-1 POWER
COEFFICIENT OF CORRELATION = 0.9979
STANDARD ERROR OF ESTIMATE = 0.0409


B:C80.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 14
AT WORD NR: 30     VOCABULARY: 19
AT WORD NR: 40     VOCABULARY: 26
AT WORD NR: 50     VOCABULARY: 33
AT WORD NR: 60     VOCABULARY: 38
AT WORD NR: 70     VOCABULARY: 44
AT WORD NR: 80     VOCABULARY: 51
AT WORD NR: 90     VOCABULARY: 57
AT WORD NR: 100    VOCABULARY: 62

F(x) =  1.25126e0 * X TO THE  8.37209e-1 POWER
COEFFICIENT OF CORRELATION = 0.9917
STANDARD ERROR OF ESTIMATE = 0.0846
```

```
B:C82.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 21
AT WORD NR: 40     VOCABULARY: 27
AT WORD NR: 50     VOCABULARY: 29
AT WORD NR: 60     VOCABULARY: 35
AT WORD NR: 70     VOCABULARY: 38
AT WORD NR: 80     VOCABULARY: 43
AT WORD NR: 90     VOCABULARY: 48
AT WORD NR: 100    VOCABULARY: 54

F(x) =  2.03783e0 * X TO THE  6.97506e-1 POWER
COEFFICIENT OF CORRELATION = 0.9955
STANDARD ERROR OF ESTIMATE = 0.0518


B:C85.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 31
AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 60     VOCABULARY: 44
AT WORD NR: 70     VOCABULARY: 47
AT WORD NR: 80     VOCABULARY: 53
AT WORD NR: 90     VOCABULARY: 58
AT WORD NR: 100    VOCABULARY: 64

F(x) =  1.63892e0 * X TO THE  7.96401e-1 POWER
COEFFICIENT OF CORRELATION = 0.9994
STANDARD ERROR OF ESTIMATE = 0.0221


B:C90.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 60     VOCABULARY: 41
AT WORD NR: 70     VOCABULARY: 47
AT WORD NR: 80     VOCABULARY: 53
AT WORD NR: 90     VOCABULARY: 58
AT WORD NR: 100    VOCABULARY: 61

F(x) =  1.44310e0 * X TO THE  8.20548e-1 POWER
COEFFICIENT OF CORRELATION = 0.9985
STANDARD ERROR OF ESTIMATE = 0.0348
```

B:C91.TXT:

AT WORD NR: 10 VOCABULARY: 8
AT WORD NR: 20 VOCABULARY: 15
AT WORD NR: 30 VOCABULARY: 23
AT WORD NR: 40 VOCABULARY: 30
AT WORD NR: 50 VOCABULARY: 36
AT WORD NR: 60 VOCABULARY: 38
AT WORD NR: 70 VOCABULARY: 45
AT WORD NR: 80 VOCABULARY: 52
AT WORD NR: 90 VOCABULARY: 56
AT WORD NR: 100 VOCABULARY: 60

F(x) = 1.11808e0 * X TO THE 8.73500e-1 POWER
COEFFICIENT OF CORRELATION = 0.9976
STANDARD ERROR OF ESTIMATE = 0.0467

B:C94.TXT:

AT WORD NR: 10 VOCABULARY: 9
AT WORD NR: 20 VOCABULARY: 15
AT WORD NR: 30 VOCABULARY: 19
AT WORD NR: 40 VOCABULARY: 24
AT WORD NR: 50 VOCABULARY: 29
AT WORD NR: 60 VOCABULARY: 37
AT WORD NR: 70 VOCABULARY: 44
AT WORD NR: 80 VOCABULARY: 47
AT WORD NR: 90 VOCABULARY: 50
AT WORD NR: 100 VOCABULARY: 53

F(x) = 1.34000e0 * X TO THE 8.02407e-1 POWER
COEFFICIENT OF CORRELATION = 0.9954
STANDARD ERROR OF ESTIMATE = 0.0602

B:C95.TXT:

AT WORD NR: 10 VOCABULARY: 10
AT WORD NR: 20 VOCABULARY: 16
AT WORD NR: 30 VOCABULARY: 22
AT WORD NR: 40 VOCABULARY: 27
AT WORD NR: 50 VOCABULARY: 34
AT WORD NR: 60 VOCABULARY: 41
AT WORD NR: 70 VOCABULARY: 47
AT WORD NR: 80 VOCABULARY: 54
AT WORD NR: 90 VOCABULARY: 60
AT WORD NR: 100 VOCABULARY: 63

F(x) = 1.37391e0 * X TO THE 8.28790e-1 POWER
COEFFICIENT OF CORRELATION = 0.9970
STANDARD ERROR OF ESTIMATE = 0.0501

B:C96.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 60     VOCABULARY: 41
AT WORD NR: 70     VOCABULARY: 50
AT WORD NR: 80     VOCABULARY: 54
AT WORD NR: 90     VOCABULARY: 61
AT WORD NR: 100    VOCABULARY: 66

F(x) =  1.47470e0 * X TO THE  8.24044e-1 POWER
COEFFICIENT OF CORRELATION = 0.9991
STANDARD ERROR OF ESTIMATE = 0.0266
```

B:C100.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 27
AT WORD NR: 40     VOCABULARY: 34
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 49
AT WORD NR: 70     VOCABULARY: 54
AT WORD NR: 80     VOCABULARY: 60
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 72

F(x) =  1.51607e0 * X TO THE  8.42227e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0311
```

B:C101.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 32
AT WORD NR: 60     VOCABULARY: 37
AT WORD NR: 70     VOCABULARY: 44
AT WORD NR: 80     VOCABULARY: 49
AT WORD NR: 90     VOCABULARY: 56
AT WORD NR: 100    VOCABULARY: 60

F(x) =  1.73046e0 * X TO THE  7.63447e-1 POWER
COEFFICIENT OF CORRELATION = 0.9970
STANDARD ERROR OF ESTIMATE = 0.0460
```

B:C102.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 23
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 35
AT WORD NR: 60     VOCABULARY: 39
AT WORD NR: 70     VOCABULARY: 44
AT WORD NR: 80     VOCABULARY: 47
AT WORD NR: 90     VOCABULARY: 52
AT WORD NR: 100    VOCABULARY: 56

F(x) =  1.81970e0 * X TO THE  7.47847e-1 POWER
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0236
```

B:C103.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 60     VOCABULARY: 43
AT WORD NR: 70     VOCABULARY: 47
AT WORD NR: 80     VOCABULARY: 52
AT WORD NR: 90     VOCABULARY: 57
AT WORD NR: 100    VOCABULARY: 60

F(x) =  1.71142e0 * X TO THE  7.79519e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0233
```

B:C104.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 27
AT WORD NR: 40     VOCABULARY: 35
AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 60     VOCABULARY: 43
AT WORD NR: 70     VOCABULARY: 49
AT WORD NR: 80     VOCABULARY: 54
AT WORD NR: 90     VOCABULARY: 62
AT WORD NR: 100    VOCABULARY: 68

F(x) =  1.67701e0 * X TO THE  8.02659e-1 POWER
COEFFICIENT OF CORRELATION = 0.9970
STANDARD ERROR OF ESTIMATE = 0.0487
```

```
B:C110.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 49
AT WORD NR: 80     VOCABULARY: 51
AT WORD NR: 90     VOCABULARY: 57
AT WORD NR: 100    VOCABULARY: 61

F(x) =  1.88790e0 * X TO THE  7.64381e-1 POWER
COEFFICIENT OF CORRELATION = 0.9956
STANDARD ERROR OF ESTIMATE = 0.0558


B:C111.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 31
AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 53
AT WORD NR: 80     VOCABULARY: 58
AT WORD NR: 90     VOCABULARY: 64
AT WORD NR: 100    VOCABULARY: 69

F(x) =  1.16394e0 * X TO THE  8.91480e-1 POWER
COEFFICIENT OF CORRELATION = 0.9998
STANDARD ERROR OF ESTIMATE = 0.0150


B:C113.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 27
AT WORD NR: 40     VOCABULARY: 35
AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 60     VOCABULARY: 44
AT WORD NR: 70     VOCABULARY: 51
AT WORD NR: 80     VOCABULARY: 55
AT WORD NR: 90     VOCABULARY: 61
AT WORD NR: 100    VOCABULARY: 62

F(x) =  1.51848e0 * X TO THE  8.25223e-1 POWER
COEFFICIENT OF CORRELATION = 0.9936
STANDARD ERROR OF ESTIMATE = 0.0731
```

```
B:C114.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 48
AT WORD NR: 70     VOCABULARY: 56
AT WORD NR: 80     VOCABULARY: 64
AT WORD NR: 90     VOCABULARY: 70
AT WORD NR: 100    VOCABULARY: 73

F(x) =  1.06023e0 * X TO THE  9.30204e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0223


B:C130.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 33
AT WORD NR: 60     VOCABULARY: 37
AT WORD NR: 70     VOCABULARY: 40
AT WORD NR: 80     VOCABULARY: 47
AT WORD NR: 90     VOCABULARY: 52
AT WORD NR: 100    VOCABULARY: 56

F(x) =  2.09279e0 * X TO THE  7.09968e-1 POWER
COEFFICIENT OF CORRELATION = 0.9955
STANDARD ERROR OF ESTIMATE = 0.0526


B:C140.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 36
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 60     VOCABULARY: 46
AT WORD NR: 70     VOCABULARY: 52
AT WORD NR: 80     VOCABULARY: 54
AT WORD NR: 90     VOCABULARY: 61
AT WORD NR: 100    VOCABULARY: 63

F(x) =  1.63549e0 * X TO THE  8.09742e-1 POWER
COEFFICIENT OF CORRELATION = 0.9952
STANDARD ERROR OF ESTIMATE = 0.0622
```

B:C141.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 60     VOCABULARY: 41
AT WORD NR: 70     VOCABULARY: 45
AT WORD NR: 80     VOCABULARY: 49
AT WORD NR: 90     VOCABULARY: 54
AT WORD NR: 100    VOCABULARY: 57

F(x) =  1.97809e0 * X TO THE  7.37278e-1 POWER
COEFFICIENT OF CORRELATION = 0.9970
STANDARD ERROR OF ESTIMATE = 0.0444
```

YOUNGER CHILDREN'S TEXT STRINGS:

	A	B	VOCABULARY (PR 100)
C62	2.1361	0.6989	53
C70	1.9941	0.7128	51
C71	1.6638	0.7536	50
C73	1.9087	0.7031	47
C77	1.4846	0.8096	61
C80	1.2513	0.8372	62
C82	2.0378	0.6975	54
C85	1.6389	0.7964	64
C90	1.4431	0.8205	61
C91	1.1181	0.8735	60
C94	1.3400	0.8024	53
C95	1.3739	0.8288	63
C96	1.4747	0.8240	66

A MEAN: 1.6050
S.DEV.: 0.3242

B MEAN: 0.7814
S.DEV.: 0.0606

VOCABULARY MEAN: 57.3077
S.DEV.: 6.1696

OLDER CHILDREN'S TEXT STRINGS:

	A	B	VOCABULARY (PR 100)
C100	1.5161	0.8422	72
C101	1.7304	0.7634	60
C102	1.8197	0.7478	56
C103	1.7114	0.7795	60
C104	1.6770	0.8027	68
C110	1.8879	0.7644	61
C111	1.1639	0.8915	69
C113	1.5185	0.8252	62
C114	1.0602	0.9302	73
C130	2.0928	0.7100	56
C140	1.6355	0.8097	63
C141	1.9781	0.7373	57

A MEAN: 1.6493
S.DEV.: 0.3045

B MEAN: 0.8003
S.DEV.: 0.0644

VOCABULARY MEAN: 63.0833
S.DEV.: 6.0221

```
B:RUSS1.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 22
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 60     VOCABULARY: 46
AT WORD NR: 70     VOCABULARY: 53
AT WORD NR: 80     VOCABULARY: 58
AT WORD NR: 90     VOCABULARY: 65
AT WORD NR: 100    VOCABULARY: 68

F(x) =  1.17697e0 * X TO THE  8.90556e-1 POWER
COEFFICIENT OF CORRELATION = 0.9975
STANDARD ERROR OF ESTIMATE = 0.0488


B:RUSS2.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 15
AT WORD NR: 30     VOCABULARY: 21
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 60     VOCABULARY: 42
AT WORD NR: 70     VOCABULARY: 47
AT WORD NR: 80     VOCABULARY: 55
AT WORD NR: 90     VOCABULARY: 63
AT WORD NR: 100    VOCABULARY: 69

F(x) =  1.20734e0 * X TO THE  8.70024e-1 POWER
COEFFICIENT OF CORRELATION = 0.9944
STANDARD ERROR OF ESTIMATE = 0.0716


B:RUSS3.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 60     VOCABULARY: 44
AT WORD NR: 70     VOCABULARY: 50
AT WORD NR: 80     VOCABULARY: 58
AT WORD NR: 90     VOCABULARY: 64
AT WORD NR: 100    VOCABULARY: 69

F(x) =  1.40527e0 * X TO THE  8.42651e-1 POWER
COEFFICIENT OF CORRELATION = 0.9990
STANDARD ERROR OF ESTIMATE = 0.0288
```

```
B:RUSS4.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 35
AT WORD NR: 60     VOCABULARY: 40
AT WORD NR: 70     VOCABULARY: 44
AT WORD NR: 80     VOCABULARY: 51
AT WORD NR: 90     VOCABULARY: 56
AT WORD NR: 100    VOCABULARY: 62

F(x) =  1.57206e0 * X TO THE  7.97275e-1 POWER
COEFFICIENT OF CORRELATION = 0.9953
STANDARD ERROR OF ESTIMATE = 0.0605


B:RUSS5.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 60     VOCABULARY: 50
AT WORD NR: 70     VOCABULARY: 56
AT WORD NR: 80     VOCABULARY: 61
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 72

F(x) =  1.32650e0 * X TO THE  8.74244e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0315


B:BRUNER.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 26
AT WORD NR: 50     VOCABULARY: 31
AT WORD NR: 60     VOCABULARY: 36
AT WORD NR: 70     VOCABULARY: 42
AT WORD NR: 80     VOCABULARY: 48
AT WORD NR: 90     VOCABULARY: 48
AT WORD NR: 100    VOCABULARY: 50

F(x) =  2.29933e0 * X TO THE  6.78168e-1 POWER
COEFFICIENT OF CORRELATION = 0.9893
STANDARD ERROR OF ESTIMATE = 0.0777
```

B:RUSS4.TXT:

```
AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 35
AT WORD NR: 60     VOCABULARY: 40
AT WORD NR: 70     VOCABULARY: 44
AT WORD NR: 80     VOCABULARY: 51
AT WORD NR: 90     VOCABULARY: 56
AT WORD NR: 100    VOCABULARY: 62

F(x) =  1.57206e0 * X TO THE  7.97275e-1 POWER
COEFFICIENT OF CORRELATION = 0.9953
STANDARD ERROR OF ESTIMATE = 0.0605
```

B:RUSS5.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 60     VOCABULARY: 50
AT WORD NR: 70     VOCABULARY: 56
AT WORD NR: 80     VOCABULARY: 61
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 72

F(x) =  1.32650e0 * X TO THE  8.74244e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0315
```

B:BRUNER.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 26
AT WORD NR: 50     VOCABULARY: 31
AT WORD NR: 60     VOCABULARY: 36
AT WORD NR: 70     VOCABULARY: 42
AT WORD NR: 80     VOCABULARY: 48
AT WORD NR: 90     VOCABULARY: 48
AT WORD NR: 100    VOCABULARY: 50

F(x) =  2.29933e0 * X TO THE  6.78168e-1 POWER
COEFFICIENT OF CORRELATION = 0.9893
STANDARD ERROR OF ESTIMATE = 0.0777
```

```
B:LABOV.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 27
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 60     VOCABULARY: 42
AT WORD NR: 70     VOCABULARY: 49
AT WORD NR: 80     VOCABULARY: 57
AT WORD NR: 90     VOCABULARY: 62
AT WORD NR: 100    VOCABULARY: 69

F(x) =  1.60724e0 * X TO THE  8.11292e-1 POWER
COEFFICIENT OF CORRELATION = 0.9981
STANDARD ERROR OF ESTIMATE = 0.0390


B:FRANKENA.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 60     VOCABULARY: 40
AT WORD NR: 70     VOCABULARY: 43
AT WORD NR: 80     VOCABULARY: 49
AT WORD NR: 90     VOCABULARY: 56
AT WORD NR: 100    VOCABULARY: 60

F(x) =  1.61118e0 * X TO THE  7.87362e-1 POWER
COEFFICIENT OF CORRELATION = 0.9953
STANDARD ERROR OF ESTIMATE = 0.0597


B:CHOMSKY.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 60     VOCABULARY: 44
AT WORD NR: 70     VOCABULARY: 48
AT WORD NR: 80     VOCABULARY: 53
AT WORD NR: 90     VOCABULARY: 58
AT WORD NR: 100    VOCABULARY: 62

F(x) =  1.74646e0 * X TO THE  7.81811e-1 POWER
COEFFICIENT OF CORRELATION = 0.9983
STANDARD ERROR OF ESTIMATE = 0.0356
```

SCIENTISTS:

	A	B	VOCABULARY (PR 100)
RUSS1	1.1770	0.8906	68
RUSS2	1.2073	0.8702	69
RUSS3	1.4053	0.8427	69
RUSS4	1.5720	0.7973	62
RUSS5	1.3265	0.8742	72
BRUNER	2.2993	0.6782	50
LABOV	1.6072	0.8129	69
FRANKENA	1.6111	0.7874	60
CHOMSKY	1.7465	0.7818	62

A MEAN: 1.6161
S.DEV.: 0.3172

B MEAN: 0.8150
S.DEV.: 0.0651

VOCABULARY MEAN: 64.5556
S.DEV.: 6.8211

B:DREC1.TXT:

```
AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 28
AT WORD NR: 40     VOCABULARY: 36
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 47
AT WORD NR: 70     VOCABULARY: 53
AT WORD NR: 80     VOCABULARY: 59
AT WORD NR: 90     VOCABULARY: 65
AT WORD NR: 100    VOCABULARY: 72

F(x) =  1.28485e0 * X TO THE  8.80128e-1 POWER
COEFFICIENT OF CORRELATION = 0.9966
STANDARD ERROR OF ESTIMATE = 0.0563
```

B:DREC2.TXT:

```
AT WORD NR: 10     VOCABULARY: 8
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 34
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 50
AT WORD NR: 70     VOCABULARY: 56
AT WORD NR: 80     VOCABULARY: 66
AT WORD NR: 90     VOCABULARY: 70
AT WORD NR: 100    VOCABULARY: 74

F(x) =  8.70253e-1 * X TO THE  9.81356e-1 POWER
COEFFICIENT OF CORRELATION = 0.9982
STANDARD ERROR OF ESTIMATE = 0.0458
```

B:MAIL.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 35
AT WORD NR: 50     VOCABULARY: 44
AT WORD NR: 60     VOCABULARY: 52
AT WORD NR: 70     VOCABULARY: 60
AT WORD NR: 80     VOCABULARY: 64
AT WORD NR: 90     VOCABULARY: 69
AT WORD NR: 100    VOCABULARY: 75

F(x) =  1.31360e0 * X TO THE  8.88350e-1 POWER
COEFFICIENT OF CORRELATION = 0.9986
STANDARD ERROR OF ESTIMATE = 0.0361
```

```
B:HERALD.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 28
AT WORD NR: 40     VOCABULARY: 35
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 60     VOCABULARY: 48
AT WORD NR: 70     VOCABULARY: 55
AT WORD NR: 80     VOCABULARY: 61
AT WORD NR: 90     VOCABULARY: 68
AT WORD NR: 100    VOCABULARY: 73

F(x) =  1.26552e0 * X TO THE  8.89357e-1 POWER
COEFFICIENT OF CORRELATION = 0.9975
STANDARD ERROR OF ESTIMATE = 0.0489


B:GUARD.TXT:

AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 25
AT WORD NR: 40     VOCABULARY: 29
AT WORD NR: 50     VOCABULARY: 34
AT WORD NR: 60     VOCABULARY: 41
AT WORD NR: 70     VOCABULARY: 49
AT WORD NR: 80     VOCABULARY: 55
AT WORD NR: 90     VOCABULARY: 60
AT WORD NR: 100    VOCABULARY: 67

F(x) =  1.27938e0 * X TO THE  8.54727e-1 POWER
COEFFICIENT OF CORRELATION = 0.9983
STANDARD ERROR OF ESTIMATE = 0.0392
```

PAPERS:

	A	B	VOCABULARY (PR 100)
DREC1	1.2849	0.8801	72
DREC2	0.8725	0.9814	74
MAIL	1.3136	0.8884	75
HERALD	1.2655	0.8894	73
GUARD	1.2794	0.8547	67

A MEAN: 1.2032
S.DEV.: 0.1857

B MEAN: 0.8988
S.DEV.: 0.0483

VOCABULARY MEAN: 72.2000
S.DEV.: 3.1145

B:PAD1.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 49
AT WORD NR: 80     VOCABULARY: 58
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 70

F(x) =  1.56629e0 * X TO THE  8.24691e-1 POWER
COEFFICIENT OF CORRELATION = 0.9977
STANDARD ERROR OF ESTIMATE = 0.0432
```

B:PAD2.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 19
AT WORD NR: 30     VOCABULARY: 26
AT WORD NR: 40     VOCABULARY: 33
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 60     VOCABULARY: 49
AT WORD NR: 70     VOCABULARY: 54
AT WORD NR: 80     VOCABULARY: 58
AT WORD NR: 90     VOCABULARY: 65
AT WORD NR: 100    VOCABULARY: 70

F(x) =  1.47679e0 * X TO THE  8.44597e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0312
```

B:PAD3.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 20
AT WORD NR: 30     VOCABULARY: 27
AT WORD NR: 40     VOCABULARY: 36
AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 60     VOCABULARY: 47
AT WORD NR: 70     VOCABULARY: 54
AT WORD NR: 80     VOCABULARY: 59
AT WORD NR: 90     VOCABULARY: 63
AT WORD NR: 100    VOCABULARY: 67

F(x) =  1.64496e0 * X TO THE  8.18935e-1 POWER
COEFFICIENT OF CORRELATION = 0.9966
STANDARD ERROR OF ESTIMATE = 0.0529
```

B:PAD4.TXT:

```
AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 17
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 32
AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 60     VOCABULARY: 47
AT WORD NR: 70     VOCABULARY: 54
AT WORD NR: 80     VOCABULARY: 60
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 73

F(x) =  1.25981e0 * X TO THE  8.81115e-1 POWER
COEFFICIENT OF CORRELATION = 0.9990
STANDARD ERROR OF ESTIMATE = 0.0308
```

B:POOH.TXT:

```
AT WORD NR: 10     VOCABULARY: 8
AT WORD NR: 20     VOCABULARY: 13
AT WORD NR: 30     VOCABULARY: 14
AT WORD NR: 40     VOCABULARY: 17
AT WORD NR: 50     VOCABULARY: 26
AT WORD NR: 60     VOCABULARY: 33
AT WORD NR: 70     VOCABULARY: 37
AT WORD NR: 80     VOCABULARY: 42
AT WORD NR: 90     VOCABULARY: 47
AT WORD NR: 100    VOCABULARY: 50

F(x) =  9.87037e-1 * X TO THE  8.42179e-1 POWER
COEFFICIENT OF CORRELATION = 0.9779
STANDARD ERROR OF ESTIMATE = 0.1401
```

B:ALICEB.TXT:

```
AT WORD NR: 10     VOCABULARY: 9
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 31
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 51
AT WORD NR: 80     VOCABULARY: 56
AT WORD NR: 90     VOCABULARY: 61
AT WORD NR: 100    VOCABULARY: 67

F(x) =  1.17858e0 * X TO THE  8.81953e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0221
```

```
B:ALICEL.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 16
AT WORD NR: 30     VOCABULARY: 21
AT WORD NR: 40     VOCABULARY: 30
AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 51
AT WORD NR: 80     VOCABULARY: 55
AT WORD NR: 90     VOCABULARY: 60
AT WORD NR: 100    VOCABULARY: 65

F(x) =  1.30627e0 * X TO THE  8.52374e-1 POWER
COEFFICIENT OF CORRELATION = 0.9960
STANDARD ERROR OF ESTIMATE = 0.0597
```

```
B:SEAGULL.TXT:

AT WORD NR: 10     VOCABULARY: 10
AT WORD NR: 20     VOCABULARY: 18
AT WORD NR: 30     VOCABULARY: 24
AT WORD NR: 40     VOCABULARY: 31
AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 60     VOCABULARY: 45
AT WORD NR: 70     VOCABULARY: 52
AT WORD NR: 80     VOCABULARY: 59
AT WORD NR: 90     VOCABULARY: 66
AT WORD NR: 100    VOCABULARY: 72

F(x) =  1.34062e0 * X TO THE  8.60550e-1 POWER
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0270
```

CHILDRENS' BOOKS:

	A	B	VOCABULARY (PR 100)
PAD1	1.5663	0.8247	70
PAD2	1.4768	0.8446	70
PAD3	1.6450	0.8189	67
PAD4	1.2598	0.8811	73
POOH	0.9870	0.8422	50
ALICEB	1.1786	0.8820	67
ALICEL	1.3063	0.8524	65
SEAGULL	1.3406	0.8606	72

A MEAN: 1.3451
S.DEV.: 0.2141

B MEAN: 0.8508
S.DEV.: 0.0233

VOCABULARY MEAN: 66.75
S.DEV.: 7.2650

ADULT TEXT STRINGS (SCIENT.+ PAPERS + CH.BOOKS):

A MEAN: 1.3968
S.DEV.: 0.2940

B MEAN: 0.8471
S.DEV.: 0.0576

VOCABUALRY MEAN: 67.0909
S.DEV.: 6.8027

OUTPUT FROM VOCOUT(600)

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```
B:C85.TXT:

AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 100    VOCABULARY: 64
AT WORD NR: 150    VOCABULARY: 84
AT WORD NR: 200    VOCABULARY: 99
AT WORD NR: 250    VOCABULARY: 114
AT WORD NR: 300    VOCABULARY: 127
AT WORD NR: 350    VOCABULARY: 134
AT WORD NR: 400    VOCABULARY: 152
AT WORD NR: 450    VOCABULARY: 168
AT WORD NR: 500    VOCABULARY: 188
AT WORD NR: 550    VOCABULARY: 201

F(x) =  2.84368e0 * X TO THE  6.68909e-1 POWER
COEFFICIENT OF CORRELATION = 0.9978
STANDARD ERROR OF ESTIMATE = 0.0349


B:C85.PRM:

AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 100    VOCABULARY: 64
AT WORD NR: 150    VOCABULARY: 92
AT WORD NR: 200    VOCABULARY: 111
AT WORD NR: 250    VOCABULARY: 129
AT WORD NR: 300    VOCABULARY: 147
AT WORD NR: 350    VOCABULARY: 162
AT WORD NR: 400    VOCABULARY: 174
AT WORD NR: 450    VOCABULARY: 180
AT WORD NR: 500    VOCABULARY: 192
AT WORD NR: 550    VOCABULARY: 201

F(x) =  2.88480e0 * X TO THE  6.81854e-1 POWER
COEFFICIENT OF CORRELATION = 0.9967
STANDARD ERROR OF ESTIMATE = 0.0435
```

B:C95.TXT:

```
AT WORD NR: 50     VOCABULARY: 34
AT WORD NR: 100    VOCABULARY: 63
AT WORD NR: 150    VOCABULARY: 78
AT WORD NR: 200    VOCABULARY: 95
AT WORD NR: 250    VOCABULARY: 116
AT WORD NR: 300    VOCABULARY: 139
AT WORD NR: 350    VOCABULARY: 159
AT WORD NR: 400    VOCABULARY: 179
AT WORD NR: 450    VOCABULARY: 198
AT WORD NR: 500    VOCABULARY: 217
AT WORD NR: 550    VOCABULARY: 236

F(x) =  1.47109e0 * X TO THE  7.99715e-1 POWER
COEFFICIENT OF CORRELATION = 0.9977
STANDARD ERROR OF ESTIMATE = 0.0423
```

B:C95.PRM:

```
AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 100    VOCABULARY: 74
AT WORD NR: 150    VOCABULARY: 104
AT WORD NR: 200    VOCABULARY: 119
AT WORD NR: 250    VOCABULARY: 137
AT WORD NR: 300    VOCABULARY: 153
AT WORD NR: 350    VOCABULARY: 171
AT WORD NR: 400    VOCABULARY: 194
AT WORD NR: 450    VOCABULARY: 210
AT WORD NR: 500    VOCABULARY: 221
AT WORD NR: 550    VOCABULARY: 236

F(x) =  2.60563e0 * X TO THE  7.17789e-1 POWER
COEFFICIENT OF CORRELATION = 0.9969
STANDARD ERROR OF ESTIMATE = 0.0446
```

```
B:C130.TXT:

AT WORD NR: 50     VOCABULARY: 33
AT WORD NR: 100    VOCABULARY: 56
AT WORD NR: 150    VOCABULARY: 73
AT WORD NR: 200    VOCABULARY: 83
AT WORD NR: 250    VOCABULARY: 101
AT WORD NR: 300    VOCABULARY: 116
AT WORD NR: 350    VOCABULARY: 136
AT WORD NR: 400    VOCABULARY: 146
AT WORD NR: 450    VOCABULARY: 161
AT WORD NR: 500    VOCABULARY: 172
AT WORD NR: 550    VOCABULARY: 178

F(x) =  2.05672e0 * X TO THE  7.09918e-1 POWER
COEFFICIENT OF CORRELATION = 0.9985
STANDARD ERROR OF ESTIMATE = 0.0309


B:C130.PRM:

AT WORD NR: 50     VOCABULARY: 33
AT WORD NR: 100    VOCABULARY: 58
AT WORD NR: 150    VOCABULARY: 76
AT WORD NR: 200    VOCABULARY: 93
AT WORD NR: 250    VOCABULARY: 107
AT WORD NR: 300    VOCABULARY: 123
AT WORD NR: 350    VOCABULARY: 142
AT WORD NR: 400    VOCABULARY: 151
AT WORD NR: 450    VOCABULARY: 160
AT WORD NR: 500    VOCABULARY: 171
AT WORD NR: 550    VOCABULARY: 178

F(x) =  2.20871e0 * X TO THE  7.03078e-1 POWER
COEFFICIENT OF CORRELATION = 0.9985
STANDARD ERROR OF ESTIMATE = 0.0308
```

B:C140.TXT:

```
AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 100    VOCABULARY: 63
AT WORD NR: 150    VOCABULARY: 76
AT WORD NR: 200    VOCABULARY: 93
AT WORD NR: 250    VOCABULARY: 109
AT WORD NR: 300    VOCABULARY: 122
AT WORD NR: 350    VOCABULARY: 132
AT WORD NR: 400    VOCABULARY: 147
AT WORD NR: 450    VOCABULARY: 154
AT WORD NR: 500    VOCABULARY: 164
AT WORD NR: 550    VOCABULARY: 177

F(x) =  3.88395e0 * X TO THE  6.02967e-1 POWER
COEFFICIENT OF CORRELATION = 0.9990
STANDARD ERROR OF ESTIMATE = 0.0211
```

B:C140.PRM:

```
AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 100    VOCABULARY: 62
AT WORD NR: 150    VOCABULARY: 80
AT WORD NR: 200    VOCABULARY: 92
AT WORD NR: 250    VOCABULARY: 110
AT WORD NR: 300    VOCABULARY: 125
AT WORD NR: 350    VOCABULARY: 135
AT WORD NR: 400    VOCABULARY: 147
AT WORD NR: 450    VOCABULARY: 159
AT WORD NR: 500    VOCABULARY: 164
AT WORD NR: 550    VOCABULARY: 177

F(x) =  3.38678e0 * X TO THE  6.28488e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0178
```

```
B:C141.TXT:

AT WORD NR: 50      VOCABULARY: 36
AT WORD NR: 100     VOCABULARY: 57
AT WORD NR: 150     VOCABULARY: 76
AT WORD NR: 200     VOCABULARY: 94
AT WORD NR: 250     VOCABULARY: 117
AT WORD NR: 300     VOCABULARY: 129
AT WORD NR: 350     VOCABULARY: 143
AT WORD NR: 400     VOCABULARY: 162
AT WORD NR: 450     VOCABULARY: 174
AT WORD NR: 500     VOCABULARY: 192
AT WORD NR: 550     VOCABULARY: 208

F(x) =  1.95658e0 * X TO THE  7.35843e-1 POWER
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0234


B:C141.PRM:

AT WORD NR: 50      VOCABULARY: 38
AT WORD NR: 100     VOCABULARY: 59
AT WORD NR: 150     VOCABULARY: 81
AT WORD NR: 200     VOCABULARY: 101
AT WORD NR: 250     VOCABULARY: 118
AT WORD NR: 300     VOCABULARY: 132
AT WORD NR: 350     VOCABULARY: 152
AT WORD NR: 400     VOCABULARY: 167
AT WORD NR: 450     VOCABULARY: 184
AT WORD NR: 500     VOCABULARY: 199
AT WORD NR: 550     VOCABULARY: 208

F(x) =  2.16623e0 * X TO THE  7.24594e-1 POWER
COEFFICIENT OF CORRELATION = 0.9994
STANDARD ERROR OF ESTIMATE = 0.0189
```

CHILDREN'S TEXT STRINGS:

	A(TEXT)	A(PERM)	DELTA A	DEV FROM TOTAL MEAN
C85	2.8437	2.8848	0.0411	-0.3400
C95	1.4710	2.6056	1.1346	0.7535
C130	2.0567	2.2087	0.1520	-0.2291
C140	3.8840	3.3868	-0.4972	-0.8783
C141	1.9566	2.1662	0.2096	-0.1715

A(TEXT) MEAN (THIS GROUP): 2.4424
VARIANCE: 0.8919
S.DEV.: 0.9444

A(PERM) MEAN (THIS GROUP): 2.6504
VARIANCE: 0.2572
S.DEV.: 0.5071

DELTA A MEAN (THIS GROUP): 0.2080
VARIANCE: 0.3467
S.DEV.: 0.5888

CHILDREN'S TEXT STRINGS:

	B(TEXT)	B(PERM)	DELTA B	DEV FROM TOTAL MEAN
C85	0.6689	0.6818	0.0129	0.0418
C95	0.7997	0.7178	-0.0819	-0.0530
C130	0.7099	0.7031	-0.0068	0.0221
C140	0.6030	0.6285	0.0255	0.0544
C141	0.7358	0.7246	-0.0112	0.0177

B(TEXT) MEAN (THIS GROUP): 0.7035
VARIANCE: 0.0054
S.DEV.: 0.0735

B(PERM) MEAN (THIS GROUP): 0.6912
VARIANCE: 0.0015
S.DEV.: 0.0387

DELTA B MEAN (THIS GROUP): -0.0123
VARIANCE: 0.0017
S.DEV.: 0.0417

B:RUSS1.TXT:

```
AT WORD NR: 50     VOCABULARY: 40
AT WORD NR: 100    VOCABULARY: 68
AT WORD NR: 150    VOCABULARY: 97
AT WORD NR: 200    VOCABULARY: 115
AT WORD NR: 250    VOCABULARY: 138
AT WORD NR: 300    VOCABULARY: 162
AT WORD NR: 350    VOCABULARY: 185
AT WORD NR: 400    VOCABULARY: 199
AT WORD NR: 450    VOCABULARY: 217
AT WORD NR: 500    VOCABULARY: 238
AT WORD NR: 550    VOCABULARY: 257
AT WORD NR: 600    VOCABULARY: 266

F(x) =  1.98534e0 * X TO THE  7.69619e-1 POWER
COEFFICIENT OF CORRELATION = 0.9996
STANDARD ERROR OF ESTIMATE = 0.0179
```

B:RUSS1.FRM:

```
AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 74
AT WORD NR: 150    VOCABULARY: 102
AT WORD NR: 200    VOCABULARY: 118
AT WORD NR: 250    VOCABULARY: 141
AT WORD NR: 300    VOCABULARY: 157
AT WORD NR: 350    VOCABULARY: 172
AT WORD NR: 400    VOCABULARY: 191
AT WORD NR: 450    VOCABULARY: 211
AT WORD NR: 500    VOCABULARY: 234
AT WORD NR: 550    VOCABULARY: 251
AT WORD NR: 600    VOCABULARY: 266

F(x) =  2.65574e0 * X TO THE  7.18065e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0262
```

B:RUSS2.TXT:

```
AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 100    VOCABULARY: 69
AT WORD NR: 150    VOCABULARY: 98
AT WORD NR: 200    VOCABULARY: 123
AT WORD NR: 250    VOCABULARY: 151
AT WORD NR: 300    VOCABULARY: 174
AT WORD NR: 350    VOCABULARY: 192
AT WORD NR: 400    VOCABULARY: 215
AT WORD NR: 450    VOCABULARY: 237
AT WORD NR: 500    VOCABULARY: 261
AT WORD NR: 550    VOCABULARY: 278
AT WORD NR: 600    VOCABULARY: 296

F(x) =  1.61316e0 * X TO THE  8.17425e-1 POWER
COEFFICIENT OF CORRELATION = 0.9998
STANDARD ERROR OF ESTIMATE = 0.0138
```

B:RUSS2.PRM:

```
AT WORD NR: 50     VOCABULARY: 44
AT WORD NR: 100    VOCABULARY: 81
AT WORD NR: 150    VOCABULARY: 106
AT WORD NR: 200    VOCABULARY: 130
AT WORD NR: 250    VOCABULARY: 155
AT WORD NR: 300    VOCABULARY: 179
AT WORD NR: 350    VOCABULARY: 203
AT WORD NR: 400    VOCABULARY: 219
AT WORD NR: 450    VOCABULARY: 244
AT WORD NR: 500    VOCABULARY: 261
AT WORD NR: 550    VOCABULARY: 279
AT WORD NR: 600    VOCABULARY: 296

F(x) =  2.35742e0 * X TO THE  7.58016e-1 POWER
COEFFICIENT OF CORRELATION = 0.9994
STANDARD ERROR OF ESTIMATE = 0.0213
```

B:RUSS3.TXT:

```
AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 100    VOCABULARY: 69
AT WORD NR: 150    VOCABULARY: 99
AT WORD NR: 200    VOCABULARY: 122
AT WORD NR: 250    VOCABULARY: 144
AT WORD NR: 300    VOCABULARY: 160
AT WORD NR: 350    VOCABULARY: 171
AT WORD NR: 400    VOCABULARY: 189
AT WORD NR: 450    VOCABULARY: 199
AT WORD NR: 500    VOCABULARY: 211
AT WORD NR: 550    VOCABULARY: 223
AT WORD NR: 600    VOCABULARY: 244
```

GEOMETRIC REGRESSION ANALYSIS:

```
F(x) =  2.38872e0 * X TO THE  7.28700e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9885
COEFFICIENT OF CORRELATION = 0.9942
STANDARD ERROR OF ESTIMATE = 0.0624
```

B:RUSS3P.TXT:

```
AT WORD NR: 50     VOCABULARY: 44
AT WORD NR: 100    VOCABULARY: 70
AT WORD NR: 150    VOCABULARY: 93
AT WORD NR: 200    VOCABULARY: 108
AT WORD NR: 250    VOCABULARY: 127
AT WORD NR: 300    VOCABULARY: 147
AT WORD NR: 350    VOCABULARY: 161
AT WORD NR: 400    VOCABULARY: 177
AT WORD NR: 450    VOCABULARY: 197
AT WORD NR: 500    VOCABULARY: 212
AT WORD NR: 550    VOCABULARY: 230
AT WORD NR: 600    VOCABULARY: 244
```

GEOMETRIC REGRESSION ANALYSIS:

```
F(x) =  2.93395e0 * X TO THE  6.87247e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9984
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0217
```

B:RUSS4.TXT:

AT WORD NR: 50 VOCABULARY: 35
AT WORD NR: 100 VOCABULARY: 62
AT WORD NR: 150 VOCABULARY: 86
AT WORD NR: 200 VOCABULARY: 111
AT WORD NR: 250 VOCABULARY: 139
AT WORD NR: 300 VOCABULARY: 164
AT WORD NR: 350 VOCABULARY: 185
AT WORD NR: 400 VOCABULARY: 208
AT WORD NR: 450 VOCABULARY: 230
AT WORD NR: 500 VOCABULARY: 250
AT WORD NR: 550 VOCABULARY: 273
AT WORD NR: 600 VOCABULARY: 295

GEOMETRIC REGRESSION ANALYSIS:

F(x) = 1.15996e0 * X TO THE 8.65273e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9995
COEFFICIENT OF CORRELATION = 0.9998
STANDARD ERROR OF ESTIMATE = 0.0153

B:RUSS4P.TXT:

AT WORD NR: 50 VOCABULARY: 38
AT WORD NR: 100 VOCABULARY: 68
AT WORD NR: 150 VOCABULARY: 99
AT WORD NR: 200 VOCABULARY: 126
AT WORD NR: 250 VOCABULARY: 154
AT WORD NR: 300 VOCABULARY: 177
AT WORD NR: 350 VOCABULARY: 194
AT WORD NR: 400 VOCABULARY: 217
AT WORD NR: 450 VOCABULARY: 242
AT WORD NR: 500 VOCABULARY: 256
AT WORD NR: 550 VOCABULARY: 275
AT WORD NR: 600 VOCABULARY: 295

GEOMETRIC REGRESSION ANALYSIS:

F(x) = 1.56054e0 * X TO THE 8.23929e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9983
COEFFICIENT OF CORRELATION = 0.9991
STANDARD ERROR OF ESTIMATE = 0.0271

```
B:RUSS5.TXT:

AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 100    VOCABULARY: 72
AT WORD NR: 150    VOCABULARY: 97
AT WORD NR: 200    VOCABULARY: 124
AT WORD NR: 250    VOCABULARY: 146
AT WORD NR: 300    VOCABULARY: 166
AT WORD NR: 350    VOCABULARY: 187
AT WORD NR: 400    VOCABULARY: 206
AT WORD NR: 450    VOCABULARY: 225
AT WORD NR: 500    VOCABULARY: 249
AT WORD NR: 550    VOCABULARY: 271
AT WORD NR: 600    VOCABULARY: 287

F(x) =  2.05733e0 * X TO THE  7.70970e-1 POWER
COEFFICIENT OF CORRELATION = 0.9998
STANDARD ERROR OF ESTIMATE = 0.0106
```

```
B:RUSS5.PRM:

AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 78
AT WORD NR: 150    VOCABULARY: 107
AT WORD NR: 200    VOCABULARY: 136
AT WORD NR: 250    VOCABULARY: 153
AT WORD NR: 300    VOCABULARY: 169
AT WORD NR: 350    VOCABULARY: 191
AT WORD NR: 400    VOCABULARY: 215
AT WORD NR: 450    VOCABULARY: 238
AT WORD NR: 500    VOCABULARY: 256
AT WORD NR: 550    VOCABULARY: 272
AT WORD NR: 600    VOCABULARY: 287

F(x) =  2.39851e0 * X TO THE  7.51085e-1 POWER
COEFFICIENT OF CORRELATION = 0.9986
STANDARD ERROR OF ESTIMATE = 0.0312
```

```
B:BRUNER.TXT:

AT WORD NR: 50     VOCABULARY: 31
AT WORD NR: 100    VOCABULARY: 50
AT WORD NR: 150    VOCABULARY: 78
AT WORD NR: 200    VOCABULARY: 103
AT WORD NR: 250    VOCABULARY: 126
AT WORD NR: 300    VOCABULARY: 147
AT WORD NR: 350    VOCABULARY: 165
AT WORD NR: 400    VOCABULARY: 186
AT WORD NR: 450    VOCABULARY: 208
AT WORD NR: 500    VOCABULARY: 232
AT WORD NR: 550    VOCABULARY: 253
AT WORD NR: 600    VOCABULARY: 273

F(x) =  8.88720e-1 * X TO THE  8.94029e-1 POWER
COEFFICIENT OF CORRELATION = 0.9988
STANDARD ERROR OF ESTIMATE = 0.0344


B:BRUNER.PRM:

AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 82
AT WORD NR: 150    VOCABULARY: 107
AT WORD NR: 200    VOCABULARY: 131
AT WORD NR: 250    VOCABULARY: 153
AT WORD NR: 300    VOCABULARY: 177
AT WORD NR: 350    VOCABULARY: 192
AT WORD NR: 400    VOCABULARY: 211
AT WORD NR: 450    VOCABULARY: 225
AT WORD NR: 500    VOCABULARY: 243
AT WORD NR: 550    VOCABULARY: 258
AT WORD NR: 600    VOCABULARY: 273

F(x) =  2.77877e0 * X TO THE  7.22222e-1 POWER
COEFFICIENT OF CORRELATION = 0.9975
STANDARD ERROR OF ESTIMATE = 0.0408
```

```
B:LABOV.TXT:

AT WORD NR: 50    VOCABULARY: 38
AT WORD NR: 100   VOCABULARY: 69
AT WORD NR: 150   VOCABULARY: 102
AT WORD NR: 200   VOCABULARY: 129
AT WORD NR: 250   VOCABULARY: 153
AT WORD NR: 300   VOCABULARY: 175
AT WORD NR: 350   VOCABULARY: 199
AT WORD NR: 400   VOCABULARY: 227
AT WORD NR: 450   VOCABULARY: 248
AT WORD NR: 500   VOCABULARY: 269
AT WORD NR: 550   VOCABULARY: 284
AT WORD NR: 600   VOCABULARY: 302

F(x) =  1.49158e0 * X TO THE  8.35772e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0247


B:LABOV.FRM:

AT WORD NR: 50    VOCABULARY: 41
AT WORD NR: 100   VOCABULARY: 72
AT WORD NR: 150   VOCABULARY: 101
AT WORD NR: 200   VOCABULARY: 127
AT WORD NR: 250   VOCABULARY: 150
AT WORD NR: 300   VOCABULARY: 177
AT WORD NR: 350   VOCABULARY: 194
AT WORD NR: 400   VOCABULARY: 217
AT WORD NR: 450   VOCABULARY: 240
AT WORD NR: 500   VOCABULARY: 261
AT WORD NR: 550   VOCABULARY: 281
AT WORD NR: 600   VOCABULARY: 302

F(x) =  1.81342e0 * X TO THE  7.99855e-1 POWER
COEFFICIENT OF CORRELATION = 0.9999
STANDARD ERROR OF ESTIMATE = 0.0095
```

```
B:FRANKENA.TXT:

AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 100    VOCABULARY: 60
AT WORD NR: 150    VOCABULARY: 87
AT WORD NR: 200    VOCABULARY: 110
AT WORD NR: 250    VOCABULARY: 128
AT WORD NR: 300    VOCABULARY: 142
AT WORD NR: 350    VOCABULARY: 162
AT WORD NR: 400    VOCABULARY: 182
AT WORD NR: 450    VOCABULARY: 198
AT WORD NR: 500    VOCABULARY: 219
AT WORD NR: 550    VOCABULARY: 233
AT WORD NR: 600    VOCABULARY: 239

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  1.76030e0 * X TO THE  7.73369e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9985
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0236


B:FRANKP.TXT:

AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 100    VOCABULARY: 66
AT WORD NR: 150    VOCABULARY: 89
AT WORD NR: 200    VOCABULARY: 111
AT WORD NR: 250    VOCABULARY: 128
AT WORD NR: 300    VOCABULARY: 148
AT WORD NR: 350    VOCABULARY: 172
AT WORD NR: 400    VOCABULARY: 185
AT WORD NR: 450    VOCABULARY: 199
AT WORD NR: 500    VOCABULARY: 209
AT WORD NR: 550    VOCABULARY: 224
AT WORD NR: 600    VOCABULARY: 239

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  2.10008e0 * X TO THE  7.44580e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9978
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0276
```

```
B:CHOM.TXT:

AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 100    VOCABULARY: 62
AT WORD NR: 150    VOCABULARY: 88
AT WORD NR: 200    VOCABULARY: 109
AT WORD NR: 250    VOCABULARY: 129
AT WORD NR: 300    VOCABULARY: 150
AT WORD NR: 350    VOCABULARY: 168
AT WORD NR: 400    VOCABULARY: 183
AT WORD NR: 450    VOCABULARY: 194
AT WORD NR: 500    VOCABULARY: 216
AT WORD NR: 550    VOCABULARY: 229
AT WORD NR: 600    VOCABULARY: 242

F(x) =  1.91789e0 * X TO THE  7.59907e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0197


B:CHOMSKY.PRM:

AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 100    VOCABULARY: 70
AT WORD NR: 150    VOCABULARY: 96
AT WORD NR: 200    VOCABULARY: 117
AT WORD NR: 250    VOCABULARY: 133
AT WORD NR: 300    VOCABULARY: 149
AT WORD NR: 350    VOCABULARY: 170
AT WORD NR: 400    VOCABULARY: 193
AT WORD NR: 450    VOCABULARY: 209
AT WORD NR: 500    VOCABULARY: 217
AT WORD NR: 550    VOCABULARY: 229
AT WORD NR: 600    VOCABULARY: 242

F(x) =  2.70357e0 * X TO THE  7.06924e-1 POWER
COEFFICIENT OF CORRELATION = 0.9991
STANDARD ERROR OF ESTIMATE = 0.0234
```

SCIENTISTS:

	A(TEXT)	A(PERM)	DELTA A	DEV FROM TOTAL MEAN
RUSS1	1.9853	2.6557	0.6704	0.2893
RUSS2	1.6132	2.3574	0.7442	0.3631
RUSS3	2.3887	2.9340	0.5453	0.1642
RUSS4	1.1600	1.5600	0.4000	0.0189
RUSS5	2.0573	2.3985	0.3412	-0.0399
BRUNER	0.8887	2.7788	1.8901	1.5090
LABOV	1.4916	1.8134	0.3218	-0.0593
FRANKENA	1.7603	2.1000	0.3397	-0.0414
CHOMSKY	1.9179	2.7036	0.7857	0.4046

A(TEXT) MEAN (THIS GROUP): 1.6959
VARIANCE: 0.2169
S.DEV.: 0.4657

A(PERM) MEAN (THIS GROUP): 2.3668
VARIANCE: 0.2147
S.DEV.: 0.4634

DELTA A MEAN (THIS GROUP): 0.6709
VARIANCE: 0.2418
S.DEV.: 0.4917

SCIENTISTS:

	B(TEXT)	B(PERM)	DELTA B	DEV FROM TOTAL MEAN
RUSS1	0.7696	0.7181	-0.0515	-0.0226
RUSS2	0.8174	0.7580	-0.0594	-0.0305
RUSS3	0.7287	0.6872	-0.0415	-0.0126
RUSS4	0.8653	0.8239	-0.0414	-0.0125
RUSS5	0.7710	0.7511	-0.0199	0.0090
BRUNER	0.8940	0.7222	-0.1718	-0.1429
LABOV	0.8358	0.7999	-0.0359	-0.0070
FRANKENA	0.7734	0.7446	-0.0288	0.0001
CHOMSKY	0.7560	0.7069	-0.0491	-0.0202

B(TEXT) MEAN (THIS GROUP): 0.8012
VARIANCE: 0.0030
S.DEV.: 0.0550

B(PERM) MEAN (THIS GROUP): 0.7458
VARIANCE: 0.0019
S.DEV.: 0.0440

DELTA B MEAN (THIS GROUP): -0.0555
VARIANCE: 0.0020
S.DEV.: 0.0452

```
B:DREC1.TXT:

AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 100    VOCABULARY: 72
AT WORD NR: 150    VOCABULARY: 101
AT WORD NR: 200    VOCABULARY: 130
AT WORD NR: 250    VOCABULARY: 148
AT WORD NR: 300    VOCABULARY: 174
AT WORD NR: 350    VOCABULARY: 200
AT WORD NR: 400    VOCABULARY: 226
AT WORD NR: 450    VOCABULARY: 249
AT WORD NR: 500    VOCABULARY: 274
AT WORD NR: 550    VOCABULARY: 297
AT WORD NR: 600    VOCABULARY: 324

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  1.60110e0 * X TO THE  8.26290e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9993
COEFFICIENT OF CORRELATION = 0.9996
STANDARD ERROR OF ESTIMATE = 0.0179

B:DREC1.PRM:

AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 79
AT WORD NR: 150    VOCABULARY: 115
AT WORD NR: 200    VOCABULARY: 142
AT WORD NR: 250    VOCABULARY: 171
AT WORD NR: 300    VOCABULARY: 194
AT WORD NR: 350    VOCABULARY: 220
AT WORD NR: 400    VOCABULARY: 237
AT WORD NR: 450    VOCABULARY: 266
AT WORD NR: 500    VOCABULARY: 285
AT WORD NR: 550    VOCABULARY: 308
AT WORD NR: 600    VOCABULARY: 324

F(x) =  1.93458e0 * X TO THE  8.05760e-1 POWER
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0298
```

```
B:DREC2.TXT:

AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 100    VOCABULARY: 74
AT WORD NR: 150    VOCABULARY: 103
AT WORD NR: 200    VOCABULARY: 122
AT WORD NR: 250    VOCABULARY: 145
AT WORD NR: 300    VOCABULARY: 168
AT WORD NR: 350    VOCABULARY: 193
AT WORD NR: 400    VOCABULARY: 218
AT WORD NR: 450    VOCABULARY: 231
AT WORD NR: 500    VOCABULARY: 246
AT WORD NR: 550    VOCABULARY: 273
AT WORD NR: 600    VOCABULARY: 290

F(x) =  2.01720e0 * X TO THE  7.77076e-1 POWER
COEFFICIENT OF CORRELATION = 0.9994
STANDARD ERROR OF ESTIMATE = 0.0222

B:DREC2.PRM:

AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 100    VOCABULARY: 69
AT WORD NR: 150    VOCABULARY: 91
AT WORD NR: 200    VOCABULARY: 117
AT WORD NR: 250    VOCABULARY: 143
AT WORD NR: 300    VOCABULARY: 167
AT WORD NR: 350    VOCABULARY: 187
AT WORD NR: 400    VOCABULARY: 211
AT WORD NR: 450    VOCABULARY: 226
AT WORD NR: 500    VOCABULARY: 251
AT WORD NR: 550    VOCABULARY: 270
AT WORD NR: 600    VOCABULARY: 290

F(x) =  1.76276e0 * X TO THE  7.96281e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0206
```

B:HERALD.TXT:

AT WORD NR: 50	VOCABULARY: 42
AT WORD NR: 100	VOCABULARY: 73
AT WORD NR: 150	VOCABULARY: 98
AT WORD NR: 200	VOCABULARY: 126
AT WORD NR: 250	VOCABULARY: 147
AT WORD NR: 300	VOCABULARY: 165
AT WORD NR: 350	VOCABULARY: 177
AT WORD NR: 400	VOCABULARY: 203
AT WORD NR: 450	VOCABULARY: 227
AT WORD NR: 500	VOCABULARY: 248
AT WORD NR: 550	VOCABULARY: 267
AT WORD NR: 600	VOCABULARY: 285

F(x) = 2.16311e0 * X TO THE 7.61296e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0232

B:HERALD.FRM:

AT WORD NR: 50	VOCABULARY: 40
AT WORD NR: 100	VOCABULARY: 70
AT WORD NR: 150	VOCABULARY: 99
AT WORD NR: 200	VOCABULARY: 131
AT WORD NR: 250	VOCABULARY: 154
AT WORD NR: 300	VOCABULARY: 176
AT WORD NR: 350	VOCABULARY: 196
AT WORD NR: 400	VOCABULARY: 216
AT WORD NR: 450	VOCABULARY: 233
AT WORD NR: 500	VOCABULARY: 251
AT WORD NR: 550	VOCABULARY: 268
AT WORD NR: 600	VOCABULARY: 285

F(x) = 1.87063e0 * X TO THE 7.91454e-1 POWER
COEFFICIENT OF CORRELATION = 0.9987
STANDARD ERROR OF ESTIMATE = 0.0319

B:GUARD.TXT:

```
AT WORD NR: 50     VOCABULARY: 34
AT WORD NR: 100    VOCABULARY: 67
AT WORD NR: 150    VOCABULARY: 90
AT WORD NR: 200    VOCABULARY: 114
AT WORD NR: 250    VOCABULARY: 133
AT WORD NR: 300    VOCABULARY: 151
AT WORD NR: 350    VOCABULARY: 178
AT WORD NR: 400    VOCABULARY: 198
AT WORD NR: 450    VOCABULARY: 218
AT WORD NR: 500    VOCABULARY: 236
AT WORD NR: 550    VOCABULARY: 250
AT WORD NR: 600    VOCABULARY: 268
```

GEOMETRIC REGRESSION ANALYSIS:

```
F(x) =  1.47574e0 * X TO THE  8.16292e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9979
COEFFICIENT OF CORRELATION = 0.9989
STANDARD ERROR OF ESTIMATE = 0.0300
```

B:GUARDP.TXT:

```
AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 100    VOCABULARY: 68
AT WORD NR: 150    VOCABULARY: 92
AT WORD NR: 200    VOCABULARY: 117
AT WORD NR: 250    VOCABULARY: 141
AT WORD NR: 300    VOCABULARY: 162
AT WORD NR: 350    VOCABULARY: 181
AT WORD NR: 400    VOCABULARY: 198
AT WORD NR: 450    VOCABULARY: 213
AT WORD NR: 500    VOCABULARY: 230
AT WORD NR: 550    VOCABULARY: 248
AT WORD NR: 600    VOCABULARY: 268
```

GEOMETRIC REGRESSION ANALYSIS:

```
F(x) =  1.95017e0 * X TO THE  7.70623e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9992
COEFFICIENT OF CORRELATION = 0.9996
STANDARD ERROR OF ESTIMATE = 0.0172
```

```
B:MAIL.TXT:

AT WORD NR: 50    VOCABULARY: 44
AT WORD NR: 100   VOCABULARY: 75
AT WORD NR: 150   VOCABULARY: 105
AT WORD NR: 200   VOCABULARY: 128
AT WORD NR: 250   VOCABULARY: 153
AT WORD NR: 300   VOCABULARY: 176
AT WORD NR: 350   VOCABULARY: 199
AT WORD NR: 400   VOCABULARY: 222
AT WORD NR: 450   VOCABULARY: 244
AT WORD NR: 500   VOCABULARY: 273
AT WORD NR: 550   VOCABULARY: 293
AT WORD NR: 600   VOCABULARY: 316

F(x) =  1.97516e0 * X TO THE  7.90052e-1 POWER
COEFFICIENT OF CORRELATION = 0.9997
STANDARD ERROR OF ESTIMATE = 0.0157


B:MAIL.PRM:

AT WORD NR: 50    VOCABULARY: 40
AT WORD NR: 100   VOCABULARY: 78
AT WORD NR: 150   VOCABULARY: 112
AT WORD NR: 200   VOCABULARY: 142
AT WORD NR: 250   VOCABULARY: 175
AT WORD NR: 300   VOCABULARY: 196
AT WORD NR: 350   VOCABULARY: 216
AT WORD NR: 400   VOCABULARY: 243
AT WORD NR: 450   VOCABULARY: 263
AT WORD NR: 500   VOCABULARY: 280
AT WORD NR: 550   VOCABULARY: 300
AT WORD NR: 600   VOCABULARY: 316

F(x) =  1.75419e0 * X TO THE  8.21041e-1 POWER
COEFFICIENT OF CORRELATION = 0.9973
STANDARD ERROR OF ESTIMATE = 0.0479
```

NEWSPAPERS:

	A(TEXT)	A(PERM)	DELTA A	DEV FROM TOTAL MEAN
G.HERALD	2.1631	1.8706	-0.2925	-0.6736
GUARDIAN	1.4757	1.9500	0.4743	0.0932
D.MAIL	1.9752	1.7542	-0.2210	-0.6021
D.RECORD1	1.6011	1.9346	0.3335	-0.0476
D.RECORD2	2.0172	1.7628	-0.2544	-0.6355

A(TEXT) MEAN (THIS GROUP): 1.8465
VARIANCE: 0.0859
S.DEV.: 0.2931

A(PERM) MEAN (THIS GROUP): 1.8544
VARIANCE: 0.0086
S.DEV.: 0.0926

DELTA A MEAN (THIS GROUP): 0.0080
VARIANCE: 0.1337
S.DEV.: 0.3657

NEWSPAPERS:

	B(TEXT)	B(PERM)	DELTA B	DEV FROM TOTAL MEAN
G.HERALD	0.7613	0.7915	0.0302	0.0591
GUARDIAN	0.8163	0.7706	-0.0457	-0.0168
D.MAIL	0.7901	0.8210	0.0309	0.0598
D.RECORD1	0.8263	0.8058	-0.0205	0.0084
D.RECORD2	0.7708	0.7963	0.0255	0.0544

B(TEXT) MEAN (THIS GROUP): 0.7930
VARIANCE: 0.0008
S.DEV.: 0.0281

B(PERM) MEAN (THIS GROUP): 0.7970
VARIANCE: 0.0003
S.DEV.: 0.0186

DELTA B MEAN (THIS GROUP): 0.0041
VARIANCE: 0.0012
S.DEV.: 0.0352

```
B:PAD1.TXT:

AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 100    VOCABULARY: 70
AT WORD NR: 150    VOCABULARY: 98
AT WORD NR: 200    VOCABULARY: 126
AT WORD NR: 250    VOCABULARY: 151
AT WORD NR: 300    VOCABULARY: 169
AT WORD NR: 350    VOCABULARY: 188
AT WORD NR: 400    VOCABULARY: 209
AT WORD NR: 450    VOCABULARY: 225
AT WORD NR: 500    VOCABULARY: 241
AT WORD NR: 550    VOCABULARY: 263
AT WORD NR: 600    VOCABULARY: 278

F(x) =  2.05571e0 * X TO THE  7.70377e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0230


B:PAD1.PRM:

AT WORD NR: 50     VOCABULARY: 47
AT WORD NR: 100    VOCABULARY: 81
AT WORD NR: 150    VOCABULARY: 107
AT WORD NR: 200    VOCABULARY: 130
AT WORD NR: 250    VOCABULARY: 158
AT WORD NR: 300    VOCABULARY: 179
AT WORD NR: 350    VOCABULARY: 197
AT WORD NR: 400    VOCABULARY: 216
AT WORD NR: 450    VOCABULARY: 228
AT WORD NR: 500    VOCABULARY: 246
AT WORD NR: 550    VOCABULARY: 265
AT WORD NR: 600    VOCABULARY: 278

F(x) =  3.00989e0 * X TO THE  7.11363e-1 POWER
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0225
```

```
B:PAD2.TXT:

AT WORD NR: 50     VOCABULARY: 42
AT WORD NR: 100    VOCABULARY: 70
AT WORD NR: 150    VOCABULARY: 92
AT WORD NR: 200    VOCABULARY: 115
AT WORD NR: 250    VOCABULARY: 136
AT WORD NR: 300    VOCABULARY: 156
AT WORD NR: 350    VOCABULARY: 177
AT WORD NR: 400    VOCABULARY: 195
AT WORD NR: 450    VOCABULARY: 217
AT WORD NR: 500    VOCABULARY: 239
AT WORD NR: 550    VOCABULARY: 256
AT WORD NR: 600    VOCABULARY: 273

F(x) =  2.12562e0 * X TO THE  7.56397e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0189
```

```
B:PAD2.PRM:

AT WORD NR: 50     VOCABULARY: 41
AT WORD NR: 100    VOCABULARY: 71
AT WORD NR: 150    VOCABULARY: 99
AT WORD NR: 200    VOCABULARY: 126
AT WORD NR: 250    VOCABULARY: 148
AT WORD NR: 300    VOCABULARY: 166
AT WORD NR: 350    VOCABULARY: 185
AT WORD NR: 400    VOCABULARY: 207
AT WORD NR: 450    VOCABULARY: 227
AT WORD NR: 500    VOCABULARY: 239
AT WORD NR: 550    VOCABULARY: 255
AT WORD NR: 600    VOCABULARY: 273

F(x) =  2.16629e0 * X TO THE  7.59671e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0231
```

```
B:PAD3.TXT:

AT WORD NR: 50     VOCABULARY: 43
AT WORD NR: 100    VOCABULARY: 67
AT WORD NR: 150    VOCABULARY: 93
AT WORD NR: 200    VOCABULARY: 114
AT WORD NR: 250    VOCABULARY: 138
AT WORD NR: 300    VOCABULARY: 156
AT WORD NR: 350    VOCABULARY: 178
AT WORD NR: 400    VOCABULARY: 197
AT WORD NR: 450    VOCABULARY: 208
AT WORD NR: 500    VOCABULARY: 228
AT WORD NR: 550    VOCABULARY: 245
AT WORD NR: 600    VOCABULARY: 260

F(x) =  2.33112e0 * X TO THE  7.37312e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0189


B:PAD3.PRM:

AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 100    VOCABULARY: 72
AT WORD NR: 150    VOCABULARY: 94
AT WORD NR: 200    VOCABULARY: 119
AT WORD NR: 250    VOCABULARY: 131
AT WORD NR: 300    VOCABULARY: 150
AT WORD NR: 350    VOCABULARY: 171
AT WORD NR: 400    VOCABULARY: 190
AT WORD NR: 450    VOCABULARY: 210
AT WORD NR: 500    VOCABULARY: 229
AT WORD NR: 550    VOCABULARY: 242
AT WORD NR: 600    VOCABULARY: 260

F(x) =  2.21388e0 * X TO THE  7.44503e-1 POWER
COEFFICIENT OF CORRELATION = 0.9987
STANDARD ERROR OF ESTIMATE = 0.0299
```

```
B:PAD4.TXT:

AT WORD NR: 50    VOCABULARY: 41
AT WORD NR: 100   VOCABULARY: 73
AT WORD NR: 150   VOCABULARY: 97
AT WORD NR: 200   VOCABULARY: 118
AT WORD NR: 250   VOCABULARY: 144
AT WORD NR: 300   VOCABULARY: 163
AT WORD NR: 350   VOCABULARY: 184
AT WORD NR: 400   VOCABULARY: 203
AT WORD NR: 450   VOCABULARY: 221
AT WORD NR: 500   VOCABULARY: 235
AT WORD NR: 550   VOCABULARY: 248
AT WORD NR: 600   VOCABULARY: 269

F(x) =  2.25415e0 * X TO THE  7.49330e-1 POWER
COEFFICIENT OF CORRELATION = 0.9995
STANDARD ERROR OF ESTIMATE = 0.0190


B:PAD4.PRM:

AT WORD NR: 50    VOCABULARY: 43
AT WORD NR: 100   VOCABULARY: 76
AT WORD NR: 150   VOCABULARY: 106
AT WORD NR: 200   VOCABULARY: 131
AT WORD NR: 250   VOCABULARY: 152
AT WORD NR: 300   VOCABULARY: 174
AT WORD NR: 350   VOCABULARY: 197
AT WORD NR: 400   VOCABULARY: 215
AT WORD NR: 450   VOCABULARY: 225
AT WORD NR: 500   VOCABULARY: 243
AT WORD NR: 550   VOCABULARY: 256
AT WORD NR: 600   VOCABULARY: 269

F(x) =  2.58192e0 * X TO THE  7.34094e-1 POWER
COEFFICIENT OF CORRELATION = 0.9980
STANDARD ERROR OF ESTIMATE = 0.0364
```

```
B:POOH.TXT:

AT WORD NR: 50     VOCABULARY: 26
AT WORD NR: 100    VOCABULARY: 50
AT WORD NR: 150    VOCABULARY: 71
AT WORD NR: 200    VOCABULARY: 91
AT WORD NR: 250    VOCABULARY: 107
AT WORD NR: 300    VOCABULARY: 122
AT WORD NR: 350    VOCABULARY: 138
AT WORD NR: 400    VOCABULARY: 161
AT WORD NR: 450    VOCABULARY: 175
AT WORD NR: 500    VOCABULARY: 188
AT WORD NR: 550    VOCABULARY: 202
AT WORD NR: 600    VOCABULARY: 215

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  1.01524e0 * X TO THE  8.41574e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9983
COEFFICIENT OF CORRELATION = 0.9992
STANDARD ERROR OF ESTIMATE = 0.0274


B:POOH.PRM:

AT WORD NR: 50     VOCABULARY: 39
AT WORD NR: 100    VOCABULARY: 65
AT WORD NR: 150    VOCABULARY: 82
AT WORD NR: 200    VOCABULARY: 103
AT WORD NR: 250    VOCABULARY: 123
AT WORD NR: 300    VOCABULARY: 141
AT WORD NR: 350    VOCABULARY: 160
AT WORD NR: 400    VOCABULARY: 176
AT WORD NR: 450    VOCABULARY: 188
AT WORD NR: 500    VOCABULARY: 196
AT WORD NR: 550    VOCABULARY: 204
AT WORD NR: 600    VOCABULARY: 215

F(x) =  2.54289e0 * X TO THE  7.00563e-1 POWER
COEFFICIENT OF CORRELATION = 0.9985
STANDARD ERROR OF ESTIMATE = 0.0302
```

B:ALICEL.TXT:

AT WORD NR: 50	VOCABULARY: 38
AT WORD NR: 100	VOCABULARY: 65
AT WORD NR: 150	VOCABULARY: 90
AT WORD NR: 200	VOCABULARY: 108
AT WORD NR: 250	VOCABULARY: 126
AT WORD NR: 300	VOCABULARY: 139
AT WORD NR: 350	VOCABULARY: 156
AT WORD NR: 400	VOCABULARY: 166
AT WORD NR: 450	VOCABULARY: 182
AT WORD NR: 500	VOCABULARY: 198
AT WORD NR: 550	VOCABULARY: 209
AT WORD NR: 600	VOCABULARY: 222

GEOMETRIC REGRESSION ANALYSIS:

F(x) = 2.61388e0 * X TO THE 6.96739e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9975
COEFFICIENT OF CORRELATION = 0.9988
STANDARD ERROR OF ESTIMATE = 0.0276

B:ALICEL.PRM:

AT WORD NR: 50	VOCABULARY: 36
AT WORD NR: 100	VOCABULARY: 66
AT WORD NR: 150	VOCABULARY: 88
AT WORD NR: 200	VOCABULARY: 111
AT WORD NR: 250	VOCABULARY: 131
AT WORD NR: 300	VOCABULARY: 147
AT WORD NR: 350	VOCABULARY: 162
AT WORD NR: 400	VOCABULARY: 174
AT WORD NR: 450	VOCABULARY: 188
AT WORD NR: 500	VOCABULARY: 203
AT WORD NR: 550	VOCABULARY: 210
AT WORD NR: 600	VOCABULARY: 222

F(x) = 2.32417e0 * X TO THE 7.20907e-1 POWER
COEFFICIENT OF CORRELATION = 0.9971
STANDARD ERROR OF ESTIMATE = 0.0437

```
B:ALICEB.TXT:

AT WORD NR: 50     VOCABULARY: 37
AT WORD NR: 100    VOCABULARY: 67
AT WORD NR: 150    VOCABULARY: 86
AT WORD NR: 200    VOCABULARY: 101
AT WORD NR: 250    VOCABULARY: 126
AT WORD NR: 300    VOCABULARY: 148
AT WORD NR: 350    VOCABULARY: 164
AT WORD NR: 400    VOCABULARY: 171
AT WORD NR: 450    VOCABULARY: 178
AT WORD NR: 500    VOCABULARY: 194
AT WORD NR: 550    VOCABULARY: 211
AT WORD NR: 600    VOCABULARY: 224

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  2.42983e0 * X TO THE  7.09971e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9946
COEFFICIENT OF CORRELATION = 0.9973
STANDARD ERROR OF ESTIMATE = 0.0414


B:ALICEBP.TXT:

AT WORD NR: 50     VOCABULARY: 36
AT WORD NR: 100    VOCABULARY: 69
AT WORD NR: 150    VOCABULARY: 94
AT WORD NR: 200    VOCABULARY: 110
AT WORD NR: 250    VOCABULARY: 123
AT WORD NR: 300    VOCABULARY: 137
AT WORD NR: 350    VOCABULARY: 160
AT WORD NR: 400    VOCABULARY: 171
AT WORD NR: 450    VOCABULARY: 184
AT WORD NR: 500    VOCABULARY: 197
AT WORD NR: 550    VOCABULARY: 213
AT WORD NR: 600    VOCABULARY: 224

GEOMETRIC REGRESSION ANALYSIS:

F(x) =  2.53646e0 * X TO THE  7.03888e-1 POWER
COEFFICIENT OF DETERMINATION (R-SQUARED) = 0.9919
COEFFICIENT OF CORRELATION = 0.9959
STANDARD ERROR OF ESTIMATE = 0.0504
```

```
B:SEAGULL.TXT:

AT WORD NR: 50     VOCABULARY: 38
AT WORD NR: 100    VOCABULARY: 72
AT WORD NR: 150    VOCABULARY: 102
AT WORD NR: 200    VOCABULARY: 126
AT WORD NR: 250    VOCABULARY: 146
AT WORD NR: 300    VOCABULARY: 173
AT WORD NR: 350    VOCABULARY: 196
AT WORD NR: 400    VOCABULARY: 218
AT WORD NR: 450    VOCABULARY: 233
AT WORD NR: 500    VOCABULARY: 252
AT WORD NR: 550    VOCABULARY: 265
AT WORD NR: 600    VOCABULARY: 283

F(x) =  1.78111e0 * X TO THE  7.98634e-1 POWER
COEFFICIENT OF CORRELATION = 0.9985
STANDARD ERROR OF ESTIMATE = 0.0346

B:SEAGULL.PRM:

AT WORD NR: 50     VOCABULARY: 46
AT WORD NR: 100    VOCABULARY: 72
AT WORD NR: 150    VOCABULARY: 100
AT WORD NR: 200    VOCABULARY: 122
AT WORD NR: 250    VOCABULARY: 141
AT WORD NR: 300    VOCABULARY: 169
AT WORD NR: 350    VOCABULARY: 191
AT WORD NR: 400    VOCABULARY: 208
AT WORD NR: 450    VOCABULARY: 232
AT WORD NR: 500    VOCABULARY: 247
AT WORD NR: 550    VOCABULARY: 266
AT WORD NR: 600    VOCABULARY: 283

F(x) =  2.40162e0 * X TO THE  7.44856e-1 POWER
COEFFICIENT OF CORRELATION = 0.9993
STANDARD ERROR OF ESTIMATE = 0.0223
```

BOOKS WRITTEN FOR CHILDREN:

	A(TEXT)	A(PERM)	DELTA A	DEV FROM TOTAL MEAN
PAD1	2.0557	3.0099	0.9542	0.5731
PAD2	2.1256	2.1663	0.0407	-0.3404
PAD3	2.3311	2.2139	-0.1172	-0.4983
PAD4	2.2541	2.5819	0.3278	-0.0533
POOH	1.0152	2.5429	1.5277	1.1466
ALICEB	2.4298	2.5360	0.1062	-0.2749
ALICEL	2.6139	2.3242	-0.2897	-0.6708
SEAGULL	1.7811	2.4016	0.6205	0.2394

A(TEXT) MEAN (THIS GROUP): 2.0758
VARIANCE: 0.2466
S.DEV.: 0.4966

A(PERM) MEAN (THIS GROUP): 2.4721
VARIANCE: 0.0711
S.DEV.: 0.2666

DELTA A MEAN (THIS GROUP): 0.3963
VARIANCE: 0.3702
S.DEV.: 0.6084

BOOKS WRITTEN FOR CHILDREN:

	B(TEXT)	B(PERM)	DELTA B	DEV FROM TOTAL MEAN
PAD1	0.7704	0.7114	-0.0590	-0.0301
PAD2	0.7564	0.7597	0.0033	0.0322
PAD3	0.7373	0.7445	0.0072	0.0361
PAD4	0.7493	0.7341	-0.0152	0.0137
POOH	0.8416	0.7006	-0.1410	-0.1121
ALICEB	0.7099	0.7038	-0.0061	0.0228
ALICEL	0.6967	0.7209	0.0242	0.0531
SEAGULL	0.7986	0.7449	-0.0537	-0.0248

B(TEXT) MEAN (THIS GROUP): 0.7575
VARIANCE: 0.0022
S.DEV.: 0.0469

B(PERM) MEAN (THIS GROUP): 0.7275
VARIANCE: 0.0005
S.DEV.: 0.0216

DELTA B MEAN (THIS GROUP): -0.0300
VARIANCE: 0.0028
S.DEV.: 0.0534

RUNS BEFORE AND AFTER PERMUTATION

Index

B:C85.TXT
1B550RFO

```
11111111110101111111011101101101100011110111100111
11110010100010110000101011101011100011001101011001
11100111101000100010000111000011000010010000110010
10001000011101011000100000000000010100000100010110
00101000111110001010010000010001010010000100000000
00110100000001011000101100010000010000000001000100
00000000000010000010010001000100010000000000000001
10000000100011010110000100110000110001010100001101
00110000001010010110001010010000101101001100000000
00100001101100010010011010000100100011110000101001
11010000000100000000010101000100101010001000001000
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        75 ***************************************************************************
  2        27 ***************************
  3         6 ******
  4         4 ****
  5         2 **
  6         0
  7         2 **
  8         0
  9         0
 10         1 *
SUM= 201
```

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        45 *********************************************
  2        20 ********************
  3        27 ***************************
  4        13 *************
  5         4 ****
  6         3 ***
  7         2 **
  8         0
  9         1 *
 10         3 ***
 11         0
 12         1 *
 13         1 *
 14         0
 15         1 *
SUM= 349
```

121

B:CB5.PRM
1B550RFO

```
11101100111111111111111111101111100000111111101111101
10101001101100011001101001110100110000011010100101
11011011001001101101010111010110111100010001100101
10110110101000010100000011010000000011001001100011
001000000000000110010000101100010100101001111111000
010011000001100001100100000000011000011101011110000000
000011100001101000011100000001000100000100010001100
1101001000000100100001000000001100000000100000010001
00000000100000000000001010000000000101100000000000000
0100000010101010000100100000000000100010000100100100
0110000100010000000001100100000000000000100010000000
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       63 ***************************************************************
  2       34 **********************************
  3        7 *******
  4        2 **
  5        2 **
  6        0
  7        2 **
  8        0
  9        0
 10        0
 11        0
 12        0
 13        0
 14        0
 15        0
 16        0
 17        1 *
SUM= 201
```

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       40 ****************************************
  2       24 ************************
  3       14 **************
  4       12 ************
  5        4 ****
  6        3 ***
  7        2 **
  8        5 *****
  9        1 *
 10        2 **
 11        1 *
 12        1 *
 13        1 *
 14        1 *
SUM= 349
```

```
B:C95.TXT
1B550RFO

1111111111110100011101111100010011001011001011111
11011110010001111101011101101100110111010010100100
01000001000000000101001000101010000101001000111001
10000010001101001111010100000000001000001110100010 0
10101100000001100100100110100110011000000100111110
00111110110111001011010011000110001010000001000010 1
11001010001010001110000001011101000011010001101000
00011101110000000111110110000100010100101011000000
10101010101001100011000000010001001001011000001011
01011001100100000001001100100000001001110101010 01
00110001011000001110000011101000011001010110000010

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       79 *******************************************************************************
  2       31 *******************************
  3       14 **************
  4        2 **
  5        4 ****
  6        1 *
  7        1 *
  8        0
  9        0
 10        0
 11        0
 12        1 *
SUM= 236
```

133

```
LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       58 **********************************************************
  2       33 *********************************
  3       18 ******************
  4        5 *****
  5        8 ********
  6        5 *****
  7        4 ****
  8        0
  9        2 **
SUM= 314
```

133

B:C95.PRM
1B550RFO

```
11111111111111101101111111100111110111011010110101
101111111101111101111011101111101100110100000010101
111011101111001011100111001110011110011010000001
10000000000101001010010101000000100000100110110001
011000000000000011000000011001010110011101011010010
0000110101000010000000010010111001000000010001011100
11100000011110010011000000000000101011010000010100100
110001011100101010010010111100000001010110100001101
01000001110000001010010010100000011110100000000010001
00000010101000000011000110000000100000000010100010000
0100101001001010000001110001000001100000000110000100
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        71 ***********************************************************************
  2        25 *************************
  3        13 *************
  4         5 *****
  5         5 *****
  6         0
  7         0
  8         2 **
  9         0
 10         0
 11         0
 12         0
 13         0
 14         0
 15         1 *
SUM= 236
```

122

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        57 *********************************************************
  2        29 *****************************
  3         7 *******
  4         5 *****
  5        10 **********
  6         6 ******
  7         2 **
  8         3 ***
  9         0
 10         0
 11         2 **
 12         1 *
SUM= 314
```

122

B:D130.TXT
1B550RF0

```
111111111111111110111111101000111010000000011010100
000111001010101000001001101111101010010110101100100
1010000011100011100000100001000100000000001010101001
100100100000000000100000000100000000011000000101010000
0100100111010110010110000000110000100000100001 0110
00000010001010100100101001010000010010000000110110 0
0001100100000100010111001011111011000000011010101000
0001010000100010011000000000000001001000000000000 0110
0101110000010100000000001100001001001110010000010 00000
1010000011000001011000000011000000000000000000001001 00
0010000000010000000000001001000000000000100010000 00
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	79	***
2	21	*********************
3	7	*******
4	3	***
5	0	
6	0	
7	1	*
8	0	
9	0	
10	0	
11	0	
12	0	
13	0	
14	0	
15	0	
16	0	
17	1	*

SUM= 178

112

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	40	**
2	25	*************************
3	7	*******
4	13	*************
5	7	*******
6	5	*****
7	4	****
8	4	****
9	2	**
10	0	
11	1	*
12	3	***
13	0	
14	0	
15	0	
16	0	
17	0	
18	0	
19	1	*

SUM= 372

112

```
B:C120.PRM
1B550RF0

11011110010101111100001111110111111110011011001010
01101010111000010011100001101100010110000110011111
01100000000010100110000100010111100000101001001110
11000001000010101101111010000001001000000101000010
00000110001000110000011000001011001000001001000100
00100100010101010000000100001001000001011100101001
11001000000000000100111100100010010111010000101011
01100000000100100000001001000000000100000000010100
00010000000001100010110010000000000000101000000000
00000000001000100001011000001010000001001001001000
01010000100000100000000000000000001010000010000000

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       78 ******************************************************************************
  2       21 *********************
  3        6 ******
  4        4 ****
  5        2 **
  6        1 *
  7        0
  8        1 *
SUM= 178    112


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       39 ***************************************
  2       26 **************************
  3        9 *********
  4       13 *************
  5       10 **********
  6        4 ****
  7        2 **
  8        2 **
  9        4 ****
 10        0
 11        0
 12        1 *
 13        1 *
 14        0
 15        0
 16        0
 17        0
 18        1 *
 19        1 *
SUM= 372    113
```

B:C140.TXT
1B550RFO

```
11111111111111111001011111101111111111111000111101
1100001001011100011100001010001011011101000000001010
0001101001000000100001000000100011000100100000101000
111101100001000000010100010000001000100001010110001
0110100010000000110100000011110100000001000000110100
1000001000110101010000101011100000000001000000000000
0000110010001100110000000100000000000000000010000010
0010000001000001100101001110000000010010001010001001
0001001010000010010000000001000000000000000010000000
1000010000000100000000000010000010101100000110000000
0001000110000010110100101100000010000000000000001100
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	73	***
2	19	*******************
3	6	******
4	3	***
5	0	
6	1	*
7	0	
8	0	
9	0	
10	0	
11	0	
12	0	
13	1	*
14	0	
15	0	
16	0	
17	1	*

SUM= 177 '04

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	33	*********************************
2	15	***************
3	17	*****************
4	8	********
5	13	*************
6	6	******
7	4	****
8	1	*
9	2	**
10	0	
11	1	*
12	0	
13	0	
14	1	*
15	2	**
16	0	
17	1	*

SUM= 373 '04

B:C140.PRM
1B550RF0

```
11111111011001111111101101101110111011101101101111
10011110100111000111010111100000010110000001001100
00101001000011000010010110000000001001110110110100
1000001000000000000000100010001000000011000011000111
0100010110000000011010011000000001101101010001100001
01000100000100111000010000000001101000100100011100 0
11000000000000000000010000100000000110011000100010 00
00011010010000100010000000010001000000001001100010 00
00101000000000000011110001000010010001000000000001 10
00001000000000001000000100000000000000010000000001 00000
01000000000001000011011000101010000000001100000001 01
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
   1        59 ***********************************************************
   2        29 *****************************
   3         9 *********
   4         3 ***
   5         1 *
   6         0
   7         0
   8         2 **
SUM= 177
```

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
   1        32 ********************************
   2        15 ***************
   3        18 ******************
   4        10 **********
   5         5 *****
   6         5 *****
   7         6 ******
   8         3 ***
   9         2 **
  10         2 **
  11         0
  12         1 *
  13         0
  14         2 **
  15         0
  16         0
  17         0
  18         1 *
SUM= 373
```

102

B:C141.TXT
1B550RFO

```
1111111111011111111110111111110001001100101110101001
10010101011010001010100100110011000111000100100010
01100101000000011011101000001010010101010000010101
01000000010110000011011011101000011001000000010101
01000110000110000101001010111010110100110101100110
11100000000000000011000000100100000101001001000010000
01000001010010000000100000001000000010011000101001101
00000010011100110111101000111001100001101000000000
0001000100101001000001001000101000000010100000000100
10000100000100110011000001101101010001001011000100
01001100001100110001101000010010000000010000011010
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	88	**
2	33	*********************************
3	8	********
4	1	*
5	0	
6	0	
7	1	*
8	0	
9	1	*
10	1	*

SUM= 208 33

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	54	**
2	34	**********************************
3	15	***************
4	9	*********
5	9	*********
6	4	****
7	5	*****
8	1	*
9	0	
10	0	
11	0	
12	1	*
13	0	
14	0	
15	1	*

SUM= 342 130

```
B:C141.PRM
1B550RFO

11111110111111111110101110011110011101011101001111
11000110001110101001000000010000100010101010011111
00000000000001111100010101111100101110011110101000
10010001001000010010100111101111101100001000010000
00100000100001001110000001100001011101010110010000
00110001010001000000001001101000101100000000010100
10001000001111011010100101010011000000000101101010
00000010010000000101100001101000001000000110110011
00001000000000100111001111000000100110000010011110
11100000100001001010000100001000100100001010001100
01000010010000000000000001000000100001000100100100

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      79 *******************************************************************************
  2      17 *****************
  3       9 *********
  4       6 ******
  5       4 ****
  6       1 *
  7       1 *
  8       0
  9       0
 10       0
 11       1 *
SUM= 208


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      41 *****************************************
  2      29 *****************************
  3      14 **************
  4      14 **************
  5       5 *****
  6       6 ******
  7       3 ***
  8       1 *
  9       3 ***
 10       0
 11       0
 12       0
 13       1 *
 14       0
 15       1 *
SUM= 342
```

118

B:RUSS1.TXT
1B600RF0

```
11111011111111011111101001010101111111111111111110110
10010011111110101011111000001110110101110100011000
11101010110001111011001011100011011010000101111011
00110011000011100010011000000000001001111011010000
01001011011010011001101011010110110001010101000000
00001000001011001110100110100110101010111011101010
11001011011011100101100000101001011000101001010010
00000110000000000001010100101010100010010001110000
11010000101000000011010000010100110101001000011100
10110100001010000100111011100110000000100101010110
00000000011010010010011111001101011101101000000000
00000010001001100000000100100000000000010000000101
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        85 *************************************************************************************
  2        38 **************************************
  3        14 **************
  4         3 ***
  5         4 ****
  6         0
  7         1 *
  8         1 *
  9         0
 10         0
 11         0
 12         0
 13         0
 14         0
 15         0
 16         1 *
SUM= 266
```

147

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        80 ********************************************************************************
  2        33 *********************************
  3        10 **********
  4         7 *******
  5         4 ****
  6         2 **
  7         3 ***
  8         1 *
  9         0
 10         3 ***
 11         0
 12         2 **
 13         0
 14         0
 15         1 *
SUM= 334
```

146

B:RUSS1.PRM
1B600RF0

```
11111111111111100110111111110110011111011111111111
11011011111100011000111111001010110111011001101010
01100111001010111110100011101011100111001100011010
01000011111100110000001010110000000010000100010000
10011110010101000011011111001010000000100110110001
00000100000100010001001000001100100110100110011001
11000101101100000100000100000000000110110001000010
11000000011101100000010101111000010000011101100000
01001100000100011100101100010001001001111100010010
00100001110000100010110011001110001110001111101001
01010001100000001001100110000101100000100101110000
00101100100000101101110000010000100000100001000100
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	65	***
2	36	************************************
3	14	**************
4	2	**
5	5	*****
6	3	***
7	0	
8	1	*
9	0	
10	0	
11	0	
12	0	
13	1	*
14	0	
15	1	*

SUM= 266 128

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	43	***
2	34	**********************************
3	20	********************
4	11	***********
5	11	***********
6	4	****
7	3	***
8	1	*
9	0	
10	0	
11	1	*

SUM= 334 ·128

```
B:RUSS2.TXT
1B600RF0

11111111111111001000001110111010011111111111111111
00000011101100100110110111101110111011111001011110
10111011001011010101010010110101111011100010011011
00011101010000101011010101100011010111100111010100
11111110101110001101101010010010010011100101101100
01011001010010100010001100010001001111101101100110
10101000100001000100110000010001101111000000010110
01000000101001011101110100011111010001010101001001
00011011100000110101010111000100111011000111000000
01100000110100000000111011110010100101100101101101
00100101101110000000001010100011001001011000000100
01110100001011110010010101010000100100001000000001

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       86 ****************************************************************
  2       34 **********************************
  3       19 *******************
  4        8 ********
  5        3 ***
  6        0
  7        1 *
  8        0
  9        0
 10        0
 11        0
 12        0
 13        0
 14        1 *
 15        0
 16        0
 17        1 *
SUM= 296


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       81 ****************************************************************
  2       35 ***********************************
  3       19 *******************
  4        6 ******
  5        3 ***
  6        3 ***
  7        2 **
  8        2 **
  9        1 *
SUM= 304
```

B:RUSS2.PRM
1B600RF0

```
11111111011111111101111111111111111111001110101111
11110011101101101110111111010111011111011101011101
11101110100100111011111000100110110110000001010000
00101001100001001100100101111010001110001110011101
11000000011100011110111100101001101100110001100011
01011011010101111001001010010111001000010101100010
11110100101111011110000000000101100101101110000001
0000000100001100100011001000111100000100000000101
11111101100100001100111110110010111000001000001001
00001100001000100001010100100010010000011011101001
00101011000010000110010110100100110010010010100000
01001110010000001001101011000000000000011010100010
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       65 *****************************************************************
  2       32 ********************************
  3       17 *****************
  4        9 *********
  5        4 ****
  6        1 *
  7        1 *
  8        2 **
  9        1 *
 10        0
 11        0
 12        0
 13        0
 14        0
 15        0
 16        0
 17        0
 18        0
 19        1 *
SUM= 296
```

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       63 ***************************************************************
  2       38 **************************************
  3       12 ************
  4        9 *********
  5        5 *****
  6        4 ****
  7        3 ***
  8        0
  9        0
 10        1 *
 11        0
 12        0
 13        1 *
SUM= 304
```

B:RUBS3.TXT
1B600RFO

```
11111111111101111101011010110110110111001100111101
1010110111001011011111101110111110101110010010111010
10011001000111110100101100101110110111011101011011
001000111101010101101100100011111000000001001001011
01010000111100001110010010101001000000110101111100
0000001000001000000010111010000000111001100100100101
00000100110000010101000000000110000000000100000001001
001010011100100001011000001110001000101000000010101
000100010100010100000110000000110000000000000100000
0000101011000000000101100001000000000110000100100000
00000000000000000001111010000000011010100001011000
10010011000001100000100001001000010110001101111111
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	77	***
2	32	********************************
3	13	*************
4	5	*****
5	5	*****
6	0	
7	1	*
8	0	
9	0	
10	0	
11	0	
12	1	*

SUM= 244

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	63	***
2	29	*****************************
3	10	**********
4	9	*********
5	6	******
6	4	****
7	4	****
8	4	****
9	2	**
10	0	
11	0	
12	1	*
13	0	
14	0	
15	0	
16	0	
17	0	
18	0	
19	0	
20	0	
21	0	
22	0	
23	0	
24	0	
25	1	*

127

B:RUSS3P.TXT PRM
15600RFO

```
11111111111111111111011110111111101111111111000111
11001010100110001011001110000110111011101101000101
11111111100100101000011010011100010111010001001010
11100101010011110000110001100110110100011010110010
01011011010001110010000001010110101000010010000101
10110101010000001000011001111100011101010100010101
00100000100100100000000010000101010111010010000100
10001000101101100101010001000000000111010000000001
10000001001001100011000100100000000010110110000100
00000000110000001011011000010000000110000000010000
11100100000110001000011001001000000001000100000001
10000000000001110000100000001000010000000000001011
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	79	***
2	32	********************************
3	12	************
4	2	**
5	2	**
6	0	
7	1	*
8	0	
9	0	
10	2	**
11	0	
12	0	
13	0	
14	0	
15	0	
16	0	
17	0	
18	0	
19	0	
20	1	*

SUM= 244

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	54	**
2	27	***************************
3	17	*****************
4	14	**************
5	2	**
6	4	****
7	3	***
8	2	**
9	4	****
10	1	*
11	0	
12	2	**

SUM= 356

130

B:RUSS4.TXT
1B600RF0

```
11111111011111101111111011011111010010111110011000000
00110110101000000111111110100101111010001110100101
001000000110110011001110101000010010111110100110011
01000001001110011101110100011101000101010111100011
1100010011011111111101010110000111010001001101111001
10000111000101111010011011010111000111001010100100
111000011001101011000101001100011010001001001100000
00101010011001111001101010010001110010011000010110
10100101101010100101010110000101100001100101000101
01000001101000100011011100000010110001011010111000
1001010010010000011000101010111001010111100110000 1
00010001010101001010101101101010010001100011010110
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       93 *********************************************************************************************
  2       40 ****************************************
  3       16 ****************
  4        7 *******
  5        3 ***
  6        0
  7        1 *
  8        3 ***
SUM= 295
```

163

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       87 ***************************************************************************************
  2       39 ***************************************
  3       21 *********************
  4        8 ********
  5        4 ****
  6        3 ***
  7        1 *
SUM= 305
```

PRM

B:RUES4F.TXT
1B600RFO

```
11110111011111111111011111111110100111100010000110
10111110111110001010110001010011010111000001111101
01111100111011011111001100110011010111010011101001
10101011011011010010011000010011100000111110111000
0110000100111111010110001011011111110000111011101111
11010010000001110111000111110011001010001000010011
10010000011011110111100010000110000101000010100010
01000011000011000001000010000000011000100110100100
100000110101111111100010100111001101111001101011010
00001010011000110101101010010001100001011010010101
1100011010101000000000011010110010010011110000000001
010001000001100010010110100000110100111110010010001
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	71	***
2	37	*************************************
3	14	**************
4	6	******
5	8	********
6	3	***
7	1	*
8	0	
9	1	*
10	1	*

SUM= 295 140

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	66	**
2	34	**********************************
3	16	****************
4	13	*************
5	8	********
6	1	*
7	0	
8	2	**
9	1	*

SUM= 305 141

```
B:RUSS5.TXT
1B600RF0

11111111111110110111011011011110011111111111111110
10110111111001101110000110110100101101101101001110
10110010100010000111100011101110011011001111010000
11111100101001010000110011011100111100000111010011
10111010011101000011000000000010011011011100010011
11001000010001100000010011110000101001110001010011
10011110101000000101010100110001100111000000011000
00101110001000000010111010000000000011101111110000
00001101100101101010010100100100111001000100001000
10011010000111011011011001011010110100000100110010
00100011001110011101010101010000010000100111001 1
00010001000011001001011010100101100000100101000000
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       71 ***********************************************************************
  2       37 *************************************
  3       22 **********************
  4        6 ******
  5        1 *
  6        3 ***
  7        0
  8        0
  9        0
 10        0
 11        0
 12        0
 13        1 *
 14        0
 15        0
 16        1 *
SUM= 287
```

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       65 *****************************************************************
  2       40 ****************************************
  3       13 *************
  4       11 ***********
  5        5 *****
  6        4 ****
  7        1 *
  8        1 *
  9        0
 10        1 *
 11        1 *
SUM= 313
```

D:RUSS5.FRM
1B600RF0

```
11111111111111101111101111111111010111111100111101
00111111111011101011101101000110111011111110101110
11111010101001101100011100010111000100111111001110
11101101111111100011100101100110101011110010000001
00010001000000110001010000011000001010011001100111
10101011010000000101000100100001010010010010000010
10101000111001110001110001101011001010000010001001
01001010101111001001010000001010010101100111010111
01010010011011001011000010110110100110101100100001
11110000001010001100000010001000000101000011111010
00000000000100000011101010011100111100000100110000
00000001011010000100101001000001010000110000100110
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        83 *****************************************************************
  2        27 ***************************
  3        16 ****************
  4         5 *****
  5         4 ****
  6         1 *
  7         2 **
  8         1 *
  9         1 *
 10         1 *
 11         0
 12         0
 13         0
 14         0
 15         1 *
SUM= 287
```

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        70 *****************************************************************
  2        34 **********************************
  3        15 ***************
  4         9 *********
  5         3 ***
  6         8 ********
  7         0
  8         1 *
  9         0
 10         0
 11         1 *
 12         1 *
SUM= 313
```

```
B:RUSS5.PRM
1B600RF0

11111111111111101111101111111111101011111111001111101
0011111111110111010111011010001101110111111110101110
1111101010100110110001110001011100010011111111001110
1110110111111110001110010110011010101111001000000001
0001000100000011000101000000110000101001100110011 1
1010101101000000000101000100100001010010010010000010
1010100011100111000111000110101100101000001000100 1
0100101010111100100101000000010100101011001110101111
0101001001101100101100000101101101001101011001000 01
1111000000101000110000001000100000001010000111111010
000000000001000000011101010011100111100000100110000
0000000101101000001001010010000010100001100001001 10
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       83 ***********************************************************************************
  2       27 ***************************
  3       16 ****************
  4        5 *****
  5        4 ****
  6        1 *
  7        2 **
  8        1 *
  9        1 *
 10        1 *
 11        0
 12        0
 13        0
 14        0
 15        1 *
SUM= 287
```

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       70 **********************************************************************
  2       34 **********************************
  3       15 ***************
  4        9 *********
  5        3 ***
  6        8 ********
  7        0
  8        1 *
  9        0
 10        0
 11        1 *
 12        1 *
SUM= 313
```

```
B:BRUNER.TXT
1B600RFO

11111111111111111111001101110010000000000001001111
11000101101110001110011101110000000000000000100100
11111110001011110110001001100000111001101100111001
00011100011000110110001110100001100101110100111011
10010001100110010011010010001010110000100111001111
10111000001010101100101001010000101001010100101010
11001000001011100110010001100001000001000001101100
00111101001100100100001010000100111000001011101001
00000101010001101110010010111001000010011010011110
0011101011000000101001010010100111011111011000100 11
01010100010110100111000010100110011001001110000010
00000001101100011100000001101010010001010101101101

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       79 *****************************************************:
   2       34 **********************************
   3       24 ************************
   4        4 ****
   5        1 *
   6        1 *
   7        1 *
   8        0
   9        0
  10        0
  11        0
  12        0
  13        0
  14        0
  15        0
  16        0
  17        0
  18        0
  19        0
  20        1 *
SUM= 273        144
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       59 ******************************************************
   2       46 **********************************************
   3       17 *****************
   4        9 *********
   5        8 ********
   6        1 *
   7        1 *
   8        1 *
   9        0
  10        0
  11        0
  12        1 *
  13        0
  14        0
  15        0
  16        1 *
 SUM= 327        144
```

B:BRUNER.PRM
1B600RF0

```
11111011111111111101111110111101111101111111111101110
11111011111111111011110111101011101101001111111110101
01110110100110111011000100100001001011011010100110
01011100101010110110101001000011000011010011010011
00000011101011000101011100010101001111100001000101
01101100010111110001110110001100000101110001110000
00110000000101000011100100001000110001001001100000
00000010000110000111010001010110110001100001001011
011010011110110000001000000100100010000000001000000
0001100001110000001111100101110000000010010000100001
110000101011000010000100001000000001000010000111001
000000110000000001010000001001101000010101100101100
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	68	**:
2	34	**********************************
3	17	*****************
4	3	***
5	6	******
6	1	*
7	0	
8	1	*
9	1	*
10	1	*
11	1	*

SUM= 273   133

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	63	***:
2	23	***********************
3	13	*************
4	19	*******************
5	3	***
6	5	*****
7	3	***
8	1	*
9	2	**
10	0	
11	1	*

SUM= 327   133

B:LABOV.TXT
1B600RFO

```
11111111111111111110011111011110011001101110011001
10010010011111101100111111001100101110010111101101
01001010110111111100110010101011111101101011110111
00101111101011010000000101011111101001100010111110
00000011011001111001000101101000110111010101010110
10101010110111001000000110100100101111000000110100
01101110000010010111011000101001110101100000101011
01101101101011001010101001101111001101111101001000
100000101001100010010000001010001110011011100101011
00010111000001001001010101010110010100101011010010
0001010010100110010000000100101000000100000100001011
1000110001011011100111010010000000100101000000010000
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	90	**
2	38	**************************************
3	13	*************
4	7	*******
5	4	****
6	5	*****
7	0	
8	0	
9	0	
10	0	
11	0	
12	0	
13	0	
14	0	
15	0	
16	0	
17	0	
18	0	
19	1	*

SUM= 302   159

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	86	**
2	44	**
3	11	***********
4	3	***
5	7	*******
6	5	*****
7	2	**

SUM= 298   158

B:LABOV.PRM
1B600RF0

```
10111111111111111111010101111111110001111101111101
11110111010110110111111001100110101010111000100110
11110010110010000010110110101111101011011110001011
00001010001001110101010000110111110011101110011110
01101100000001101111001111010010011001000010001011
00100001111111110011111110001000001101110101011000
00101011001000000011000100100001101000100010001110
10001011110000101011010100010101100110010010100110
00000111000111011110011100101100000001011100110001
00100100111001100001000001101010010110011001011001
00100010010011000001000011001000111000110001101111
11010011111000000011001111000010010100010010010001
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	72	**
2	37	*************************************
3	13	*************
4	8	********
5	6	******
6	2	**
7	1	*
8	0	
9	2	**
10	0	
11	0	
12	0	
13	0	
14	0	
15	0	
16	0	
17	0	
18	1	*

SUM= 302

142

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	59	***
2	42	**
3	20	********************
4	9	*********
5	5	*****
6	1	*
7	4	****

SUM= 298

140

```
P:FRANLENA.TXT
1B600RF0

11111110111111111110110111111011000010011010110110
01010000110001000101111101010010011110110101000011
00011111100101110110111001111111000000001001001101
10001000011100100001101011011100110111000110010010
01000010111010000000000101101110010010001000101
10000011101010001001010000010100101000100000000000
0000000101000010110000011001100110110110000011 10001
01000011101001010001101100000100000000101010100111
00101000010111000100000101000000101000101100000011
1111110101011000000000000100010001011101000000001111
11110011100000000000000001100110100001000000000000
01000000000000000000000110000101000000000000000000100

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        72 ************************************************************************
  2        30 ******************************
  3        13 *************
  4         2 **
  5         1 *
  6         2 **
  7         2 **
  8         2 **
  9         0
 10         0
 11         1 *
SUM= 237
```

125

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        55 *******************************************************
  2        26 **************************
  3        15 ***************
  4        12 ************
  5         5 *****
  6         2 **
  7         1 *
  8         2 **
  9         0
 10         1 *
 11         1 *
 12         1 *
 13         0
 14         0
 15         0
 16         1 *
 17         1 *
 18         1 *
 19         1 *
SUM= 363
```

125

PRM
B:FRANLF?.TXT
1E±00RFO

```
11101111011111111111011111111010011111000110010101111
11010110111101010011101100110111001110101010001001
110100101101110111100100010000000011001100010101100
0011000110111100001110010001010011110110000100011010
00001001010100000110010101101100011000001000001010
00001011100000000010000000100101110010000111111110
01011001110010011111100000000011110110010110001001
000010101000100000010010001000000000010001101011000
10000101001001000010001000100000010000100001100011
000001100010001010001100001001000000001000000000000
101000000000100000111000011110000000110000000100000110
000000010000110000001100001000000110101000010100101 1
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       77 *****************************************************************************
  2       30 ******************************
  3       12 ************
  4        6 ******
  5        2 **
  6        1 *
  7        1 *
  8        0
  9        1 *
 10        1 *
SUM= 239
```

(9)

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       48 ************************************************
  2       26 **************************
  3       19 *******************
  4       15 ***************
  5        9 *********
  6        5 *****
  7        1 *
  8        3 ***
  9        3 ***
 10        0
 11        1 *
SUM= 361
```

(5)

B:CHOMSKY.TXT
1B600RFO

```
11111111111110111111110011101000111111111010000110
11110001110000111010100011100100101101011010100100
01001000101010010011111111010001101100100101111100
01100100001100101000100110101111101001001010000010
00000000000010110011101001000011011011101010100101
10000000000001110101100011001011010100110101010101
11000011010000000001000000111000101111001100010100
10110010000001001000000000000100101100001001001110
00100000000000100010000100101011000010010000000001
11011010110101000100100100101011001100110001100000
00100000000000001011000011001000100100100110000
00011100001100101000010000000010100010000000010010
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1        88 ****************************************************************************************
  2        31 *******************************
  3        12 ************
  4         2 **
  5         2 **
  6         0
  7         0
  8         2 **
  9         1 *
 10         0
 11         0
 12         0
 13         1 *
SUM= 242
```

129

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1        57 *********************************************************
  2        40 ****************************************
  3        17 *****************
  4        11 ***********
  5         1 *
  6         2 **
  7         2 **
  8         2 **
  9         2 **
 10         0
 11         1 *
 12         2 **
 13         2 **
SUM= 358
```

129

E:CHOMSKY.PRM
1B600RFO

```
11111101111111111110011110111111111110111110011 10111
10110011010001100111101011000010111100001110111011
01011111100011111110000001101010011100001111010000
01000101101000101010100110011100000001101000111100
01010010000111001000000100010010001110010010010000
00000100010011010000001100011101000000110010100001 00
10000010000001000010110110100000011100101101111011
10010001010110010111000100011011001001101100011001
00100000010001000000110000001110100000110110001101 00
00000010001000000000100001100000000000001100000000100
11000000000100000000000000011010000000100101100001 1
00011000100010011000100000001010000010001000010000 10
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       67 *******************************************************************
  2       33 *********************************
  3       12 ************
  4        7 *******
  5        1 *
  6        2 **
  7        1 *
  8        0
  9        0
 10        1 *
 11        1 *
SUM= 242
```

126

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       44 ********************************************
  2       27 ***************************
  3       22 **********************
  4        9 *********
  5        7 *******
  6        8 ********
  7        2 **
  8        2 **
  9        2 **
 10        0
 11        0
 12        0
 13        1 *
 14        1 *
SUM= 358
```

126

```
B:DREC1.TXT
1B600RF0

11111111101011111111111111111111101110110010101110
01110011011101110001101011011011100101010111110101
00001010111110101100110001001111110111010110110101
00101011001110111100001000111011111001100110110111
01100011001010001100000101011100100100000000000111
01010101011010111110001010100001001001110111101001
01011100111101111111110000101010000101010001010010
11000111000110001101010001101100110001100111011101
00011001110011101101111101001011010010000001100000
01101101011100010110100010100111100010010110110100
01111010110101011000101000010010000011101100000111
01111000101111101100100011100001111101110000011010

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      72 ************************************************************************
  2      38 **************************************
  3      24 ************************
  4       6 ******
  5       7 *******
  6       1 *
  7       0
  8       0
  9       2 **
 10       0
 11       0
 12       0
 13       0
 14       0
 15       0
 16       0
 17       0
 18       0
 19       0
 20       0
 21       1 *
SUM= 324


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      89 *****************************************************************************************
  2      28 ****************************
  3      20 ********************
  4       7 *******
  5       4 ****
  6       2 **
  7       0
  8       0
  9       0
 10       0
 11       1 *
SUM= 276
```

```
B:BREC1.PRN
1B600RFO

11111111111111111011111011111100111111111110101110
10111111111111011011001100101101111011101001101111
11000011100111110111111011111110110110011011110111
01010011000101111010100100111101101010101010111010
01111011100010111100100000100010110111010111110111
00110011000000111100110100101010011110001101011000
11001101010111111100011001000011110100100001100110
00110010010000001001000100010001001001100111100001
01111101111111100110001100101001100010101000011111
10111000001001111100000100000011000001000011100110
10110010100000101001001100101100100001011011110110
00101001000000101100010010111100000000010111000000

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      65 *****************************************************************
  2      34 **********************************
  3      11 ***********
  4      12 ************
  5       5 *****
  6       4 ****
  7       3 ***
  8       0
  9       0
 10       1 *
 11       0
 12       1 *
 13       0
 14       0
 15       0
 16       0
 17       0
 18       1 *
SUM= 324
```

137

```
LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      67 *******************************************************************
  2      39 ***************************************
  3      13 *************
  4       7 *******
  5       5 *****
  6       5 *****
  7       0
  8       0
  9       1 *
SUM= 276
```

137

B:BREED.TXT
1B600RF0

```
1110111011111011111011111111111111101011111111001101
11011111111111001100111111111111010100100101001001 0
11111011001001010011101100010110010111101011000111
00010110001111100000000101100110000001100010100101 00
10001001111100101101010011010010010001000011100110
10111001101100000001010101000001001001101011011 1001
01000100110101110010000101110111001010100110101011
00101111111001110100101000001001110110111001000100
01010100000000101001110001000000101000010000000100
11000010100111000000000100010010011000000001001001 00
11010111010101101101101010101001100011001011010100
01010100110000000000100101100000010000100110100101 10
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	92	**
2	34	**********************************
3	17	*****************
4	2	**
5	4	****
6	0	
7	2	**
8	0	
9	0	
10	1	*
11	0	
12	1	*
13	0	
14	0	
15	1	*

SUM= 290 154

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	76	**
2	47	***
3	14	**************
4	5	*****
5	4	****
6	2	**
7	3	***
8	2	**
9	1	*

SUM= 310 154

```
B:DREE2.FRM
1B60DFF0

11111111111111101110111111101111111101111011100010
11101001101110100010111011001010100011101101001101
11111100000100000101000100100100111000011111010010
00111011011111111010001011110000100100000110010011
10101111001010001111101111011011100100001010010000
00110000111110011010111110001000010100011100001011
10111100000100101010111000110010000010011100000001
00101111000110010001111100010101110000001110101010
00000101100000000011000011100110000111000000110000
01111101100111100011011001001010000011011000100110
00000001000011010010100010111011101100100000101100
11001000011000101111010111010010001010000000101000

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       68 ********************************************************************
  2       26 **************************
  3       21 *********************
  4        8 ********
  5        6 ******
  6        0
  7        2 **
  8        2 **
  9        0
 10        0
 11        0
 12        0
 13        0
 14        0
 15        1 *
SUM= 290
      134

LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       60 ************************************************************
  2       29 *****************************
  3       19 *******************
  4       10 **********
  5        8 ********
  6        4 ****
  7        2 **
  8        1 *
  9        1 *
SUM= 310
      134
```

```
E:HERALD.TXT
1B600RF0

11111101111111111111111111101110011101111110010111
00110111010110111011011011001101111111001100101010
10110111011000100101110001010101100100110011000011
01001111001001000110100001111001111011011110101110
01011011000011011000111001010000010010110010000011
00000111000001101011101001101001100010000001000010
0101001011011001000010000001000000000100010000000000
10110110110011110001001010010111100101101001011000
10100110111101001101100000100011011100100100011010
001000001000100010010010010000101111100101101110110
1100110010000011000100001000000010000100111101001110
01111011000001001001010000010001110010010000010100
```

```
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       76 ****************************************************************************
  2       42 ******************************************
  3       15 ***************
  4        9 *********
  5        1 *
  6        2 **
  7        1 *
  8        0
  9        0
 10        0
 11        0
 12        0
 13        0
 14        0
 15        0
 16        0
 17        0
 18        0
 19        0
 20        1 *
SUM= 285
```

147

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       63 ***************************************************************
  2       46 **********************************************
  3       15 ***************
  4       10 **********
  5        8 ********
  6        3 ***
  7        0
  8        1 *
  9        1 *
SUM= 315
```

147

B:HERALD.PRM
1B600RF0

```
11011111111111111111111001100100111111111110011011
01101011011110001111110101110110100110110001001101
10111101100101101001101010001101011011110101000111
10110101110111001010111101011000010111100111111101
00100110100110110101001000001001111001101111000100
00011100110001001110011111110010010001000000010101
00001101000101100100001000101101111000010101101000
00110100101010010011110110100000110001000000100101
11000000100111101100110010011001010000000100000000
10001001001110010010000100011110000000010100101001
10011010101010100010000000100110001010100001100000
11000001000100100011100001000000000110000100111101 0
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	80	**
2	39	***************************************
3	8	********
4	13	*************
5	0	
6	1	*
7	2	**
8	0	
9	0	
10	0	
11	1	*
12	0	
13	0	
14	0	
15	0	
16	0	
17	0	
18	0	
19	0	
20	1	*

SUM= 285

145

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	66	**
2	41	***
3	16	****************
4	8	********
5	6	******
6	2	**
7	3	***
8	3	***

SUM= 315

145

B:GUARD.TXT
1B600RF0

```
1111111101101110111111111101110100001110000001011101
11011110011111111101010101011101001101001111001110
00011100111000011110110101101011101100000000100010
10010000000111101011101011110010000010111010011001
10010010010011000100001000001001010010011011011001
00110101100010000100100101111000100000110001000001
10111011001011001011001100011111011100110010000011
00001010001010000100101010001011000111000110101110
0010010111100001010000001101100110000001010010011100
1000010101000000010000110100101100111000000100110001
000000000001011000000000000110011100100111001001000
010100001010000100000010110010101000100010101000111
```

LENGTH OF RUNS OF ONES

```
LENGTH .  NUMBER
OF RUN    OF RUNS
  1        82 **********************************************************************************
  2        32 ********************************
  3        21 *********************
  4         6 ******
  5         2 **
  6         0
  7         0
  8         2 **
  9         1 *
SUM= 268
```

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        62 **************************************************************
  2        40 ****************************************
  3        15 ***************
  4        13 *************
  5        10 **********
  6         1 *
  7         1 *
  8         1 *
  9         0
 10         0
 11         2 **
SUM= 332
```

145

```
B:GUARDF.TXT
1B600RF0

11111111011111100111111111101011011101011010110111
110011100110011111011101111100101010011001000110011
10110001100001011001110011010100100111010010101010
11111010110001101000110010001000110000111100110101
01000011010001010110101010011101000110011111001100
00000000001011101001101100100111110101000011000101
01001001101110001010000011010011010100000000110100
0010010100000000010110000011000101001000101100110010
000000000111010110100000010010000001100101001000001
10100000100000000000010101101001110100000101010001
00100110001000001010010100010001011001101001000110
11011010000100000101101000001111001011001000100100

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      90 ******************************************************************************************
  2      42 ******************************************
  3      11 ***********
  4       3 ***
  5       5 *****
  6       1 *
  7       0
  8       1 *
  9       0
 10       1 *
SUM= 268
```

154

```
LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1      74 **************************************************************************
  2      41 *****************************************
  3      18 ******************
  4       8 ********
  5       7 *******
  6       1 *
  7       0
  8       2 **
  9       0
 10       1 *
 11       1 *
 12       1 *
SUM= 332
```

154

```
B:MAIL.TXT
1B600RFO

1111111111111111011111011111100111111101111111111101
111011111101110111110100010001100110110011010101101
11010111011101110101001110101110100100111110010100
1010010101101010001001011000000011111100011100000101
100001110000000101000001101111011000111110011010011
001001110000010110100010111100010001011001110101100
1011001110000110011111011011000000011010100010001010
001110101101010111100101000010001110000000110100110
10000010100110101110110010000101101000100100101101
11101010111101001110000101110110011001100110111100
000110101100010101010100100001001001110000000011110
110101001000101110100110000011101110011010010000001

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        75 ***************************************************************************
   2        36 ************************************
   3        20 ********************
   4        10 **********
   5         6 ******
   6         1 *
   7         1 *
   8         0
   9         0
  10         0
  11         1 *
  12         0
  13         0
  14         0
  15         1 *
SUM= 316
```

151

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        82 **********************************************************************************
   2        35 ***********************************
   3        15 ***************
   4         9 *********
   5         4 ****
   6         4 ****
   7         1 *
SUM= 284
```

150

```
B:MAIL.PRM
1B600RFO

11111111111111101011111101011101001101111101101111
11111111101011110101110111011101111011011110101110
11101001111100011111101011101001101110101111010111
11100010011011111001000111111111010010011011111000
01111111101111010110101111100010100101001011111011
10001000010111100000110010000111111000010111100000
10111001110000110000000110001110001000000011111000
01111100011110111001101001000101000011011011110010
11110001000001110010011000101100100001010000011001
10001000000000110001000101101101100001000001010110
00011001110100111001100100011111010000000000000110
00100010000000011001110100001000001001011100010010

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       56 ********************************************************
   2       26 **************************
   3       18 ******************
   4       10 **********
   5        9 *********
   6        4 ****
   7        0
   8        1 *
   9        1 *
  10        0
  11        0
  12        0
  13        1 *
  14        0
  15        1 *
SUM= 316
```

127

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       62 **************************************************************
   2       25 *************************
   3       18 ******************
   4       11 ***********
   5        6 ******
   6        0
   7        2 **
   8        1 *
   9        1 *
  10        0
  11        0
  12        0
  13        1 *
SUM= 284
```

127

```
BPAD1.TXT
1E500RF0

11111111111111111111111110100010101011101111101111
001100110000111001001101111111111101011110000110101
111111100000001011011111110100001011010111001011100
10110111001011001101010110110101011010001001011011
10110111001101000010100001110111001010010100101110
00100100000101001011001101001000100101001110000010
011000100000000010110000001110001111000101001001110
010101000011011001011110000001110010010001010000110
010000011100010010110100001100000000000100101001100
00100010111010000001000000010111000110010000001000010
10010010100101100001011101000010101101000101011100
000010000110001010000000011110000010010001011000100

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      87 ***************************************************************************************
   2      30 ******************************
   3      19 *******************
   4       5 *****
   5       1 *
   6       1 *
   7       0
   8       1 *
   9       0
  10       1 *
  11       0
  12       0
  13       0
  14       0
  15       0
  16       0
  17       0
  18       0
  19       0
  20       0
  21       0
  22       0
  23       0
  24       0
  25       1 *
SUM= 278


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      68 ********************************************************************
   2      36 ************************************
   3      15 ***************
   4      13 *************
   5       7 *******
   6       3 ***
   7       2 **
   8       1 *
   9       0
  10       1 *
SUM= 322
```

E:PAD1.PRM
1B600RFO

```
11111111111101111111111111111011111111111111111101
11011111101100111101101010011010101110011111110101
00111001100010010111101110111111010100001101001001 0
10100011011001100011010101001100101001011000001110
00111111101111011001100101010011011101001010010100
00100110110100000101010111011001101011010000100000
00000010000100101110011011000010101001001011100000
01001100000001000111011000100101001010110001101000
0010100010000000000000000100100001110000011000000101
01101001000111000100101100001001000100000001100001 1
000001000000001000001001001010100111001100001111111
0001000001001000001000001001000000100111000000001101
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	82	**
2	32	********************************
3	14	**************
4	3	***
5	1	*
6	1	*
7	3	***
8	0	
9	0	
10	0	
11	0	
12	1	*
13	0	
14	0	
15	0	
16	1	*
17	0	
18	1	*

SUM= 278   139

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	62	**
2	37	*************************************
3	12	************
4	11	***********
5	8	********
6	3	***
7	2	**
8	1	*
9	0	
10	0	
11	1	*
12	0	
13	0	
14	0	
15	1	*

SUM= 322

138

```
B:PAD2.TXT
1B600RF0

11111111111110111111111011110010111001111111101111
00111110111010100011101000100101111101100100101101
11000100110001110010001000000111011011010001101010
11000101001101010101101000000001011011110000101110
00000101100010110010000010000000101111110101010111
01000010011100000100101010000100101101000001101111
01000101010010010001011110110011101001100001000010
00010101110101000010010100000100010000010110100011
01000100010100101111000010000101110000010111110011
11111011110000000011000001010001010011010001010101
10000101001101110100010011101000001010000000010000
00110100001001000100011100010100100000010110011000

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        93 *********************************************************************************************
  2        26 **************************
  3        14 **************
  4         7 *******
  5         3 ***
  6         1 *
  7         1 *
  8         2 **
  9         0
 10         0
 11         0
 12         0
 13         0
 14         1 *
SUM= 273
```

158

```
LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        74 **************************************************************************
  2        26 **************************
  3        21 *********************
  4        11 ***********
  5         8 ********
  6         5 *****
  7         0
  8         3 ***
SUM= 327
```

148

```
B:PAD2.PRM
1B=00RFO

11111111111110111111111111011011111111110111001000
10110110111001100011110101011001001111110011001011
10001010111100100110011111000001011101101111100100
00101101001011101000110101100100111110101110010101
00011101101010000100110001111010000010001110011001
100110001100010000000001000011000000101011011010 11
01100001011010100100000110000110010010001110010100
10111001100001101000000100100010011101001111000101
00100010101010110010101110111000000010000000111100
000101100000000000001000001100010010010100000001010
00100100010100100011100001010000100000001110110000
10000100111110000000010001110000010111001000000001110

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       76 ****************************************************************************
   2       31 *******************************
   3       18 ******************
   4        6 ******
   5        2 **
   6        2 **
   7        0
   8        0
   9        0
  10        1 *
  11        1 *
  12        0
  13        0
  14        1 *
SUM= 273


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       59 ***********************************************************
   2       35 ***********************************
   3       18 ******************
   4       11 ***********
   5        5 *****
   6        2 **
   7        6 ******
   8        0
   9        1 *
  10        0
  11        0
  12        1 *
SUM= 327
```

138

B:PAD3.TXT
1E600RFO

```
11111111111111111111111110101011101111111011011101
00100010111111101001011100100100011010101001000101
00111001111101011111001101001001001101001001100010
01101011001000000101011001001100000000011110011101
11010101101101010001111000001000100100101101010110
01100010000000101100000000000101010011000111001011
01110000000101000010111111010010011000111000101001 0
11110000010101000000100100011011001110001000000110
00001000100010000000100100001011010000000000000010010
10101101100101001000000100001001110000010100111 0001
11000000000000010010001001001001001011000100111011
00001000010011001000100010001010100011000000011001
```

LENGTH OF RUNS OF ONES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        92 *******************************************************************
  2        29 *****************************
  3        13 *************
  4         4 ****
  5         2 **
  6         1 *
  7         2 **
  8         0
  9         0
 10         0
 11         0
 12         0
 13         0
 14         0
 15         0
 16         0
 17         0
 18         0
 19         0
 20         0
 21         0
 22         0
 23         0
 24         0
 25         1 *
SUM= 260
```

191

LENGTH OF RUNS OF ZEROES

```
LENGTH    NUMBER
OF RUN    OF RUNS
  1        58 **********************************************************
  2        43 *******************************************
  3        21 *********************
  4         6 ******
  5         4 ****
  6         4 ****
  7         3 ***
  8         0
  9         1 *
 10         1 *
 11         0
 12         1 *
 13         1 *
```

```
B:PAD3.PRM
1B600RF0

11111111101011101111101111111111110111111011000001
11110110111111110101110011110010110010110111000101
00011001000010100111000000101111010100111000100111
11111000010100111010011011011010100111010010010000
00000110001101000100000000000010000111000001100000
00101100010101000011100000110000100111100010100100
10000110110001110001100111000110001001101010000100
11100101100010100011011000001110100001000000000101
10011011100000010101001000000010011100011011110000
00001100100111001011101001101100011000100000000010
01000100100000100000000101001110000000100010110000
010111000100001001111101000001011100100000011000000

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1      67 *******************************************************************
   2      30 ******************************
   3      20 ********************
   4       5 *****
   5       2 **
   6       1 *
   7       0
   8       2 **
   9       1 *
  10       0
  11       0
  12       1 *
SUM= 260


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1      50 **************************************************
   2      31 *******************************
   3      19 *******************
   4       9 *********
   5       7 *******
   6       4 ****
   7       3 ***
   8       2 **
   9       3 ***
  10       0
  11       0
  12       1 *
SUM= 340
```

120

```
B:FAD4.TXT
1B600RFO

11111111111110011011111111101001111110011110111111111
1001111001101001111111010101011101101001111101101101
1101100101001111010010100111010111100100001001000
0111001111000000101001101100100001000000000010110111
10111000101011001001001111000110111001000111100101
0110110001010000000110010000111011001010001010010000
0110001000011000111011100011000000000111110100101000
1001001010010010100100100001010110000101110100010
0000010101000000100000011101000000001101111011100010
000000001000010000101011100000110010010000001010010
0010000000001010101010011001000000100000000001010100
1010100100101010100011001010100100010100101001101O

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       96 ***************************************************************
   2       24 ************************
   3       13 *************
   4       10 **********
   5        1 *
   6        2 **
   7        0
   8        1 *
   9        1 *
  10        0
  11        0
  12        1 *
SUM= 269     149


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       68 ***************************************************************
   2       43 *******************************************
   3       14 **************
   4        9 *********
   5        6 ******
   6        2 **
   7        2 **
   8        2 **
   9        3 ***
SUM= 331     149
```

B:FAD4.FRM
1B600RF0

```
11111101111111111111111110111110111111111111110101100
11111111110000010111111001000001011110111110111011001
01111001100110110110111011001110110100010011110011
11011101101100010010101010001100101001110110011000
00110000001011110110110011001110001000101000000000110
00000101100011101101010010011000011101011000101010
10100100011101010000100100000001001011011011101101
00110100100000000011000000110101000100011111000100
00000010000000000100001100001000100110001000000001000
01011010100001001001000000110100100101011000110000
00010001000100010110000100010000000000101000100101
11011000000000100010001001010110000001000000000001000
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	75	***
2	39	***************************************
3	10	**********
4	5	*****
5	3	***
6	1	*
7	1	*
8	0	
9	0	
10	1	*
11	0	
12	0	
13	1	*
14	0	
15	1	*

SUM= 269

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	62	**
2	28	****************************
3	22	**********************
4	9	*********
5	4	****
6	4	****
7	1	*
8	4	****
9	2	**
10	1	*

SUM= 331

```
B:FOOH.TXT
1B600RFO

1111111100110110010000001000000000001110001011111111
1111001011100011001001101100011111000000100101000001
0010000001000000110101101110000111000000111011100001 1
1000110101000010110001010011000011011000000101100 10
0000110000100000001000011010001100000101001010011 01
0100000010001001000000010100101011011001000000010100
0100000000111000111000000001000110100000001001100110
000110100010000001110110100010111011110000100101101
0010001110010010100100000000010011000100000100000100
0000100000000010000000110010001101010011100000000010
01000000000000001000100010001011000100000100111101
0110100100001001000000000000100010101010000000101000
```

LENGTH OF RUNS OF ONES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       83 ***********************************************************************************
  2       30 ******************************
  3       13 *************
  4        2 **
  5        1 *
  6        0
  7        0
  8        1 *
  9        0
 10        0
 11        0
 12        1 *
SUM= 215   131
```

LENGTH OF RUNS OF ZEROES

```
LENGTH   NUMBER
OF RUN   OF RUNS
  1       44 ********************************************
  2       28 ****************************
  3       21 *********************
  4       11 ***********
  5       12 ************
  6        5 *****
  7        3 ***
  8        4 ****
  9        0
 10        1 *
 11        1 *
 12        0
 13        0
 14        1 *
SUM= 385   131
```

B:POOH.FRM
1B600RF0

```
11111111111111110111110010111110101011111100011110
1111001100011100111001011100110111000011110000000010
10000010011001000010100010100100011001000101001010
000110000010100010111100010010101100110010110010001
00011001011000100011011100010110000000111101100000
01000001000100010001000100111001111000110010000101 0
1100000100000110010000010010110110100001001011110 00
11011001010000110000011001000010100000000000000010110
01100010000001000001000000010010010000000010001 0011
00000000001000100100000000000000010001000000001110
00010100000001010000000000010000001000000000100 10000
10001001010110000000100000001010000000001000010 00000
```

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	82	**
2	26	**************************
3	7	*******
4	7	*******
5	2	**
6	1	*
7	0	
8	0	
9	0	
10	0	
11	0	
12	0	
13	0	
14	0	
15	0	
16	1	*

SUM= 215

126

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	37	*************************************
2	30	******************************
3	23	***********************
4	13	*************
5	6	******
6	5	*****
7	6	******
8	1	*
9	1	*
10	1	*
11	1	*
12	1	*
13	0	
14	0	
15	1	*

SUM= 385

126

```
B:ALICEL.TXT
1B600RF0

11111111110110111001100110001101111111111011101111
11011001111111011000001011010000111101000110111000
00011011100100111011001110011011111000000111001000
01010011001010110010010010000000001011000011100001
00011000000000110000000010000111010101111110011000
01101010000100000000000000000001000100011001101001
01011100011010010000001000000011001101001000100010
00010100101000010010000011000000000001010000000000
00110110010101010000000000000011000001100010010101
00100001101000000011010111001100000000000110001100
00000000011000000011001000000000101000000101010100
00010010000001001001001001000011010001100100000000

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       67 *******************************************************************
   2       37 *************************************
   3       11 ***********
   4        1 *
   5        1 *
   6        2 **
   7        1 *
   8        0
   9        0
  10        2 **
SUM= 222


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       45 *********************************************
   2       32 ********************************
   3       11 ***********
   4       11 ***********
   5        4 ****
   6        5 *****
   7        4 ****
   8        1 *
   9        2 **
  10        1 *
  11        3 ***
  12        1 *
  13        0
  14        1 *
  15        0
  16        0
  17        0
  18        0
  19        1 *
SUM= 378
```

122

```
B:ALICEL.FRM
1B600RF0

11111111111111111011111100101110000010110100011111
11000110011111011001101001000011111110101111100101
10011110111101010000000010100011110110101001000000
10010011110110000000110110110011000111100100001100
00100001000001011100010000101110001111101010010010
00101011000111110000001101000001010000100000100000
00010000100110011010001001010000101100100000010000
00000010111000101001000000000000000000011100100100
11000010001010001111000000000010000100000011100000
01011000101000000001100010000000011000101000011010
00000001010010110000000000000010000001000000000000
00101000000000000001010000000110010001011000100100

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       73 *************************************************************************
  2       25 *************************
  3        6 ******
  4        6 ******
  5        4 ****
  6        1 *
  7        2 **
  8        0
  9        0
 10        0
 11        0
 12        0
 13        0
 14        0
 15        0
 16        0
 17        1 *
SUM= 222


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       42 ******************************************
  2       25 *************************
  3       16 ****************
  4       13 *************
  5        3 ***
  6        6 ******
  7        2 **
  8        5 *****
  9        0
 10        2 **
 11        0
 12        0
 13        0
 14        3 ***
 15        0
 16        0
 17        0
 18        0
 19        1 *
SUM= 378
```

```
B:ALICEB.TXT
1B600RFO

11111110111111101100111111010111110011010101111100
11111110011100101101110000111010111001001100110101
01001001010111000100100011100000111010100001000001
01100100000000100001011100010000000010111000001010
01000001001111001110001111000011010101110110011100
00100010010101010000001001101111001100011001110101
11011001001001001000000110000011000001000011010000
00000011000000010000011010000001000000000000000000
00000001000000000000000000111010001001000000000000
00000000000010110010100110000011110110010000001010
10010000100001010001000001101000010001010100010111
00010110101000000000001000010100110100000100001000

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       77 *****************************************************************************
  2       23 ***********************
  3       16 ****************
  4        4 ****
  5        2 **
  6        1 *
  7        3 ***
SUM= 224    126


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       51 ***************************************************
  2       30 ******************************
  3       12 ************
  4       11 ***********
  5       10 **********
  6        4 ****
  7        1 *
  8        2 **
  9        0
 10        1 *
 11        1 *
 12        0
 13        0
 14        0
 15        0
 16        0
 17        0
 18        1 *
 19        0
 20        0
 21        0
 22        0
 23        0
 24        1 *
 25        1 *
SUM= 376    126
```

```
B:ALICEB.PRM
1B600RFO

11011111111111111100011010101110010110111111010110
00111111111100100111100110111111110011011001001110
11101000110110110100100101010010000100111001101110
00100011000000001110011010010010010100000100001010
00000010100001000010100000001010000000100111001010
10010100000010010000000100000000011111101000000001
10000110010000100100011010000011000001000000101000
11101010000111001010000100100101010111101000001000
00100100100000010000000000100011000000010000010001
00000100000100110110101000000010010000110110000011
01000000000000000101110101100100010001001000010000
00000011000000011000000100010101100000001000001010

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1      87 ***************************************************************************************
   2      27 ***************************
   3      10 **********
   4       2 **
   5       0
   6       2 **
   7       0
   8       1 *
   9       0
  10       1 *
  11       0
  12       0
  13       0
  14       0
  15       1 *
SUM= 224


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1      49 *************************************************
   2      31 *******************************
   3      12 ************
   4      10 **********
   5      11 ***********
   6       5 *****
   7       8 ********
   8       2 **
   9       1 *
  10       1 *
  11       0
  12       0
  13       1 *
SUM= 376
```

```
B:SEAGULL.TXT
1B600RF0

11111111110111110111011101001111110110100111110101
01001111111111111000111010111011111010101010111001
00110111010110100100100111110101011101111110010110
10101111101000000101100010000110010010010011001111
11101010110110100000100000001010101110000010000110
00100010101000000111111110111001110110111010010101
11110101100011000100100100010111000001110010100011
10100110011101010100100100011010100110001001101000
00100110001010000100110010011000101100100000000000
00100000011010101100111101000100111011000000000100
01000000100000100100000011001000101000001010100010
10001010001000000100001011101100110100001001100100

LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       92 ********************************************************************************************
  2       28 ****************************
  3       16 ****************
  4        3 ***
  5        5 *****
  6        2 **
  7        0
  8        2 **
  9        0
 10        1 *
 11        0
 12        1 *
SUM= 283


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       74 **************************************************************************
  2       38 **************************************
  3       18 ******************
  4        5 *****
  5        9 *********
  6        3 ***
  7        1 *
  8        0
  9        0
 10        1 *
 11        0
 12        0
 13        1 *
SUM= 317
```

```
B:SEAGULL.FRM
1B600RF0

11111111111110111101011111111111111111111111101111
11110001011111101110001001010001101001000110001110
00111100101100011100100111101110010100110011110110
10101101110000001101101100010000100011001010010101
10100101100001000011100101000000011100000110011001
00101001011110011111101011010110010011101111100000
10010100100000010101111110100001100011101000001110
01010111101010001110000100000110010000000010001000
11011011010111000101110001000000001011000110010111
00000001010000011000000101000010010101001010011010
00010110011101100010000001011000011110100010100000
00110000010110101010101010100000000110000010011000 00

LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1     78 ******************************************************************************
   2     32 ********************************
   3     15 ***************
   4      7 *******
   5      1 *
   6      3 ***
   7      0
   8      1 *
   9      0
  10      0
  11      0
  12      0
  13      1 *
  14      0
  15      0
  16      0
  17      0
  18      0
  19      0
  20      0
  21      0
  22      0
  23      0
  24      1 *
SUM= 283
```

139

```
LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1     66 ******************************************************************
   2     29 *****************************
   3     18 ******************
   4      9 *********
   5      7 *******
   6      4 ****
   7      4 ****
   8      2 **
SUM= 317
```

139

NUMBER OF RUNS BEFORE AND AFTER PERMUTATION:

CHILDREN'S TEXT STRINGS: (numbers in () are adjusted for length)

	natural text	permutated text	text - perm
C85	242 (264)	222 (242)	20 (22)
C95	266 (290)	244 (266)	22 (24)
C130	224 (244)	226 (247)	-2 (-3)
C140	208 (227)	205 (224)	3 (3)
C141	266 (290)	236 (257)	30 (33)
Mean	241.2 (263)	226.6 (247.2)	15.4 (17)

NEWSPAPERS:

	natural text	permutated text	text - perm
HERALD	294	290	4
GUARDIAN	291	308	-17
MAIL	301	254	47
DRECORD1	302	274	28
DRECORD2	308	268	40
Mean	299.2	278.8	20.4

BOOKS WRITTEN FOR CHILDREN:

	natural text	permutated text	text - perm
PAD1	292	277	15
PAD2	296	276	20
PAD3	287	258	29
PAD4	274	298	-24
POOH	262	252	10
ALICEB	252	262	-10
ALICEL	244	236	8
SEAGULL	300	278	22
Mean	275.9	267.1	8.8

SCIENTISTS:

	natural text	permutated text	text - perm
RUSS1	293	256	37
RUSS2	305	272	33
RUSS3	267	261	6
RUSS4	326	283	43
RUSS5	284	284	0
BRUNER	289	266	23
LABOV	316	282	34
FRANKENA	261	250	11
CHOMSKY	278	250	28
Mean	291.0	267.1	23.9

APPENDIX TO CHAPTER 10.

Optimal size of Reference Field

Reduced 0.25

114C,265B364RF108SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.8								
0.016	6.4	0.031	0.4	0.047	9.6	0.063	4.0	0.078	34.5
0.094	25.0	0.109	35.6	0.125	25.9	0.141	0.9	0.156	21.9
0.172	19.0	0.188	3.2	0.203	11.3	0.219	6.5	0.234	1.4
0.250	19.9	0.266	18.2	0.281	5.9	0.297	30.3	0.313	13.0
0.328	6.8	0.344	22.4	0.359	11.6	0.375	19.4	0.391	2.5
0.406	7.2	0.422	3.1	0.438	33.8	0.453	14.2	0.469	1.6
0.484	20.4	0.500	26.8						

MEAN POWER DENSITY: 14.14
DEGREES OF FREEDOM = 3
CHISQUARE = 269.20
ST.DEVIATION = 10.91
MPD UPPER 0.95 CONF LIMIT = 18.61
MPD LOWER 0.95 CONF LIMIT = 9.67

Reduced 0.5

114C,265B364RF72SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.5								
0.016	10.0	0.031	8.4	0.047	7.4	0.063	2.3	0.078	17.3
0.094	26.5	0.109	12.0	0.125	12.5	0.141	1.7	0.156	12.9
0.172	14.4	0.188	10.9	0.203	7.8	0.219	2.4	0.234	2.6
0.250	20.4	0.266	18.1	0.281	6.9	0.297	20.1	0.313	10.4
0.328	12.8	0.344	23.2	0.359	16.0	0.375	6.9	0.391	2.5
0.406	3.3	0.422	1.6	0.438	23.1	0.453	10.7	0.469	3.3
0.484	21.4	0.500	9.2						

MEAN POWER DENSITY: 10.93
DEGREES OF FREEDOM = 3
CHISQUARE = 155.54
ST.DEVIATION = 7.29
MPD UPPER 0.95 CONF LIMIT = 13.91
MPD LOWER 0.95 CONF LIMIT = 7.94

NOT ALTERED

114C,265B364RF144SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.4								
0.016	6.1	0.031	6.2	0.047	0.1	0.063	10.3	0.078	52.9
0.094	15.3	0.109	39.5	0.125	23.1	0.141	1.7	0.156	30.2
0.172	11.7	0.188	7.3	0.203	16.6	0.219	0.8	0.234	6.4
0.250	23.8	0.266	23.2	0.281	12.3	0.297	46.0	0.313	26.7
0.328	10.7	0.344	17.0	0.359	17.7	0.375	22.4	0.391	3.9
0.406	18.9	0.422	0.2	0.438	22.9	0.453	25.6	0.469	3.4
0.484	39.8	0.500	82.3						

MEAN POWER DENSITY: 19.10
DEGREES OF FREEDOM = 3
CHISQUARE = 520.69
ST.DEVIATION = 17.63
MPD UPPER 0.95 CONF LIMIT = 26.33
MPD LOWER 0.95 CONF LIMIT = 11.88

NOT ALTERED

114C,265B364RF144SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.4								
0.016	6.1	0.031	6.2	0.047	0.1	0.063	10.3	0.078	52.9
0.094	15.3	0.109	39.5	0.125	23.1	0.141	1.7	0.156	30.2
0.172	11.7	0.188	7.3	0.203	16.6	0.219	0.8	0.234	6.4
0.250	23.8	0.266	23.2	0.281	12.3	0.297	46.0	0.313	26.7
0.328	10.7	0.344	17.0	0.359	17.7	0.375	22.4	0.391	3.9
0.406	18.9	0.422	0.2	0.438	22.9	0.453	25.6	0.469	3.4
0.484	39.8	0.500	82.3						

MEAN POWER DENSITY: 19.10
DEGREES OF FREEDOM = 3
CHISQUARE = 520.69
ST.DEVIATION = 17.63
MPD UPPER 0.95 CONF LIMIT = 26.33
MPD LOWER 0.95 CONF LIMIT = 11.88

1.25
Extended 0.25

114C.265B364RF180SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.8								
0.016	10.0	0.031	4.2	0.047	3.4	0.063	4.5	0.078	41.4
0.094	23.1	0.109	31.5	0.125	30.1	0.141	10.7	0.156	17.9
0.172	6.7	0.188	5.4	0.203	19.6	0.219	5.7	0.234	7.7
0.250	23.7	0.266	37.0	0.281	12.6	0.297	69.5	0.313	44.1
0.328	6.4	0.344	23.1	0.359	25.2	0.375	34.0	0.391	2.4
0.406	22.9	0.422	2.5	0.438	32.8	0.453	32.3	0.469	9.2
0.484	50.8	0.500	36.1						

MEAN POWER DENSITY: 20.96
DEGREES OF FREEDOM = 3
CHISQUARE = 413.59
ST.DEVIATION = 16.46
MPD UPPER 0.95 CONF LIMIT = 27.70
MPD LOWER 0.95 CONF LIMIT = 14.21

Extended 0.5

114C.265B364RF216SOF1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.0								
0.016	9.6	0.031	4.5	0.047	2.0	0.063	14.6	0.078	36.6
0.094	23.0	0.109	38.5	0.125	36.2	0.141	8.0	0.156	32.3
0.172	21.1	0.188	7.9	0.203	20.3	0.219	28.9	0.234	21.2
0.250	18.4	0.266	30.3	0.281	13.4	0.297	52.8	0.313	41.5
0.328	23.0	0.344	28.2	0.359	16.9	0.375	25.1	0.391	16.9
0.406	8.0	0.422	0.1	0.438	16.3	0.453	42.9	0.469	14.4
0.484	67.8	0.500	33.6						

MEAN POWER DENSITY: 23.10
DEGREES OF FREEDOM = 3
CHISQUARE = 317.36
ST.DEVIATION = 15.14
MPD UPPER 0.95 CONF LIMIT = 29.30
MPD LOWER 0.95 CONF LIMIT = 16.90

APPENDIX TO CHAPTER 11.

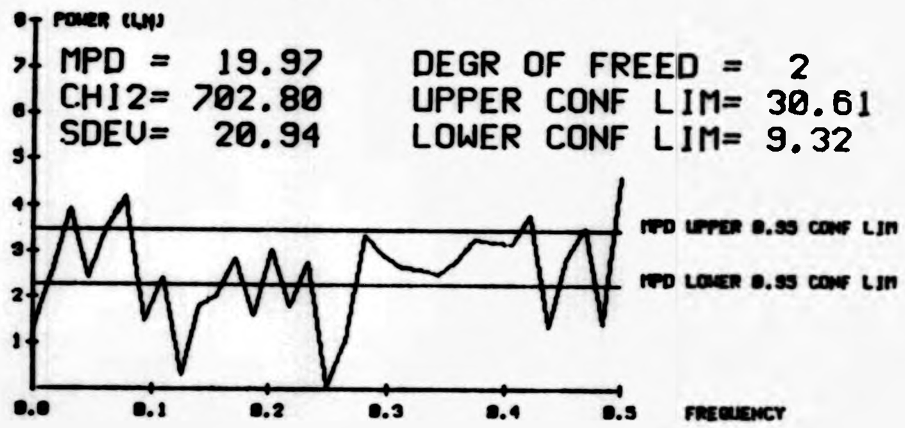
Power spectral analyses of text strings.

WINDOW-GROUP 64

Index

Power spectra of natural text strings:

62C,37B100RF16
POWER SPECTRUM

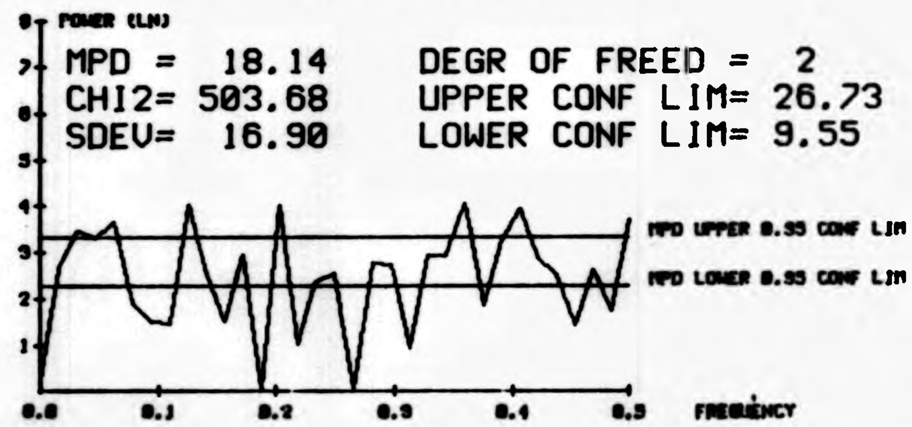


62C,37B100RF16 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.6								
0.016	11.8	0.031	50.3	0.047	11.0	0.063	33.2	0.078	65.0
0.094	4.3	0.109	11.2	0.125	1.3	0.141	6.0	0.156	7.7
0.172	17.4	0.188	4.8	0.203	21.0	0.219	5.9	0.234	15.8
0.250	1.0	0.266	2.9	0.281	28.9	0.297	18.9	0.313	14.3
0.328	13.3	0.344	11.8	0.359	16.6	0.375	26.9	0.391	24.5
0.406	23.3	0.422	43.9	0.438	3.7	0.453	17.9	0.469	34.5
0.484	4.1	0.500	102.2						

MEAN POWER DENSITY: 19.97
DEGREES OF FREEDOM = 2
CHISQUARE = 702.80
ST.DEVIATION = 20.94
MPD UPPER 0.95 CONF LIMIT = 30.61
MPD LOWER 0.95 CONF LIMIT = 9.32
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

70C,109B172RF53
POWER SPECTRUM

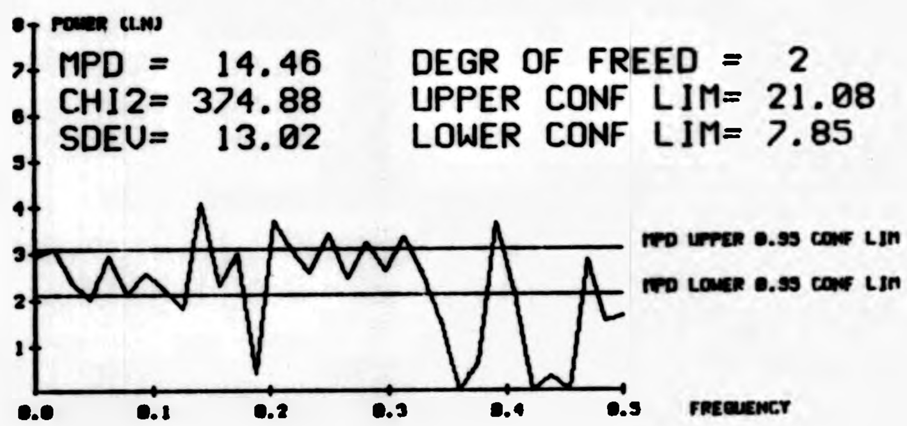


70C,109B172RF53 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.2								
0.016	13.9	0.031	31.6	0.047	26.2	0.063	37.9	0.078	6.5
0.094	4.4	0.109	4.2	0.125	54.4	0.141	12.4	0.156	4.4
0.172	18.3	0.188	0.6	0.203	54.4	0.219	2.7	0.234	10.5
0.250	12.2	0.266	0.7	0.281	15.7	0.297	14.9	0.313	2.5
0.328	18.9	0.344	18.9	0.359	56.9	0.375	6.4	0.391	25.6
0.406	50.6	0.422	17.4	0.438	11.9	0.453	4.1	0.469	13.3
0.484	5.6	0.500	39.4						

MEAN POWER DENSITY: 18.14
DEGREES OF FREEDOM = 2
CHISQUARE = 503.68
ST.DEVIATION = 16.90
MPD UPPER 0.95 CONF LIMIT = 26.73
MPD LOWER 0.95 CONF LIMIT = 9.55
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

71C,30B101RF29
POWER SPECTRUM

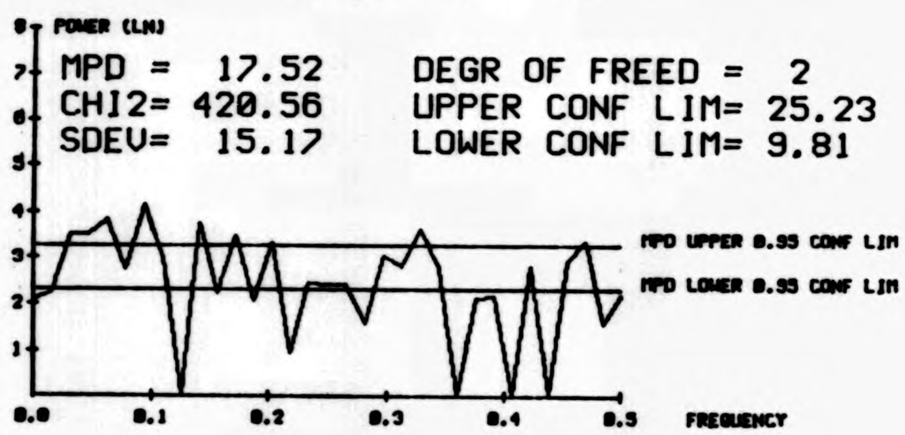


71C,30B101RF29 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	18.5								
0.016	21.9	0.031	10.7	0.047	7.5	0.063	18.2	0.078	8.3
0.094	12.7	0.109	9.1	0.125	5.9	0.141	58.4	0.156	9.6
0.172	19.3	0.188	1.4	0.203	39.3	0.219	20.9	0.234	13.0
0.250	29.9	0.266	11.4	0.281	24.8	0.297	13.4	0.313	27.6
0.328	13.0	0.344	4.6	0.359	0.2	0.375	1.8	0.391	37.8
0.406	8.7	0.422	0.3	0.438	1.4	0.453	0.7	0.469	17.2
0.484	4.5	0.500	5.1						

MEAN POWER DENSITY: 14.46
DEGREES OF FREEDOM = 2
CHISQUARE = 374.88
ST.DEVIATION = 13.02
MPD UPPER 0.95 CONF LIMIT = 21.08
MPD LOWER 0.95 CONF LIMIT = 7.85
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

73C,40B103RF26
POWER SPECTRUM

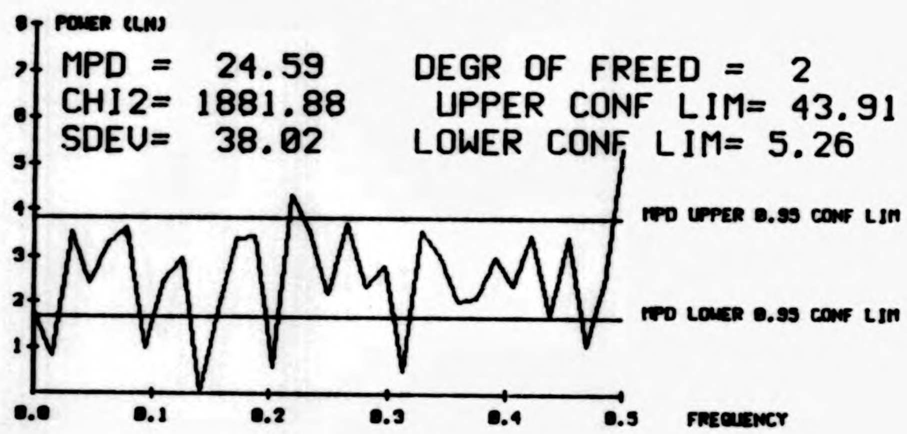


73C,40B103RF26 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.0								
0.016	9.4	0.031	33.2	0.047	33.1	0.063	46.0	0.078	15.2
0.094	64.1	0.109	19.4	0.125	1.0	0.141	43.5	0.156	8.9
0.172	31.9	0.188	7.8	0.203	28.0	0.219	2.5	0.234	11.6
0.250	11.2	0.266	11.2	0.281	4.7	0.297	20.6	0.313	16.7
0.328	37.9	0.344	15.6	0.359	1.0	0.375	8.2	0.391	8.7
0.406	0.6	0.422	16.6	0.438	1.0	0.453	18.4	0.469	28.6
0.484	4.7	0.500	8.8						

MEAN POWER DENSITY: 17.52
DEGREES OF FREEDOM = 2
CHISQUARE = 420.56
ST.DEVIATION = 15.17
MPD UPPER 0.95 CONF LIMIT = 25.23
MPD LOWER 0.95 CONF LIMIT = 9.81
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

77C,55B118RF53
POWER SPECTRUM

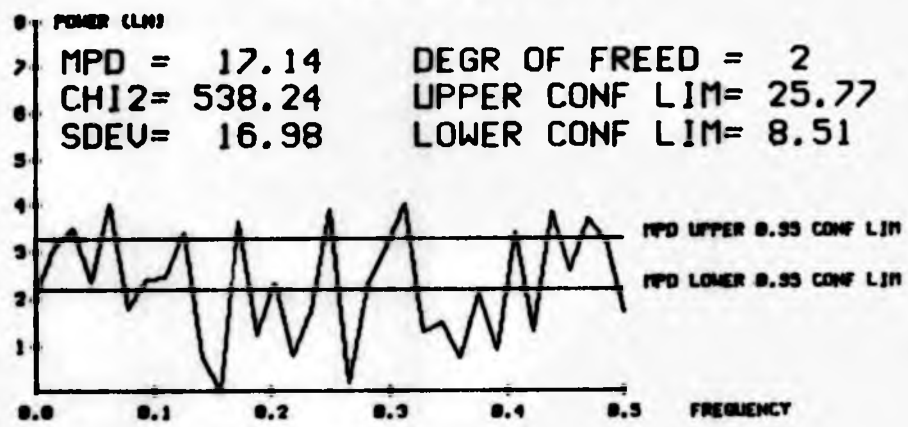


77C,55B118RF53   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.8								
0.016	2.2	0.031	34.2	0.047	11.0	0.063	26.9	0.078	36.6
0.094	2.6	0.109	11.9	0.125	19.6	0.141	0.7	0.156	6.1
0.172	29.9	0.188	30.8	0.203	1.7	0.219	75.5	0.234	35.7
0.250	8.6	0.266	41.9	0.281	10.0	0.297	16.6	0.313	1.6
0.328	34.8	0.344	20.8	0.359	7.3	0.375	8.0	0.391	20.4
0.406	10.6	0.422	32.6	0.438	5.4	0.453	31.4	0.469	2.8
0.484	11.1	0.500	216.2						

MEAN POWER DENSITY: 24.59
DEGREES OF FREEDOM = 2
CHISQUARE = 1881.88
ST.DEVIATION = 38.02
MPD UPPER 0.95 CONF LIMIT = 43.91
MPD LOWER 0.95 CONF LIMIT = 5.26
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 2
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 6
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 8

80C,103B166RF48
POWER SPECTRUM

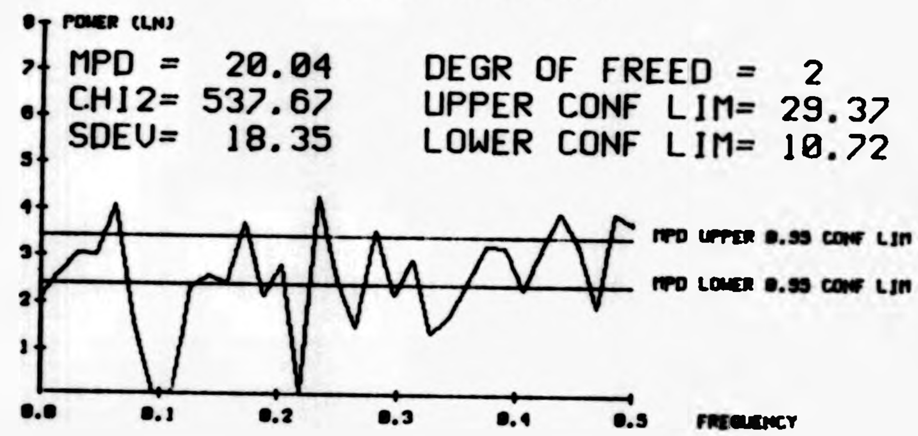


80C,103B166RF48 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.7								
0.016	22.0	0.031	31.9	0.047	10.1	0.063	55.3	0.078	5.9
0.094	10.8	0.109	11.7	0.125	30.3	0.141	2.0	0.156	0.3
0.172	38.0	0.188	3.3	0.203	10.3	0.219	2.2	0.234	5.6
0.250	48.2	0.266	1.2	0.281	10.1	0.297	21.4	0.313	54.8
0.328	3.6	0.344	4.3	0.359	2.0	0.375	8.1	0.391	2.4
0.406	29.5	0.422	3.6	0.438	45.7	0.453	13.1	0.469	40.4
0.484	24.5	0.500	5.5						

MEAN POWER DENSITY: 17.14
DEGREES OF FREEDOM = 2
CHISQUARE = 538.24
ST.DEVIATION = 16.98
MPD UPPER 0.95 CONF LIMIT = 25.77
MPD LOWER 0.95 CONF LIMIT = 8.51
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

82C,101B164RF35
POWER SPECTRUM

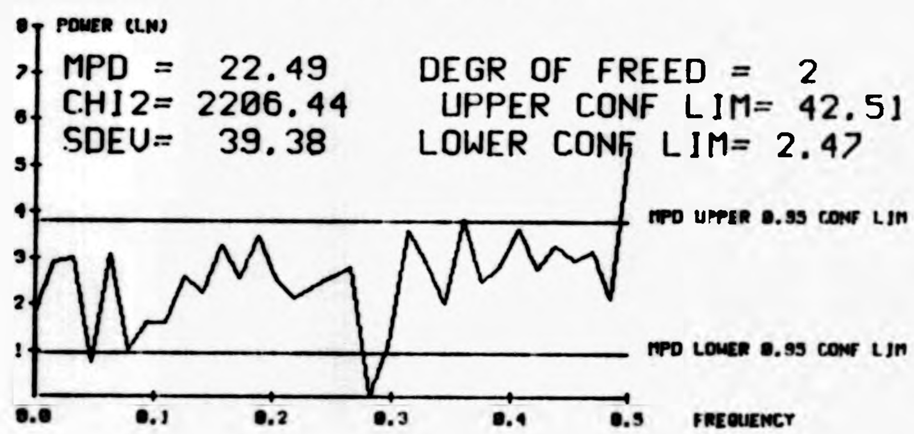


82C,101B164RF35 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.9								
0.016	13.5	0.031	21.3	0.047	19.8	0.063	60.1	0.078	4.7
0.094	0.7	0.109	0.3	0.125	10.1	0.141	12.7	0.156	11.0
0.172	41.3	0.188	8.3	0.203	16.3	0.219	1.0	0.234	71.8
0.250	11.9	0.266	4.5	0.281	35.0	0.297	8.7	0.313	18.6
0.328	4.0	0.344	5.5	0.359	11.3	0.375	25.3	0.391	24.7
0.406	9.9	0.422	23.3	0.438	52.9	0.453	25.3	0.469	6.8
0.484	51.5	0.500	41.6						

MEAN POWER DENSITY: 20.04
DEGREES OF FREEDOM = 2
CHISQUARE = 537.67
ST.DEVIATION = 18.35
MPD UPPER 0.95 CONF LIMIT = 29.37
MPD LOWER 0.95 CONF LIMIT = 10.72
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

85C
FIE1,201B264RF76S0F1
POWER SPECTRUM

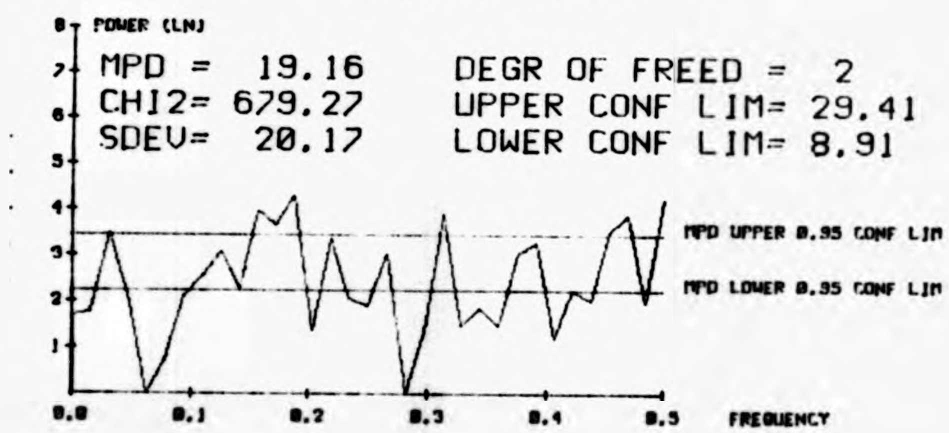


85C
FIE1,201B264RF76S0F1 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.9								
0.016	18.7	0.031	20.2	0.047	2.1	0.063	22.0	0.078	2.7
0.094	4.9	0.109	5.0	0.125	13.5	0.141	9.4	0.156	26.5
0.172	12.8	0.188	32.1	0.203	12.6	0.219	8.2	0.234	10.6
0.250	13.2	0.266	16.3	0.281	0.2	0.297	3.0	0.313	35.9
0.328	18.2	0.344	7.3	0.359	46.8	0.375	11.9	0.391	17.1
0.406	38.7	0.422	15.7	0.438	26.2	0.453	19.0	0.469	23.9
0.484	8.4	0.500	233.0						

MEAN POWER DENSITY: 22.49
DEGREES OF FREEDOM = 2
CHISQUARE = 2206.44
ST.DEVIATION = 39.38
MPD UPPER 0.95 CONF LIMIT = 42.51
MPD LOWER 0.95 CONF LIMIT = 2.47
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 2
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 2
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 4

90C,199B263RF42
POWER SPECTRUM

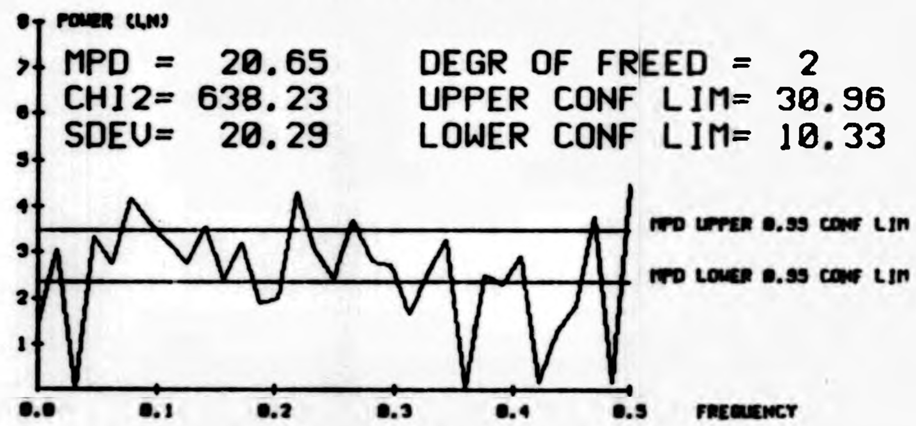


90C,199B263RF42 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.4								
0.016	5.8	0.031	32.4	0.047	8.3	0.063	0.2	0.078	2.1
0.094	8.3	0.109	13.1	0.125	21.9	0.141	9.4	0.156	52.8
0.172	37.4	0.188	72.7	0.203	3.8	0.219	28.2	0.234	7.6
0.250	6.7	0.266	21.0	0.281	0.2	0.297	3.8	0.313	49.7
0.328	4.2	0.344	6.4	0.359	4.2	0.375	21.0	0.391	26.6
0.406	3.2	0.422	9.4	0.438	7.3	0.453	33.9	0.469	48.1
0.484	7.0	0.500	70.3						

MEAN POWER DENSITY: 19.16
DEGREES OF FREEDOM = 2
CHISQUARE = 679.27
ST.DEVIATION = 20.17
MPD UPPER 0.95 CONF LIMIT = 29.41
MPD LOWER 0.95 CONF LIMIT = 8.91
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

91C,187B250RF72
POWER SPECTRUM

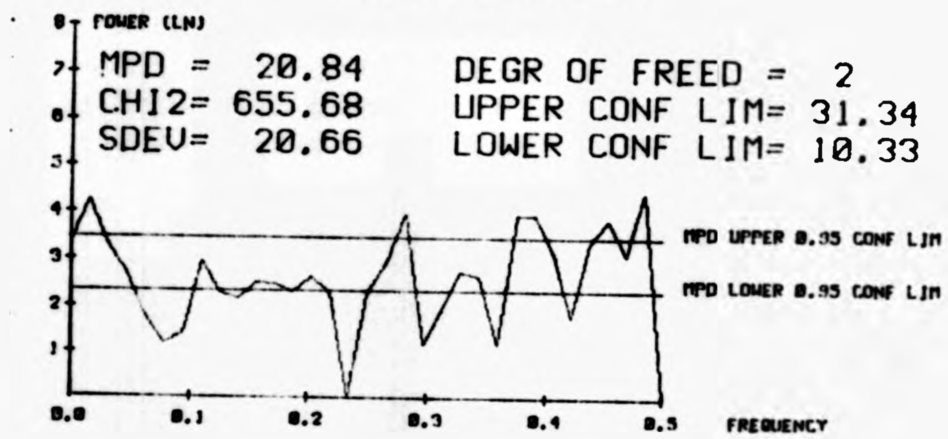


91C,187B250RF72 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.0								
0.016	20.6	0.031	0.6	0.047	27.8	0.063	14.9	0.078	63.4
0.094	36.3	0.109	23.3	0.125	15.0	0.141	33.3	0.156	10.7
0.172	23.8	0.188	6.5	0.203	7.5	0.219	71.7	0.234	20.2
0.250	11.2	0.266	40.2	0.281	15.6	0.297	14.9	0.313	5.2
0.328	12.6	0.344	25.2	0.359	0.1	0.375	12.0	0.391	9.9
0.406	17.9	0.422	1.2	0.438	3.6	0.453	6.3	0.469	42.1
0.484	1.2	0.500	82.8						

MEAN POWER DENSITY: 20.65
DEGREES OF FREEDOM = 2
CHISQUARE = 638.23
ST.DEVIATION = 20.29
MPD UPPER 0.95 CONF LIMIT = 30.96
MPD LOWER 0.95 CONF LIMIT = 10.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

94C,126B189RF72
POWER SPECTRUM

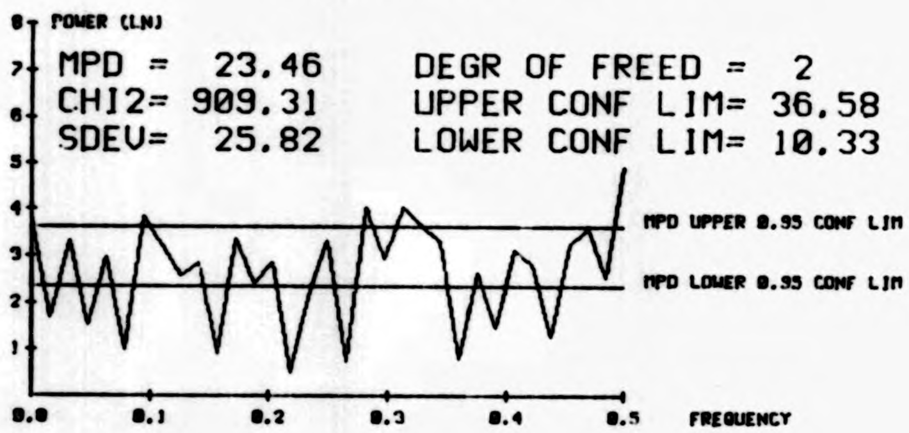


94C,126B189RF72 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	27.6								
0.016	68.1	0.031	26.5	0.047	15.0	0.063	5.9	0.078	3.2
0.094	4.1	0.109	19.6	0.125	9.8	0.141	8.5	0.156	12.4
0.172	11.8	0.188	10.3	0.203	14.2	0.219	9.7	0.234	0.9
0.250	9.7	0.266	18.4	0.281	52.3	0.297	3.2	0.313	6.7
0.328	15.7	0.344	14.1	0.359	3.2	0.375	52.6	0.391	52.5
0.406	23.2	0.422	5.7	0.438	29.3	0.453	46.2	0.469	22.8
0.484	84.0	0.500	0.1						

MEAN POWER DENSITY: 20.84
DEGREES OF FREEDOM = 2
CHISQUARE = 655.68
ST.DEVIATION = 20.66
MPD UPPER 0.95 CONF LIMIT = 31.34
MPD LOWER 0.95 CONF LIMIT = 10.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

95C,201B264RF173
POWER SPECTRUM

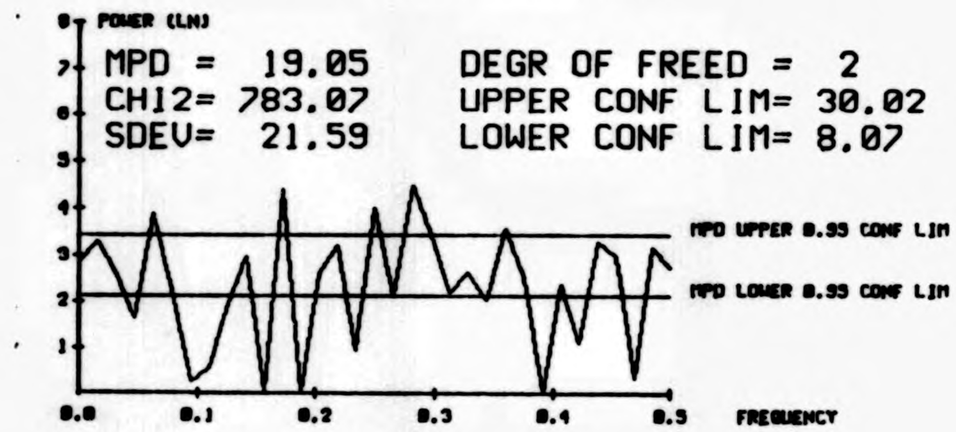


95C,201B264RF173 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	44.0								
0.016	5.1	0.031	27.9	0.047	4.4	0.063	19.4	0.078	2.7
0.094	47.2	0.109	24.8	0.125	12.9	0.141	17.0	0.156	2.4
0.172	28.3	0.188	11.1	0.203	17.2	0.219	1.6	0.234	8.2
0.250	28.0	0.266	2.1	0.281	55.9	0.297	18.3	0.313	56.3
0.328	37.6	0.344	26.1	0.359	2.1	0.375	14.1	0.391	4.3
0.406	22.7	0.422	16.3	0.438	3.4	0.453	25.0	0.469	37.2
0.484	12.4	0.500	138.0						

MEAN POWER DENSITY: 23.46
DEGREES OF FREEDOM = 2
CHISQUARE = 909.31
ST.DEVIATION = 25.82
MPD UPPER 0.95 CONF LIMIT = 36.58
MPD LOWER 0.95 CONF LIMIT = 10.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 10
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

96C,198B261RF106
POWER SPECTRUM

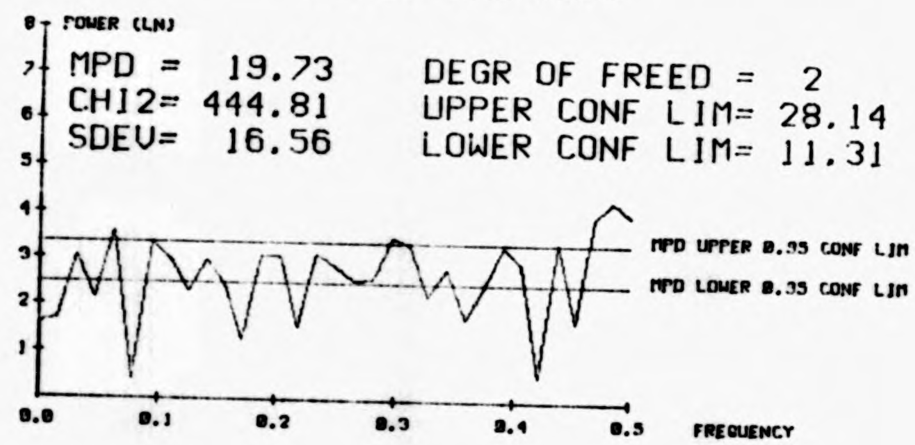


96C,198B261RF106 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	16.9								
0.016	26.9	0.031	13.2	0.047	4.9	0.063	48.6	0.078	9.0
0.094	1.3	0.109	1.8	0.125	6.7	0.141	19.5	0.156	0.0
0.172	80.5	0.188	0.5	0.203	13.2	0.219	24.6	0.234	2.5
0.250	55.5	0.266	7.9	0.281	88.5	0.297	30.1	0.313	8.6
0.328	13.7	0.344	7.4	0.359	34.9	0.375	11.9	0.391	0.4
0.406	10.6	0.422	2.9	0.438	26.1	0.453	19.1	0.469	1.4
0.484	24.0	0.500	15.3						

MEAN POWER DENSITY: 19.05
DEGREES OF FREEDOM = 2
CHISQUARE = 783.07
ST.DEVIATION = 21.59
MPD UPPER 0.95 CONF LIMIT = 30.02
MPD LOWER 0.95 CONF LIMIT = 8.07
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

100C,142B205RF120
POWER SPECTRUM

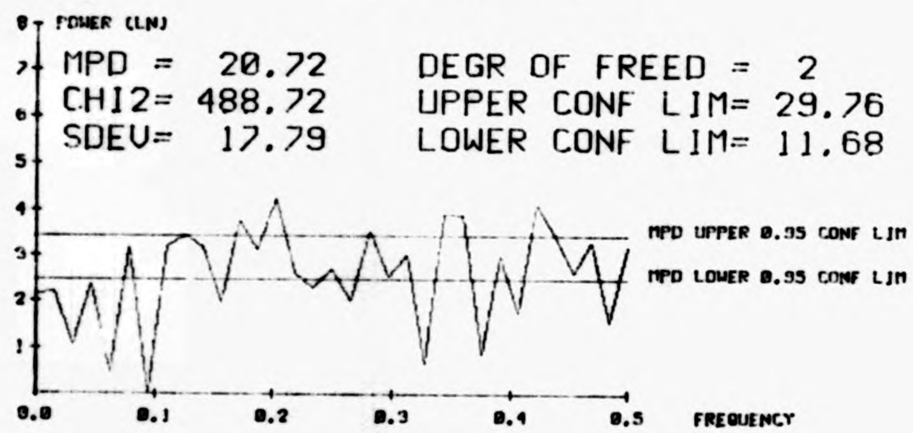


100C,142B205RF120 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.0								
0.016	5.4	0.031	20.8	0.047	8.4	0.063	36.3	0.078	1.5
0.094	28.4	0.109	19.1	0.125	9.8	0.141	19.7	0.156	11.6
0.172	3.4	0.188	22.0	0.203	21.6	0.219	4.5	0.234	22.6
0.250	16.8	0.266	12.5	0.281	12.9	0.297	32.2	0.313	27.7
0.328	9.0	0.344	16.7	0.359	5.5	0.375	11.7	0.391	27.3
0.406	18.3	0.422	1.7	0.438	30.1	0.453	5.5	0.469	52.0
0.484	75.6	0.500	55.5						

MEAN POWER DENSITY: 19.73
DEGREES OF FREEDOM = 2
CHISQUARE = 444.81
ST.DEVIATION = 16.56
MPD UPPER 0.95 CONF LIMIT = 28.14
MPD LOWER 0.95 CONF LIMIT = 11.31
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

101C,192B255RF78
POWER SPECTRUM

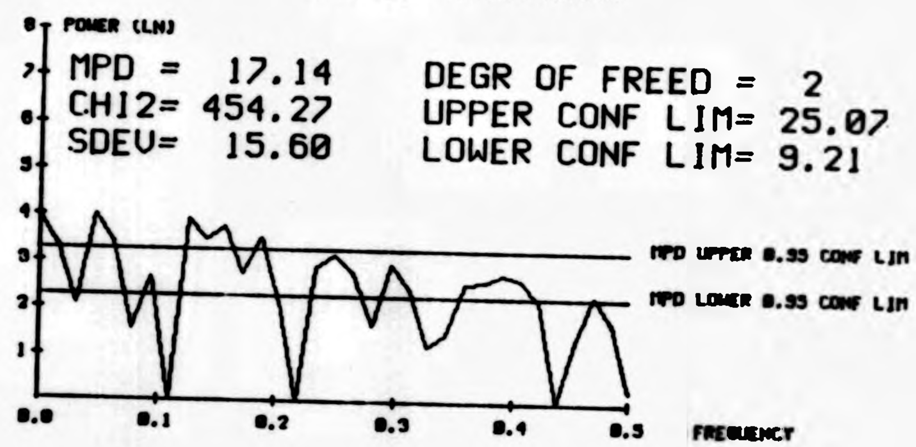


101C,192B255RF78 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.6								
0.016	9.0	0.031	2.9	0.047	10.7	0.063	1.5	0.078	23.8
0.094	0.6	0.109	24.4	0.125	31.0	0.141	24.0	0.156	7.2
0.172	43.2	0.188	23.0	0.203	68.7	0.219	13.6	0.234	9.7
0.250	14.6	0.266	7.5	0.281	33.3	0.297	12.3	0.313	20.4
0.328	1.9	0.344	51.0	0.359	49.1	0.375	2.3	0.391	20.4
0.406	5.5	0.422	62.7	0.438	31.6	0.453	13.3	0.469	27.1
0.484	4.5	0.500	24.8						

MEAN POWER DENSITY: 20.72
DEGREES OF FREEDOM = 2
CHISQUARE = 488.72
ST.DEVIATION = 17.79
MPD UPPER 0.95 CONF LIMIT = 29.76
MPD LOWER 0.95 CONF LIMIT = 11.68
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

102C,101B164RF102
POWER SPECTRUM

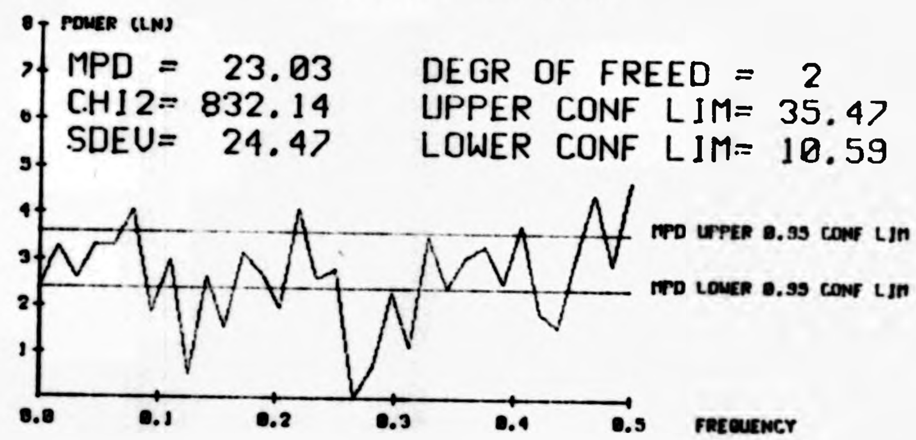


102C,101B164RF102 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	53.1								
0.016	27.3	0.031	7.8	0.047	55.3	0.063	30.2	0.078	4.6
0.094	14.0	0.109	0.8	0.125	51.3	0.141	32.8	0.156	42.9
0.172	15.3	0.188	33.4	0.203	8.3	0.219	0.5	0.234	17.6
0.250	23.5	0.266	15.8	0.281	5.2	0.297	19.5	0.313	11.0
0.328	3.3	0.344	4.3	0.359	13.0	0.375	13.3	0.391	16.1
0.406	14.2	0.422	9.1	0.438	0.9	0.453	3.9	0.469	10.3
0.484	5.9	0.500	1.3						

MEAN POWER DENSITY: 17.14
DEGREES OF FREEDOM = 2
CHISQUARE = 454.27
ST.DEVIATION = 15.60
MPD UPPER 0.95 CONF LIMIT = 25.07
MPD LOWER 0.95 CONF LIMIT = 9.21
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 21

103C,158B221RF65
POWER SPECTRUM

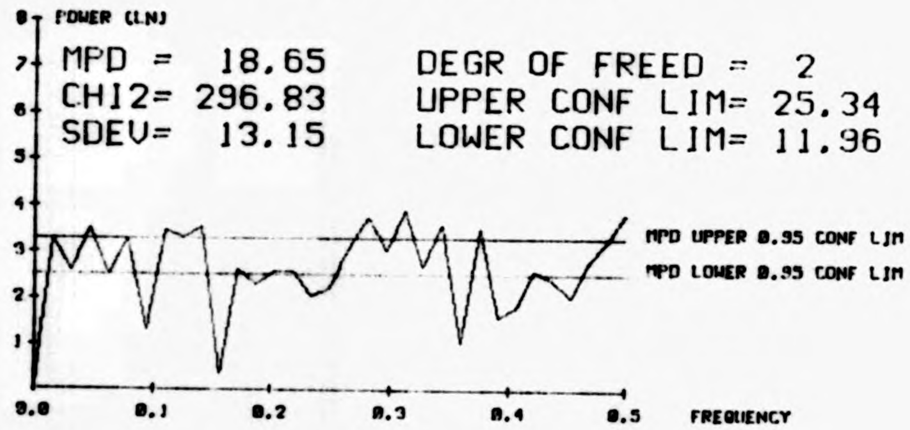


103C,158B221RF65 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.2								
0.016	26.6	0.031	13.4	0.047	27.3	0.063	28.0	0.078	57.8
0.094	6.4	0.109	20.4	0.125	1.6	0.141	13.7	0.156	4.6
0.172	23.5	0.188	15.0	0.203	7.1	0.219	60.1	0.234	13.4
0.250	16.6	0.266	0.5	0.281	2.0	0.297	10.3	0.313	3.1
0.328	33.9	0.344	10.9	0.359	21.4	0.375	27.7	0.391	12.3
0.406	42.9	0.422	6.5	0.438	4.7	0.453	22.5	0.469	83.6
0.484	18.4	0.500	112.8						

MEAN POWER DENSITY: 23.03
DEGREES OF FREEDOM = 2
CHISQUARE = 832.14
ST.DEVIATION = 24.47
MPD UPPER 0.95 CONF LIMIT = 35.47
MPD LOWER 0.95 CONF LIMIT = 10.59
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 10
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 15

104C,151B214RF118
POWER SPECTRUM



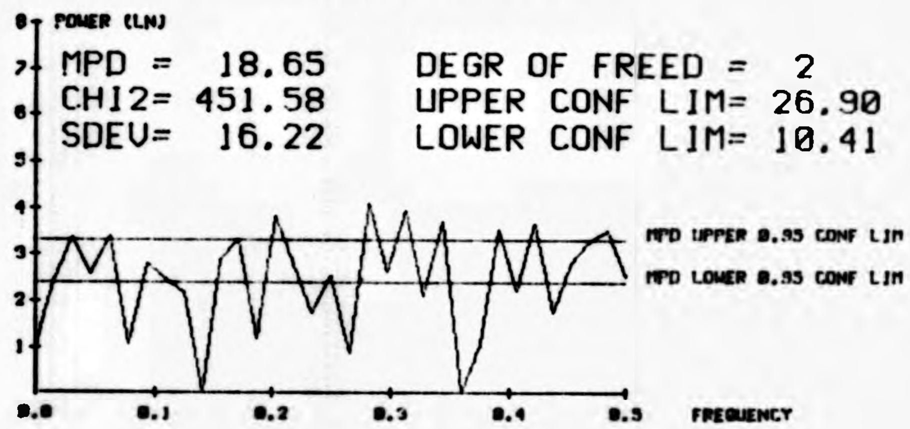
104C,151B214RF118 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.1								
0.016	25.4	0.031	12.9	0.047	33.0	0.063	12.0	0.078	25.5
0.094	3.6	0.109	31.0	0.125	26.1	0.141	34.2	0.156	1.4
0.172	13.5	0.188	9.9	0.203	12.8	0.219	12.7	0.234	7.6
0.250	9.0	0.266	21.6	0.281	40.9	0.297	19.8	0.313	49.2
0.328	14.3	0.344	35.0	0.359	2.7	0.375	32.9	0.391	4.8
0.406	6.0	0.422	13.0	0.438	10.7	0.453	7.4	0.469	16.0
0.484	24.4	0.500	45.1						

MEAN POWER DENSITY: 18.65
DEGREES OF FREEDOM = 2
CHISQUARE = 296.83
ST.DEVIATION = 13.15
MPD UPPER 0.95 CONF LIMIT = 25.34
MPD LOWER 0.95 CONF LIMIT = 11.96
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

11ØC,201B264RF94

POWER SPECTRUM

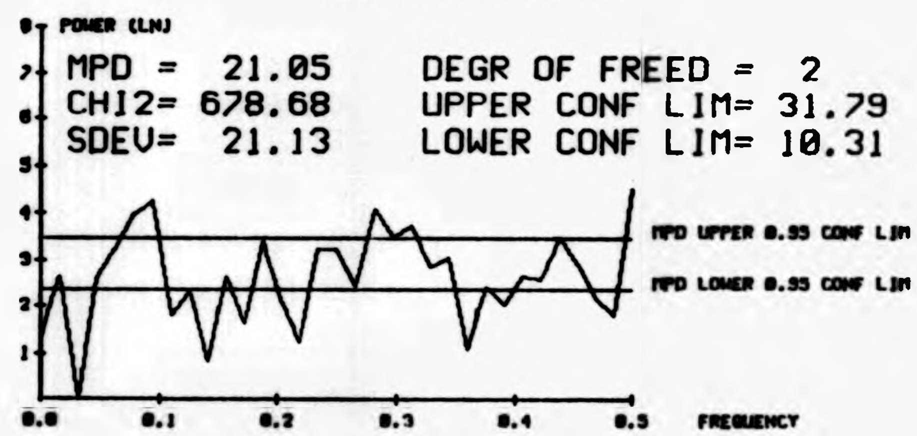


110C,201B264RF94 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.7								
0.016	11.1	0.031	28.4	0.047	12.7	0.063	29.5	0.078	2.8
0.094	16.7	0.109	11.5	0.125	8.8	0.141	0.5	0.156	18.1
0.172	28.2	0.188	3.2	0.203	47.4	0.219	16.0	0.234	5.6
0.250	12.5	0.266	2.3	0.281	61.2	0.297	13.3	0.313	52.8
0.328	8.1	0.344	41.2	0.359	0.3	0.375	2.9	0.391	34.7
0.406	9.1	0.422	39.1	0.438	5.7	0.453	16.4	0.469	26.3
0.484	33.9	0.500	12.4						

MEAN POWER DENSITY: 18.65
DEGREES OF FREEDOM = 2
CHISQUARE = 451.58
ST.DEVIATION = 16.22
MPD UPPER 0.95 CONF LIMIT = 26.90
MPD LOWER 0.95 CONF LIMIT = 10.41
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

111C,161B224RF96
POWER SPECTRUM

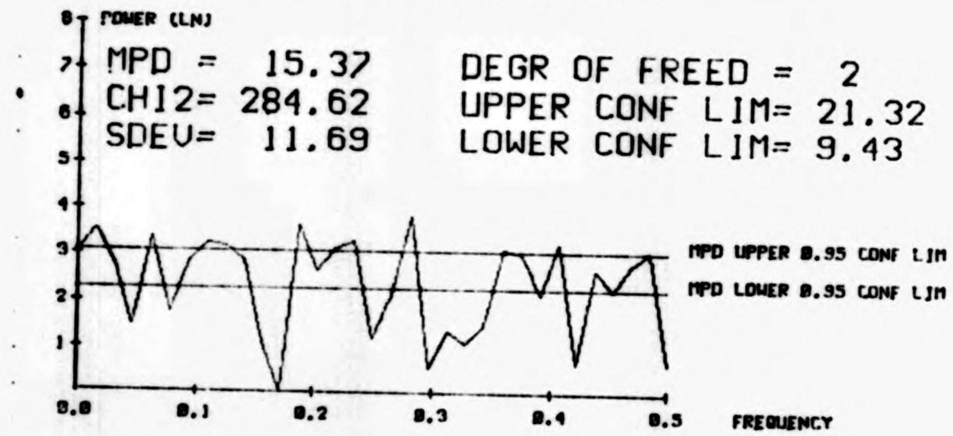


111C,161B224RF96 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.6								
0.016	14.1	0.031	0.8	0.047	13.2	0.063	25.3	0.078	51.5
0.094	69.7	0.109	5.7	0.125	9.8	0.141	2.3	0.156	13.8
0.172	4.9	0.188	29.8	0.203	8.5	0.219	3.3	0.234	25.3
0.250	25.3	0.266	11.1	0.281	59.0	0.297	32.9	0.313	41.7
0.328	17.0	0.344	20.7	0.359	2.8	0.375	11.0	0.391	7.5
0.406	13.8	0.422	12.9	0.438	32.5	0.453	17.8	0.469	8.4
0.484	5.7	0.500	92.8						

MEAN POWER DENSITY: 21.05
DEGREES OF FREEDOM = 2
CHISQUARE = 678.68
ST.DEVIATION = 21.13
MPD UPPER 0.95 CONF LIMIT = 31.79
MPD LOWER 0.95 CONF LIMIT = 10.31
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

113C,101B164RF35
POWER SPECTRUM

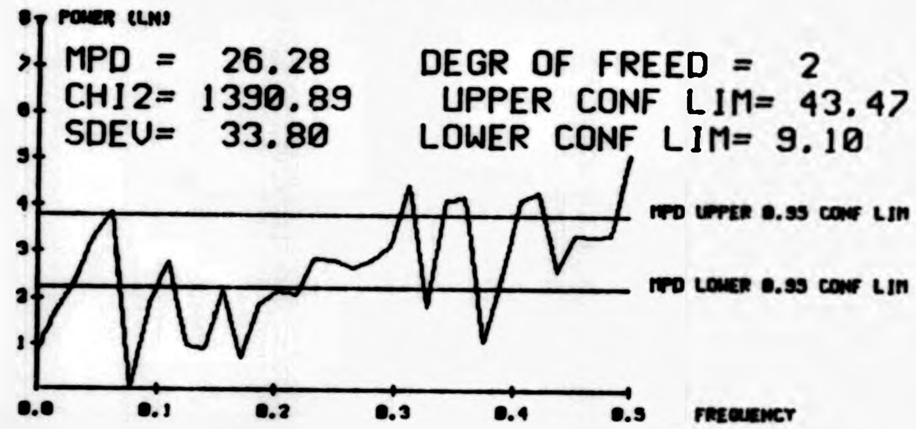


113C,101B164RF35 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	19.8								
0.016	33.4	0.031	16.0	0.047	4.2	0.063	28.6	0.078	5.6
0.094	16.9	0.109	25.4	0.125	23.8	0.141	17.1	0.156	3.0
0.172	0.8	0.188	38.2	0.203	13.8	0.219	22.5	0.234	26.4
0.250	3.1	0.266	8.3	0.281	45.9	0.297	1.7	0.313	3.9
0.328	2.9	0.344	4.5	0.359	22.2	0.375	20.3	0.391	8.2
0.406	25.5	0.422	1.9	0.438	14.5	0.453	9.2	0.469	16.1
0.484	21.7	0.500	1.9						

MEAN POWER DENSITY: 15.37
DEGREES OF FREEDOM = 2
CHISQUARE = 284.62
ST.DEVIATION = 11.69
MPD UPPER 0.95 CONF LIMIT = 21.32
MPD LOWER 0.95 CONF LIMIT = 9.43
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

114C,201B264RF104
POWER SPECTRUM

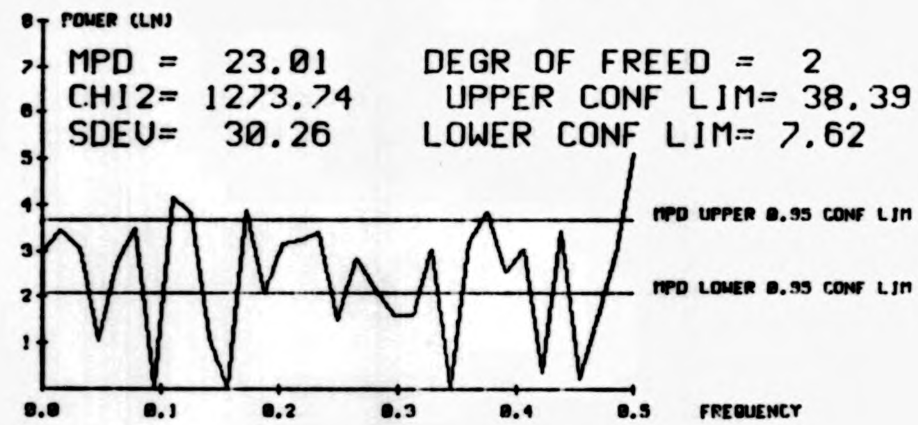


114C,201B264RF104 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.2								
0.016	5.6	0.031	10.2	0.047	26.8	0.063	47.0	0.078	0.5
0.094	6.6	0.109	15.6	0.125	2.6	0.141	2.4	0.156	8.8
0.172	2.0	0.188	6.5	0.203	8.8	0.219	8.2	0.234	17.2
0.250	16.5	0.266	13.8	0.281	16.2	0.297	22.9	0.313	83.4
0.328	6.2	0.344	61.2	0.359	63.6	0.375	2.8	0.391	11.6
0.406	61.2	0.422	73.0	0.438	12.7	0.453	29.2	0.469	27.2
0.484	28.7	0.500	166.1						

MEAN POWER DENSITY: 26.28
DEGREES OF FREEDOM = 2
CHISQUARE = 1390.89
ST.DEVIATION = 33.80
MPD UPPER 0.95 CONF LIMIT = 43.47
MPD LOWER 0.95 CONF LIMIT = 9.10
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

130C,151B214RF38
POWER SPECTRUM

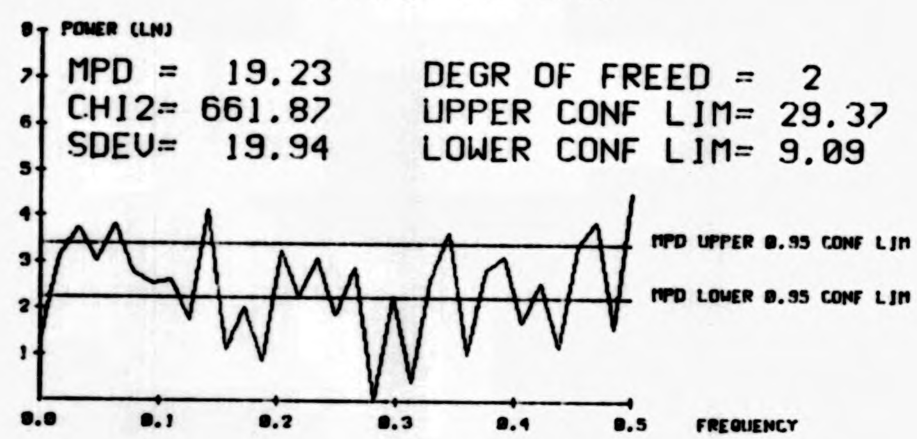


130C,151B214RF38 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	19.1								
0.016	31.0	0.031	21.0	0.047	2.8	0.063	15.9	0.078	32.8
0.094	0.9	0.109	63.1	0.125	45.3	0.141	2.9	0.156	0.4
0.172	49.4	0.188	7.8	0.203	23.7	0.219	25.2	0.234	30.0
0.250	4.2	0.266	16.9	0.281	8.2	0.297	4.8	0.313	4.7
0.328	21.1	0.344	0.2	0.359	25.0	0.375	47.0	0.391	12.3
0.406	21.2	0.422	1.4	0.438	30.9	0.453	1.2	0.469	4.6
0.484	18.5	0.500	165.6						

MEAN POWER DENSITY: 23.01
DEGREES OF FREEDOM = 2
CHISQUARE = 1273.74
ST.DEVIATION = 30.26
MPD UPPER 0.95 CONF LIMIT = 38.39
MPD LOWER 0.95 CONF LIMIT = 7.62
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 16

140C,201B264RF96
POWER SPECTRUM



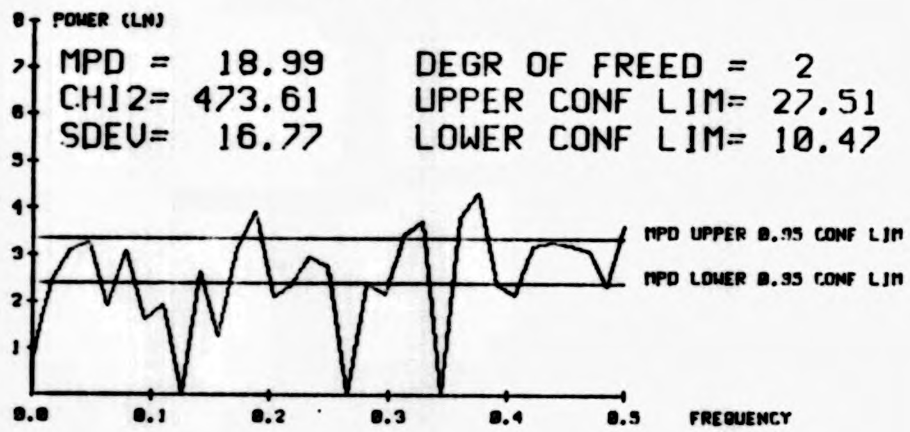
140C,201B264RF96 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.5								
0.016	22.3	0.031	41.8	0.047	20.3	0.063	44.0	0.078	15.9
0.094	12.4	0.109	13.6	0.125	5.5	0.141	62.5	0.156	3.0
0.172	7.4	0.188	2.3	0.203	25.3	0.219	9.3	0.234	21.4
0.250	6.3	0.266	17.6	0.281	0.6	0.297	9.5	0.313	1.5
0.328	13.4	0.344	38.5	0.359	2.7	0.375	16.9	0.391	22.8
0.406	5.3	0.422	13.0	0.438	3.2	0.453	29.3	0.469	47.6
0.484	4.7	0.500	90.9						

MEAN POWER DENSITY: 19.23
DEGREES OF FREEDOM = 2
CHISQUARE = 661.87
ST.DEVIATION = 19.94
MPD UPPER 0.95 CONF LIMIT = 29.37
MPD LOWER 0.95 CONF LIMIT = 9.09
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

141C,201B264RF88

POWER SPECTRUM

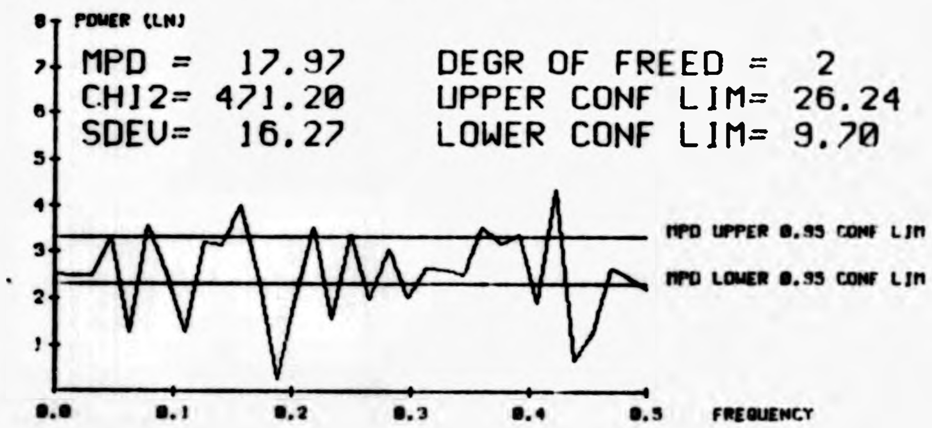


141C,201B264RF88 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.1								
0.016	11.3	0.031	22.8	0.047	27.0	0.063	6.7	0.078	21.4
0.094	4.9	0.109	6.7	0.125	0.3	0.141	14.3	0.156	3.4
0.172	23.2	0.188	51.4	0.203	8.0	0.219	10.6	0.234	19.1
0.250	15.0	0.266	0.6	0.281	10.5	0.297	8.7	0.313	31.3
0.328	41.2	0.344	0.6	0.359	45.1	0.375	76.1	0.391	10.8
0.406	8.2	0.422	24.5	0.438	27.0	0.453	24.2	0.469	21.8
0.484	10.4	0.500	37.6						

MEAN POWER DENSITY: 18.99
DEGREES OF FREEDOM = 2
CHISQUARE = 473.61
ST.DEVIATION = 16.77
MPD UPPER 0.95 CONF LIMIT = 27.51
MPD LOWER 0.95 CONF LIMIT = 10.47
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

1RUS,301B364RF104
POWER SPECTRUM

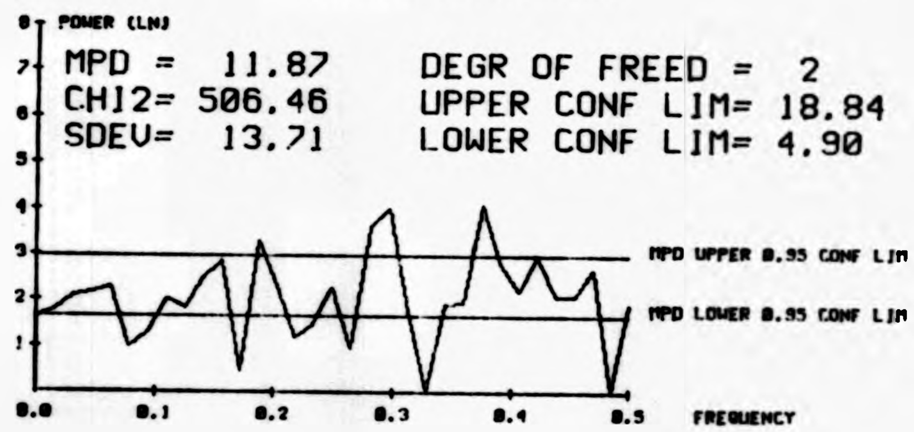


1RUS,301B364RF104   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.7								
0.016	11.9	0.031	12.2	0.047	27.1	0.063	3.4	0.078	35.4
0.094	12.7	0.109	3.4	0.125	24.1	0.141	22.7	0.156	54.4
0.172	10.5	0.188	1.3	0.203	7.7	0.219	33.3	0.234	4.6
0.250	29.0	0.266	7.2	0.281	20.6	0.297	7.4	0.313	14.1
0.328	13.4	0.344	11.9	0.359	34.4	0.375	23.8	0.391	28.7
0.406	6.5	0.422	78.9	0.438	1.9	0.453	3.5	0.469	13.9
0.484	11.7	0.500	8.9						

MEAN POWER DENSITY: 17.97
DEGREES OF FREEDOM = 2
CHISQUARE = 471.20
ST.DEVIATION = 16.27
MPD UPPER 0.95 CONF LIMIT = 26.24
MPD LOWER 0.95 CONF LIMIT = 9.70
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

2RUS,201B264RF118
POWER SPECTRUM

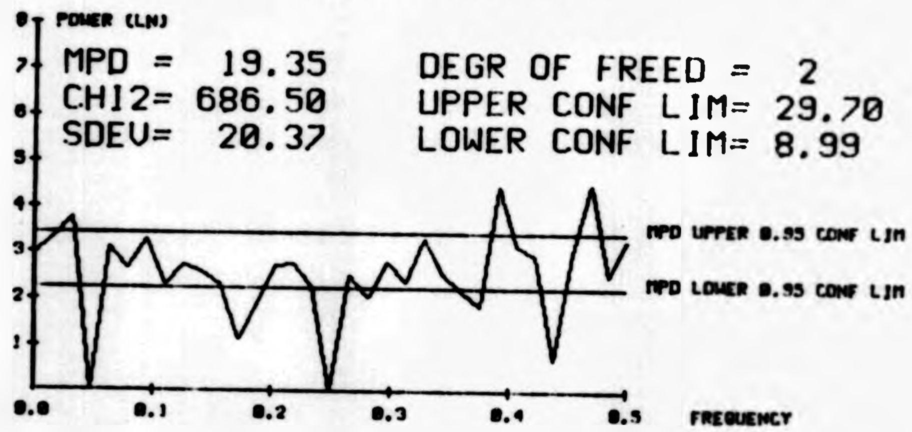


2RUS,201B264RF118 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.0								
0.016	5.9	0.031	7.9	0.047	8.6	0.063	9.7	0.078	2.6
0.094	3.6	0.109	7.3	0.125	6.2	0.141	12.0	0.156	17.2
0.172	1.5	0.188	26.5	0.203	9.8	0.219	3.1	0.234	4.2
0.250	9.2	0.266	2.5	0.281	36.5	0.297	55.0	0.313	5.5
0.328	0.2	0.344	6.5	0.359	6.8	0.375	58.1	0.391	15.9
0.406	8.7	0.422	18.8	0.438	7.8	0.453	7.6	0.469	14.2
0.484	0.7	0.500	6.6						

MEAN POWER DENSITY: 11.87
DEGREES OF FREEDOM = 2
CHISQUARE = 506.46
ST.DEVIATION = 13.71
MPD UPPER 0.95 CONF LIMIT = 18.84
MPD LOWER 0.95 CONF LIMIT = 4.90
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 4
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 8
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 12

3RUS,301B364RF98
POWER SPECTRUM



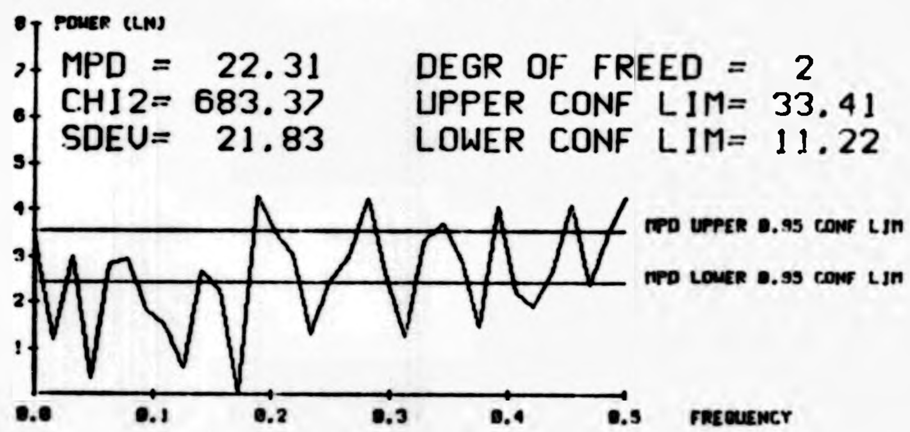
3RUS,301B364RF98 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	19.1								
0.016	27.4	0.031	42.7	0.047	0.5	0.063	23.0	0.078	14.1
0.094	26.3	0.109	9.9	0.125	15.3	0.141	12.8	0.156	9.8
0.172	3.1	0.188	6.6	0.203	15.2	0.219	15.9	0.234	9.8
0.250	0.4	0.266	12.4	0.281	7.7	0.297	16.4	0.313	10.6
0.328	27.2	0.344	12.3	0.359	8.7	0.375	6.3	0.391	89.4
0.406	24.0	0.422	18.7	0.438	2.0	0.453	21.3	0.469	90.6
0.484	12.0	0.500	26.9						

MEAN POWER DENSITY: 19.35
DEGREES OF FREEDOM = 2
CHISQUARE = 686.50
ST.DEVIATION = 20.37
MPD UPPER 0.95 CONF LIMIT = 29.70
MPD LOWER 0.95 CONF LIMIT = 8.99
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 3
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 8
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 11

4RUS,301B364RF168

POWER SPECTRUM

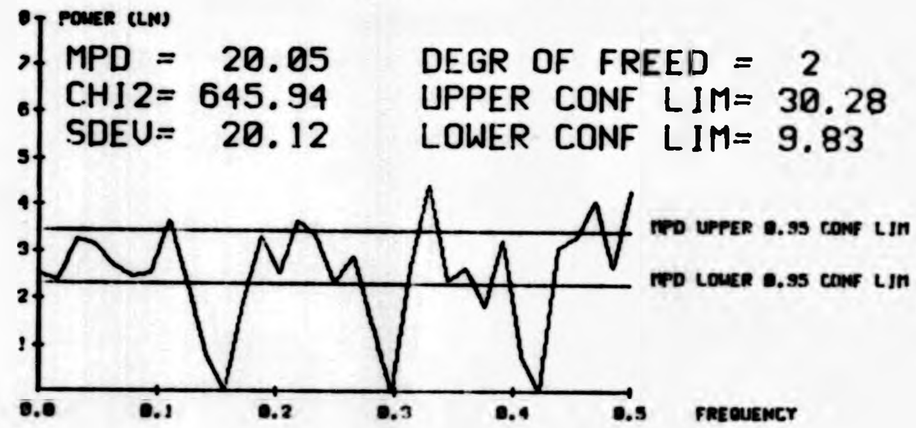


4RUS,301B364RF168 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	30.4								
0.016	3.2	0.031	19.8	0.047	1.4	0.063	17.4	0.078	19.3
0.094	6.2	0.109	4.4	0.125	1.8	0.141	14.5	0.156	9.3
0.172	0.5	0.188	72.4	0.203	34.4	0.219	20.9	0.234	3.6
0.250	11.4	0.266	19.7	0.281	69.5	0.297	11.9	0.313	3.5
0.328	29.1	0.344	41.1	0.359	19.0	0.375	4.2	0.391	59.4
0.406	9.0	0.422	6.5	0.438	15.4	0.453	62.5	0.469	10.8
0.484	33.0	0.500	70.9						

MEAN POWER DENSITY: 22.31
DEGREES OF FREEDOM = 2
CHISQUARE = 683.37
ST.DEVIATION = 21.83
MPD UPPER 0.95 CONF LIMIT = 33.41
MPD LOWER 0.95 CONF LIMIT = 11.22
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

5RUS,301B364RF136
POWER SPECTRUM

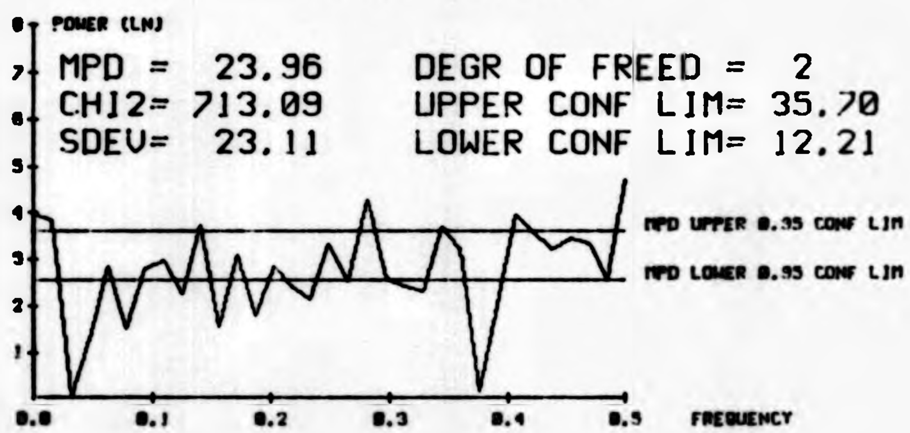


5RUS,301B364RF136 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.3								
0.016	10.5	0.031	25.1	0.047	22.9	0.063	14.7	0.078	11.3
0.094	12.6	0.109	38.8	0.125	9.3	0.141	2.2	0.156	0.4
0.172	6.9	0.188	27.2	0.203	12.7	0.219	38.4	0.234	27.4
0.250	10.4	0.266	17.7	0.281	4.1	0.297	0.7	0.313	14.7
0.328	85.7	0.344	10.4	0.359	13.8	0.375	6.0	0.391	25.3
0.406	2.2	0.422	0.8	0.438	21.4	0.453	28.1	0.469	58.0
0.484	13.9	0.500	75.8						

MEAN POWER DENSITY: 20.05
DEGREES OF FREEDOM = 2
CHISQUARE = 645.94
ST.DEVIATION = 20.12
MPD UPPER 0.95 CONF LIMIT = 30.28
MPD LOWER 0.95 CONF LIMIT = 9.83
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 9
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 14

1FRK,301B364RF152
POWER SPECTRUM



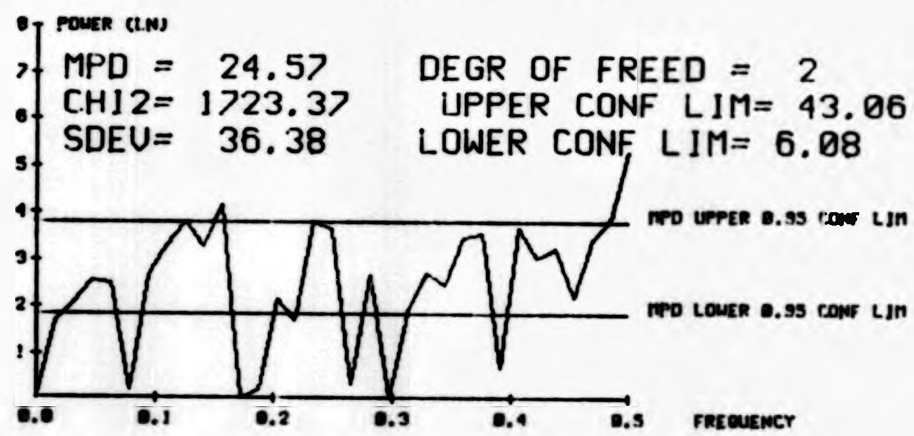
1FRK,301B364RF152 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	51.5								
0.016	44.2	0.031	0.3	0.047	3.6	0.063	17.2	0.078	4.4
0.094	16.6	0.109	19.2	0.125	9.5	0.141	41.2	0.156	4.5
0.172	21.7	0.188	5.9	0.203	17.0	0.219	10.9	0.234	8.4
0.250	28.0	0.266	12.3	0.281	73.3	0.297	12.9	0.313	11.2
0.328	9.8	0.344	39.2	0.359	24.5	0.375	1.1	0.391	7.3
0.406	51.9	0.422	35.8	0.438	24.4	0.453	31.1	0.469	28.1
0.484	12.7	0.500	110.8						

MEAN POWER DENSITY: 23.96
DEGREES OF FREEDOM = 2
CHISQUARE = 713.09
ST.DEVIATION = 23.11
MPD UPPER 0.95 CONF LIMIT = 35.70
MPD LOWER 0.95 CONF LIMIT = 12.21
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

LAB,401B464RF136

POWER SPECTRUM

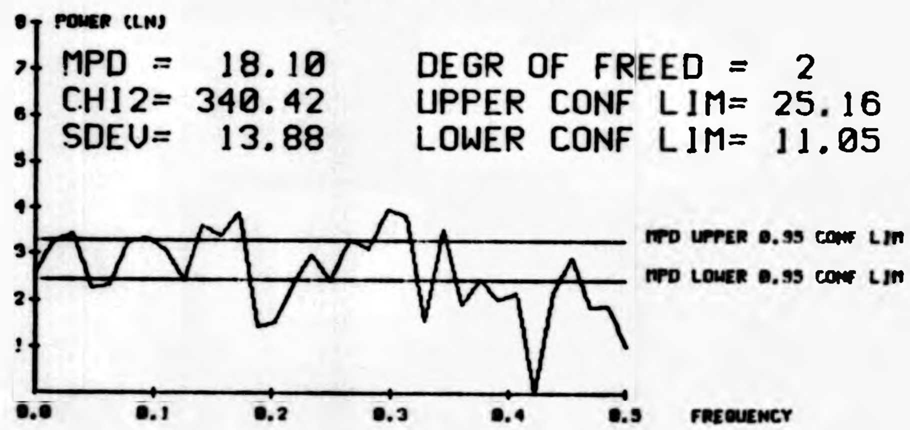


LAB,401B464RF136 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.3								
0.016	5.4	0.031	8.2	0.047	12.9	0.063	11.9	0.078	1.2
0.094	14.9	0.109	27.3	0.125	44.2	0.141	26.8	0.156	63.5
0.172	0.1	0.188	1.2	0.203	8.7	0.219	5.3	0.234	45.0
0.250	38.5	0.266	1.3	0.281	14.6	0.297	0.6	0.313	6.6
0.328	15.3	0.344	11.3	0.359	32.0	0.375	35.2	0.391	1.9
0.406	40.1	0.422	20.9	0.438	25.6	0.453	8.5	0.469	31.2
0.484	45.8	0.500	204.6						

MEAN POWER DENSITY: 24.57
DEGREES OF FREEDOM = 2
CHISQUARE = 1723.37
ST.DEVIATION = 36.38
MPD UPPER 0.95 CONF LIMIT = 43.06
MPD LOWER 0.95 CONF LIMIT = 6.08
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 9
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 14

BRU,301B364RF136
POWER SPECTRUM

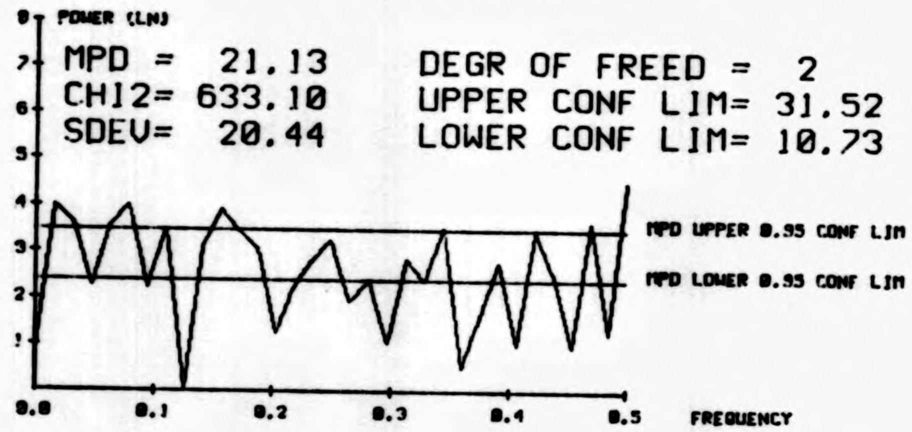


BRU,301B364RF136 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	13.1								
0.016	25.2	0.031	29.5	0.047	9.5	0.063	10.3	0.078	25.2
0.094	27.3	0.109	20.5	0.125	10.9	0.141	36.6	0.156	29.3
0.172	48.9	0.188	4.1	0.203	4.6	0.219	10.7	0.234	19.6
0.250	10.9	0.266	27.0	0.281	22.0	0.297	53.2	0.313	44.4
0.328	4.5	0.344	33.3	0.359	6.5	0.375	11.3	0.391	7.4
0.406	8.6	0.422	0.4	0.438	8.9	0.453	18.4	0.469	6.2
0.484	6.6	0.500	2.7						

MEAN POWER DENSITY: 18.10
DEGREES OF FREEDOM = 2
CHISQUARE = 340.42
ST.DEVIATION = 13.88
MPD UPPER 0.95 CONF LIMIT = 25.16
MPD LOWER 0.95 CONF LIMIT = 11.05
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

CHOM,301B364RF104
POWER SPECTRUM

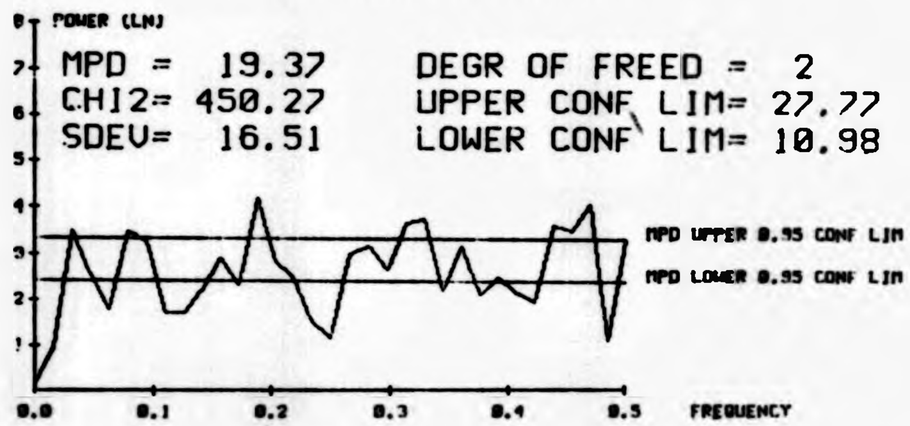


CHOM,301B364RF104 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.2								
0.016	53.6	0.031	36.9	0.047	9.3	0.063	35.1	0.078	54.0
0.094	8.9	0.109	33.0	0.125	0.0	0.141	21.5	0.156	51.4
0.172	31.0	0.188	20.7	0.203	3.3	0.219	9.3	0.234	16.6
0.250	25.0	0.266	6.9	0.281	10.7	0.297	2.7	0.313	17.2
0.328	10.5	0.344	33.7	0.359	1.6	0.375	5.0	0.391	15.8
0.406	2.6	0.422	31.5	0.438	11.8	0.453	2.5	0.469	37.8
0.484	3.3	0.500	91.6						

MEAN POWER DENSITY: 21.13
DEGREES OF FREEDOM = 2
CHISQUARE = 633.10
ST.DEVIATION = 20.44
MPD UPPER 0.95 CONF LIMIT = 31.52
MPD LOWER 0.95 CONF LIMIT = 10.73
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

1REC,201B264RF100
POWER SPECTRUM

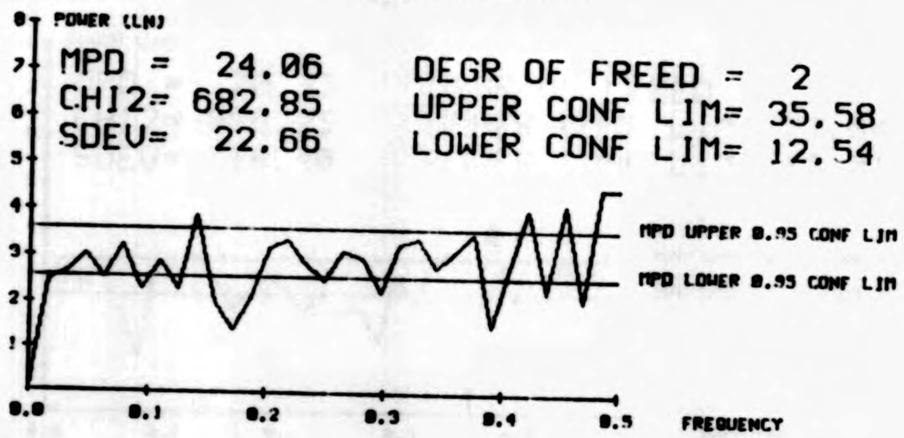


1REC,201B264RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.1								
0.016	2.5	0.031	32.3	0.047	12.2	0.063	5.8	0.078	32.8
0.094	25.0	0.109	5.3	0.125	5.4	0.141	8.9	0.156	18.3
0.172	10.0	0.188	67.5	0.203	16.8	0.219	11.9	0.234	4.7
0.250	3.2	0.266	21.2	0.281	24.8	0.297	14.6	0.313	39.7
0.328	42.5	0.344	9.2	0.359	24.1	0.375	8.4	0.391	12.5
0.406	8.6	0.422	7.1	0.438	38.3	0.453	33.7	0.469	58.8
0.484	3.0	0.500	28.9						

MEAN POWER DENSITY: 19.37
DEGREES OF FREEDOM = 2
CHISQUARE = 450.27
ST.DEVIATION = 16.51
MPD UPPER 0.95 CONF LIMIT = 27.77
MPD LOWER 0.95 CONF LIMIT = 10.98
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

2REC,251B315RF130
POWER SPECTRUM

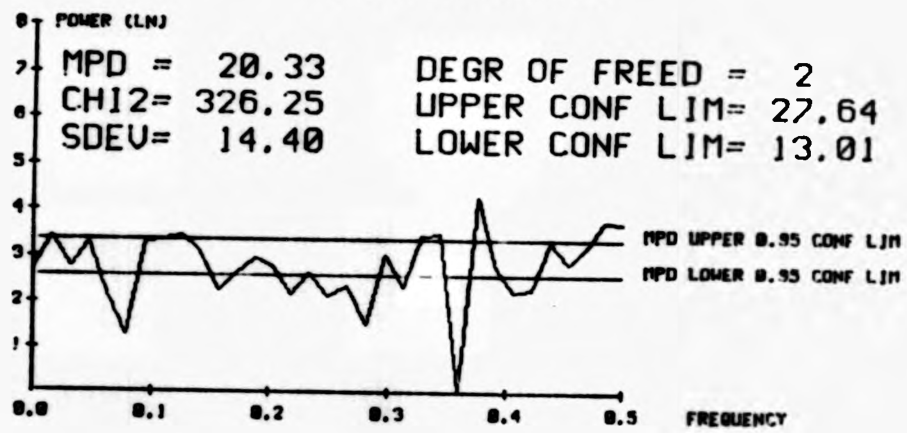


2REC,251B315RF130 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.6								
0.016	11.9	0.031	13.9	0.047	20.5	0.063	12.6	0.078	25.7
0.094	10.0	0.109	18.1	0.125	9.6	0.141	48.4	0.156	7.3
0.172	4.1	0.188	8.2	0.203	24.2	0.219	28.3	0.234	16.8
0.250	11.7	0.266	22.3	0.281	19.6	0.297	9.3	0.313	26.5
0.328	29.6	0.344	15.6	0.359	22.3	0.375	33.8	0.391	4.4
0.406	16.7	0.422	56.9	0.438	9.5	0.453	63.3	0.469	7.7
0.484	91.8	0.500	92.8						

MEAN POWER DENSITY: 24.06
DEGREES OF FREEDOM = 2
CHISQUARE = 682.85
ST.DEVIATION = 22.66
MPD UPPER 0.95 CONF LIMIT = 35.58
MPD LOWER 0.95 CONF LIMIT = 12.54
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

HRLD,201B264RF116
POWER SPECTRUM

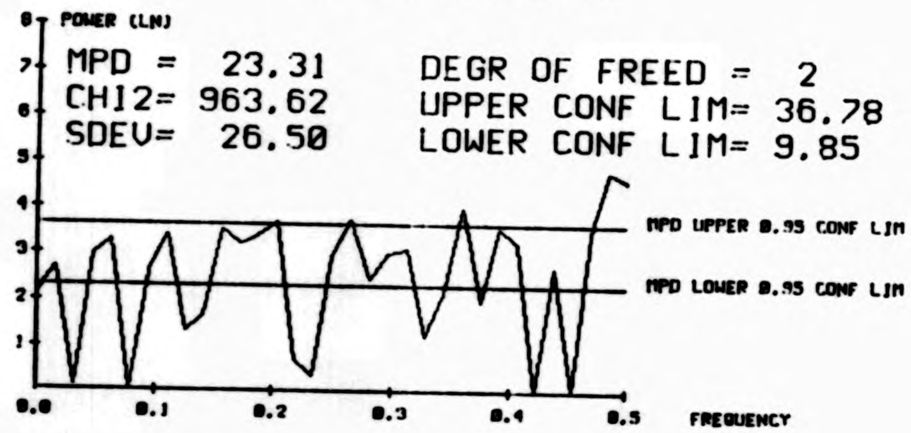


HRLD,201B264RF116 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.1								
0.016	30.6	0.031	15.5	0.047	26.4	0.063	8.6	0.078	3.5
0.094	27.9	0.109	28.4	0.125	30.8	0.141	21.9	0.156	9.2
0.172	14.1	0.188	19.4	0.203	16.0	0.219	8.5	0.234	13.8
0.250	8.3	0.266	10.5	0.281	4.4	0.297	21.1	0.313	10.1
0.328	30.8	0.344	33.0	0.359	0.3	0.375	73.5	0.391	15.5
0.406	9.2	0.422	9.7	0.438	27.4	0.453	17.0	0.469	25.7
0.484	43.6	0.500	40.9						

MEAN POWER DENSITY: 20.33
DEGREES OF FREEDOM = 2
CHISQUARE = 326.25
ST.DEVIATION = 14.40
MPD UPPER 0.95 CONF LIMIT = 27.64
MPD LOWER 0.95 CONF LIMIT = 13.01
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

MAIL,301B364RF270
POWER SPECTRUM

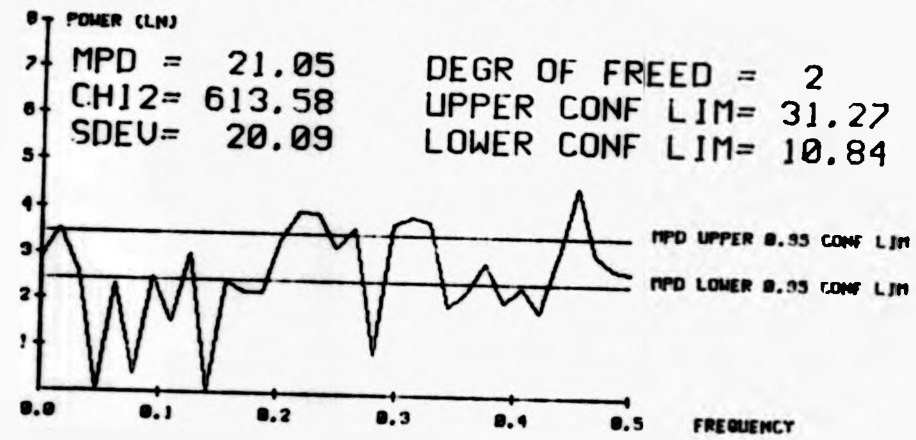


MAIL,301B364RF270 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.3								
0.016	14.4	0.031	1.1	0.047	19.2	0.063	26.9	0.078	0.6
0.094	13.3	0.109	30.1	0.125	3.7	0.141	5.3	0.156	33.2
0.172	24.7	0.188	30.0	0.203	40.3	0.219	2.0	0.234	1.4
0.250	19.0	0.266	41.0	0.281	11.4	0.297	20.1	0.313	21.5
0.328	3.3	0.344	8.6	0.359	55.4	0.375	7.2	0.391	35.6
0.406	24.6	0.422	0.1	0.438	15.1	0.453	0.3	0.469	32.8
0.484	121.0	0.500	98.0						

MEAN POWER DENSITY: 23.31
DEGREES OF FREEDOM = 2
CHISQUARE = 963.62
ST.DEVIATION = 26.50
MPD UPPER 0.95 CONF LIMIT = 36.78
MPD LOWER 0.95 CONF LIMIT = 9.85
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

GUAR,201B264RF76
POWER SPECTRUM

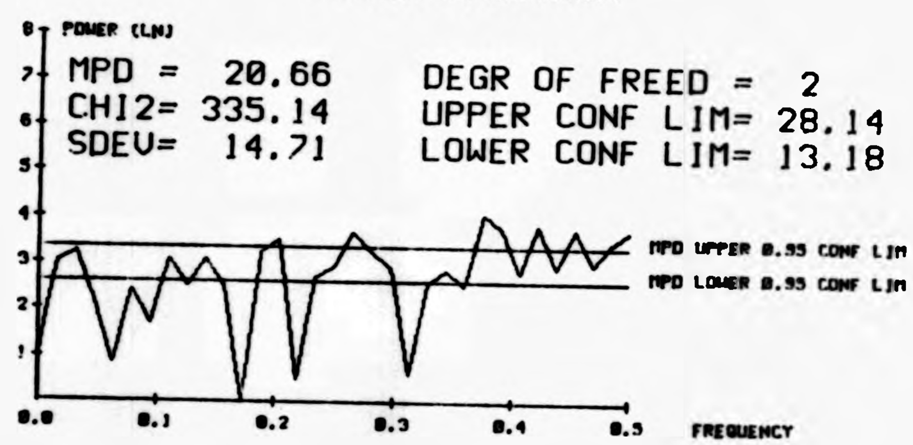


GUAR,201B264RF76 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	18.0								
0.016	34.4	0.031	12.9	0.047	0.9	0.063	10.2	0.078	1.4
0.094	11.8	0.109	4.3	0.125	20.4	0.141	0.0	0.156	10.8
0.172	8.7	0.188	8.6	0.203	28.2	0.219	52.3	0.234	49.7
0.250	23.7	0.266	36.2	0.281	2.3	0.297	41.1	0.313	48.9
0.328	43.2	0.344	6.6	0.359	9.5	0.375	17.7	0.391	7.3
0.406	10.5	0.422	6.0	0.438	21.8	0.453	95.1	0.469	21.4
0.484	16.0	0.500	14.5						

MEAN POWER DENSITY: 21.05
DEGREES OF FREEDOM = 2
CHISQUARE = 613.58
ST.DEVIATION = 20.09
MPD UPPER 0.95 CONF LIMIT = 31.27
MPD LOWER 0.95 CONF LIMIT = 10.84
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

PAD1,201B264RF116
POWER SPECTRUM

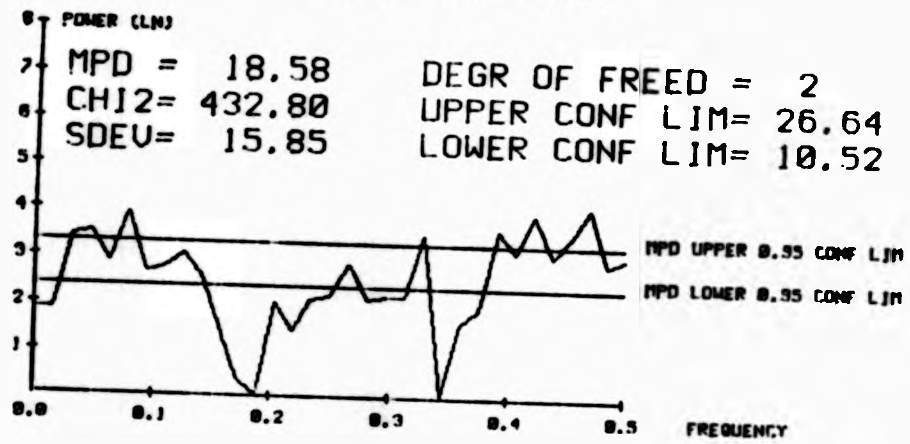


PAD1,201B264RF116   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.9								
0.016	20.8	0.031	25.4	0.047	8.2	0.063	2.3	0.078	11.1
0.094	5.3	0.109	21.5	0.125	11.9	0.141	21.6	0.156	12.0
0.172	1.0	0.188	25.7	0.203	34.4	0.219	1.6	0.234	14.8
0.250	18.4	0.266	38.9	0.281	25.4	0.297	17.5	0.313	1.9
0.328	13.1	0.344	17.4	0.359	12.0	0.375	59.3	0.391	43.3
0.406	15.5	0.422	46.9	0.438	17.6	0.453	43.1	0.469	19.1
0.484	31.5	0.500	40.6						

MEAN POWER DENSITY: 20.66
DEGREES OF FREEDOM = 2
CHISQUARE = 335.14
ST.DEVIATION = 14.71
MPD UPPER 0.95 CONF LIMIT = 28.14
MPD LOWER 0.95 CONF LIMIT = 13.18
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

PAD2,201B264RF116
POWER SPECTRUM

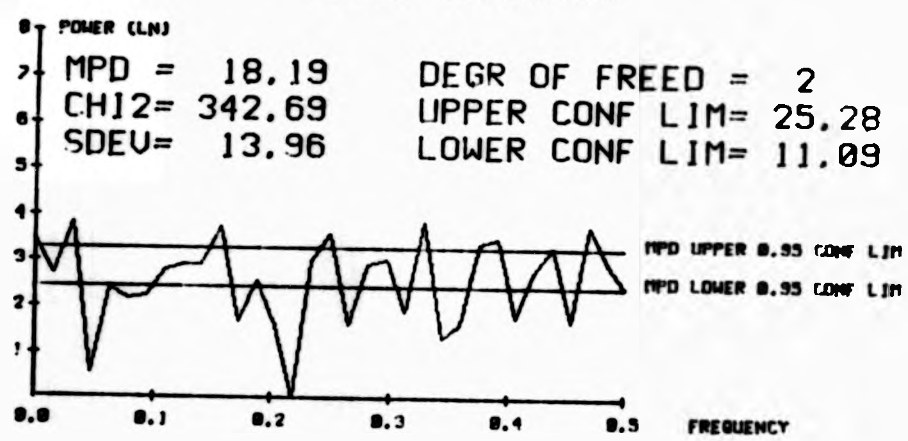


PAD2,201B264RF116 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.5								
0.016	6.5	0.031	31.5	0.047	33.4	0.063	17.9	0.078	51.4
0.094	14.8	0.109	16.7	0.125	21.8	0.141	13.6	0.156	4.4
0.172	1.5	0.188	0.5	0.203	7.6	0.219	4.3	0.234	8.4
0.250	9.1	0.266	17.6	0.281	8.4	0.297	9.1	0.313	8.9
0.328	34.3	0.344	1.1	0.359	5.2	0.375	7.0	0.391	37.9
0.406	23.4	0.422	52.7	0.438	21.7	0.453	33.7	0.469	62.5
0.484	18.2	0.500	21.7						

MEAN POWER DENSITY: 18.58
DEGREES OF FREEDOM = 2
CHISQUARE = 432.80
ST.DEVIATION = 15.85
MPD UPPER 0.95 CONF LIMIT = 26.64
MPD LOWER 0.95 CONF LIMIT = 10.52
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

PAD3,201B264RF100
POWER SPECTRUM

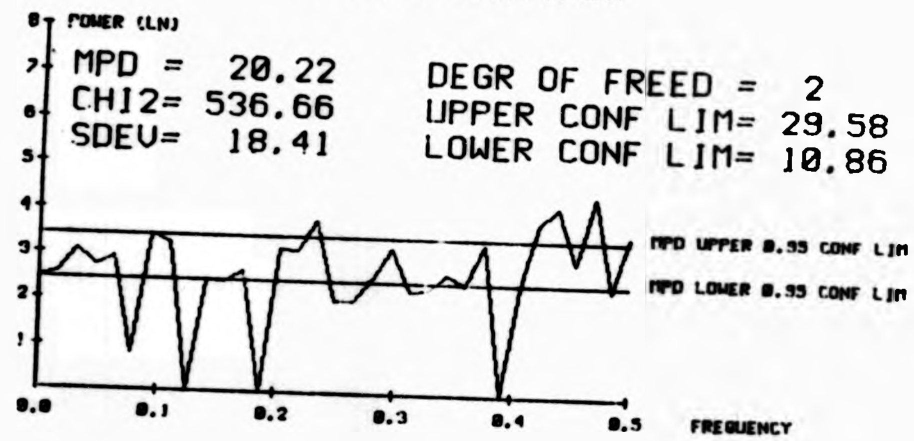


PAD3,201B264RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	31.7								
0.016	14.8	0.031	46.3	0.047	1.6	0.063	10.8	0.078	8.5
0.094	9.2	0.109	16.4	0.125	18.6	0.141	18.4	0.156	42.7
0.172	5.3	0.188	12.9	0.203	4.9	0.219	0.8	0.234	19.7
0.250	36.0	0.266	5.0	0.281	18.7	0.297	20.7	0.313	6.5
0.328	47.9	0.344	3.8	0.359	5.2	0.375	29.6	0.391	33.8
0.406	5.8	0.422	15.7	0.438	27.5	0.453	5.4	0.469	45.3
0.484	19.1	0.500	11.3						

MEAN POWER DENSITY: 18.19
DEGREES OF FREEDOM = 2
CHISQUARE = 342.69
ST.DEVIATION = 13.96
MPD UPPER 0.95 CONF LIMIT = 25.28
MPD LOWER 0.95 CONF LIMIT = 11.09
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

PAD4,251B314RF144
POWER SPECTRUM

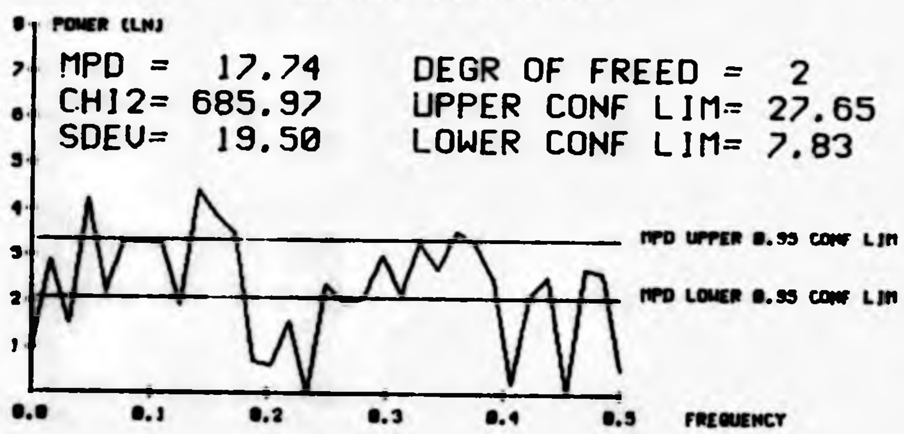


PAD4,251B314RF144 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.6								
0.016	12.9	0.031	21.9	0.047	15.0	0.063	18.3	0.078	2.2
0.094	31.4	0.109	25.7	0.125	0.6	0.141	11.4	0.156	11.0
0.172	14.2	0.188	0.8	0.203	24.0	0.219	23.1	0.234	45.3
0.250	7.4	0.266	7.4	0.281	12.4	0.297	24.5	0.313	9.4
0.328	9.9	0.344	14.2	0.359	10.9	0.375	27.7	0.391	1.1
0.406	11.2	0.422	45.7	0.438	67.8	0.453	18.7	0.469	84.2
0.484	10.1	0.500	35.6						

MEAN POWER DENSITY: 20.22
DEGREES OF FREEDOM = 2
CHISQUARE = 536.66
ST.DEVIATION = 18.41
MPD UPPER 0.95 CONF LIMIT = 29.58
MPD LOWER 0.95 CONF LIMIT = 10.86
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 9
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 15

POOH,201B264RF60
POWER SPECTRUM

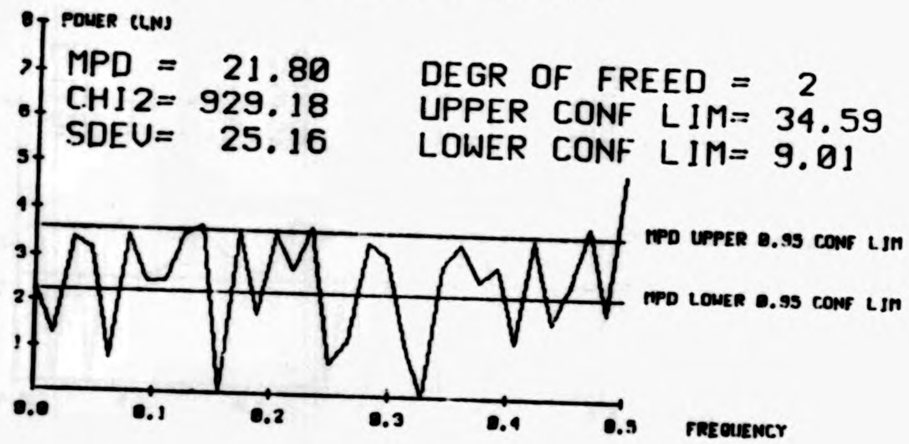


POOH,201B264RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.5								
0.016	17.8	0.031	4.4	0.047	69.9	0.063	8.7	0.078	28.1
0.094	26.1	0.109	25.2	0.125	6.6	0.141	86.1	0.156	47.6
0.172	32.5	0.188	1.9	0.203	1.8	0.219	4.8	0.234	0.1
0.250	10.8	0.266	7.2	0.281	8.1	0.297	20.4	0.313	8.3
0.328	26.9	0.344	14.6	0.359	35.8	0.375	25.1	0.391	12.0
0.406	1.2	0.422	8.4	0.438	12.4	0.453	0.3	0.469	15.0
0.484	13.2	0.500	1.7						

MEAN POWER DENSITY: 17.74
DEGREES OF FREEDOM = 2
CHISQUARE = 685.97
ST.DEVIATION = 19.50
MPD UPPER 0.95 CONF LIMIT = 27.65
MPD LOWER 0.95 CONF LIMIT = 7.83
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

ALIB,201B264RF148
POWER SPECTRUM

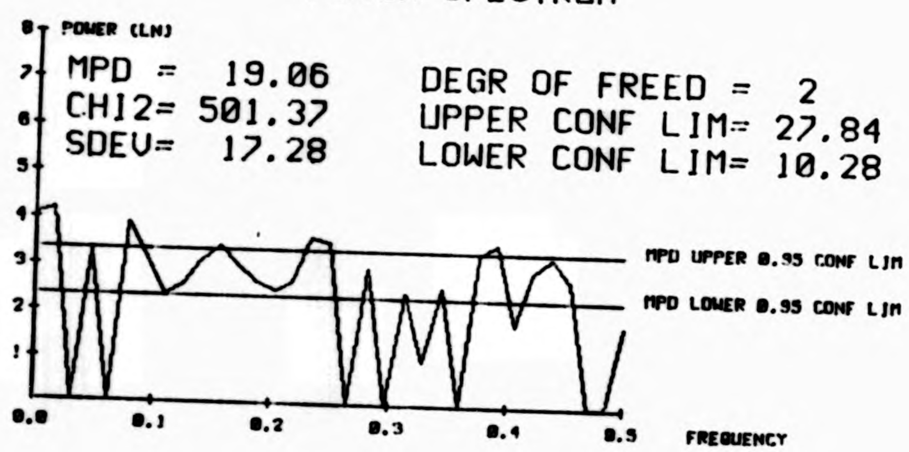


ALIB,201B264RF148 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	10.1								
0.016	3.5	0.031	30.1	0.047	23.2	0.063	2.0	0.078	32.2
0.094	11.5	0.109	12.0	0.125	33.5	0.141	40.1	0.156	0.5
0.172	36.4	0.188	5.5	0.203	35.7	0.219	15.7	0.234	40.2
0.250	1.9	0.266	3.3	0.281	30.5	0.297	21.5	0.313	3.2
0.328	0.6	0.344	18.4	0.359	30.3	0.375	13.0	0.391	18.9
0.406	3.3	0.422	34.1	0.438	5.1	0.453	12.3	0.469	45.5
0.484	6.6	0.500	138.4						

MEAN POWER DENSITY: 21.80
DEGREES OF FREEDOM = 2
CHISQUARE = 929.18
ST.DEVIATION = 25.16
MPD UPPER 0.95 CONF LIMIT = 34.59
MPD LOWER 0.95 CONF LIMIT = 9.01
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

ALIL,201B264RF68
POWER SPECTRUM

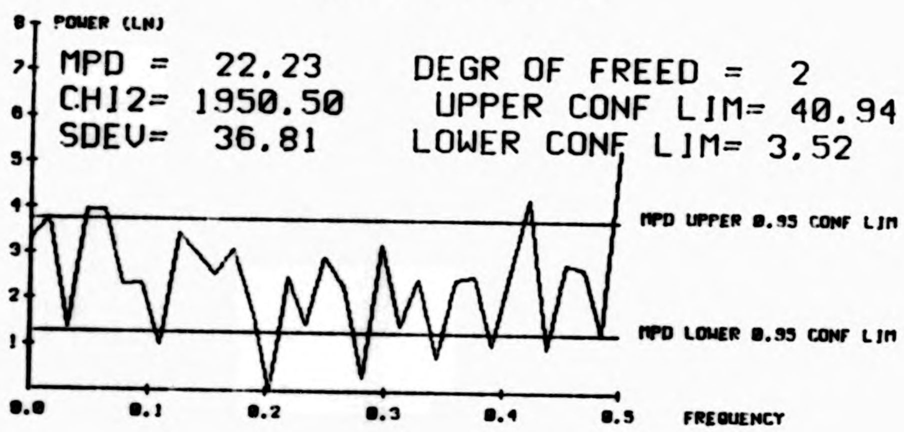


ALIL,201B264RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	59.9								
0.016	67.3	0.031	1.1	0.047	27.6	0.063	0.2	0.078	50.6
0.094	23.3	0.109	10.6	0.125	13.6	0.141	22.9	0.156	31.8
0.172	20.1	0.188	13.9	0.203	11.9	0.219	14.8	0.234	38.0
0.250	34.1	0.266	0.8	0.281	20.4	0.297	0.1	0.313	12.2
0.328	2.6	0.344	13.7	0.359	0.5	0.375	27.4	0.391	35.5
0.406	6.0	0.422	19.5	0.438	26.3	0.453	15.6	0.469	0.0
0.484	0.3	0.500	6.4						

MEAN POWER DENSITY: 19.06
DEGREES OF FREEDOM = 2
CHISQUARE = 501.37
ST.DEVIATION = 17.28
MPD UPPER 0.95 CONF LIMIT = 27.84
MPD LOWER 0.95 CONF LIMIT = 10.28
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 10
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

GULL,201B264RF68
POWER SPECTRUM



GULL,201B264RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	26.6								
0.016	43.8	0.031	3.7	0.047	53.0	0.063	53.4	0.078	9.7
0.094	10.3	0.109	2.6	0.125	31.4	0.141	20.3	0.156	12.2
0.172	21.3	0.188	6.0	0.203	0.0	0.219	11.7	0.234	4.2
0.250	18.5	0.266	9.8	0.281	1.3	0.297	24.3	0.313	4.0
0.328	11.7	0.344	2.0	0.359	11.3	0.375	12.6	0.391	2.7
0.406	13.7	0.422	69.5	0.438	2.6	0.453	16.2	0.469	14.7
0.484	3.5	0.500	204.9						

MEAN POWER DENSITY: 22.23
DEGREES OF FREEDOM = 2
CHISQUARE = 1950.50
ST.DEVIATION = 36.81
MPD UPPER 0.95 CONF LIMIT = 40.94
MPD LOWER 0.95 CONF LIMIT = 3.52
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 5
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 6
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 11

WINDOW-GROUP 128

Index

Power spectra and power in frequency points:

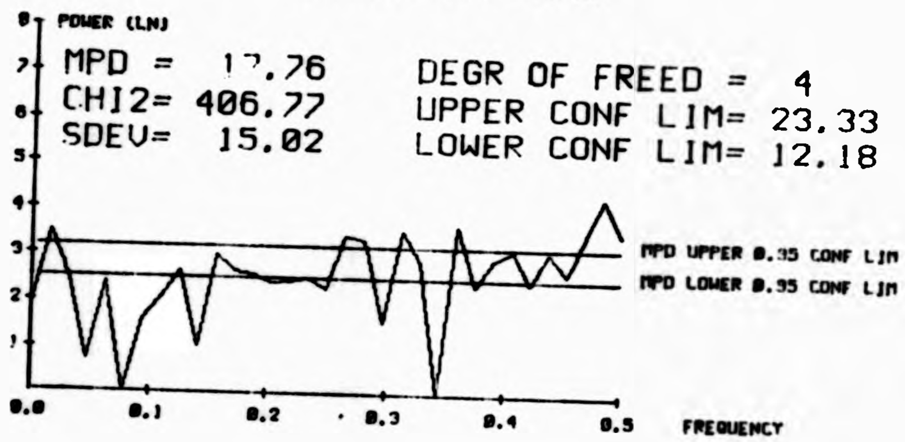
Power in frequency points AFTER permutation:

Statisitics:

Runs before permutation:

Runs after permutation:

C85 FIE1,201B328RF68
POWER SPECTRUM

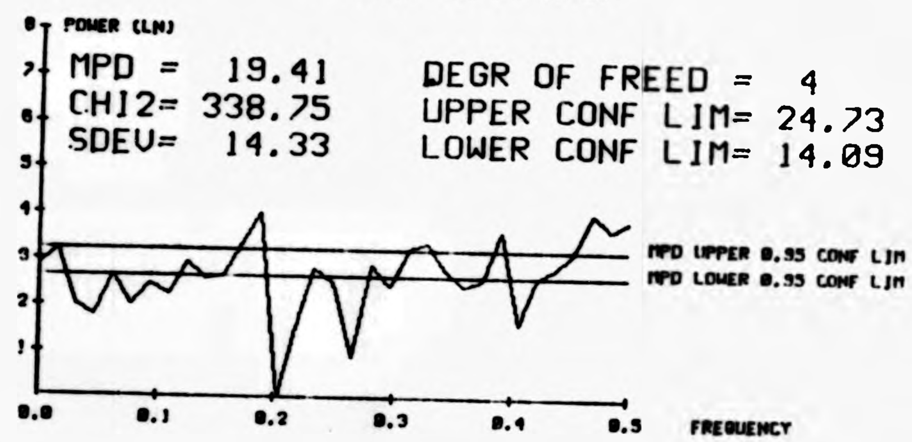


C85
FIE1,201B328RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.4								
0.016	32.2	0.031	11.4	0.047	2.0	0.063	11.1	0.078	0.5
0.094	4.9	0.109	8.1	0.125	13.8	0.141	2.7	0.156	19.7
0.172	14.2	0.188	13.0	0.203	10.9	0.219	11.6	0.234	12.7
0.250	9.7	0.266	31.2	0.281	28.2	0.297	4.7	0.313	34.5
0.328	17.5	0.344	0.6	0.359	40.0	0.375	10.7	0.391	19.1
0.406	23.6	0.422	11.7	0.438	22.3	0.453	14.1	0.469	33.3
0.484	75.6	0.500	33.8						

MEAN POWER DENSITY: 17.76
DEGREES OF FREEDOM = 4
CHISQUARE = 406.77
ST.DEVIATION = 15.02
MPD UPPER 0.95 CONF LIMIT = 23.33
MPD LOWER 0.95 CONF LIMIT = 12.18
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

95C,201B328RF140
POWER SPECTRUM

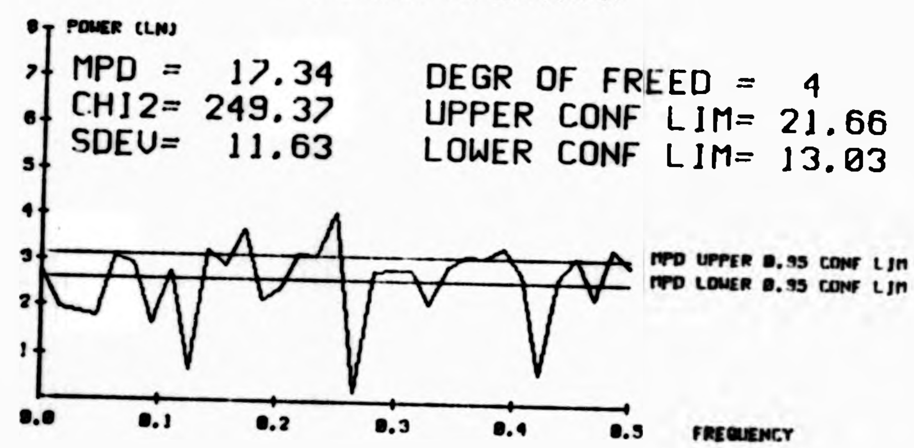


95C,201B328RF140   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	17.6								
0.016	26.0	0.031	7.5	0.047	5.8	0.063	14.7	0.078	7.4
0.094	11.8	0.109	9.3	0.125	19.3	0.141	13.4	0.156	14.7
0.172	28.7	0.188	53.9	0.203	0.7	0.219	4.6	0.234	17.4
0.250	12.5	0.266	2.5	0.281	18.8	0.297	11.6	0.313	26.3
0.328	29.6	0.344	16.2	0.359	11.5	0.375	13.6	0.391	37.6
0.406	4.9	0.422	13.8	0.438	18.1	0.453	25.3	0.469	57.7
0.484	40.0	0.500	48.0						

MEAN POWER DENSITY: 19.41
DEGREES OF FREEDOM = 4
CHISQUARE = 338.75
ST.DEVIATION = 14.33
MPD UPPER 0.95 CONF LIMIT = 24.73
MPD LOWER 0.95 CONF LIMIT = 14.09
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

96C,190B317RF92
POWER SPECTRUM

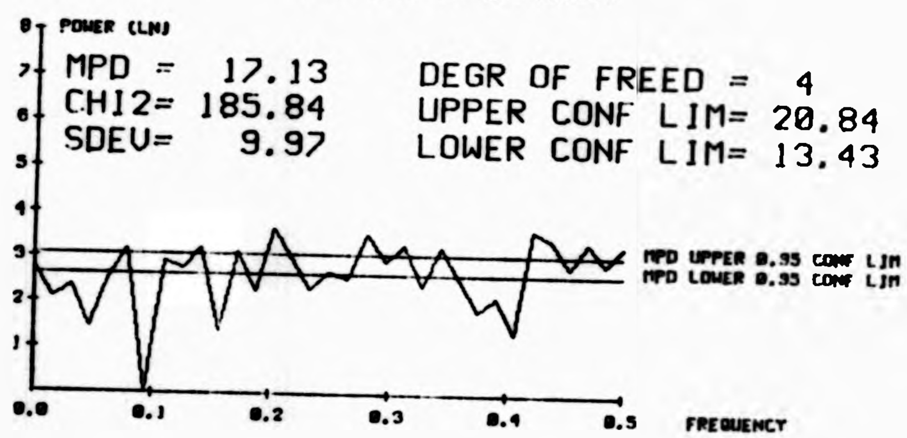


96C,190B317RF92 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.7								
0.016	6.8	0.031	6.2	0.047	5.9	0.063	22.1	0.078	18.9
0.094	5.0	0.109	15.7	0.125	1.9	0.141	25.5	0.156	17.6
0.172	39.3	0.188	8.4	0.203	10.8	0.219	24.0	0.234	23.0
0.250	59.4	0.266	1.2	0.281	16.6	0.297	17.2	0.313	17.0
0.328	7.9	0.344	18.4	0.359	23.6	0.375	22.2	0.391	28.5
0.406	16.0	0.422	1.9	0.438	14.4	0.453	23.5	0.469	9.5
0.484	28.7	0.500	19.4						

MEAN POWER DENSITY: 17.34
DEGREES OF FREEDOM = 4
CHISQUARE = 249.37
ST.DEVIATION = 11.63
MPD UPPER 0.95 CONF LIMIT = 21.66
MPD LOWER 0.95 CONF LIMIT = 13.03
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

101C,128B255RF93
POWER SPECTRUM

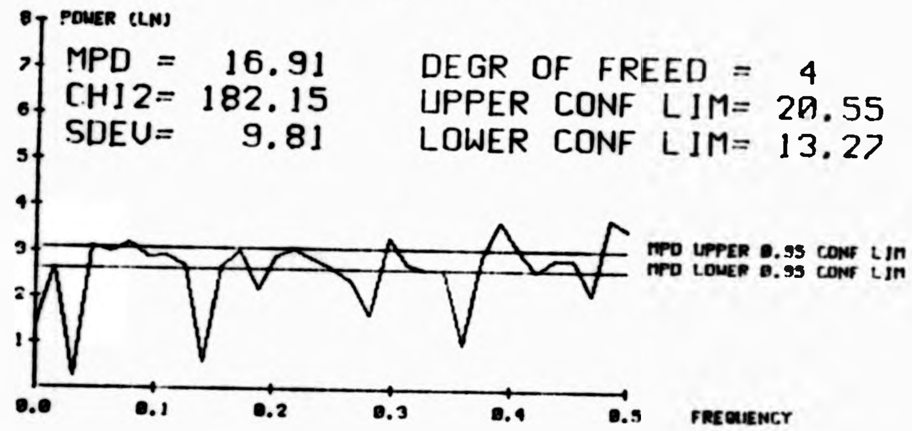


101C,128B255RF93 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.7								
0.016	7.9	0.031	10.5	0.047	4.0	0.063	12.6	0.078	23.4
0.094	0.1	0.109	18.4	0.125	15.9	0.141	24.2	0.156	3.7
0.172	23.0	0.188	9.5	0.203	37.8	0.219	19.4	0.234	9.7
0.250	14.5	0.266	12.7	0.281	34.1	0.297	18.5	0.313	27.0
0.328	10.5	0.344	25.5	0.359	12.3	0.375	6.0	0.391	8.5
0.406	3.7	0.422	37.4	0.438	29.5	0.453	16.5	0.469	28.7
0.484	17.6	0.500	26.6						

MEAN POWER DENSITY: 17.13
DEGREES OF FREEDOM = 4
CHISQUARE = 185.84
ST.DEVIATION = 9.97
MPD UPPER 0.95 CONF LIMIT = 20.84
MPD LOWER 0.95 CONF LIMIT = 13.43
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

103C,94B221RF73
POWER SPECTRUM

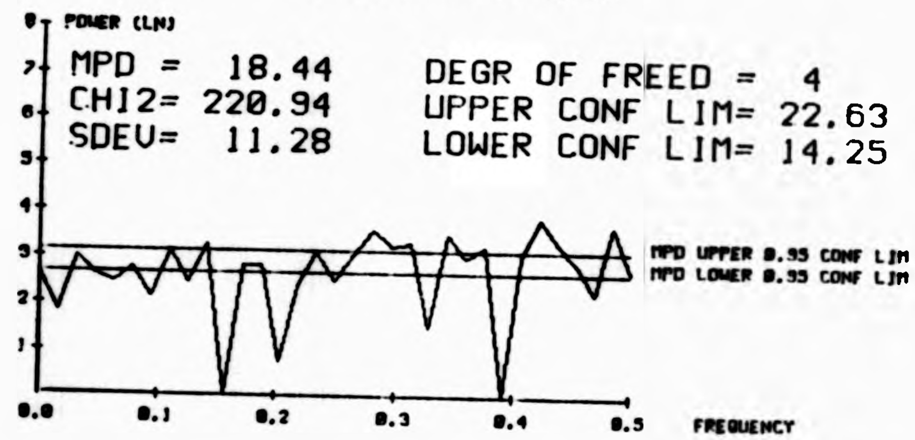


103C,94B221RF73 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.7								
0.016	14.2	0.031	1.3	0.047	22.9	0.063	20.2	0.078	24.7
0.094	17.9	0.109	18.7	0.125	14.6	0.141	1.7	0.156	14.8
0.172	21.3	0.188	8.6	0.203	18.7	0.219	21.4	0.234	16.9
0.250	13.9	0.266	10.6	0.281	4.9	0.297	27.7	0.313	15.3
0.328	13.3	0.344	13.6	0.359	2.6	0.375	18.0	0.391	40.3
0.406	22.0	0.422	13.4	0.438	17.7	0.453	18.0	0.469	7.9
0.484	43.4	0.500	33.7						

MEAN POWER DENSITY: 16.91
DEGREES OF FREEDOM = 4
CHISQUARE = 182.15
ST.DEVIATION = 9.81
MPD UPPER 0.95 CONF LIMIT = 20.55
MPD LOWER 0.95 CONF LIMIT = 13.27
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 8
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 17

104C,87B214RF82
POWER SPECTRUM

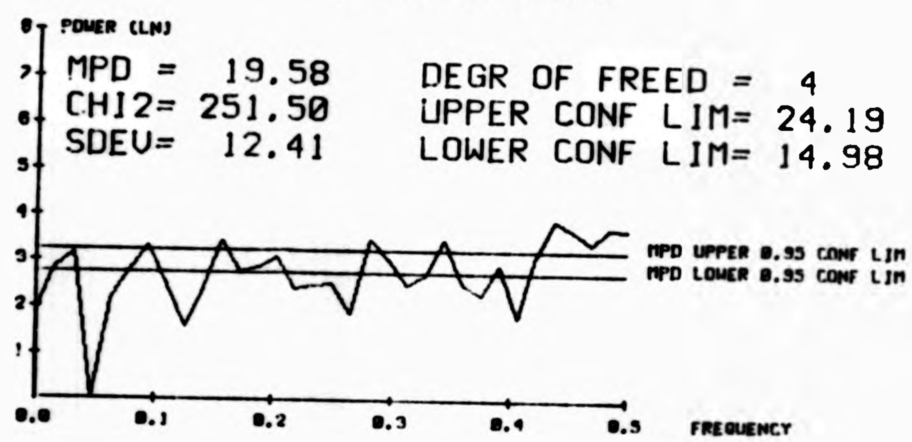


104C,87B214RF82 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	13.9								
0.016	5.9	0.031	20.3	0.047	13.5	0.063	11.3	0.078	16.0
0.094	8.3	0.109	22.9	0.125	11.5	0.141	27.0	0.156	0.5
0.172	17.3	0.188	17.1	0.203	2.1	0.219	10.9	0.234	22.2
0.250	12.2	0.266	22.1	0.281	36.4	0.297	26.0	0.313	27.3
0.328	4.3	0.344	33.3	0.359	19.8	0.375	25.3	0.391	0.8
0.406	20.7	0.422	48.7	0.438	27.2	0.453	17.6	0.469	9.5
0.484	41.3	0.500	15.4						

MEAN POWER DENSITY: 18.44
DEGREES OF FREEDOM = 4
CHISQUARE = 220.94
ST.DEVIATION = 11.28
MPD UPPER 0.95 CONF LIMIT = 22.63
MPD LOWER 0.95 CONF LIMIT = 14.25
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

110C,137B266RF100
POWER SPECTRUM

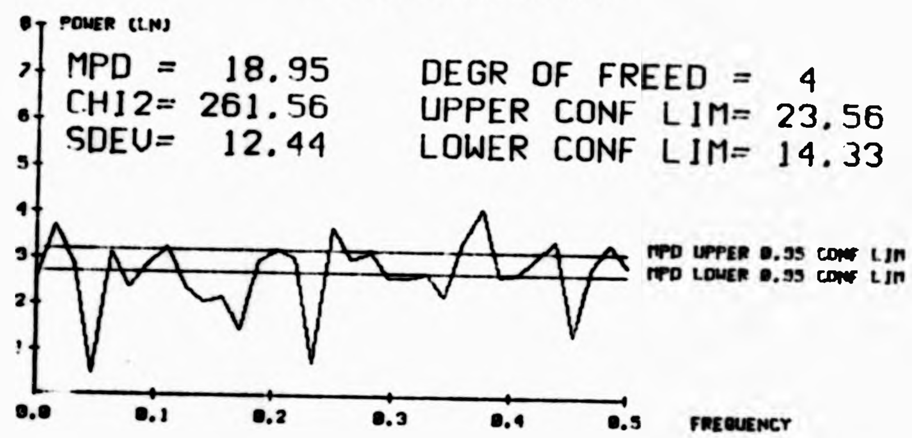


110C,137B266RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.6								
0.016	17.0	0.031	23.8	0.047	0.7	0.063	8.8	0.078	15.6
0.094	27.2	0.109	11.4	0.125	4.8	0.141	11.2	0.156	31.3
0.172	15.9	0.188	18.0	0.203	21.4	0.219	10.9	0.234	12.2
0.250	12.4	0.266	6.7	0.281	32.8	0.297	21.0	0.313	12.2
0.328	15.4	0.344	32.9	0.359	12.5	0.375	9.9	0.391	18.4
0.406	6.1	0.422	23.6	0.438	50.7	0.453	40.4	0.469	29.4
0.484	43.1	0.500	42.0						

MEAN POWER DENSITY: 19.58
DEGREES OF FREEDOM = 4
CHISQUARE = 251.50
ST.DEVIATION = 12.41
MPD UPPER 0.95 CONF LIMIT = 24.19
MPD LOWER 0.95 CONF LIMIT = 14.98
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

113C,43B170RF42
POWER SPECTRUM

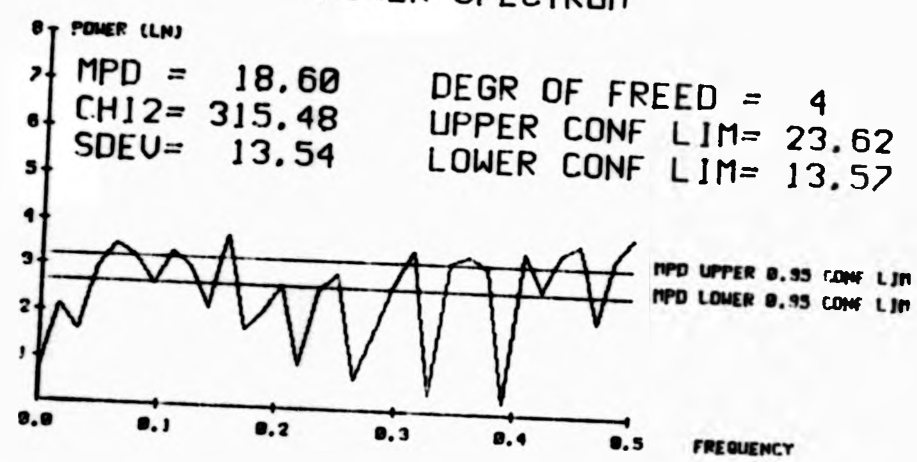


113C,43B170RF42 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.6								
0.016	39.1	0.031	16.2	0.047	1.6	0.063	22.9	0.078	10.6
0.094	17.6	0.109	25.8	0.125	10.5	0.141	7.7	0.156	8.6
0.172	4.1	0.188	19.3	0.203	24.2	0.219	20.3	0.234	2.1
0.250	39.3	0.266	20.3	0.281	23.7	0.297	13.6	0.313	13.2
0.328	15.5	0.344	8.9	0.359	31.6	0.375	62.4	0.391	14.1
0.406	15.0	0.422	21.4	0.438	31.7	0.453	4.0	0.469	18.5
0.484	30.5	0.500	18.2						

MEAN POWER DENSITY: 18.95
DEGREES OF FREEDOM = 4
CHISQUARE = 261.56
ST.DEVIATION = 12.44
MPD UPPER 0.95 CONF LIMIT = 23.56
MPD LOWER 0.95 CONF LIMIT = 14.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

114C,201B328RF116
POWER SPECTRUM

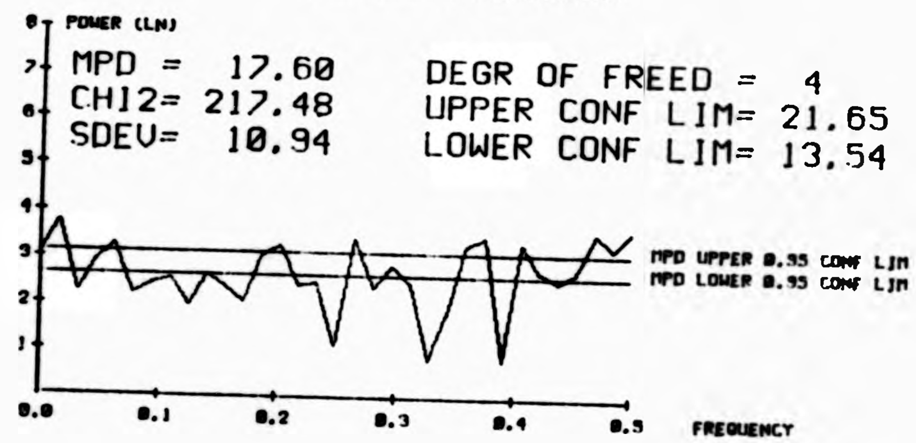


114C,201B328RF116 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.0								
0.016	8.4	0.031	4.9	0.047	19.3	0.063	32.3	0.078	24.7
0.094	13.6	0.109	27.6	0.125	19.5	0.141	8.2	0.156	41.2
0.172	5.4	0.188	8.1	0.203	14.1	0.219	2.5	0.234	12.9
0.250	18.7	0.266	1.9	0.281	5.5	0.297	15.7	0.313	33.0
0.328	1.4	0.344	25.8	0.359	30.3	0.375	22.7	0.391	1.3
0.406	33.8	0.422	14.6	0.438	33.9	0.453	40.7	0.469	7.8
0.484	30.7	0.500	51.0						

MEAN POWER DENSITY: 18.60
DEGREES OF FREEDOM = 4
CHISQUARE = 315.48
ST.DEVIATION = 13.54
MPD UPPER 0.95 CONF LIMIT = 23.62
MPD LOWER 0.95 CONF LIMIT = 13.57
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

130C,201B328RF60
POWER SPECTRUM

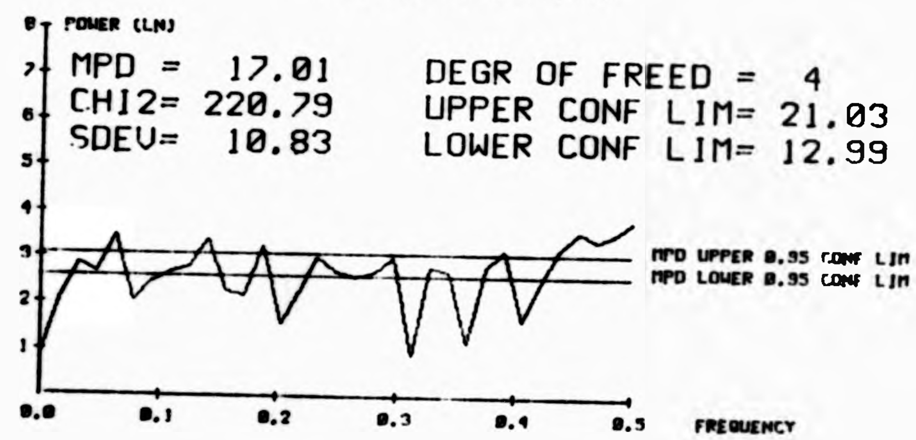


130C,201B328RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	21.7								
0.016	43.2	0.031	9.5	0.047	18.4	0.063	26.4	0.078	9.2
0.094	11.2	0.109	12.9	0.125	7.1	0.141	14.1	0.156	10.7
0.172	7.8	0.188	21.7	0.203	27.0	0.219	10.9	0.234	11.8
0.250	2.9	0.266	30.8	0.281	10.7	0.297	17.1	0.313	11.3
0.328	2.2	0.344	6.2	0.359	27.9	0.375	32.3	0.391	2.2
0.406	29.3	0.422	15.0	0.438	12.6	0.453	16.1	0.469	36.1
0.484	25.3	0.500	38.9						

MEAN POWER DENSITY: 17.60
DEGREES OF FREEDOM = 4
CHISQUARE = 217.48
ST.DEVIATION = 10.94
MPD UPPER 0.95 CONF LIMIT = 21.65
MPD LOWER 0.95 CONF LIMIT = 13.54
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

140C,201B328RF92
POWER SPECTRUM

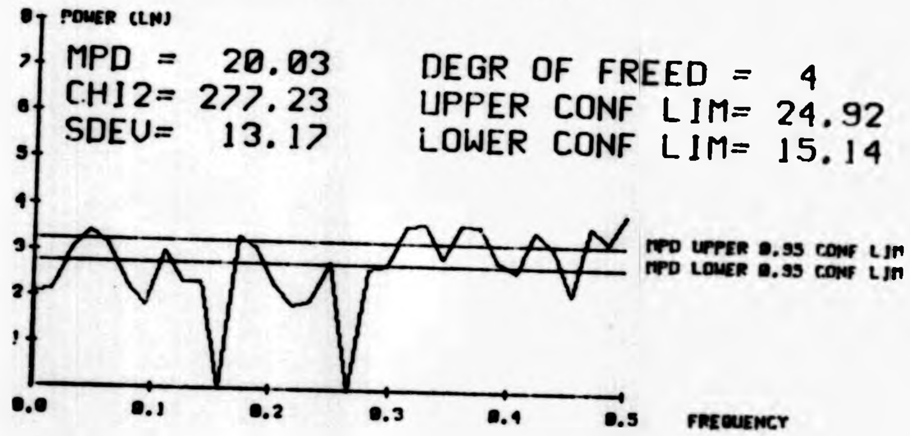


140C,201B328RF92 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.3								
0.016	7.5	0.031	17.3	0.047	14.0	0.063	32.2	0.078	7.8
0.094	12.1	0.109	14.4	0.125	16.4	0.141	29.7	0.156	9.5
0.172	8.7	0.188	25.5	0.203	4.7	0.219	9.5	0.234	19.7
0.250	14.6	0.266	12.8	0.281	14.6	0.297	19.7	0.313	2.4
0.328	16.7	0.344	14.9	0.359	3.1	0.375	16.7	0.391	23.1
0.406	5.1	0.422	11.8	0.438	24.3	0.453	37.7	0.469	30.0
0.484	35.8	0.500	46.4						

MEAN POWER DENSITY: 17.01
DEGREES OF FREEDOM = 4
CHISQUARE = 220.79
ST.DEVIATION = 10.83
MPD UPPER 0.95 CONF LIMIT = 21.03
MPD LOWER 0.95 CONF LIMIT = 12.99
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

141C,201B328RF68
POWER SPECTRUM

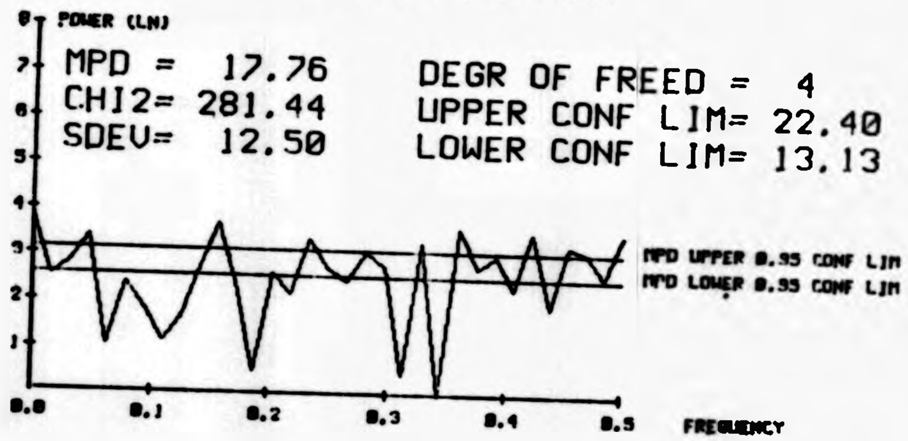


141C,201B328RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.0								
0.016	8.5	0.031	20.7	0.047	31.2	0.063	22.4	0.078	9.8
0.094	6.0	0.109	19.8	0.125	10.3	0.141	10.4	0.156	0.5
0.172	28.9	0.188	22.0	0.203	9.8	0.219	6.3	0.234	7.2
0.250	16.8	0.266	0.6	0.281	14.4	0.297	15.7	0.313	38.1
0.328	39.3	0.344	18.6	0.359	40.4	0.375	38.2	0.391	17.2
0.406	13.9	0.422	34.6	0.438	23.7	0.453	8.7	0.469	39.9
0.484	27.6	0.500	51.6						

MEAN POWER DENSITY: 20.03
DEGREES OF FREEDOM = 4
CHISQUARE = 277.23
ST.DEVIATION = 13.17
MPD UPPER 0.95 CONF LIMIT = 24.92
MPD LOWER 0.95 CONF LIMIT = 15.14
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

1RUS,273B400RF125
POWER SPECTRUM

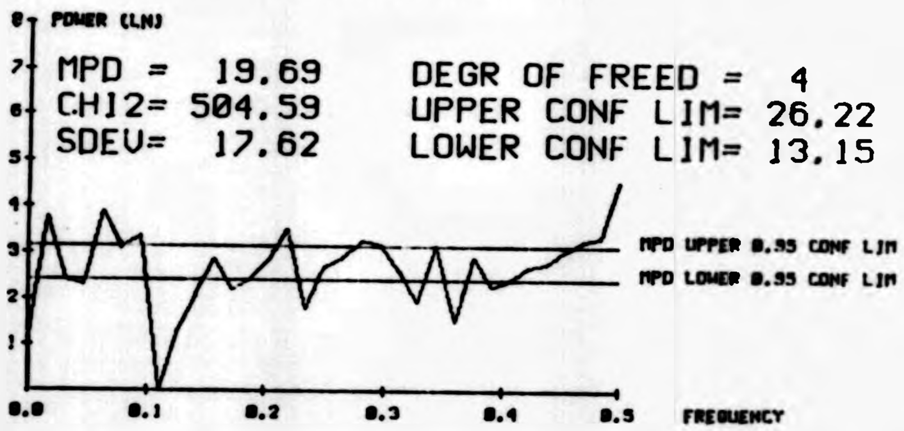


1RUS,273B400RF125 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	44.5								
0.016	12.3	0.031	16.9	0.047	30.1	0.063	2.8	0.078	11.1
0.094	6.3	0.109	3.1	0.125	5.3	0.141	15.0	0.156	41.8
0.172	10.9	0.188	1.6	0.203	14.3	0.219	8.9	0.234	29.6
0.250	16.1	0.266	12.1	0.281	22.5	0.297	16.6	0.313	1.6
0.328	28.4	0.344	0.9	0.359	39.8	0.375	16.3	0.391	21.5
0.406	10.6	0.422	36.4	0.438	7.2	0.453	27.8	0.469	23.6
0.484	14.1	0.500	36.2						

MEAN POWER DENSITY: 17.76
DEGREES OF FREEDOM = 4
CHISQUARE = 281.44
ST.DEVIATION = 12.50
MPD UPPER 0.95 CONF LIMIT = 22.40
MPD LOWER 0.95 CONF LIMIT = 13.13
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

2RUS,273B400RF164
POWER SPECTRUM

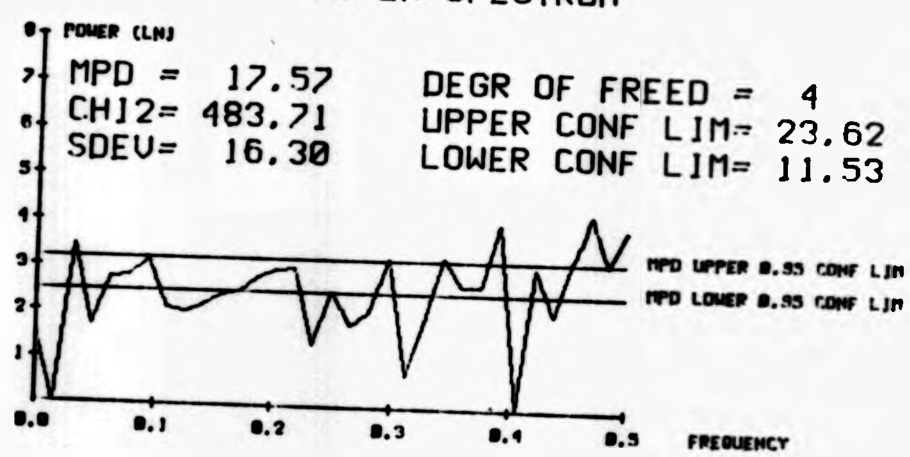


2RUS,273B400RF164 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.1								
0.016	43.3	0.031	11.1	0.047	9.7	0.063	49.3	0.078	22.3
0.094	28.4	0.109	0.0	0.125	3.4	0.141	8.0	0.156	18.2
0.172	9.0	0.188	11.8	0.203	18.0	0.219	34.1	0.234	5.7
0.250	15.3	0.266	18.3	0.281	26.1	0.297	23.3	0.313	13.2
0.328	6.9	0.344	23.6	0.359	4.4	0.375	18.8	0.391	9.7
0.406	11.3	0.422	15.2	0.438	16.4	0.453	21.7	0.469	26.3
0.484	28.3	0.500	95.5						

MEAN POWER DENSITY: 19.69
DEGREES OF FREEDOM = 4
CHISQUARE = 504.59
ST.DEVIATION = 17.62
MPD UPPER 0.95 CONF LIMIT = 26.22
MPD LOWER 0.95 CONF LIMIT = 13.15
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

3RUS,273B400RF106
POWER SPECTRUM

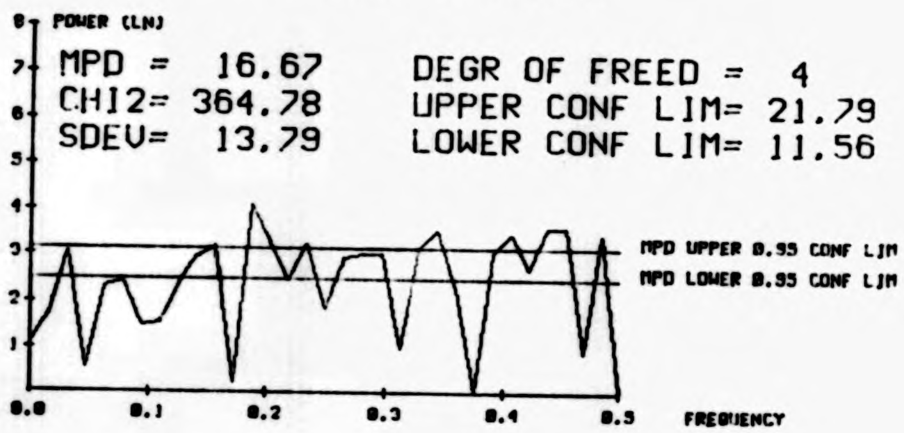


3RUS,273B400RF106 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.7								
0.016	0.0	0.031	32.2	0.047	5.3	0.063	16.0	0.078	16.5
0.094	24.0	0.109	7.9	0.125	7.5	0.141	8.6	0.156	11.0
0.172	11.9	0.188	16.4	0.203	19.2	0.219	19.8	0.234	3.8
0.250	11.8	0.266	5.9	0.281	8.2	0.297	25.8	0.313	2.0
0.328	6.5	0.344	26.4	0.359	14.0	0.375	13.9	0.391	56.2
0.406	0.4	0.422	22.0	0.438	7.8	0.453	25.1	0.469	72.8
0.484	24.0	0.500	52.5						

MEAN POWER DENSITY: 17.57
DEGREES OF FREEDOM = 4
CHISQUARE = 483.71
ST.DEVIATION = 16.30
MPD UPPER 0.95 CONF LIMIT = 23.62
MPD LOWER 0.95 CONF LIMIT = 11.53
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

4RUS,273B400RF216
POWER SPECTRUM

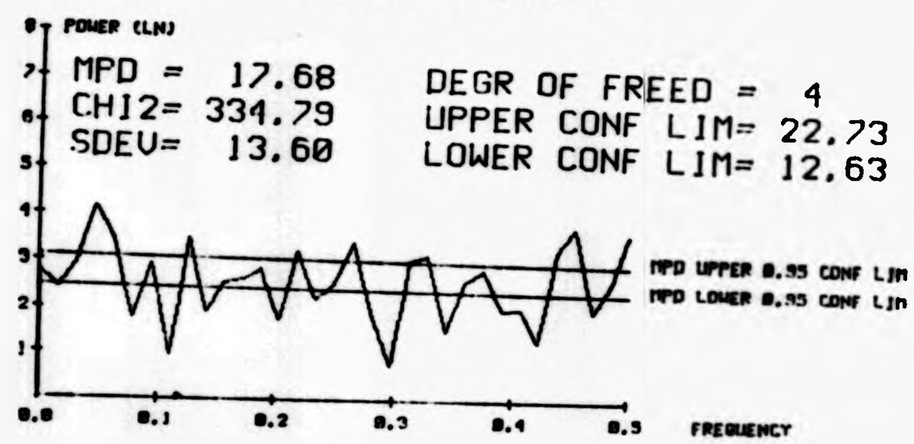


4RUS,273B400RF216 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.9								
0.016	5.5	0.031	21.2	0.047	1.7	0.063	10.2	0.078	11.6
0.094	4.3	0.109	4.8	0.125	10.9	0.141	19.5	0.156	23.5
0.172	1.2	0.188	61.3	0.203	25.3	0.219	11.5	0.234	24.9
0.250	6.4	0.266	18.3	0.281	20.3	0.297	20.4	0.313	2.6
0.328	22.6	0.344	34.2	0.359	9.8	0.375	0.9	0.391	20.8
0.406	31.1	0.422	14.4	0.438	36.7	0.453	37.3	0.469	2.4
0.484	30.7	0.500	0.9						

MEAN POWER DENSITY: 16.67
DEGREES OF FREEDOM = 4
CHISQUARE = 364.78
ST.DEVIATION = 13.79
MPD UPPER 0.95 CONF LIMIT = 21.79
MPD LOWER 0.95 CONF LIMIT = 11.56
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

5RUS,273B400RF206
POWER SPECTRUM

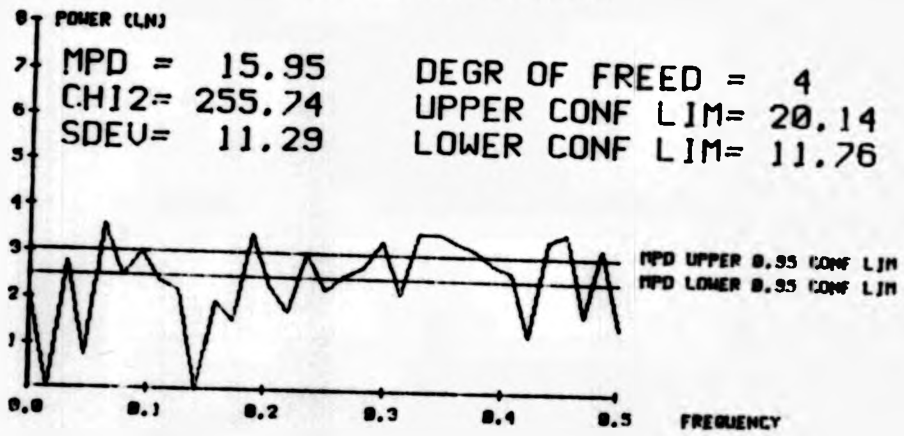


5RUS,273B400RF206 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	16.4								
0.016	11.5	0.031	19.2	0.047	63.7	0.063	31.1	0.078	5.8
0.094	19.3	0.109	2.5	0.125	32.1	0.141	6.9	0.156	13.7
0.172	14.4	0.188	18.1	0.203	5.7	0.219	25.7	0.234	9.5
0.250	13.2	0.266	30.8	0.281	6.3	0.297	2.1	0.313	21.6
0.328	24.2	0.344	4.6	0.359	14.4	0.375	18.5	0.391	7.8
0.406	8.1	0.422	3.7	0.438	27.9	0.453	43.8	0.469	7.4
0.484	13.8	0.500	39.6						

MEAN POWER DENSITY: 17.68
DEGREES OF FREEDOM = 4
CHISQUARE = 334.79
ST.DEVIATION = 13.60
MPD UPPER 0.95 CONF LIMIT = 22.73
MPD LOWER 0.95 CONF LIMIT = 12.63
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

LAB,273B400RF254
POWER SPECTRUM

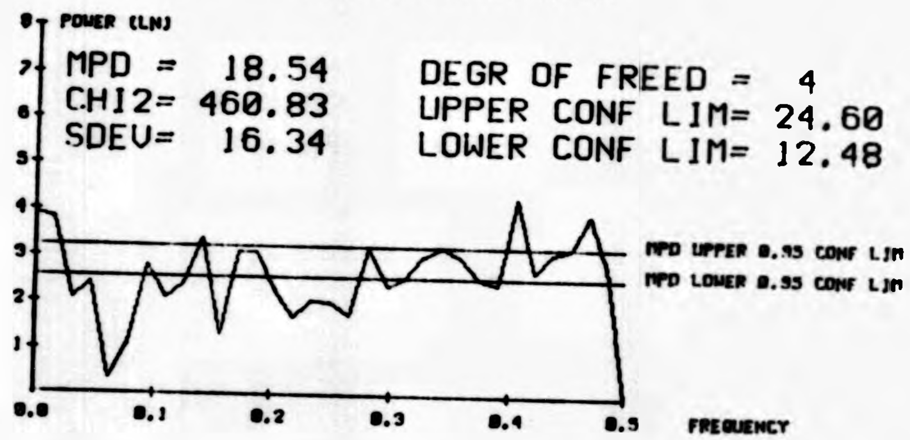


LAB,273B400RF254 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.2								
0.016	0.1	0.031	15.6	0.047	2.0	0.063	37.2	0.078	12.1
0.094	20.4	0.109	10.8	0.125	8.8	0.141	0.4	0.156	7.1
0.172	4.8	0.188	31.4	0.203	9.7	0.219	5.8	0.234	20.4
0.250	9.4	0.266	12.8	0.281	15.7	0.297	27.9	0.313	8.7
0.328	34.2	0.344	34.4	0.359	27.9	0.375	23.8	0.391	17.0
0.406	14.7	0.422	3.7	0.438	30.4	0.453	34.5	0.469	5.9
0.484	25.9	0.500	4.6						

MEAN POWER DENSITY: 15.95
DEGREES OF FREEDOM = 4
CHISQUARE = 255.74
ST.DEVIATION = 11.29
MPD UPPER 0.95 CONF LIMIT = 20.14
MPD LOWER 0.95 CONF LIMIT = 11.76
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

1FRK,273B400RF74
POWER SPECTRUM

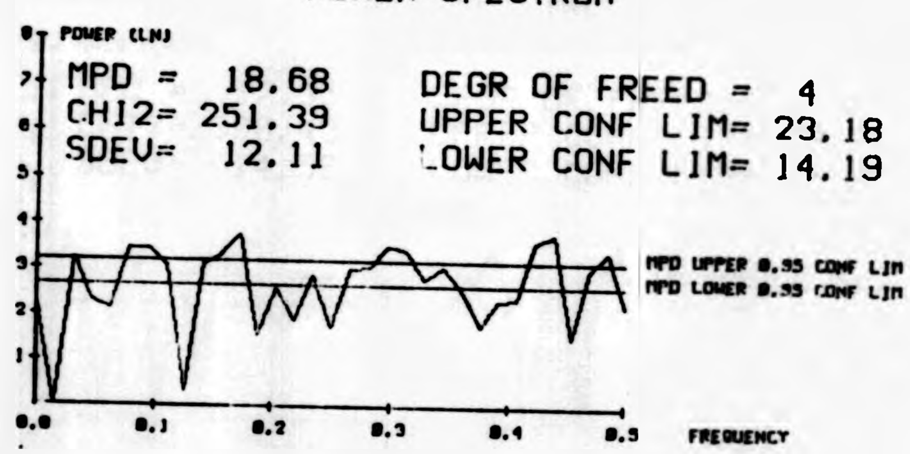


1FRK,273B400RF74   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	51.0								
0.016	45.2	0.031	7.6	0.047	11.2	0.063	1.4	0.078	3.0
0.094	16.7	0.109	8.0	0.125	11.1	0.141	29.6	0.156	3.7
0.172	22.4	0.188	22.6	0.203	9.5	0.219	5.4	0.234	7.7
0.250	7.4	0.266	5.6	0.281	24.9	0.297	10.6	0.313	13.2
0.328	20.7	0.344	25.2	0.359	19.7	0.375	12.3	0.391	11.0
0.406	73.9	0.422	14.8	0.438	22.6	0.453	25.1	0.469	51.8
0.484	17.1	0.500	0.1						

MEAN POWER DENSITY: 18.54
DEGREES OF FREEDOM = 4
CHISQUARE = 460.83
ST.DEVIATION = 16.34
MPD UPPER 0.95 CONF LIMIT = 24.60
MPD LOWER 0.95 CONF LIMIT = 12.48
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

BRU,273B400RF152
POWER SPECTRUM

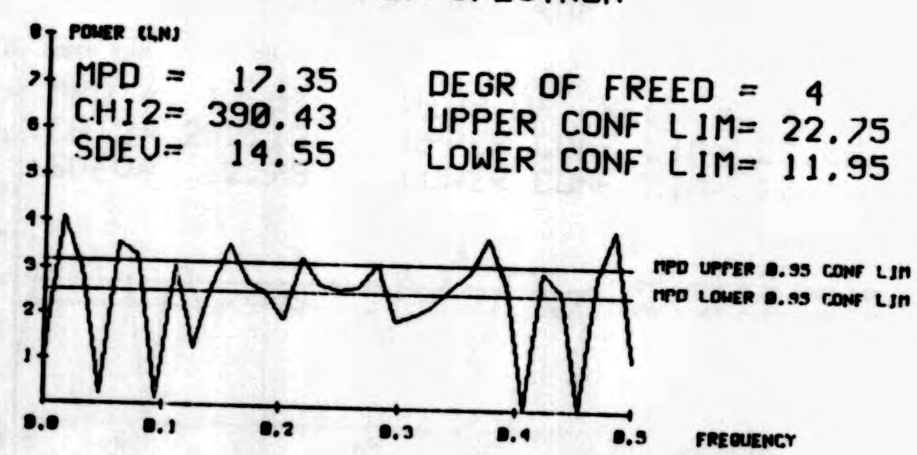


BRU,273B400RF152 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.2								
0.016	0.8	0.031	25.4	0.047	9.6	0.063	8.4	0.078	31.5
0.094	31.3	0.109	21.3	0.125	1.4	0.141	23.7	0.156	29.1
0.172	42.5	0.188	4.5	0.203	13.2	0.219	6.4	0.234	17.7
0.250	5.7	0.266	20.5	0.281	22.0	0.297	34.2	0.313	30.3
0.328	16.8	0.344	21.8	0.359	13.5	0.375	5.9	0.391	10.7
0.406	11.0	0.422	37.7	0.438	44.0	0.453	4.5	0.469	21.6
0.484	31.1	0.500	9.3						

MEAN POWER DENSITY: 18.68
DEGREES OF FREEDOM = 4
CHISQUARE = 251.39
ST.DEVIATION = 12.11
MPD UPPER 0.95 CONF LIMIT = 23.18
MPD LOWER 0.95 CONF LIMIT = 14.19
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

CHOM,273B400RF96
POWER SPECTRUM

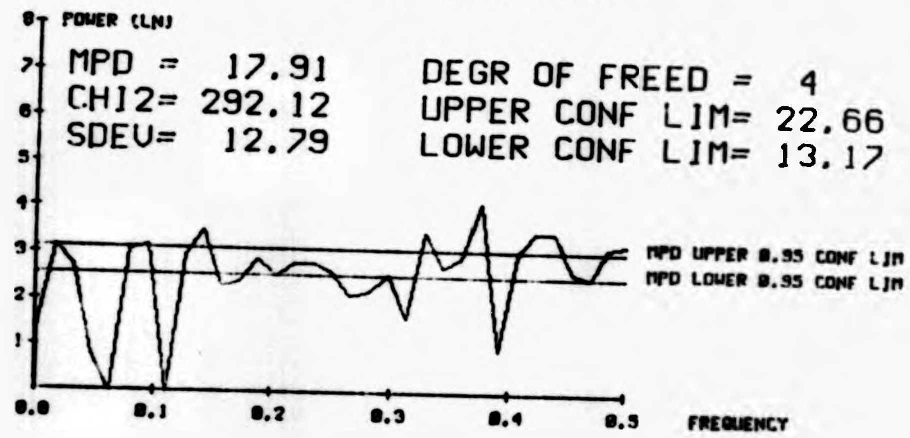


CHOM,273B400RF96 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.8								
0.016	58.2	0.031	19.2	0.047	1.2	0.063	35.6	0.078	26.5
0.094	1.1	0.109	21.8	0.125	3.4	0.141	13.3	0.156	35.7
0.172	15.3	0.188	11.9	0.203	6.6	0.219	26.7	0.234	14.5
0.250	13.2	0.266	14.1	0.281	23.1	0.297	6.6	0.313	7.7
0.328	9.6	0.344	14.0	0.359	20.5	0.375	43.7	0.391	15.6
0.406	0.2	0.422	20.8	0.438	13.3	0.453	0.6	0.469	19.5
0.484	53.1	0.500	2.9						

MEAN POWER DENSITY: 17.35
DEGREES OF FREEDOM = 4
CHISQUARE = 390.43
ST.DEVIATION = 14.55
MPD UPPER 0.95 CONF LIMIT = 22.75
MPD LOWER 0.95 CONF LIMIT = 11.95
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

1REC,401B528RF350
POWER SPECTRUM

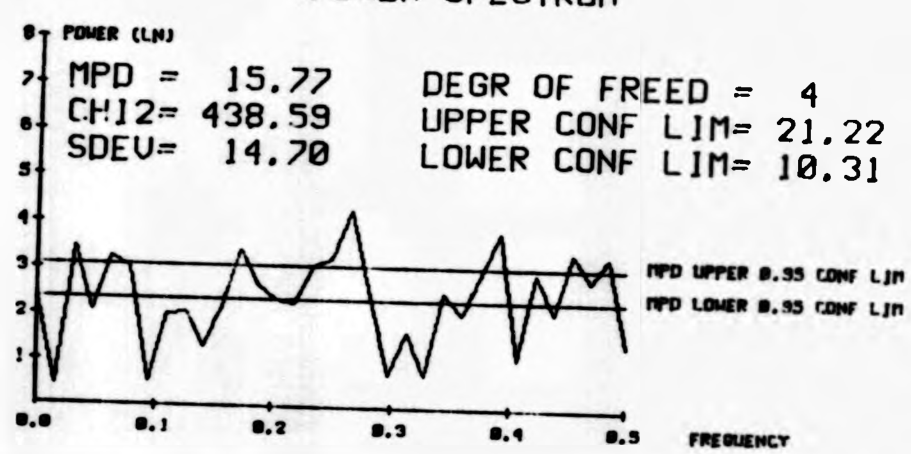


1REC,401B528RF350 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.5								
0.016	23.4	0.031	15.2	0.047	2.2	0.063	0.7	0.078	22.9
0.094	24.2	0.109	0.9	0.125	19.9	0.141	33.5	0.156	10.0
0.172	11.4	0.188	18.5	0.203	12.9	0.219	16.9	0.234	16.9
0.250	14.1	0.266	8.4	0.281	9.4	0.297	13.6	0.313	5.2
0.328	34.3	0.344	15.6	0.359	19.8	0.375	63.5	0.391	2.6
0.406	21.9	0.422	34.9	0.438	34.7	0.453	14.7	0.469	13.1
0.484	25.1	0.500	27.2						

MEAN POWER DENSITY: 17.91
DEGREES OF FREEDOM = 4
CHISQUARE = 292.12
ST.DEVIATION = 12.79
MPD UPPER 0.95 CONF LIMIT = 22.66
MPD LOWER 0.95 CONF LIMIT = 13.17
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

2REC,301B428RF264
POWER SPECTRUM

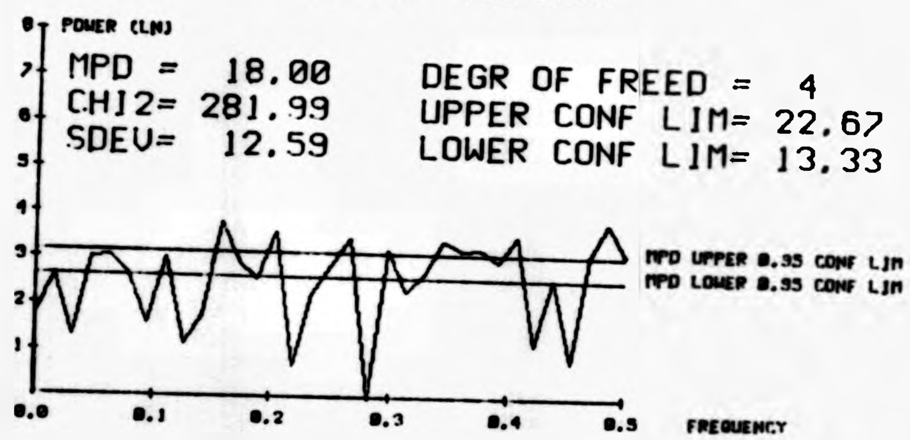


2REC,301B428RF264 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	10.1								
0.016	1.5	0.031	31.0	0.047	7.8	0.063	25.4	0.078	20.0
0.094	1.7	0.109	7.3	0.125	7.8	0.141	3.7	0.156	8.6
0.172	30.1	0.188	13.8	0.203	10.2	0.219	9.2	0.234	21.9
0.250	25.5	0.266	71.2	0.281	11.1	0.297	2.0	0.313	5.1
0.328	2.1	0.344	12.5	0.359	7.7	0.375	18.9	0.391	46.4
0.406	3.0	0.422	19.1	0.438	7.9	0.453	29.9	0.469	16.1
0.484	27.6	0.500	4.1						

MEAN POWER DENSITY: 15.77
DEGREES OF FREEDOM = 4
CHISQUARE = 438.59
ST.DEVIATION = 14.70
MPD UPPER 0.95 CONF LIMIT = 21.22
MPD LOWER 0.95 CONF LIMIT = 10.31
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

MAIL,301B428RF250
POWER SPECTRUM

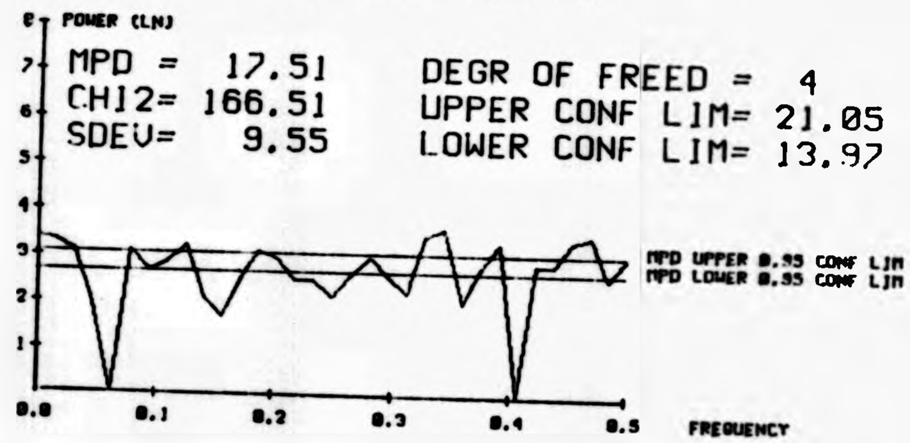


MAIL,301B428RF250 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.6								
0.016	13.7	0.031	3.5	0.047	19.8	0.063	21.2	0.078	14.1
0.094	4.7	0.109	20.4	0.125	3.1	0.141	5.8	0.156	44.3
0.172	18.7	0.188	13.2	0.203	36.6	0.219	2.0	0.234	9.8
0.250	17.5	0.266	32.6	0.281	0.7	0.297	26.0	0.313	10.4
0.328	14.9	0.344	31.0	0.359	25.3	0.375	26.5	0.391	20.1
0.406	35.7	0.422	3.4	0.438	14.0	0.453	2.4	0.469	24.9
0.484	48.0	0.500	24.3						

MEAN POWER DENSITY: 18.00
DEGREES OF FREEDOM = 4
CHISQUARE = 281.99
ST.DEVIATION = 12.59
MPD UPPER 0.95 CONF LIMIT = 22.67
MPD LOWER 0.95 CONF LIMIT = 13.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

HRLD,301B428RF138
POWER SPECTRUM

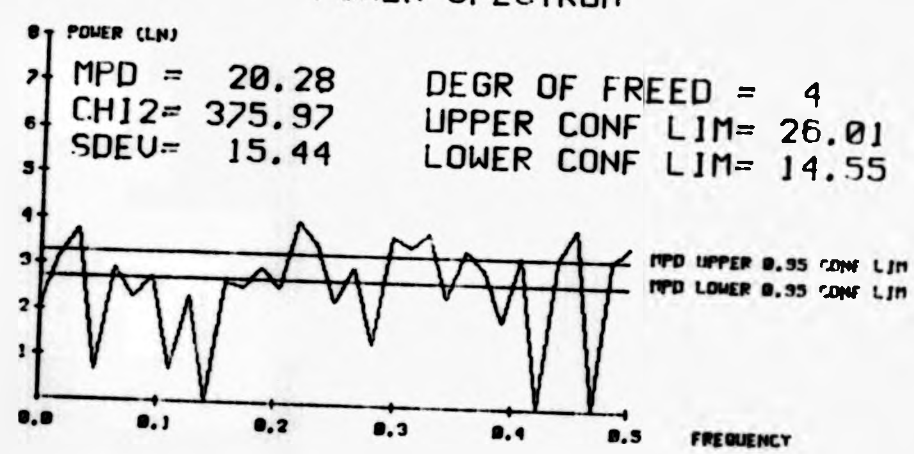


HRLD,301B428RF138 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	29.5								
0.016	27.6	0.031	21.7	0.047	6.8	0.063	0.2	0.078	23.0
0.094	14.7	0.109	17.6	0.125	25.7	0.141	7.8	0.156	5.5
0.172	12.2	0.188	23.0	0.203	19.4	0.219	11.9	0.234	12.0
0.250	8.4	0.266	13.3	0.281	20.2	0.297	12.8	0.313	9.0
0.328	32.4	0.344	37.7	0.359	7.5	0.375	16.5	0.391	27.8
0.406	0.8	0.422	17.7	0.438	17.7	0.453	30.5	0.469	33.2
0.484	12.8	0.500	21.0						

MEAN POWER DENSITY: 17.51
DEGREES OF FREEDOM = 4
CHISQUARE = 166.51
ST.DEVIATION = 9.55
MPD UPPER 0.95 CONF LIMIT = 21.05
MPD LOWER 0.95 CONF LIMIT = 13.97
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

GUAR,201B328RF100
POWER SPECTRUM

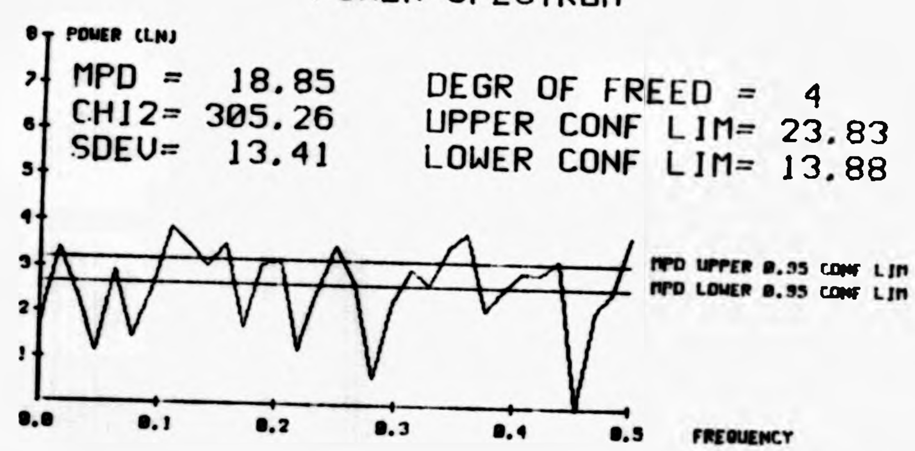


GUAR,201B328RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.5								
0.016	23.3	0.031	42.5	0.047	1.9	0.063	18.4	0.078	9.7
0.094	15.2	0.109	1.9	0.125	10.0	0.141	0.8	0.156	14.3
0.172	12.6	0.188	19.3	0.203	12.5	0.219	53.9	0.234	33.5
0.250	9.6	0.266	20.2	0.281	3.7	0.297	41.1	0.313	32.5
0.328	44.3	0.344	10.6	0.359	31.5	0.375	20.4	0.391	6.6
0.406	27.3	0.422	0.8	0.438	26.6	0.453	53.2	0.469	0.8
0.484	25.6	0.500	36.9						

MEAN POWER DENSITY: 20.28
DEGREES OF FREEDOM = 4
CHISQUARE = 375.97
ST.DEVIATION = 15.44
MPD UPPER 0.95 CONF LIMIT = 26.01
MPD LOWER 0.95 CONF LIMIT = 14.55
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

PAD1,273B400RF166
POWER SPECTRUM

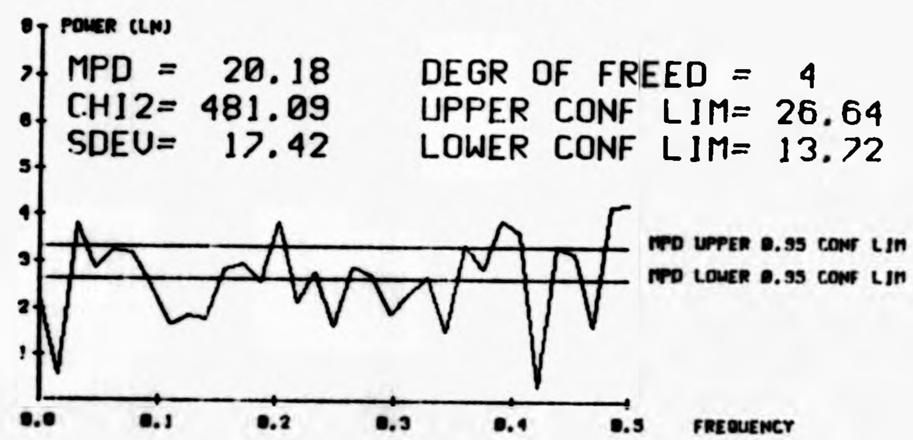


PAD1,273B400RF166 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.4								
0.016	29.6	0.031	10.6	0.047	3.0	0.063	18.7	0.078	4.2
0.094	12.3	0.109	48.3	0.125	32.2	0.141	21.3	0.156	33.6
0.172	5.4	0.188	22.3	0.203	24.1	0.219	3.3	0.234	12.0
0.250	33.6	0.266	14.7	0.281	1.8	0.297	10.2	0.313	20.6
0.328	14.3	0.344	34.2	0.359	46.9	0.375	8.4	0.391	13.6
0.406	20.4	0.422	19.6	0.438	26.5	0.453	0.9	0.469	8.6
0.484	14.0	0.500	47.3						

MEAN POWER DENSITY: 18.85
DEGREES OF FREEDOM = 4
CHISQUARE = 305.26
ST.DEVIATION = 13.41
MPD UPPER 0.95 CONF LIMIT = 23.83
MPD LOWER 0.95 CONF LIMIT = 13.88
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

PAD2,273B400RF119
POWER SPECTRUM

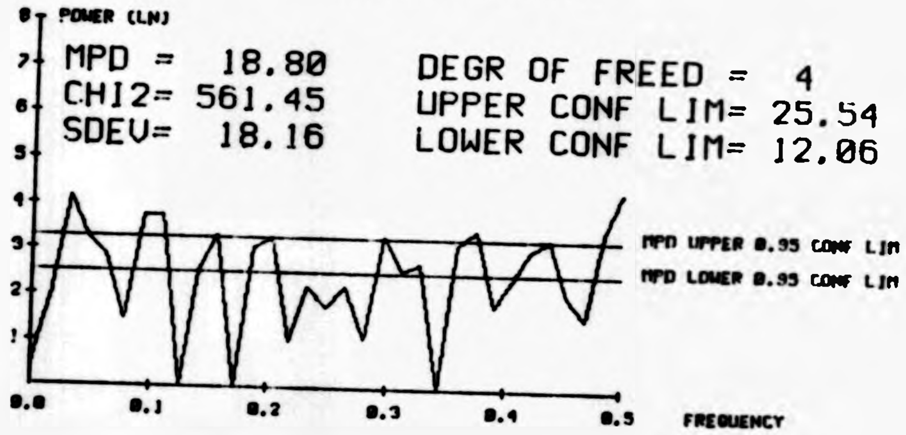


PAD2,273B400RF119 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.4								
0.016	1.7	0.031	44.8	0.047	17.1	0.063	25.2	0.078	23.9
0.094	12.0	0.109	5.2	0.125	6.4	0.141	5.8	0.156	17.2
0.172	19.2	0.188	12.7	0.203	45.7	0.219	8.4	0.234	16.1
0.250	4.9	0.266	17.8	0.281	14.7	0.297	6.5	0.313	10.0
0.328	14.8	0.344	4.3	0.359	28.6	0.375	17.0	0.391	48.0
0.406	37.1	0.422	1.3	0.438	27.6	0.453	23.3	0.469	5.0
0.484	65.6	0.500	68.6						

MEAN POWER DENSITY: 20.18
DEGREES OF FREEDOM = 4
CHISQUARE = 481.09
ST.DEVIATION = 17.42
MPD UPPER 0.95 CONF LIMIT = 26.64
MPD LOWER 0.95 CONF LIMIT = 13.72
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

PAD3,273B400RF166
POWER SPECTRUM

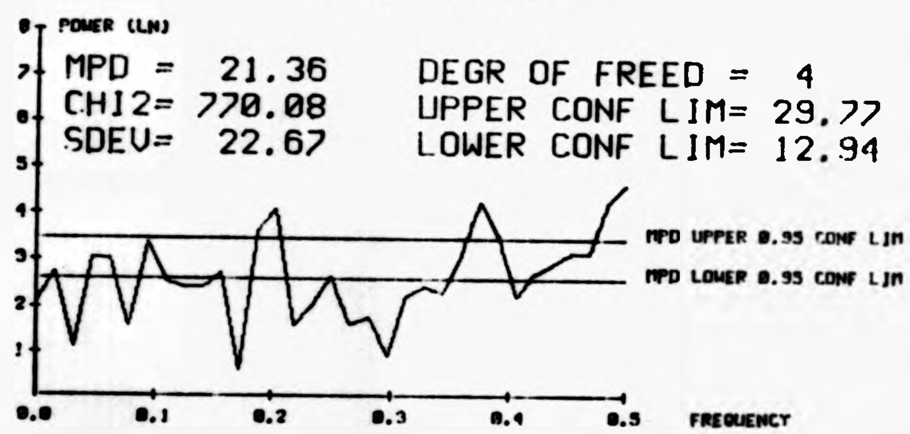


PAD3,273B400RF166 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.6								
0.016	6.6	0.031	63.3	0.047	25.9	0.063	16.9	0.078	4.2
0.094	42.4	0.109	42.8	0.125	0.3	0.141	13.2	0.156	27.4
0.172	0.1	0.188	21.9	0.203	26.3	0.219	2.7	0.234	8.9
0.250	5.9	0.266	9.0	0.281	3.0	0.297	27.7	0.313	13.0
0.328	15.2	0.344	0.1	0.359	23.4	0.375	32.3	0.391	6.1
0.406	11.0	0.422	20.5	0.438	27.0	0.453	7.6	0.469	4.8
0.484	31.0	0.500	78.3						

MEAN POWER DENSITY: 18.80
DEGREES OF FREEDOM = 4
CHISQUARE = 561.45
ST.DEVIATION = 18.16
MPD UPPER 0.95 CONF LIMIT = 25.54
MPD LOWER 0.95 CONF LIMIT = 12.06
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

PAD4,273B400RF157
POWER SPECTRUM

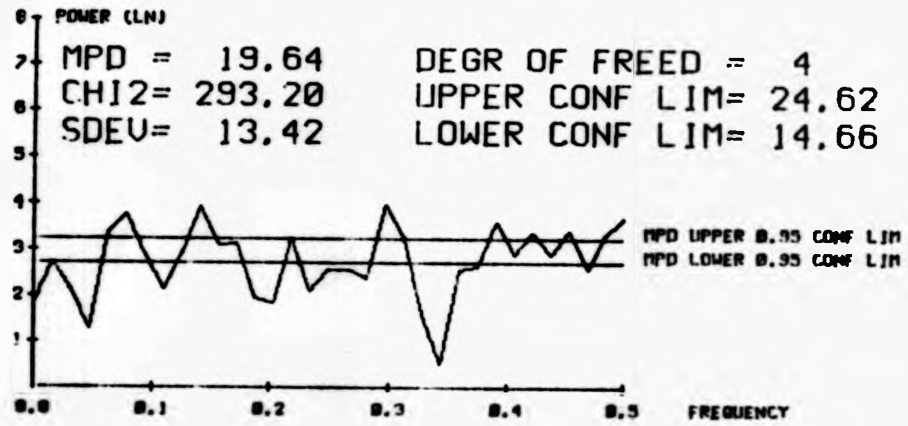


PAD4,273B400RF157 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.9								
0.016	15.3	0.031	2.9	0.047	20.8	0.063	20.4	0.078	4.8
0.094	28.9	0.109	12.7	0.125	11.1	0.141	11.1	0.156	15.2
0.172	1.8	0.188	36.7	0.203	59.9	0.219	4.8	0.234	7.3
0.250	14.3	0.266	4.9	0.281	5.8	0.297	2.4	0.313	9.6
0.328	11.7	0.344	9.9	0.359	23.0	0.375	68.1	0.391	32.2
0.406	9.0	0.422	15.3	0.438	18.2	0.453	23.6	0.469	23.7
0.484	69.5	0.500	102.3						

MEAN POWER DENSITY: 21.36
DEGREES OF FREEDOM = 4
CHISQUARE = 770.08
ST.DEVIATION = 22.67
MPD UPPER 0.95 CONF LIMIT = 29.77
MPD LOWER 0.95 CONF LIMIT = 12.94
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

POOH,273B400RF106
POWER SPECTRUM

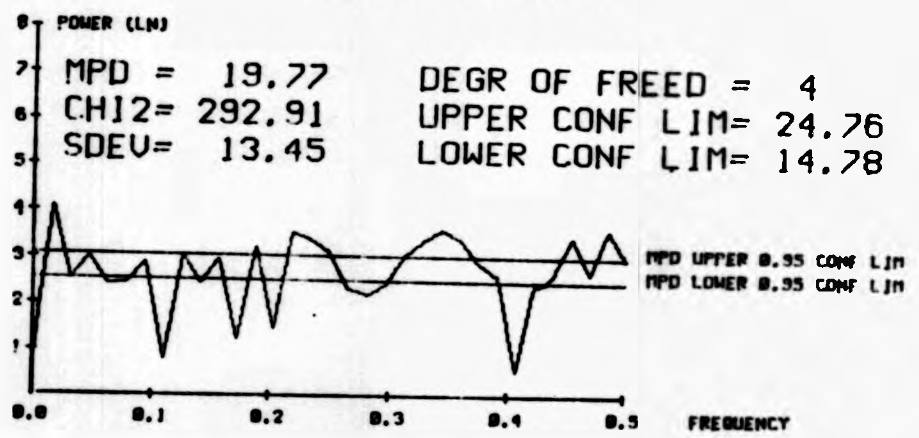


POOH,273B400RF106   POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.0								
0.016	15.2	0.031	8.2	0.047	3.4	0.063	28.5	0.078	43.6
0.094	17.4	0.109	8.3	0.125	18.3	0.141	49.5	0.156	21.4
0.172	22.8	0.188	6.9	0.203	6.1	0.219	25.3	0.234	8.1
0.250	12.8	0.266	13.1	0.281	10.4	0.297	53.4	0.313	25.4
0.328	4.7	0.344	1.6	0.359	12.8	0.375	14.0	0.391	36.2
0.406	18.1	0.422	28.4	0.438	17.7	0.453	30.1	0.469	12.9
0.484	27.8	0.500	39.7						

MEAN POWER DENSITY: 19.64
DEGREES OF FREEDOM = 4
CHISQUARE = 293.20
ST.DEVIATION = 13.42
MPD UPPER 0.95 CONF LIMIT = 24.62
MPD LOWER 0.95 CONF LIMIT = 14.66
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

ALIL,273B400RF110
POWER SPECTRUM

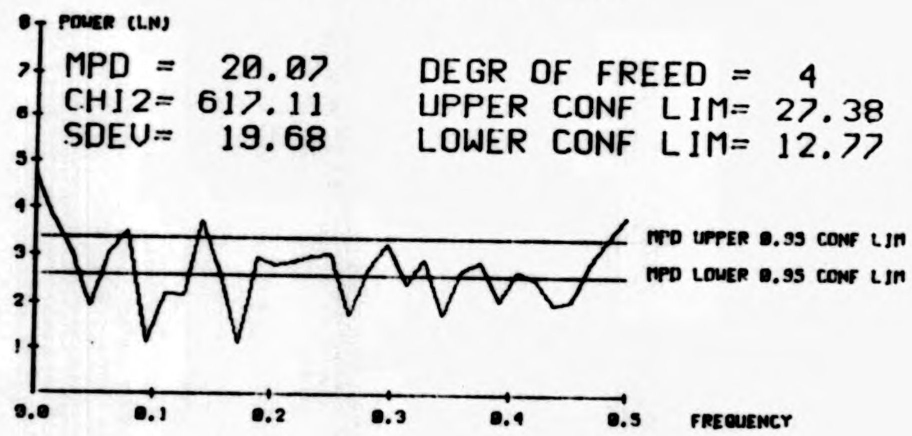


ALIL,273B400RF110 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.2								
0.016	59.3	0.031	12.4	0.047	19.7	0.063	10.9	0.078	11.6
0.094	17.8	0.109	2.2	0.125	20.9	0.141	11.4	0.156	19.2
0.172	3.4	0.188	25.3	0.203	4.4	0.219	34.7	0.234	29.7
0.250	22.3	0.266	10.2	0.281	9.1	0.297	12.0	0.313	21.9
0.328	30.2	0.344	38.4	0.359	30.2	0.375	17.5	0.391	13.4
0.406	1.7	0.422	12.5	0.438	17.5	0.453	40.4	0.469	17.7
0.484	47.4	0.500	24.5						

MEAN POWER DENSITY: 19.77
DEGREES OF FREEDOM = 4
CHISQUARE = 292.91
ST.DEVIATION = 13.45
MPD UPPER 0.95 CONF LIMIT = 24.76
MPD LOWER 0.95 CONF LIMIT = 14.78
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

ALIB,273B400RF62
POWER SPECTRUM

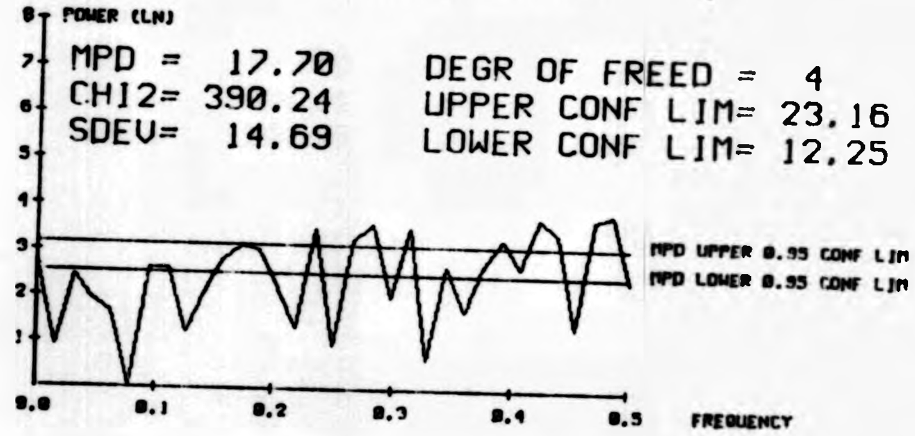


ALIB,273B400RF62 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	111.6								
0.016	41.2	0.031	20.4	0.047	6.5	0.063	20.8	0.078	32.5
0.094	3.0	0.109	9.0	0.125	8.6	0.141	40.6	0.156	13.3
0.172	2.9	0.188	19.0	0.203	16.5	0.219	17.5	0.234	20.4
0.250	20.5	0.266	5.5	0.281	15.8	0.297	26.0	0.313	11.1
0.328	18.7	0.344	5.5	0.359	15.0	0.375	18.2	0.391	7.7
0.406	14.6	0.422	12.4	0.438	7.1	0.453	8.1	0.469	17.9
0.484	28.9	0.500	45.8						

MEAN POWER DENSITY: 20.07
DEGREES OF FREEDOM = 4
CHISQUARE = 617.11
ST.DEVIATION = 19.68
MPD UPPER 0.95 CONF LIMIT = 27.38
MPD LOWER 0.95 CONF LIMIT = 12.77
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 18

GULL,273B400RF252
POWER SPECTRUM



GULL,273B400RF252 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.7								
0.016	2.4	0.031	11.3	0.047	6.9	0.063	5.2	0.078	0.2
0.094	13.8	0.109	14.2	0.125	3.4	0.141	8.2	0.156	17.4
0.172	23.6	0.188	21.3	0.203	9.2	0.219	3.7	0.234	35.8
0.250	2.6	0.266	28.2	0.281	39.8	0.297	7.7	0.313	36.8
0.328	2.0	0.344	16.0	0.359	5.8	0.375	16.5	0.391	28.8
0.406	15.1	0.422	46.2	0.438	32.9	0.453	4.0	0.469	46.3
0.484	52.0	0.500	11.3						

MEAN POWER DENSITY: 17.70
DEGREES OF FREEDOM = 4
CHISQUARE = 390.24
ST.DEVIATION = 14.69
MPD UPPER 0.95 CONF LIMIT = 23.16
MPD LOWER 0.95 CONF LIMIT = 12.25
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

FIE1,201B328RF68 POWER DENSITY IN FREQUENCY POINTS:
C85,

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.1								
0.016	14.0	0.031	14.5	0.047	6.9	0.063	8.5	0.078	11.6
0.094	7.1	0.109	4.8	0.125	45.6	0.141	11.8	0.156	1.3
0.172	17.4	0.188	6.2	0.203	0.9	0.219	25.2	0.234	33.3
0.250	8.1	0.266	9.1	0.281	26.4	0.297	8.2	0.313	26.1
0.328	18.9	0.344	3.2	0.359	12.9	0.375	5.3	0.391	15.3
0.406	31.5	0.422	19.4	0.438	27.3	0.453	26.8	0.469	5.8
0.484	7.3	0.500	2.6						

MEAN POWER DENSITY: 14.39
DEGREES OF FREEDOM = 4
PRM
CHISQUARE = 254.35
ST.DEVIATION = 10.69
MPD UPPER 0.95 CONF LIMIT = 18.36
MPD LOWER 0.95 CONF LIMIT = 10.42
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

95C,201B328RF140 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.2								
0.016	8.3	0.031	19.1	0.047	28.8	0.063	5.2	0.078	18.3
0.094	2.2	0.109	49.0	0.125	16.0	0.141	31.6	0.156	5.9
0.172	3.0	0.188	28.9	0.203	33.3	0.219	3.8	0.234	4.5
0.250	8.4	0.266	13.7	0.281	5.9	0.297	5.5	0.313	7.5
0.328	12.1	0.344	9.0	0.359	7.6	0.375	26.5	0.391	7.1
0.406	21.6	0.422	45.7	0.438	26.9	0.453	1.3	0.469	15.6
0.484	5.8	0.500	10.2						

MEAN POWER DENSITY: 14.80 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 348.41
ST.DEVIATION = 12.70
MPD UPPER 0.95 CONF LIMIT = 19.52
MPD LOWER 0.95 CONF LIMIT = 10.09
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

96C, 190B317RF92 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	30.7								
0.016	25.7	0.031	30.3	0.047	81.7	0.063	6.8	0.078	24.2
0.094	3.0	0.109	11.4	0.125	22.8	0.141	21.1	0.156	21.7
0.172	5.1	0.188	7.7	0.203	0.3	0.219	27.7	0.234	23.5
0.250	7.5	0.266	11.2	0.281	24.4	0.297	18.2	0.313	13.1
0.328	4.6	0.344	9.3	0.359	9.1	0.375	10.2	0.391	17.5
0.406	11.6	0.422	44.0	0.438	38.3	0.453	26.2	0.469	47.2
0.484	14.1	0.500	6.1						

MEAN POWER DENSITY: 19.89 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 418.39
ST.DEVIATION = 16.13
MPD UPPER 0.95 CONF LIMIT = 25.87
MPD LOWER 0.95 CONF LIMIT = 13.90
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

101C, 128B255RF93 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	41.0								
0.016	36.7	0.031	6.3	0.047	19.9	0.063	27.8	0.078	15.3
0.094	12.8	0.109	28.4	0.125	18.8	0.141	8.8	0.156	14.7
0.172	8.3	0.188	6.3	0.203	50.3	0.219	15.3	0.234	14.8
0.250	1.3	0.266	22.6	0.281	15.9	0.297	32.6	0.313	2.0
0.328	27.8	0.344	13.3	0.359	0.8	0.375	10.5	0.391	14.2
0.406	24.0	0.422	1.3	0.438	43.6	0.453	24.8	0.469	15.3
0.484	16.0	0.500	41.6						

MEAN POWER DENSITY: 19.19 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 283.65
ST.DEVIATION = 13.04
MPD UPPER 0.95 CONF LIMIT = 24.03
MPD LOWER 0.95 CONF LIMIT = 14.35
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

<u>103C</u>,94B221RF73 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.2								
0.016	16.6	0.031	19.1	0.047	11.1	0.063	20.7	0.078	2.1
0.094	22.9	0.109	21.4	0.125	6.0	0.141	39.4	0.156	20.7
0.172	12.8	0.188	18.8	0.203	34.1	0.219	17.2	0.234	7.5
0.250	7.0	0.266	24.4	0.281	21.2	0.297	4.9	0.313	20.8
0.328	6.3	0.344	2.7	0.359	12.0	0.375	44.5	0.391	40.7
0.406	36.5	0.422	9.3	0.438	38.9	0.453	56.0	0.469	4.7
0.484	23.0	0.500	5.0						

MEAN POWER DENSITY: 19.13 PRH
DEGREES OF FREEDOM = 4
CHISQUARE = 322.28
ST.DEVIATION = 13.88
MPD UPPER 0.95 CONF LIMIT = 24.28
MPD LOWER 0.95 CONF LIMIT = 13.98
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

<u>104C</u>,87B214RF82 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.4								
0.016	9.6	0.031	43.4	0.047	41.5	0.063	0.7	0.078	8.8
0.094	20.5	0.109	21.5	0.125	8.2	0.141	11.7	0.156	3.0
0.172	28.4	0.188	29.0	0.203	4.0	0.219	9.5	0.234	16.7
0.250	12.7	0.266	6.5	0.281	17.6	0.297	20.9	0.313	2.9
0.328	18.2	0.344	9.9	0.359	4.7	0.375	47.8	0.391	18.6
0.406	12.4	0.422	20.0	0.438	5.9	0.453	17.4	0.469	11.6
0.484	37.6	0.500	7.0						

MEAN POWER DENSITY: 16.38 PRH
DEGREES OF FREEDOM = 4
CHISQUARE = 288.57
ST.DEVIATION = 12.15
MPD UPPER 0.95 CONF LIMIT = 20.89
MPD LOWER 0.95 CONF LIMIT = 11.87
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

110C,137B266RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.0								
0.016	10.4	0.031	2.1	0.047	8.6	0.063	11.2	0.078	31.6
0.094	13.6	0.109	24.6	0.125	16.2	0.141	20.4	0.156	37.0
0.172	17.4	0.188	27.8	0.203	0.3	0.219	28.2	0.234	17.9
0.250	5.1	0.266	18.8	0.281	26.6	0.297	13.4	0.313	21.7
0.328	20.0	0.344	16.5	0.359	44.9	0.375	26.5	0.391	6.5
0.406	13.6	0.422	12.4	0.438	9.0	0.453	19.1	0.469	6.8
0.484	35.6	0.500	83.0						

MEAN POWER DENSITY: 19.72 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 389.43
ST.DEVIATION = 15.49
MPD UPPER 0.95 CONF LIMIT = 25.47
MPD LOWER 0.95 CONF LIMIT = 13.97
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

113C,43B170RF42 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	16.5								
0.016	12.5	0.031	0.6	0.047	17.6	0.063	37.1	0.078	0.4
0.094	19.3	0.109	3.8	0.125	31.6	0.141	19.2	0.156	8.0
0.172	5.6	0.188	20.4	0.203	29.6	0.219	16.1	0.234	16.4
0.250	32.7	0.266	11.9	0.281	30.6	0.297	34.5	0.313	33.5
0.328	8.3	0.344	20.7	0.359	28.4	0.375	14.7	0.391	25.1
0.406	7.8	0.422	21.4	0.438	26.3	0.453	40.0	0.469	3.5
0.484	35.4	0.500	25.5						

MEAN POWER DENSITY: 19.85 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 207.77
ST.DEVIATION = 11.35
MPD UPPER 0.95 CONF LIMIT = 24.06
MPD LOWER 0.95 CONF LIMIT = 15.63
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 11
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

114C, 201B328RF116 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.0								
0.016	5.9	0.031	28.8	0.047	41.3	0.063	58.5	0.078	20.8
0.094	8.7	0.109	15.5	0.125	11.0	0.141	8.8	0.156	17.7
0.172	10.7	0.188	4.5	0.203	1.8	0.219	1.5	0.234	16.3
0.250	8.5	0.266	19.1	0.281	29.3	0.297	0.2	0.313	6.2
0.328	5.5	0.344	8.6	0.359	22.8	0.375	55.3	0.391	31.0
0.406	12.3	0.422	24.8	0.438	0.0	0.453	34.8	0.469	53.9
0.484	15.3	0.500	46.3						

MEAN POWER DENSITY: 19.15 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 461.43
ST.DEVIATION = 16.62
MPD UPPER 0.95 CONF LIMIT = 25.31
MPD LOWER 0.95 CONF LIMIT = 12.98
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

130C, 201B328RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.3								
0.016	6.3	0.031	11.9	0.047	10.4	0.063	17.3	0.078	1.1
0.094	13.1	0.109	14.1	0.125	21.7	0.141	8.2	0.156	13.2
0.172	26.4	0.188	26.3	0.203	26.0	0.219	49.3	0.234	18.2
0.250	9.3	0.266	20.2	0.281	14.0	0.297	28.4	0.313	18.3
0.328	11.1	0.344	29.0	0.359	26.2	0.375	4.9	0.391	2.6
0.406	1.4	0.422	4.8	0.438	52.4	0.453	28.4	0.469	5.0
0.484	28.4	0.500	6.9						

MEAN POWER DENSITY: 16.81 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 305.05
ST.DEVIATION = 12.66
MPD UPPER 0.95 CONF LIMIT = 21.51
MPD LOWER 0.95 CONF LIMIT = 12.11
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

140C,201B328RF92 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	24.6								
0.016	8.5	0.031	16.6	0.047	2.4	0.063	25.9	0.078	53.2
0.094	22.3	0.109	10.0	0.125	4.3	0.141	9.4	0.156	22.7
0.172	44.3	0.188	24.8	0.203	12.7	0.219	20.5	0.234	25.3
0.250	2.8	0.266	11.8	0.281	18.0	0.297	8.2	0.313	6.0
0.328	12.6	0.344	18.7	0.359	1.4	0.375	10.2	0.391	4.6
0.406	19.4	0.422	1.9	0.438	20.4	0.453	29.4	0.469	5.4
0.484	22.4	0.500	1.2						

MEAN POWER DENSITY: 15.81 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 292.89
ST.DEVIATION = 12.03
MPD UPPER 0.95 CONF LIMIT = 20.28
MPD LOWER 0.95 CONF LIMIT = 11.35
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

141C,201B328RF68 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.8								
0.016	18.5	0.031	3.8	0.047	18.4	0.063	24.8	0.078	6.0
0.094	11.1	0.109	35.7	0.125	1.6	0.141	2.2	0.156	6.4
0.172	31.8	0.188	24.1	0.203	1.2	0.219	22.6	0.234	12.2
0.250	17.5	0.266	35.2	0.281	25.4	0.297	18.2	0.313	10.4
0.328	2.0	0.344	21.2	0.359	25.7	0.375	32.2	0.391	35.3
0.406	27.1	0.422	5.8	0.438	14.4	0.453	11.2	0.469	46.8
0.484	43.4	0.500	16.3						

MEAN POWER DENSITY: 18.79 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 266.28
ST.DEVIATION = 12.51
MPD UPPER 0.95 CONF LIMIT = 23.43
MPD LOWER 0.95 CONF LIMIT = 14.15
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

1RUS, 273B400RF125 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.3								
0.016	23.4	0.031	4.7	0.047	15.0	0.063	17.0	0.078	20.1
0.094	12.3	0.109	6.3	0.125	17.4	0.141	9.6	0.156	36.0
0.172	45.9	0.188	4.0	0.203	21.8	0.219	13.9	0.234	12.4
0.250	26.6	0.266	0.7	0.281	7.3	0.297	17.7	0.313	10.4
0.328	12.7	0.344	26.3	0.359	37.1	0.375	2.0	0.391	33.0
0.406	34.3	0.422	3.8	0.438	18.6	0.453	21.6	0.469	9.7
0.484	21.6	0.500	18.2						

MEAN POWER DENSITY: 17.06
DEGREES OF FREEDOM = 4
CHISQUARE = 241.83
ST.DEVIATION = 11.35
MPD UPPER 0.95 CONF LIMIT = 21.27
MPD LOWER 0.95 CONF LIMIT = 12.84
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

2RUS, 273B400RF164 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	22.7								
0.016	10.4	0.031	11.5	0.047	5.1	0.063	16.1	0.078	7.5
0.094	12.3	0.109	48.5	0.125	12.8	0.141	4.3	0.156	33.3
0.172	22.0	0.188	9.3	0.203	3.6	0.219	42.9	0.234	36.6
0.250	2.5	0.266	22.7	0.281	2.6	0.297	6.0	0.313	16.5
0.328	7.6	0.344	4.0	0.359	16.1	0.375	15.0	0.391	9.5
0.406	31.3	0.422	10.1	0.438	11.3	0.453	40.3	0.469	22.3
0.484	32.9	0.500	63.7						

MEAN POWER DENSITY: 18.59
DEGREES OF FREEDOM = 4
CHISQUARE = 387.83
ST.DEVIATION = 15.01
MPD UPPER 0.95 CONF LIMIT = 24.16
MPD LOWER 0.95 CONF LIMIT = 13.02
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

3RUS,273B400RF106 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	20.2								
0.016	8.1	0.031	10.6	0.047	10.4	0.063	5.6	0.078	3.6
0.094	30.1	0.109	12.2	0.125	37.3	0.141	12.1	0.156	8.5
0.172	24.2	0.188	0.5	0.203	12.5	0.219	11.3	0.234	11.3
0.250	3.2	0.266	1.1	0.281	22.1	0.297	21.5	0.313	13.8
0.328	20.7	0.344	77.2	0.359	13.3	0.375	26.1	0.391	6.9
0.406	30.1	0.422	22.1	0.438	26.3	0.453	38.8	0.469	7.6
0.484	50.1	0.500	46.6						

MEAN POWER DENSITY: 19.57 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 435.69
ST.DEVIATION = 16.32
MPD UPPER 0.95 CONF LIMIT = 25.63
MPD LOWER 0.95 CONF LIMIT = 13.51
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

4RUS,273B400RF216 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.8								
0.016	15.4	0.031	29.2	0.047	11.2	0.063	19.1	0.078	12.9
0.094	0.4	0.109	19.3	0.125	9.0	0.141	1.2	0.156	28.1
0.172	42.5	0.188	16.2	0.203	20.0	0.219	19.0	0.234	10.4
0.250	22.2	0.266	33.0	0.281	30.3	0.297	0.3	0.313	13.7
0.328	28.4	0.344	11.4	0.359	9.7	0.375	13.3	0.391	27.3
0.406	10.9	0.422	13.7	0.438	38.2	0.453	26.7	0.469	6.0
0.484	43.5	0.500	100.3						

MEAN POWER DENSITY: 20.80 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 517.11
ST.DEVIATION = 18.34
MPD UPPER 0.95 CONF LIMIT = 27.61
MPD LOWER 0.95 CONF LIMIT = 14.00
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

5RUS,273B400RF206 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	32.5								
0.016	9.7	0.031	37.7	0.047	16.0	0.063	39.5	0.078	44.8
0.094	1.3	0.109	22.6	0.125	9.0	0.141	23.4	0.156	1.0
0.172	28.5	0.188	1.4	0.203	21.8	0.219	0.2	0.234	18.3
0.250	16.5	0.266	9.1	0.281	11.8	0.297	7.2	0.313	5.5
0.328	8.8	0.344	32.8	0.359	13.5	0.375	4.0	0.391	20.4
0.406	19.1	0.422	28.2	0.438	43.1	0.453	6.2	0.469	24.1
0.484	0.4	0.500	4.2						

MEAN POWER DENSITY: 17.05 PRK
DEGREES OF FREEDOM = 4
CHISQUARE = 326.23
ST.DEVIATION = 13.18
MPD UPPER 0.95 CONF LIMIT = 21.94
MPD LOWER 0.95 CONF LIMIT = 12.16
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

LABO,273B400RF254 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.3								
0.016	19.0	0.031	23.0	0.047	12.8	0.063	20.9	0.078	32.2
0.094	10.8	0.109	12.3	0.125	10.9	0.141	20.0	0.156	0.5
0.172	14.5	0.188	16.9	0.203	26.3	0.219	4.8	0.234	24.6
0.250	3.0	0.266	5.8	0.281	18.7	0.297	10.1	0.313	0.5
0.328	10.4	0.344	21.6	0.359	4.5	0.375	42.0	0.391	12.0
0.406	14.7	0.422	2.5	0.438	12.8	0.453	37.4	0.469	11.8
0.484	31.2	0.500	13.0						

MEAN POWER DENSITY: 15.54 PRK
DEGREES OF FREEDOM = 4
CHISQUARE = 215.86
ST.DEVIATION = 10.24
MPD UPPER 0.95 CONF LIMIT = 19.34
MPD LOWER 0.95 CONF LIMIT = 11.74
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

1FRK,273B400RF74 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.9								
0.016	7.5	0.031	1.6	0.047	9.4	0.063	0.7	0.078	12.5
0.094	35.9	0.109	30.8	0.125	16.7	0.141	7.0	0.156	4.8
0.172	11.3	0.188	12.6	0.203	15.5	0.219	3.5	0.234	16.4
0.250	27.6	0.266	19.0	0.281	12.4	0.297	21.4	0.313	16.3
0.328	24.2	0.344	23.0	0.359	28.4	0.375	19.7	0.391	1.9
0.406	34.0	0.422	6.7	0.438	9.3	0.453	14.6	0.469	18.9
0.484	16.5	0.500	10.2						

MEAN POWER DENSITY: 14.95 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 192.99
ST.DEVIATION = 9.49
MPD UPPER 0.95 CONF LIMIT = 18.47
MPD LOWER 0.95 CONF LIMIT = 11.42
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

BRUN,273B400RF152 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.1								
0.016	16.0	0.031	10.2	0.047	7.8	0.063	14.7	0.078	8.3
0.094	33.4	0.109	17.2	0.125	5.2	0.141	9.1	0.156	45.7
0.172	39.0	0.188	1.1	0.203	11.1	0.219	3.8	0.234	10.8
0.250	3.1	0.266	18.0	0.281	9.8	0.297	16.9	0.313	20.2
0.328	20.9	0.344	63.3	0.359	37.4	0.375	3.6	0.391	25.9
0.406	11.4	0.422	1.4	0.438	25.8	0.453	29.8	0.469	1.6
0.484	54.0	0.500	34.2						

MEAN POWER DENSITY: 18.54 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 440.44
ST.DEVIATION = 15.98
MPD UPPER 0.95 CONF LIMIT = 24.47
MPD LOWER 0.95 CONF LIMIT = 12.61
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

CHOM.273B400RF96 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	13.4								
0.016	10.5	0.031	43.2	0.047	2.8	0.063	50.9	0.078	8.4
0.094	24.9	0.109	27.8	0.125	5.7	0.141	9.5	0.156	3.6
0.172	4.2	0.188	15.6	0.203	21.7	0.219	9.1	0.234	11.8
0.250	30.5	0.266	25.8	0.281	22.6	0.297	12.7	0.313	49.5
0.328	7.0	0.344	17.7	0.359	28.7	0.375	12.9	0.391	17.1
0.406	9.8	0.422	20.8	0.438	28.5	0.453	9.3	0.469	13.8
0.484	16.2	0.500	22.8						

MEAN POWER DENSITY: 18.45 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 262.42
ST.DEVIATION = 12.30
MPD UPPER 0.95 CONF LIMIT = 23.01
MPD LOWER 0.95 CONF LIMIT = 13.88
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

1REC,401B528RF350 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.5								
0.016	25.4	0.031	12.2	0.047	19.6	0.063	11.0	0.078	7.4
0.094	2.0	0.109	8.0	0.125	17.3	0.141	4.2	0.156	32.1
0.172	27.8	0.188	23.6	0.203	22.2	0.219	11.0	0.234	13.9
0.250	5.9	0.266	0.2	0.281	33.7	0.297	15.4	0.313	4.9
0.328	5.5	0.344	8.3	0.359	0.7	0.375	36.2	0.391	50.1
0.406	8.4	0.422	37.4	0.438	12.5	0.453	31.6	0.469	2.8
0.484	21.2	0.500	12.4						

MEAN POWER DENSITY: 16.19 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 304.49
ST.DEVIATION = 12.41
MPD UPPER 0.95 CONF LIMIT = 20.80
MPD LOWER 0.95 CONF LIMIT = 11.58
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

2REC,301B428RF264 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.2								
0.016	5.7	0.031	28.2	0.047	6.1	0.063	69.0	0.078	24.8
0.094	13.9	0.109	8.4	0.125	3.5	0.141	27.4	0.156	22.8
0.172	7.3	0.188	8.2	0.203	6.5	0.219	12.7	0.234	37.1
0.250	20.3	0.266	8.6	0.281	3.1	0.297	17.3	0.313	19.3
0.328	50.3	0.344	45.4	0.359	32.7	0.375	9.6	0.391	12.2
0.406	5.1	0.422	8.4	0.438	7.7	0.453	11.2	0.469	8.7
0.484	14.9	0.500	3.1						

MEAN POWER DENSITY: 17.23 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 431.51
ST.DEVIATION = 15.24
MPD UPPER 0.95 CONF LIMIT = 22.89
MPD LOWER 0.95 CONF LIMIT = 11.57
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

HRLD,301B428RF138 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.8								
0.016	14.9	0.031	15.8	0.047	32.0	0.063	35.2	0.078	16.3
0.094	11.8	0.109	21.6	0.125	23.3	0.141	5.2	0.156	25.6
0.172	46.1	0.188	25.4	0.203	18.9	0.219	19.4	0.234	2.4
0.250	7.9	0.266	19.8	0.281	4.1	0.297	26.6	0.313	10.9
0.328	4.9	0.344	4.1	0.359	14.1	0.375	25.7	0.391	6.8
0.406	17.1	0.422	13.7	0.438	9.8	0.453	11.9	0.469	3.0
0.484	16.5	0.500	15.8						

MEAN POWER DENSITY: 16.11 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 205.13
ST.DEVIATION = 10.16
MPD UPPER 0.95 CONF LIMIT = 19.88
MPD LOWER 0.95 CONF LIMIT = 12.33
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

MAIL,301B428RF250 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.3								
0.016	24.2	0.031	9.5	0.047	21.8	0.063	36.6	0.078	11.4
0.094	5.5	0.109	19.0	0.125	23.1	0.141	12.7	0.156	17.0
0.172	25.2	0.188	21.6	0.203	12.1	0.219	16.8	0.234	2.9
0.250	27.9	0.266	28.2	0.281	36.8	0.297	28.9	0.313	10.7
0.328	29.2	0.344	12.8	0.359	8.6	0.375	16.9	0.391	9.3
0.406	20.8	0.422	2.3	0.438	6.8	0.453	10.9	0.469	33.6
0.484	29.2	0.500	7.3						

MEAN POWER DENSITY: 17.84 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 173.16
ST.DEVIATION = 9.83
MPD UPPER 0.95 CONF LIMIT = 21.49
MPD LOWER 0.95 CONF LIMIT = 14.19
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

GUAR,201B328RF100 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.2								
0.016	31.5	0.031	14.6	0.047	7.2	0.063	4.7	0.078	13.9
0.094	11.3	0.109	5.8	0.125	5.0	0.141	12.8	0.156	19.5
0.172	5.6	0.188	23.6	0.203	42.8	0.219	9.2	0.234	19.8
0.250	23.7	0.266	35.4	0.281	4.2	0.297	27.5	0.313	15.6
0.328	2.4	0.344	4.9	0.359	7.3	0.375	11.7	0.391	21.9
0.406	38.4	0.422	2.7	0.438	41.1	0.453	39.8	0.469	0.7
0.484	23.6	0.500	12.6						

MEAN POWER DENSITY: 16.72 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 299.07
ST.DEVIATION = 12.50
MPD UPPER 0.95 CONF LIMIT = 21.36
MPD LOWER 0.95 CONF LIMIT = 12.08
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

PAD1,273B400RF166 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.8								
0.016	8.8	0.031	1.0	0.047	40.7	0.063	24.5	0.078	15.1
0.094	10.0	0.109	1.6	0.125	31.4	0.141	30.6	0.156	3.6
0.172	19.1	0.188	10.0	0.203	26.2	0.219	31.9	0.234	4.8
0.250	27.3	0.266	12.8	0.281	41.3	0.297	5.9	0.313	7.0
0.328	17.4	0.344	11.8	0.359	16.5	0.375	10.0	0.391	21.5
0.406	15.8	0.422	11.2	0.438	29.9	0.453	6.4	0.469	12.8
0.484	7.6	0.500	25.3						

MEAN POWER DENSITY: 16.39 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 249.08
ST.DEVIATION = 11.29
MPD UPPER 0.95 CONF LIMIT = 20.58
MPD LOWER 0.95 CONF LIMIT = 12.20
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

PAD2,273B400RF119 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.5								
0.016	12.2	0.031	3.4	0.047	15.3	0.063	0.1	0.078	28.8
0.094	26.7	0.109	15.6	0.125	0.1	0.141	19.0	0.156	28.0
0.172	16.9	0.188	24.0	0.203	8.7	0.219	11.6	0.234	16.3
0.250	18.8	0.266	34.0	0.281	12.0	0.297	3.2	0.313	22.1
0.328	6.8	0.344	27.8	0.359	2.3	0.375	2.5	0.391	2.4
0.406	43.7	0.422	6.6	0.438	11.8	0.453	6.2	0.469	27.1
0.484	15.1	0.500	61.1						

MEAN POWER DENSITY: 16.20 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 360.13
ST.DEVIATION = 13.50
MPD UPPER 0.95 CONF LIMIT = 21.21
MPD LOWER 0.95 CONF LIMIT = 11.18
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

PAD3,273B400RF166 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.5								
0.016	34.9	0.031	4.4	0.047	41.6	0.063	33.3	0.078	35.3
0.094	36.6	0.109	11.3	0.125	5.7	0.141	12.2	0.156	33.1
0.172	6.6	0.188	8.6	0.203	0.0	0.219	1.3	0.234	20.3
0.250	5.7	0.266	0.3	0.281	32.9	0.297	14.0	0.313	44.4
0.328	10.4	0.344	10.3	0.359	12.7	0.375	18.9	0.391	32.4
0.406	8.9	0.422	7.4	0.438	35.0	0.453	21.2	0.469	35.0
0.484	17.5	0.500	24.7						

MEAN POWER DENSITY: 18.92 PRH
DEGREES OF FREEDOM = 4
CHISQUARE = 309.88
ST.DEVIATION = 13.54
MPD UPPER 0.95 CONF LIMIT = 23.95
MPD LOWER 0.95 CONF LIMIT = 13.90
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

PAD4,273B400RF157 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.8								
0.016	5.4	0.031	29.5	0.047	24.7	0.063	23.1	0.078	17.0
0.094	23.1	0.109	6.1	0.125	3.8	0.141	8.9	0.156	10.3
0.172	16.2	0.188	4.2	0.203	11.5	0.219	8.6	0.234	18.4
0.250	30.7	0.266	1.6	0.281	12.1	0.297	11.5	0.313	21.0
0.328	3.3	0.344	21.0	0.359	3.2	0.375	17.1	0.391	4.7
0.406	32.6	0.422	25.1	0.438	5.1	0.453	11.4	0.469	24.0
0.484	24.7	0.500	12.1						

MEAN POWER DENSITY: 14.33 PRH
DEGREES OF FREEDOM = 4
CHISQUARE = 193.52
ST.DEVIATION = 9.31
MPD UPPER 0.95 CONF LIMIT = 17.79
MPD LOWER 0.95 CONF LIMIT = 10.88
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

POOH,273B400RF106 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.5								
0.016	18.4	0.031	7.2	0.047	2.9	0.063	9.2	0.078	13.6
0.094	19.7	0.109	16.0	0.125	11.3	0.141	24.0	0.156	6.1
0.172	7.7	0.188	5.2	0.203	7.3	0.219	9.3	0.234	44.7
0.250	23.8	0.266	12.6	0.281	7.5	0.297	32.9	0.313	37.1
0.328	16.0	0.344	58.5	0.359	27.1	0.375	20.1	0.391	14.1
0.406	10.7	0.422	47.3	0.438	22.3	0.453	22.8	0.469	12.8
0.484	48.8	0.500	83.4						

MEAN POWER DENSITY: 21.39 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 482.97
ST.DEVIATION = 17.97
MPD UPPER 0.95 CONF LIMIT = 28.06
MPD LOWER 0.95 CONF LIMIT = 14.72
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

ALIL,273B400RF110 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	8.3								
0.016	31.7	0.031	18.1	0.047	11.3	0.063	30.3	0.078	9.0
0.094	16.5	0.109	24.0	0.125	21.1	0.141	1.4	0.156	31.5
0.172	5.5	0.188	17.8	0.203	3.7	0.219	39.5	0.234	1.0
0.250	39.3	0.266	19.4	0.281	17.9	0.297	10.8	0.313	5.5
0.328	22.0	0.344	35.5	0.359	17.2	0.375	14.8	0.391	30.9
0.406	25.1	0.422	24.4	0.438	26.1	0.453	38.3	0.469	20.2
0.484	5.4	0.500	9.7						

MEAN POWER DENSITY: 19.19 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 213.34
ST.DEVIATION = 11.31
MPD UPPER 0.95 CONF LIMIT = 23.38
MPD LOWER 0.95 CONF LIMIT = 14.99
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

ALIB,273B400RF62 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	12.0								
0.016	28.9	0.031	12.2	0.047	17.8	0.063	31.4	0.078	21.2
0.094	6.3	0.109	26.4	0.125	10.7	0.141	28.7	0.156	22.4
0.172	0.4	0.188	2.6	0.203	12.4	0.219	14.7	0.234	9.5
0.250	27.3	0.266	2.8	0.281	38.0	0.297	1.1	0.313	38.1
0.328	17.7	0.344	19.0	0.359	22.4	0.375	19.3	0.391	55.9
0.406	6.7	0.422	11.5	0.438	1.6	0.453	14.8	0.469	10.0
0.484	55.8	0.500	55.7						

MEAN POWER DENSITY: 19.85 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 380.36
ST.DEVIATION = 15.36
MPD UPPER 0.95 CONF LIMIT = 25.56
MPD LOWER 0.95 CONF LIMIT = 14.15
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

GULL,273B400RF252 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	0.1								
0.016	32.1	0.031	21.4	0.047	1.8	0.063	29.0	0.078	15.6
0.094	13.7	0.109	11.1	0.125	30.1	0.141	17.2	0.156	23.8
0.172	16.6	0.188	1.4	0.203	43.4	0.219	13.9	0.234	7.5
0.250	10.3	0.266	19.3	0.281	11.9	0.297	3.7	0.313	1.5
0.328	30.4	0.344	36.3	0.359	12.8	0.375	16.8	0.391	6.9
0.406	7.3	0.422	6.1	0.438	4.1	0.453	23.8	0.469	2.6
0.484	20.5	0.500	23.2						

MEAN POWER DENSITY: 15.64 PRM
DEGREES OF FREEDOM = 4
CHISQUARE = 255.73
ST.DEVIATION = 11.18
MPD UPPER 0.95 CONF LIMIT = 19.79
MPD LOWER 0.95 CONF LIMIT = 11.49
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

CHILDRENS' TEXT STRINGS:

	MPD(TEXT)	MPD(PERM)	DELTA MPD	DEV FROM TOTAL MEAN
C85	17.76	14.39	-3.37	-2.66
C95	19.41	14.80	-4.61	-3.90
C96	17.34	19.89	2.55	3.25
C101	17.13	19.19	2.06	2.76
C103	16.91	19.13	2.22	2.92
C104	18.44	16.38	-2.06	-1.35
C110	19.58	19.72	0.14	0.84
C113	18.95	19.85	0.90	1.60
C114	18.60	19.15	0.55	1.25
C130	17.60	16.81	-0.79	-0.08
C140	17.01	15.81	-1.20	-0.49
C141	20.03	18.79	-1.24	-0.53

MPD(TEXT) MEAN (THIS GROUP): 18.23
VARIANCE: 1.18
S.DEV.: 1.09

MPD(PERM) MEAN (THIS GROUP): 17.83
VARIANCE: 4.21
S.DEV.: 2.05

MPD DELTA MEAN (THIS GROUP): -0.40
VARIANCE: 5.03
S.DEV.: 2.24

SCIENTISTS:

	MPD(TEXT)	MPD(PERM)	DELTA MPD	DEV FROM TOTAL MEAN
RUSS1	17.76	17.06	-0.70	0.68
RUSS2	19.69	18.59	-1.10	-0.39
RUSS3	17.57	19.57	2.00	2.71
RUSS4	16.67	20.80	4.13	4.84
RUSS5	17.68	17.05	-0.63	0.08
LABOV	15.95	15.54	-0.41	0.30
BRUNER	18.68	18.54	-0.14	0.57
FRANKENA	18.54	14.95	-3.59	-2.88
CHOMSKY	17.35	18.45	1.10	1.81

MPD(TEXT) MEAN (THIS GROUP): 17.77
VARIANCE: 1.23
S.DEV.: 1.11

MPD(PERM) MEAN (THIS GROUP): 17.84
VARIANCE: 3.51
S.DEV.: 1.87

MPD DELTA MEAN (THIS GROUP): 0.07
VARIANCE: 4.67
S.DEV.: 2.16

NEWSPAPERS:

	MPD(TEXT)	MPD(PERM)	DELTA MPD	DEV FROM TOTAL MEAN
DAILY RECORD1	17.91	16.19	-1.72	-1.01
DAILY RECORD2	15.77	17.23	1.46	2.17
DAILY MAIL	18.00	17.84	-0.16	0.55
GLASGOW HERALD	17.51	16.11	-1.40	-0.69
GUARDIAN	20.28	16.72	-3.56	-2.85

MPD(TEXT) MEAN (THIS GROUP): 17.89
VARIANCE: 2.59
S.DEV.: 1.61

MPD(PERM) MEAN (THIS GROUP): 16.82
VARIANCE: 0.53
S.DEV.: 0.73

MPD DELTA MEAN (THIS GROUP): -1.0760
VARIANCE: 3.49
S.DEV.: 1.87

BOOKS WRITTEN FOR CHILDREN:

	MPD(TEXT)	MPD(PERM)	DELTA MPD	DEV FROM TOTAL MEAN
PAD1	18.85	16.39	-2.46	-1.75
PAD2	20.18	16.20	-3.98	-3.27
PAD3	18.80	18.92	0.12	0.83
PAD4	21.36	14.33	-7.03	-6.32
POOH	19.64	21.39	1.75	2.46
ALICEL	19.77	19.19	-0.58	0.13
ALICEB	20.07	19.85	-0.22	0.49
SEAGULL	17.70	15.64	-2.06	-1.35

MPD(TEXT) MEAN (THIS GROUP): 19.55
VARIANCE: 1.21
S.DEV.: 1.10

MPD(PERM) MEAN (THIS GROUP): 17.74
VARIANCE: 5.93
S.DEV.: 2.43

MPD DELTA MEAN (THIS GROUP): -1.81
VARIANCE: 7.55
S.DEV.: 2.75

MPD(TEXT) MEAN ALL SAMPLES: 18.37
VARIANCE: 1.74
S.DEV.: 1.32

MPD(PERM) MEAN ALL SAMPLES: 17.66
VARIANCE: 3.70
S.DEV.: 1.92

MPD DELTA MEAN ALL SAMPLES: -0.71
VARIANCE: 5.35
S.DEV.: 2.31

CHILDRENS' TEXT STRINGS:

	CHI2(TEXT)	CHI2(PERM)	DELTA CHI2	DEV FROM TOTAL MEAN
C85	406.77	254.35	-152.42	-122.87
C95	338.75	348.41	9.66	39.21
C96	249.39	418.39	169.00	198.55
C101	185.84	283.65	97.81	127.36
C103	182.15	322.28	140.13	169.68
C104	220.94	288.57	67.63	97.18
C110	251.50	389.43	137.93	167.48
C113	261.56	207.77	-53.79	-24.24
C114	315.48	461.43	145.95	175.50
C130	217.48	305.05	87.57	117.12
C140	220.79	292.89	72.10	101.65
C141	277.23	266.28	-10.95	18.60

CHI2(TEXT) MEAN (THIS GROUP): 260.66
VARIANCE: 4339.22
S.DEV.: 65.87

CHI2(PERM) MEAN (THIS GROUP): 319.88
VARIANCE: 5306.79
S.DEV.: 72.85

CHI2 DELTA MEAN (THIS GROUP): 59.22
VARIANCE: 9071.61
S.DEV.: 95.25

SCIENTISTS:

	CHI2(TEXT)	CHI2(PERM)	DELTA CHI2	DEV FROM TOTAL MEAN
RUSS1	281.44	241.83	-39.61	-10.06
RUSS2	504.59	387.83	-116.76	-87.21
RUSS3	483.71	435.69	-48.02	-18.47
RUSS4	364.78	517.11	152.33	181.88
RUSS5	334.79	326.23	-8.56	20.99
LABOV	255.74	215.86	-39.88	-10.33
BRUNER	251.39	440.44	189.05	218.60
FRANKENA	460.83	192.99	-267.84	-238.29
CHOMSKY	390.43	262.42	-128.01	-98.46

CHI2(TEXT) MEAN (THIS GROUP): 369.74
VARIANCE: 9493.11
S.DEV.: 97.43

CHI2(PERM) MEAN (THIS GROUP): 335.60
VARIANCE: 13199.30
S.DEV.: 114.89

CHI2 DELTA MEAN (THIS GROUP): -34.14
VARIANCE: 19468.50
S.DEV.: 139.53

NEWSPAPERS:

	CHI2(TEXT)	CHI2(PERM)	DELTA CHI2	DEV FROM TOTAL MEAN
DAILY REC 1	292.12	304.49	12.37	41.92
DAILY REC 2	438.59	431.51	-7.08	22.47
DAILY MAIL	281.99	173.16	-108.83	-79.28
GLASGOW HER.	166.51	205.13	38.62	68.17
GUARDIAN	375.97	299.07	-76.90	-47.35

CHI2(TEXT) MEAN (THIS GROUP): 311.04
VARIANCE: 10643.90
S.DEV.: 103.17

CHI2(PERM) MEAN (THIS GROUP): 282.67
VARIANCE: 10225.80
S.DEV.: 101.12

CHI2 DELTA MEAN (THIS GROUP): -28.36
VARIANCE: 3857.41
S.DEV.: 62.11

BOOKS WRITTEN FOR CHILDREN:

	CHI2(TEXT)	CHI2(PERM)	DELTA CHI2	DEV FROM TOTAL MEAN
PAD1	305.26	249.08	-56.18	-26.63
PAD2	481.09	360.13	-120.96	-91.41
PAD3	561.45	309.88	-251.57	-222.02
PAD4	770.08	193.52	-576.56	-547.60
POOH	293.20	482.97	189.77	219.32
ALICEL	292.91	213.34	-79.57	-50.02
ALICEB	617.11	380.36	-236.75	-207.20
SEAGULL	390.24	255.73	-134.51	-104.96

CHI2(TEXT) MEAN (THIS GROUP): 463.92
VARIANCE: 30857.10
S.DEV.: 175.66

CHI2(PERM) MEAN (THIS GROUP): 305.63
VARIANCE: 9542.34
S.DEV.: 97.68

CHI2 DELTA MEAN (THIS GROUP): -158.29
VARIANCE: 47076.40
S.DEV.: 216.97

CHI2(TEXT) MEAN ALL SAMPLES: 344.77
VARIANCE: 17940.10
S.DEV.: 133.94

CHI2(PERM) MEAN ALL SAMPLES 315.21
VARIANCE: 8536.37
S.DEV.: 92.39

CHI2 DELTA MEAN ALL SAMPLES: -29.55
VARIANCE: 25086.40
S.DEV.: 158.39

```
b:c85.txt
201B328RF68

0010110011111010101001000000110010100100000101101110
0011010110010101100010110001000000100000010001000101
01110010000100000001001001101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       25 *************************
   2        8 ********
   3        2 **
   4        0
   5        1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 52


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       14 ***************
   2        9 *********
   3        5 *****
   4        2 **
   5        3 ***
   6        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 76
```

```
B:C95.TXT
201B32BRF140

10101100000000110010010011010011001100000001001111 10
00111110110111101011010011000110001010000010010101
11001010001010001110000010101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        20 ********************
   2         9 *********
   3         2 **
   4         1 *
   5         2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        13 *************
   2        10 **********
   3         5 *****
   4         1 *
   5         1 *
   6         1 *
   7         1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

B:C96.TXT
190B317RF92

```
10011101110101011100111100011101111011001000110100
110000000001101000110000000110001000010000100001100
00001101011011001110000010011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        11 ***********
   2        11 ***********
   3         5 *****
   4         2 **
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        10 **********
   2         5 *****
   3         5 *****
   4         4 ****
   5         0
   6         2 **
   7         0
   8         0
   9         1 *
TOTAL OF NUMBER OF RUNS= 27
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:C101.TXT
128B255RF93

10110111010101011001001000101101110011000000100110
00000011010111011001111001110010010010000001001001 0
10001010010000101000100000011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        22 **********************
   2         8 ********
   3         4 ****
   4         1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 54


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        12 ************
   2        13 *************
   3         3 ***
   4         1 *
   5         2 **
   6         1 *
   7         1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 74
```

```
B:C103.TXT
94B221RF73

01000101111010000101101011101110110010001010001011
000101001101000111010000000101000001110001000000000
0010100000001100110000000111
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       17 *****************
   2        7 *******
   3        5 *****
   4        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 50


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       14 **************
   2        3 ***
   3        6 ******
   4        2 **
   5        0
   6        0
   7        3 ***
   8        0
   9        0
  10        0
  11        1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 78
```

```
B:C104.TXT
87B214RFB2

10100101111101001001000101010010101100011100100100
01110010000101001110000010100010110000001010101101
1101110001001000101110110001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       26 **************************
   2        4 ****
   3        6 ******
   4        0
   5        1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 57


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2       10 **********
   3        7 *******
   4        1 *
   5        1 *
   6        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 71
```

```
B:C110.TXT
137B266RF100

00101011000001010001100111111001011111110000010111
01001010000011010010100011000100100000000001000001
100111011001001010101000011001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      22 **********************
   2       7 *******
   3       2 **
   4       0
   5       0
   6       1 *
   7       1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 55


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      12 ************
   2      10 **********
   3       3 ***
   4       1 *
   5       4 ****
   6       0
   7       0
   8       0
   9       0
  10       1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 75
```

```
B:C113.TXT
43B170RF42

10001101101001001001110110110000101011011000111100
00000100000000011011010100100100101000000100000000101
100100000101000110111100001010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       20 ********************
   2       10 **********
   3        2 **
   4        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 50


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2        7 *******
   3        2 **
   4        4 ****
   5        1 *
   6        0
   7        2 **
   8        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 78
```

```
B:C114.TXT
201B328RF116

10111010110000100101011010101100001001100000001000
000010111111001010110001111000001011101100010100110
0100100000011000010110001000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        9 *********
   3        2 **
   4        1 *
   5        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 52


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       13 *************
   2        7 *******
   3        4 ****
   4        3 ***
   5        1 *
   6        1 *
   7        2 **
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 76
```

```
B:C130.TXT
201B328RF60

01011101111101111111110010001110000010000001000110110
00000010001010100100101001010000010010000001101100
0001100100001000101110010111
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       18 ******************
  2        6 ******
  3        4 ****
  4        0
  5        1 *
  6        0
  7        0
  8        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 55


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       11 ***********
  2        7 *******
  3        4 ****
  4        2 **
  5        3 ***
  6        1 *
  7        1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 73
```

```
B:C140.TXT
201B328RF92

0111100010000000111100101111101111010101000101111100
100000010001101010100101010111001010001110100011000
00001100100011001100000101010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        5 *****
   3        2 **
   4        3 ***
   5        2 **
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 59


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       17 *****************
   2        6 ******
   3        6 ******
   4        1 *
   5        1 *
   6        1 *
   7        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 69
```

```
B:C141.TXT
201B328RF68

01010110000110000101001010111110110100110101100110
11101000000000000010110000011010000101001001000010000
010000011100101011111000000100
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        9 *********
   3        2 **
   4        1 *
   5        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 52


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        7 *******
   3        1 *
   4        4 ****
   5        2 **
   6        1 *
   7        0
   8        0
   9        0
  10        0
  11        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 76
```

```
B:RUSS1.TXT
273B400RF125

01111001101011101110111010101100101101101111010110
000010100101100010100101001000100110000000000000101
0110101011100010010001110000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       20 ********************
   2        8 ********
   3        5 *****
   4        1 *
   5        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 60


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        7 *******
   3        4 ****
   4        1 *
   5        1 *
   6        0
   7        0
   8        0
   9        0
  10        0
  11        0
  12        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 68
```

```
B:RUSS2.TXT
273B400RF164

11001100010111111011011001101010100010000100010011
0000110001101111100000000101110100000010100101110111
0100011111011101010101001001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        19 *******************
   2         8 ********
   3         4 ****
   4         1 *
   5         1 *
   6         1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 62


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        18 ******************
   2         6 ******
   3         5 *****
   4         2 **
   5         0
   6         1 *
   7         1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 66
```

```
B:RUSS3.TXT
273B400RF106

11010100001111011101001001110000010011010111010100
0000101100000000001000000010010010100111001101010110
0000111000100010110101010101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       23 ***********************
   2        6 ******
   3        5 *****
   4        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 54


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        7 *******
   3        2 **
   4        1 *
   5        2 **
   6        2 **
   7        0
   8        0
   9        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 74
```

```
B:RUSS4.TXT
273B400RF216

10110101110001110010101001001110000110011010110001
010011000110100010010011000000010101001100111100110
1010010001110010011101010110
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        21 *********************
  2        10 **********
  3         5 *****
  4         1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 60


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        15 ***************
  2        14 **************
  3         5 *****
  4         1 *
  5         0
  6         1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 68
```

```
B:RUSS4.TXT
273B400RF216

10110101110001110010101001001110000110011010110001
01001100011010001001001100000010101001100111100110
1010010001110010011101010110
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        21 *********************
   2        10 **********
   3         5 *****
   4         1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 60


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        15 ***************
   2        14 **************
   3         5 *****
   4         1 *
   5         0
   6         1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 68
```

B:RUSS5.TXT
273B400RF206

01111100101010011100010100111011111101010001001010
10100110101100111000000110110010111000100000001111
10100000000000111011111110010
LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	17	*****************
2	4	****
3	5	*****
4	0	
5	1	*
6	3	***

TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 63

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	16	****************
2	8	********
3	3	***
4	0	
5	0	
6	1	*
7	1	*
8	0	
9	0	
10	0	
11	1	*

TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 65

```
B:LABOV.TXT
273B400RF254

01101001001011110000001101000110111000001001011101
10001010011101011000001010110110110110101100101010
10011011110011011111101001000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        18 ******************
   2        11 ***********
   3         4 ****
   4         2 **
   5         1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 65


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        22 **********************
   2         8 ********
   3         3 ***
   4         0
   5         2 **
   6         1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 63
```

```
B:FRANKENA.TXT
273B400RF74

01010101001010001000101000010000010101000010110000
0110011101101101110101110110110001110110101101111
11001011000000000101010100111
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       20 ********************
   2       10 **********
   3        4 ****
   4        1 *
   5        0
   6        1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 62


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       23 ***********************
   2        4 ****
   3        3 ***
   4        2 **
   5        2 **
   6        0
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 66
```

```
B:BRUNER.TXT
273B400RF152

10011100011010010101001010101101100000101110011001
00111000110000010000011011000011110100110010010000
1110001100111000001011101001
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       17 *****************
  2        9 *********
  3        6 ******
  4        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 57


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       11 ***********
  2       10 **********
  3        4 ****
  4        2 **
  5        4 ****
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 71
```

```
B:CHOMSKY.TXT
273B400RF96

001101111111010011010101010111000011010000000000100
000011100011111111110001010011110010000000100100000
0000000100101100011001001110
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      16 ****************
   2       5 *****
   3       3 ***
   4       1 *
   5       0
   6       0
   7       1 *
   8       0
   9       0
  10       1 *
TOTAL OF NUMBER OF RUNS= 27
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      10 **********
   2       8 ********
   3       3 ***
   4       1 *
   5       0
   6       2 **
   7       0
   8       0
   9       1 *
  10       0
  11       0
  12       1 *
TOTAL OF NUMBER OF RUNS= 26
```

```
B:DREC1.TXT
401B528RF350

00011001110011101101111101001011010010000001100000
01101101011100010110100010100111100010010110110100
0111101011010101100010110101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2       12 ************
   3        3 ***
   4        2 **
   5        1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 65


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        6 ******
   3        6 ******
   4        0
   5        0
   6        2 **
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 63
```

```
B:DREC2.TXT
301B428RF264

01000100111101110010000101110111001010100110101011
00111111111001110100101000001001110110111001000100
0101010001000010100111000100
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        4 ****
   3        7 *******
   4        1 *
   5        0
   6        0
   7        0
   8        0
   9        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 63


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2       11 ***********
   3        5 *****
   4        2 **
   5        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 65
```

```
B:MAIL.TXT
301B428RF250

10110011100001100111101101100000011010100010101010
00111010110101011110010100001000111000000110100110
1000001010111010111011001000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        19 *******************
   2         9 *********
   3         5 *****
   4         2 **
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 60


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        19 *******************
   2         6 ******
   3         4 ****
   4         2 **
   5         1 *
   6         2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 68
```

```
B:HERALD.TXT
301B428RF138

01110010110110010010100000010100000010001100100000
11111110110011110001001010010111100101101001011000
1010011011110100110111000010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        8 ********
   3        1 *
   4        4 ****
   5        0
   6        0
   7        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 61


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2       11 ***********
   3        3 ***
   4        1 *
   5        1 *
   6        2 **
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 67
```

```
B:GUARD.TXT
201B328RF100

10010010010011000100001000101001010110011011011001
001101011000100000110100101111010100000110001000001
1011101100101100101100110001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        21 *********************
  2        14 **************
  3         1 *
  4         1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        14 **************
  2        11 ***********
  3         6 ******
  4         2 **
  5         2 **
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:FAD1.TXT
273B400RF166

11010010001011010011100000100110001100000001011000
000111000111100111100100111001110100000110110010111
100000111001001000101000011 0
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       13 *************
   2        8 ********
   3        5 *****
   4        3 ***
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        9 *********
   2       10 **********
   3        4 ****
   4        2 **
   5        2 **
   6        1 *
   7        1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:PAD2.TXT
273B400RF119

101000001001011010000011011110100010101001001000101
11111100111010011000110000100001010111010100001001
0100000101011000010110100011
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       25 *************************
  2        7 *******
  3        2 **
  4        1 *
  5        0
  6        0
  7        1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       16 ****************
  2        7 *******
  3        4 ****
  4        5 *****
  5        2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:PAD3.TXT
273B400RF166

00001011101001100011110010110111000000101000010111
11101001001100011100010100101111000010101000000100
10001101100111011100000000110
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       17 *****************
  2        6 ******
  3        5 *****
  4        2 **
  5        0
  6        1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       13 *************
  2        7 *******
  3        4 ****
  4        3 ***
  5        0
  6        2 **
  7        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

```
B:PAD4.TXT
273B400RF157

10000111011001010101010010101110001000011000111011
10001100000110111110100101001001001010010010101101
1000010101100001011101000100
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       24 ************************
  2        7 *******
  3        5 *****
  4        0
  5        1 *
TOTAL OF NUMBER OF RUNS= 37
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       18 ******************
  2        9 *********
  3        4 ****
  4        3 ***
  5        2 **
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

```
B:POOH.TXT
273B400RF106

101001010110110010000001011001000000010111000111000
000110101111000000110011001100001101000110000111011
0100010111111110000100101101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2       11 ***********
   3        3 ***
   4        1 *
   5        0
   6        0
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2        7 *******
   3        3 ***
   4        3 ***
   5        1 *
   6        3 ***
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

```
B:ALICEB.TXT
273B400RF62

101110111110111011111011101011111110100100110100001
111001001100000100001101000000000011010000010000001
1110001001000000000000000000
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       12 ************
   2        4 ****
   3        3 ***
   4        3 ***
   5        1 *
   6        0
   7        1 *
TOTAL OF NUMBER OF RUNS= 24
NUMBEROFRUNS*LENGTHOFRUNS= 53


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1        9 *********
   2        6 ******
   3        1 *
   4        2 **
   5        3 ***
   6        0
   7        0
   8        0
   9        0
  10        1 *
  11        0
  12        0
  13        0
```

```
B:ALICEL.TXT
273B400RF110

10000000010011000110011011010101110101101101001000
101000000110011010010001000100101010110101001111100
0011001000011001010100000000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       22 **********************
   2       11 ***********
   3        1 *
   4        0
   5        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 52


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        9 *********
   3        4 ****
   4        2 **
   5        1 *
   6        0
   7        0
   8        1 *
   9        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 76
```

```
B:SEAGULL.TXT
273B400RF252

11011100111011011101001010101111010110001100010010
01000101110100011100101000111010011001110101010010
0100011010100110001001101000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       22 **********************
   2        8 ********
   3        7 *******
   4        1 *
TOTAL OF NUMBER OF RUNS= 38
NUMBEROFRUNS*LENGTHOFRUNS= 63


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2       11 ***********
   3        8 ********
TOTAL OF NUMBER OF RUNS= 38
NUMBEROFRUNS*LENGTHOFRUNS= 65
```

```
B:C85.PRM
201B328RF68

000111011111111001010010101001000111100001011011101
1000001000001011000000010000010011000010011100010000
10010011101011000000010010000
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       19 *******************
   2        5 *****
   3        4 ****
   4        1 *
   5        0
   6        0
   7        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 52


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1        9 *********
   2        8 ********
   3        4 ****
   4        3 ***
   5        3 ***
   6        2 **
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 76
```

```
B:C95.PRM
201B32BRF140

01100101010100111110110001011110000101000001110001
01101111000110111100010100101001000000000101110100
0100001010000101111010011100
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       20 ********************
   2        3 ***
   3        4 ****
   4        4 ****
   5        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 59


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        6 ******
   3        5 *****
   4        3 ***
   5        1 *
   6        0
   7        0
   8        0
   9        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 69
```

```
B:C96.PRM
190B317RF92

01110010101101000110111011010000001000000000010110
00100010010001111011111110111000000111001111110101
0100100000101000101100010000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        17 *****************
   2         5 *****
   3         3 ***
   4         2 **
   5         0
   6         1 *
   7         1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 57


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        14 **************
   2         4 ****
   3         6 ******
   4         1 *
   5         1 *
   6         2 **
   7         0
   8         0
   9         0
  10         1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 71
```

```
B:C101.PRM
128B255RF93

00000111001010010000110001001010101010000000110100
11101100011011111010101101010101101010110001011001
00000001000001001110100000011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       23 ***********************
   2        9 *********
   3        3 ***
   4        0
   5        1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 55


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        6 ******
   3        3 ***
   4        1 *
   5        3 ***
   6        0
   7        2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 73
```

```
B:C103.PRM
94B221RF73

10101011101001010100111000001100010100001010000010
101111011010100000110100000001100001000010110001100
01100000000011010000101100010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        9 *********
   3        2 **
   4        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 49


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        3 ***
   3        4 ****
   4        4 ****
   5        3 ***
   6        1 *
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 79
```

```
B:C104.PRM
87B214RF82

01101010010001011101111101110011000001001011101101
11100000111000010011100010010101100101000010000010
1101011011000000100001001001
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       19 *******************
  2        6 ******
  3        6 ******
  4        1 *
  5        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       15 ***************
  2        8 ********
  3        2 **
  4        3 ***
  5        3 ***
  6        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

```
B:C110.PRM  .
137B266RF100

01011000111010011011001001110010000010101101100001
110010110101010101000101001111000011000000010010100
0001100000100010110001101000001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       20 ********************
   2       11 ***********
   3        3 ***
   4        1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 55


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        7 *******
   3        4 ****
   4        3 ***
   5        3 ***
   6        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 75
```

```
B:C113.PRM
43B170RF42

01100111101010110010100110010011001000111001110000
00101100010100000000100001011000100000001001000000
1001001010101001000110111011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        7 *******
   3        4 ****
   4        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 51


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2       11 ***********
   3        4 ****
   4        1 *
   5        0
   6        1 *
   7        3 ***
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 77
```

```
B:C114.PRM
201B328RF116

010100001001000111110000000000101101010001010110100
00010001000111110110011010100100101001011100011000
00100111110000001010010001011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       22 **********************
  2        7 *******
  3        1 *
  4        1 *
  5        2 **
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 53


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1       14 **************
  2        7 *******
  3        6 ******
  4        1 *
  5        2 **
  6        1 *
  7        0
  8        0
  9        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 75
```

```
B:C130.PRM
201B328RF60

1110000011001110001101010100111010000010001001110011
11001001010110010110000010010100100100000001000001
0100010001111001100110110010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       20 ********************
   2        7 *******
   3        4 ****
   4        2 **
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 54


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       11 ***********
   2       13 *************
   3        4 ****
   4        2 **
   5        2 **
   6        0
   7        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 74
```

B:C140.PRM
201B328RF92

11110110111010101111111100010001100100111001110011
10100000010001011000000000011111000001110100001000
0111000110000110001100010010
LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	11	***********
2	6	******
3	6	******
4	1	*
5	1	*
6	0	
7	0	
8	1	*

TOTAL OF NUMBER OF RUNS= 26
NUMBEROFRUNS*LENGTHOFRUNS= 58

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	9	*********
2	5	*****
3	6	******
4	3	***
5	1	*
6	1	*
7	0	
8	0	
9	0	
10	1	*

TOTAL OF NUMBER OF RUNS= 26
NUMBEROFRUNS*LENGTHOFRUNS= 70

B:C141.PRM
201B328RF68

10010011010100100001100111101000000010000001101100
0100111100111010100001011100101001100010110011 0010
0101001001000100010011000000
LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	21	*********************
2	8	********
3	2	**
4	2	**

TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 51

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	9	*********
2	13	*************
3	5	*****
4	2	**
5	0	
6	2	**
7	1	*

TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 77

```
B:RUSS1.PRM
273B400RF125

11011110110000110110110100111100111001010100100000
10000011010110110101100011010101011000011000011011
0000000011000111001000100011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       13 *************
   2       16 ****************
   3        2 **
   4        2 **
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 59


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       17 *****************
   2        5 *****
   3        4 ****
   4        3 ***
   5        2 **
   6        0
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 69
```

```
B:RUSS2.PRM
273B400RF164

10111110011101110111001110011101010111001100001010
0000101011000101111101000110010100011100000011000101
10000000001011101010100100101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       19 *******************
   2        5 *****
   3        8 ********
   4        1 *
   5        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 62


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        8 ********
   3        4 ****
   4        1 *
   5        2 **
   6        0
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 66
```

```
B:RUSS3.PRM
273B400RF106

10101001011001001000101001011001011000101011000010
01011011010001111000011111010111010010110000010000
001000000101010010011000000110
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        24 ************************
   2         9 *********
   3         1 *
   4         1 *
   5         1 *
TOTAL OF NUMBER OF RUNS= 36
NUMBEROFRUNS*LENGTHOFRUNS= 54


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        16 ****************
   2        10 **********
   3         3 ***
   4         2 **
   5         3 ***
   6         1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 74
```

```
B:RUSS4.PRM
273B400RF216

00111001101101110001001000110111100100101100010100
00100110111011100111100110000011001000000101001011
10001100010100111011000010101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       17 *****************
   2        9 *********
   3        6 ******
   4        2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 61


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2       11 ***********
   3        6 ******
   4        1 *
   5        1 *
   6        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 67
```

```
B:RUSS5.PRM
273B400RF206

1101111111000000010110101011011111111010000001101011
000100011010011100000000010010001110011010000100010
111100000011111011011000011010
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       13 *************
   2       10 **********
   3        2 **
   4        1 *
   5        1 *
   6        1 *
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 62


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       16 ****************
   2        3 ***
   3        5 *****
   4        1 *
   5        2 **
   6        0
   7        1 *
   8        1 *
TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 66
```

```
B:LABOV.PRM
273B400RF254

110010110000101111111110110101111100000000010110011
00001010111011010101110001001111011100010110100000
1111010111000100001000110000
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        14 **************
   2         8 ********
   3         4 ****
   4         2 **
   5         1 *
   6         0
   7         0
   8         0
   9         1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 64


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        17 *****************
   2         3 ***
   3         4 ****
   4         4 ****
   5         1 *
   6         0
   7         0
   8         1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 64
```

```
B:FRANKENA.PRM
273B400RF74

10010101100101011001000111110010011101001001011011
00101100001001110000011111010111101100100010011100
0100100010000110110001101100
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       18 ******************
   2       10 **********
   3        3 ***
   4        1 *
   5        2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 61


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2       12 ************
   3        6 ******
   4        2 **
   5        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 67
```

```
B:BRUNER.PRM
273B400RF152

00001110110100011111000110010010010010010010111100
100100110000010111011010001100001100010010000010000
1010101101001011011011100011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        20 ********************
   2        10 **********
   3         3 ***
   4         1 *
   5         1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        12 ************
   2        11 ***********
   3         5 *****
   4         4 ****
   5         1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

```
B:CHOMSKY.PRM
273B400RF96

010111111000100100100110010100110101010001001000000
0100010111111010001000010011101000000111111001100
0000110111101001000110000010
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       19 *******************
  2        6 ******
  3        1 *
  4        1 *
  5        1 *
  6        1 *
  7        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
  1       11 ***********
  2        9 *********
  3        5 *****
  4        1 *
  5        1 *
  6        2 **
  7        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:DREC1.PRM
401B52BRF350

00000101101110111010011101001000010100011100001100
00101011010100101100101011111111111100100111001110
0110000101001010010000110111
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       20 ********************
   2        6 ******
   3        7 *******
   4        0
   5        0
   6        0
   7        0
   8        0
   9        0
  10        0
  11        0
  12        1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 65


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       15 ***************
   2       10 **********
   3        1 *
   4        5 *****
   5        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 63
```

```
B:DREC2.PRM
301B428RF264

1110100101101101100100100000100100010001111111100
0111101011001001011011111010000010001111110001001 1
0111000110010000110010110000
LENGTH OF RUNS OF ONES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       15 ***************
   2        9 *********
   3        2 **
   4        1 *
   5        1 *
   6        1 *
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 62


LENGTH OF RUNS OF ZEROES

LENGTH   NUMBER
OF RUN   OF RUNS
   1       11 ***********
   2        9 *********
   3        5 *****
   4        3 ***
   5        2 **
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 66
```

```
B:MAIL.FRM
301B428RF250

0101110000011001101000110010011101000000101101101111
10100010011101110100000011000010101000111110011000
0110110111010010000010001011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        14 **************
   2        11 ***********
   3         5 *****
   4         0
   5         2 **
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 61


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        15 ***************
   2         6 ******
   3         4 ****
   4         3 ***
   5         2 **
   6         1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 67
```

B:HERALD.FRM
301B428RF138

1010100011110111110010100000000011110100100111011011
111001100000101110111100011010011000101000000100110
001011000000101111111001000000

LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS
1	15 ***************
2	6 ******
3	2 **
4	4 ****
5	1 *
6	1 *

TOTAL OF NUMBER OF RUNS= 29
NUMBEROFRUNS*LENGTHOFRUNS= 60

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS
1	11 ***********
2	8 ********
3	4 ****
4	0
5	3 ***
6	1 *
7	0
8	1 *

TOTAL OF NUMBER OF RUNS= 28
NUMBEROFRUNS*LENGTHOFRUNS= 68

```
B:GUARD.PRM
201B328RF100

00010000101011000101000111110011010111011000001110
10010000101010010101100101100111001100110000101 0001
0001000100100100000111001111 0
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        22 **********************
  2         7 *******
  3         4 ****
  4         1 *
  5         1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 57


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
  1        13 *************
  2        10 **********
  3         7 *******
  4         3 ***
  5         1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 71
```

```
B:PAD1.PRM
273B400RF166

11000101100110111001011010110010000111011100100100
1000001011011111010000000011100011110010010000100101
00010000010001110010101001001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       21 *********************
   2        6 ******
   3        5 *****
   4        2 **
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 56


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2       12 ************
   3        4 ****
   4        3 ***
   5        1 *
   6        0
   7        1 *
TOTAL OF NUMBER OF RUNS= 33
NUMBEROFRUNS*LENGTHOFRUNS= 72
```

```
B:PAD2.FRM
273B400RF119

001101000000110011100101111100001101101110001101001
1000101000101000000011100001000101110110000000001001
0100111011000100011011001011
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2       11 ***********
   3        5 *****
   4        0
   5        1 *
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 57


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2        7 *******
   3        6 ******
   4        2 **
   5        1 *
   6        1 *
   7        0
   8        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 71
```

```
B:PAD3.PRM
273B400RF166

00111110100010111111101100100010100010000001111001001
000010101110100001010000101011110000011111110110101
0100000000000110001011001011O
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      21 *********************
   2       5 *****
   3       1 *
   4       3 ***
   5       0
   6       2 **
TOTAL OF NUMBER OF RUNS= 32
NUMBEROFRUNS*LENGTHOFRUNS= 58


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1      16 ****************
   2       5 *****
   3       4 ****
   4       3 ***
   5       2 **
   6       0
   7       0
   8       0
   9       0
  10       1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 70
```

B:PAD4.PRM
273B400RF157

0111100100001100010001001001111110001110110000000101
1010101111111100000011001101000000000000111111100010
0010110001101101011000101010
LENGTH OF RUNS OF ONES

LENGTH OF RUN	NUMBER OF RUNS	
1	14	**************
2	9	*********
3	1	*
4	0	
5	2	**
6	0	
7	2	**

TOTAL OF NUMBER OF RUNS= 28
NUMBEROFRUNS*LENGTHOFRUNS= 59

LENGTH OF RUNS OF ZEROES

LENGTH OF RUN	NUMBER OF RUNS	
1	13	*************
2	4	****
3	7	*******
4	1	*
5	0	
6	2	**
7	0	
8	0	
9	0	
10	0	
11	1	*

TOTAL OF NUMBER OF RUNS= 28
NUMBEROFRUNS*LENGTHOFRUNS= 69

```
B:FOOH.FRM
273B400RF106

00100101001100110101011111010101110011011000010001
10110010010101011011100100111100000100011100001001
10110000101000000001100100110
LENGTH OF RUNS OF ONES

LENGTH     NUMBER
OF RUN     OF RUNS
   1        19 *******************
   2        11 ***********
   3         3 ***
   4         1 *
   5         1 *
TOTAL OF NUMBER OF RUNS= 35
NUMBEROFRUNS*LENGTHOFRUNS= 59


LENGTH OF RUNS OF ZEROES

LENGTH     NUMBER
OF RUN     OF RUNS
   1        15 ***************
   2        12 ************
   3         2 **
   4         3 ***
   5         1 *
   6         0
   7         1 *
TOTAL OF NUMBER OF RUNS= 34
NUMBEROFRUNS*LENGTHOFRUNS= 69
```

```
B:ALICEB.PRM
273B400RF62

001111111110110101100111010000001110100100101001000
001000001110000010011011001000000000101101101001100 1
000000101010001100001101000 0
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        18 ******************
   2         9 *********
   3         3 ***
   4         0
   5         0
   6         0
   7         0
   8         0
   9         1 *
TOTAL OF NUMBER OF RUNS= 31
NUMBEROFRUNS*LENGTHOFRUNS= 54


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        12 ************
   2         9 *********
   3         1 *
   4         4 ****
   5         2 **
   6         1 *
   7         0
   8         0
   9         1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 74
```

```
B:ALICEL.PRM
273B400RF110

00100111110101000100001001100001001000100111111011
00011011010110001011010011100000001111000101110000
0011010010000100010000000001
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       18 ******************
   2        7 *******
   3        2 **
   4        1 *
   5        1 *
   6        1 *
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 53


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1        9 *********
   2        7 *******
   3        6 ******
   4        3 ***
   5        0
   6        1 *
   7        1 *
   8        0
   9        1 *
TOTAL OF NUMBER OF RUNS= 28
NUMBEROFRUNS*LENGTHOFRUNS= 75
```

```
B:SEAGULL.PRM
273B400RF252

10101000011111110011110111111100010100111000110010
00010001111011101011001001111011000000110000001000
00011011010110010110100000101
LENGTH OF RUNS OF ONES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       15 ***************
   2        8 ********
   3        2 **
   4        3 ***
   5        0
   6        0
   7        2 **
TOTAL OF NUMBER OF RUNS= 30
NUMBEROFRUNS*LENGTHOFRUNS= 63


LENGTH OF RUNS OF ZEROES

LENGTH    NUMBER
OF RUN    OF RUNS
   1       12 ************
   2        7 *******
   3        3 ***
   4        3 ***
   5        0
   6        3 ***
TOTAL OF NUMBER OF RUNS= 28
NUMBEROFRUNS*LENGTHOFRUNS= 65
```

WINDOW-GROUP 256

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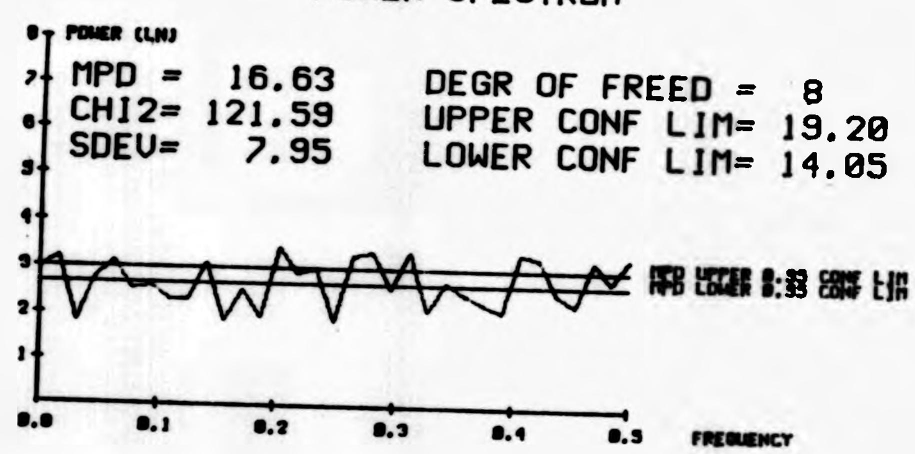
Power spectra of natural text strings:

C85 FIE1,301B556RF90

POWER SPECTRUM



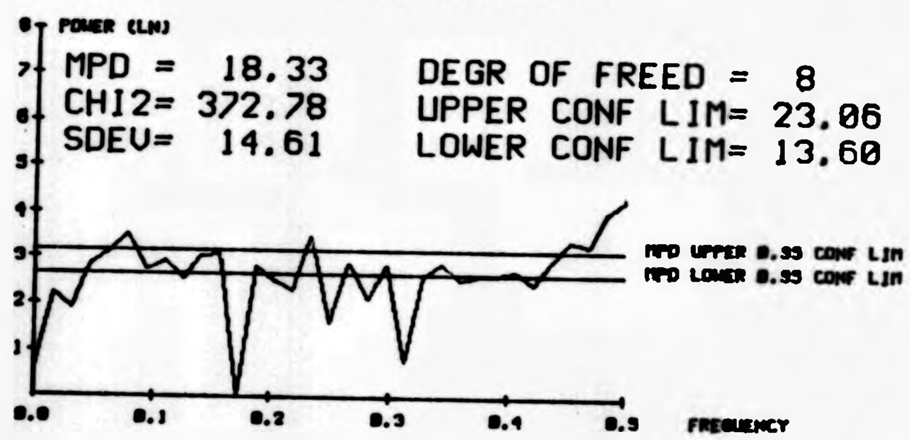
C85

FIE1,301B556RF90 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	19.1								
0.016	24.8	0.031	6.0	0.047	16.0	0.063	22.3	0.078	12.6
0.094	13.7	0.109	9.8	0.125	9.8	0.141	22.0	0.156	6.3
0.172	12.3	0.188	6.8	0.203	31.0	0.219	17.7	0.234	20.0
0.250	6.4	0.266	26.4	0.281	28.9	0.297	12.9	0.313	29.0
0.328	7.9	0.344	15.3	0.359	11.7	0.375	9.3	0.391	8.0
0.406	28.5	0.422	25.9	0.438	12.2	0.453	9.3	0.469	24.1
0.484	15.7	0.500	26.9						

MEAN POWER DENSITY: 16.63
DEGREES OF FREEDOM = 8
CHISQUARE = 121.59
ST.DEVIATION = 7.95
MPD UPPER 0.95 CONF LIMIT = 19.20
MPD LOWER 0.95 CONF LIMIT = 14.05
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

95C,301B556RF120
POWER SPECTRUM

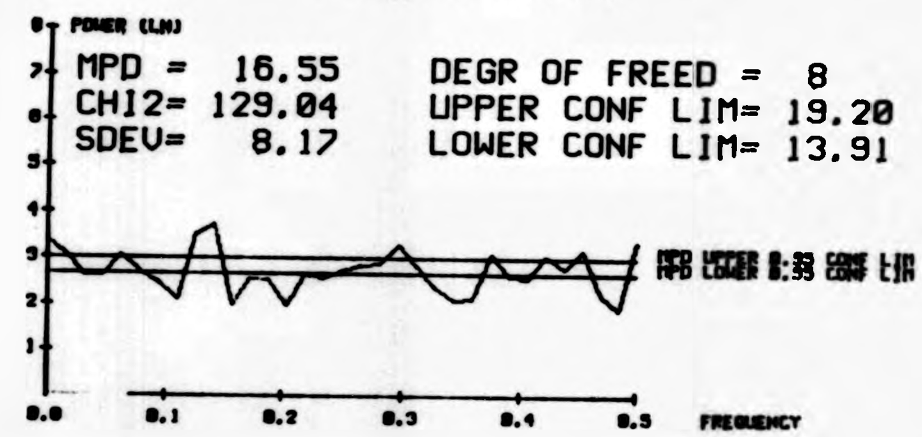


95C,301B556RF120 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	1.8								
0.016	8.9	0.031	6.5	0.047	17.2	0.063	22.9	0.078	33.2
0.094	15.0	0.109	18.7	0.125	12.6	0.141	21.3	0.156	21.7
0.172	0.6	0.188	16.3	0.203	12.0	0.219	9.7	0.234	32.5
0.250	5.0	0.266	17.7	0.281	8.2	0.297	16.9	0.313	2.2
0.328	13.4	0.344	17.7	0.359	12.5	0.375	14.0	0.391	14.3
0.406	15.4	0.422	11.7	0.438	19.2	0.453	29.6	0.469	26.4
0.484	56.1	0.500	73.8						

MEAN POWER DENSITY: 18.33
DEGREES OF FREEDOM = 8
CHISQUARE = 372.78
ST.DEVIATION = 14.61
MPD UPPER 0.95 CONF LIMIT = 23.06
MPD LOWER 0.95 CONF LIMIT = 13.60
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

130C,301B556RF60
POWER SPECTRUM

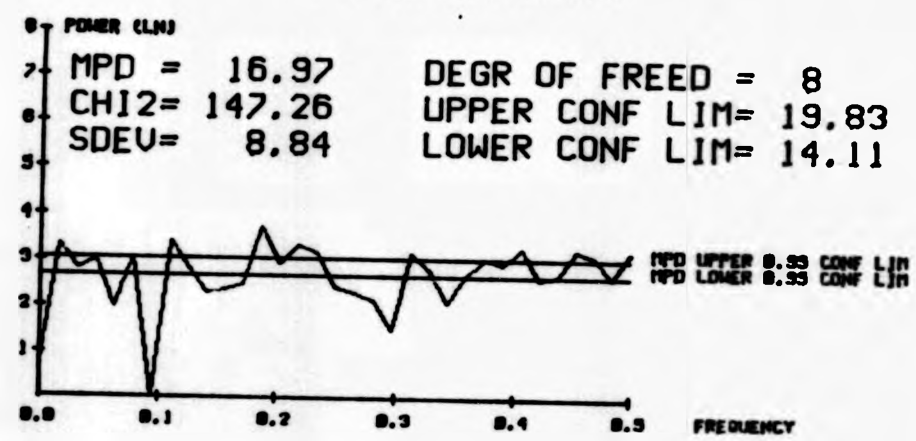


130C,301B556RF60 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	29.0								
0.016	21.3	0.031	13.6	0.047	13.4	0.063	20.9	0.078	14.8
0.094	11.4	0.109	7.9	0.125	33.4	0.141	41.0	0.156	7.0
0.172	12.9	0.188	12.5	0.203	7.2	0.219	14.1	0.234	13.0
0.250	15.4	0.266	16.9	0.281	17.7	0.297	26.5	0.313	16.2
0.328	10.6	0.344	7.9	0.359	8.3	0.375	21.8	0.391	13.4
0.406	13.0	0.422	20.7	0.438	16.0	0.453	24.0	0.469	9.0
0.484	6.5	0.500	28.8						

MEAN POWER DENSITY: 16.55
DEGREES OF FREEDOM = 8
CHISQUARE = 129.04
ST.DEVIATION = 8.17
MPD UPPER 0.95 CONF LIMIT = 19.20
MPD LOWER 0.95 CONF LIMIT = 13.91
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

140C,301B556RF56
POWER SPECTRUM

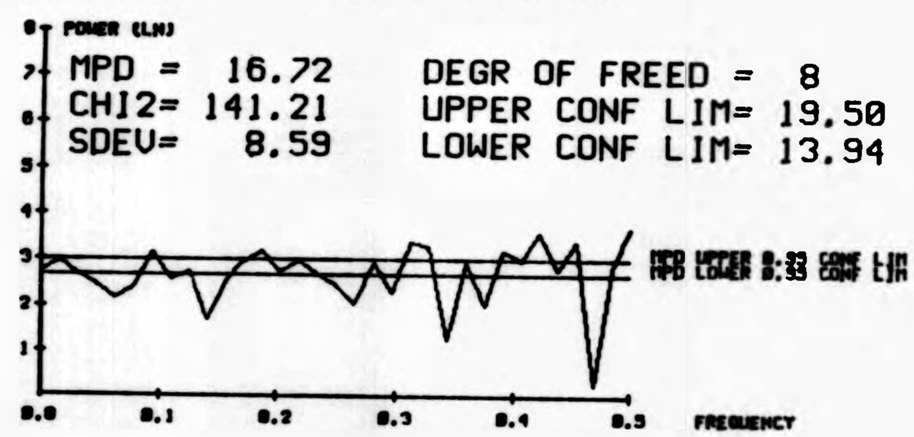


140C,301B556RF56 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.0								
0.016	27.8	0.031	16.6	0.047	19.7	0.063	7.0	0.078	21.1
0.094	0.4	0.109	30.2	0.125	16.1	0.141	9.7	0.156	10.7
0.172	12.0	0.188	40.8	0.203	18.5	0.219	27.8	0.234	23.5
0.250	11.2	0.266	9.8	0.281	8.3	0.297	4.4	0.313	23.7
0.328	16.2	0.344	8.0	0.359	14.8	0.375	20.7	0.391	18.7
0.406	26.5	0.422	13.6	0.438	14.5	0.453	25.5	0.469	21.6
0.484	14.0	0.500	24.5						

MEAN POWER DENSITY: 16.97
DEGREES OF FREEDOM = 8
CHISQUARE = 147.26
ST.DEVIATION = 8.84
MPD UPPER 0.95 CONF LIMIT = 19.83
MPD LOWER 0.95 CONF LIMIT = 14.11
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

141C,301B556RF80
POWER SPECTRUM

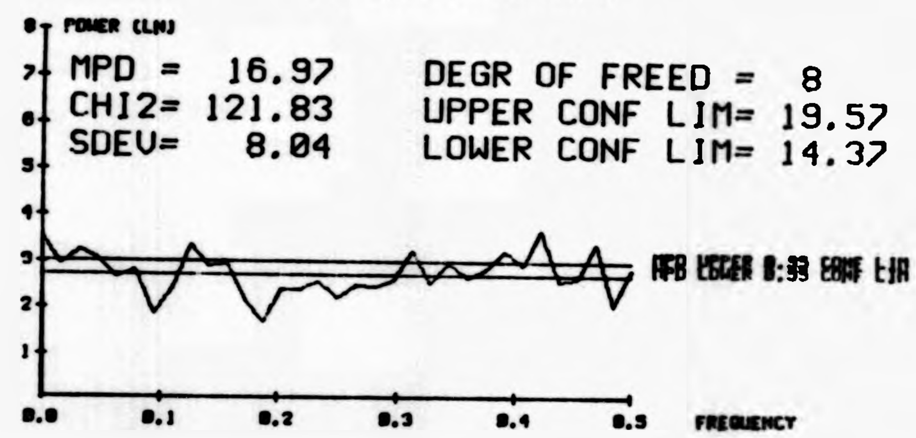


141C,301B556RF80 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.1								
0.016	19.2	0.031	14.2	0.047	11.4	0.063	8.7	0.078	10.8
0.094	22.8	0.109	13.0	0.125	15.1	0.141	5.4	0.156	12.4
0.172	19.5	0.188	23.2	0.203	15.1	0.219	19.1	0.234	14.4
0.250	11.7	0.266	7.6	0.281	18.8	0.297	10.0	0.313	29.0
0.328	25.8	0.344	3.4	0.359	18.5	0.375	7.4	0.391	23.3
0.406	19.1	0.422	34.8	0.438	16.0	0.453	29.2	0.469	1.3
0.484	16.6	0.500	39.7						

MEAN POWER DENSITY: 16.72
DEGREES OF FREEDOM = 8
CHISQUARE = 141.21
ST.DEVIATION = 8.59
MPD UPPER 0.95 CONF LIMIT = 19.50
MPD LOWER 0.95 CONF LIMIT = 13.94
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

1RUS,301B556RF157
POWER SPECTRUM

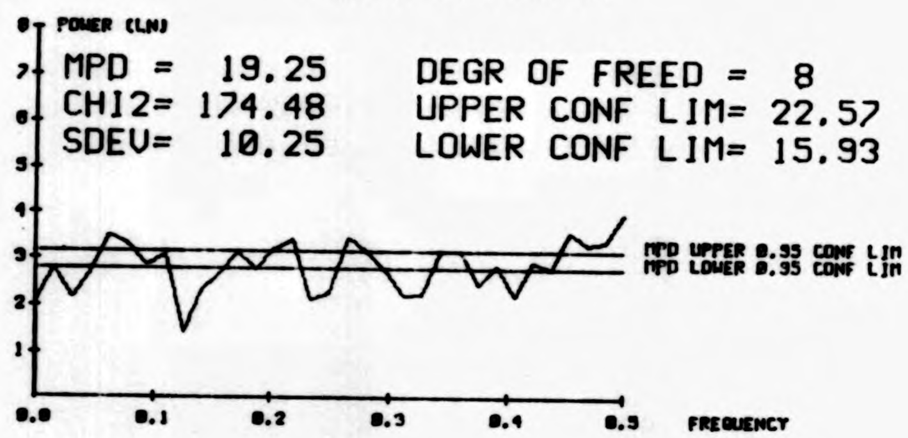


1RUS,301B556RF157 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	33.9								
0.016	18.8	0.031	25.1	0.047	20.9	0.063	14.0	0.078	16.2
0.094	6.3	0.109	11.2	0.125	29.3	0.141	17.5	0.156	19.5
0.172	8.4	0.188	5.3	0.203	11.0	0.219	10.8	0.234	13.2
0.250	9.1	0.266	12.0	0.281	11.6	0.297	13.3	0.313	25.3
0.328	12.4	0.344	19.4	0.359	14.2	0.375	17.0	0.391	25.4
0.406	18.4	0.422	39.1	0.438	12.9	0.453	13.7	0.469	30.1
0.484	7.5	0.500	17.3						

MEAN POWER DENSITY: 16.97
DEGREES OF FREEDOM = 8
CHISQUARE = 121.83
ST.DEVIATION = 8.04
MPD UPPER 0.95 CONF LIMIT = 19.57
MPD LOWER 0.95 CONF LIMIT = 14.37
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

2RUS,301B556RF164
POWER SPECTRUM

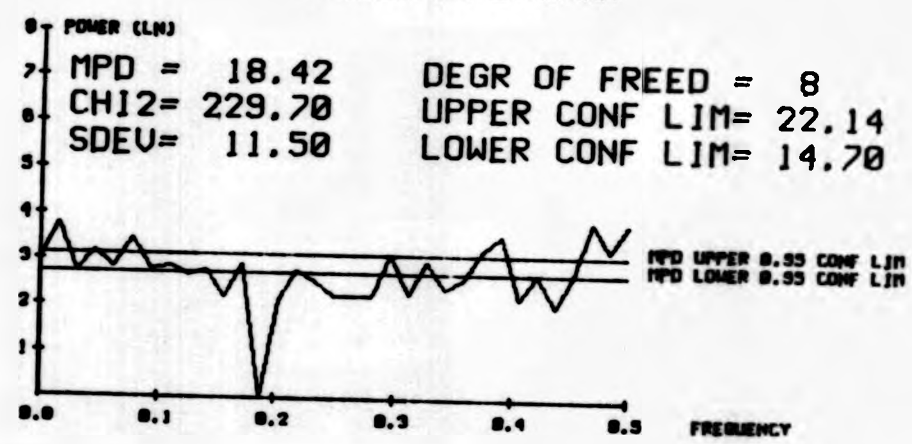


2RUS,301B556RF164 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.9								
0.016	15.9	0.031	8.7	0.047	14.5	0.063	32.5	0.078	26.7
0.094	16.8	0.109	21.7	0.125	4.1	0.141	10.3	0.156	14.8
0.172	22.4	0.188	15.5	0.203	24.7	0.219	29.6	0.234	8.4
0.250	9.6	0.266	31.2	0.281	23.0	0.297	15.0	0.313	9.1
0.328	9.2	0.344	23.9	0.359	23.7	0.375	11.4	0.391	17.2
0.406	9.1	0.422	18.8	0.438	16.0	0.453	34.9	0.469	26.2
0.484	29.0	0.500	53.2						

MEAN POWER DENSITY: 19.25
DEGREES OF FREEDOM = 8
CHISQUARE = 174.48
ST.DEVIATION = 10.25
MPD UPPER 0.95 CONF LIMIT = 22.57
MPD LOWER 0.95 CONF LIMIT = 15.93
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

3RUS,301B556RF82
POWER SPECTRUM

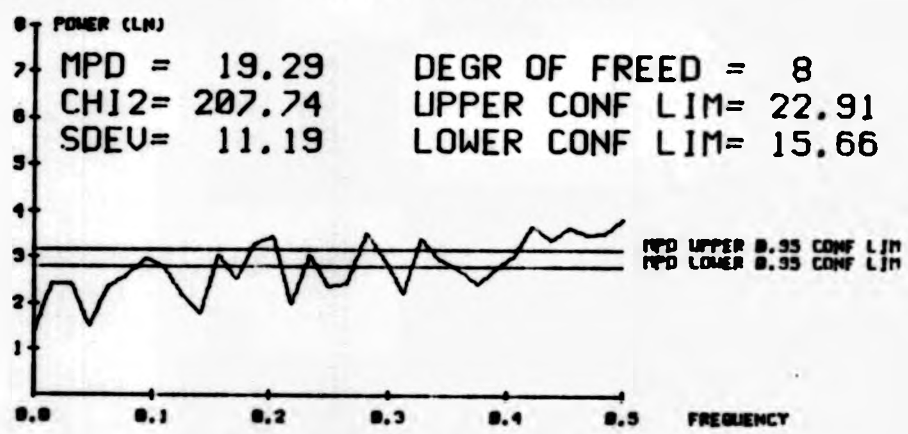


3RUS,301B556RF82 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	20.4								
0.016	42.7	0.031	15.5	0.047	23.8	0.063	16.7	0.078	31.6
0.094	15.7	0.109	17.2	0.125	14.3	0.141	15.7	0.156	8.6
0.172	17.7	0.188	0.8	0.203	8.2	0.219	15.6	0.234	12.4
0.250	9.1	0.266	9.1	0.281	9.0	0.297	22.4	0.313	9.4
0.328	19.5	0.344	10.7	0.359	13.3	0.375	25.1	0.391	35.6
0.406	8.5	0.422	14.8	0.438	7.4	0.453	15.4	0.469	49.1
0.484	25.6	0.500	46.9						

MEAN POWER DENSITY: 18.42
DEGREES OF FREEDOM = 8
CHISQUARE = 229.70
ST.DEVIATION = 11.50
MPD UPPER 0.95 CONF LIMIT = 22.14
MPD LOWER 0.95 CONF LIMIT = 14.70
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 22

4RUS,301B556RF248
POWER SPECTRUM

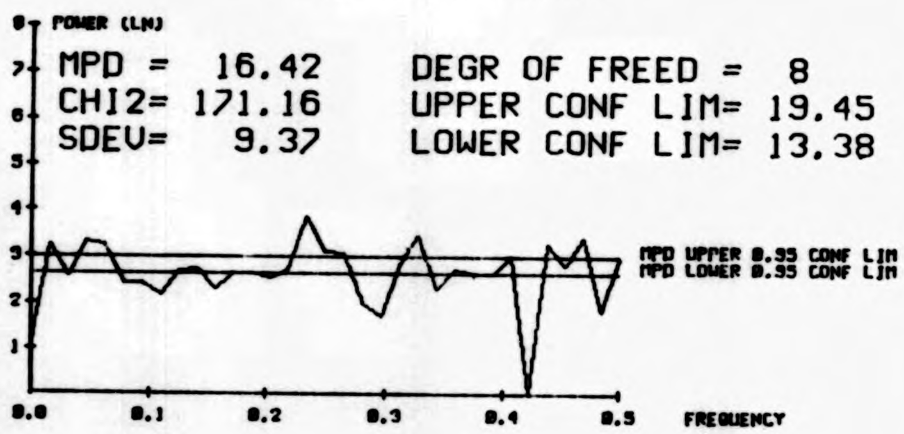


4RUS,301B556RF248 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.8								
0.016	11.5	0.031	11.5	0.047	4.5	0.063	10.8	0.078	13.3
0.094	19.0	0.109	15.8	0.125	8.6	0.141	5.8	0.156	20.7
0.172	12.4	0.188	26.7	0.203	31.2	0.219	7.0	0.234	20.7
0.250	10.7	0.266	11.5	0.281	33.2	0.297	18.4	0.313	8.9
0.328	29.9	0.344	18.7	0.359	15.0	0.375	11.2	0.391	15.6
0.406	21.3	0.422	38.9	0.438	29.3	0.453	38.3	0.469	32.3
0.484	33.5	0.500	46.5						

MEAN POWER DENSITY: 19.29
DEGREES OF FREEDOM = 8
CHISQUARE = 207.74
ST.DEVIATION = 11.19
MPD UPPER 0.95 CONF LIMIT = 22.91
MPD LOWER 0.95 CONF LIMIT = 15.66
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

5RUS,301B556RF142
POWER SPECTRUM

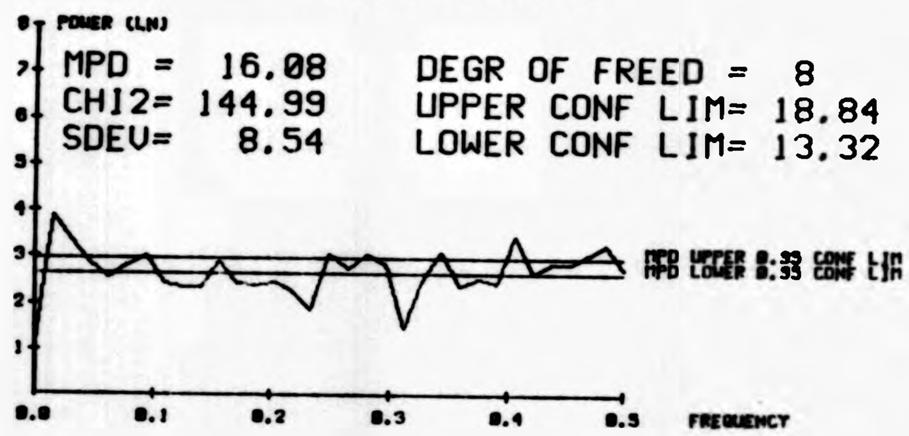


5RUS,301B556RF142 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.0								
0.016	25.6	0.031	12.7	0.047	27.2	0.063	25.2	0.078	11.0
0.094	11.0	0.109	8.6	0.125	14.7	0.141	15.3	0.156	9.9
0.172	13.8	0.188	14.0	0.203	12.5	0.219	15.5	0.234	46.8
0.250	21.4	0.266	21.2	0.281	7.0	0.297	5.3	0.313	17.3
0.328	30.6	0.344	9.8	0.359	15.0	0.375	13.7	0.391	13.5
0.406	20.4	0.422	0.3	0.438	26.8	0.453	16.6	0.469	30.4
0.484	6.1	0.500	19.5						

MEAN POWER DENSITY: 16.42
DEGREES OF FREEDOM = 8
CHISQUARE = 171.16
ST.DEVIATION = 9.37
MPD UPPER 0.95 CONF LIMIT = 19.45
MPD LOWER 0.95 CONF LIMIT = 13.38
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

1FRK,301B556RF88
POWER SPECTRUM

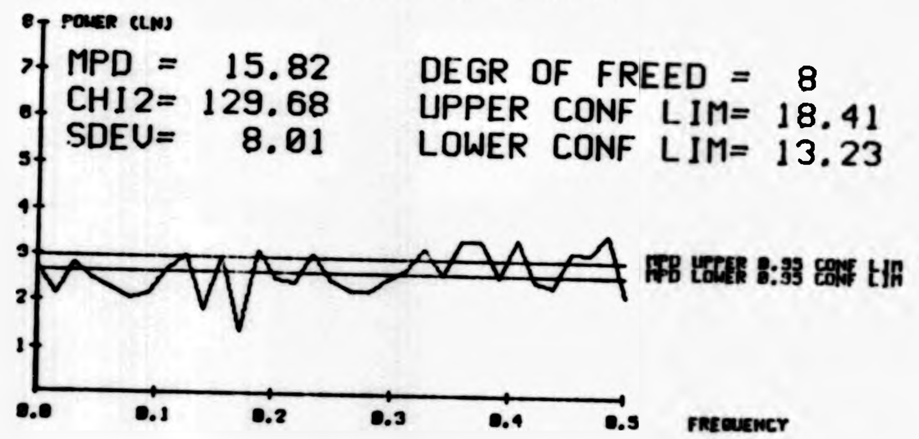


1FRK,301B556RF88 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	3.0								
0.016	48.4	0.031	27.2	0.047	16.8	0.063	12.6	0.078	16.7
0.094	19.8	0.109	11.1	0.125	10.3	0.141	10.3	0.156	17.5
0.172	11.2	0.188	10.7	0.203	11.6	0.219	9.5	0.234	6.3
0.250	21.0	0.266	15.4	0.281	20.8	0.297	16.5	0.313	4.3
0.328	12.0	0.344	22.0	0.359	10.8	0.375	12.5	0.391	10.9
0.406	31.1	0.422	13.9	0.438	17.3	0.453	17.0	0.469	20.9
0.484	26.0	0.500	15.4						

MEAN POWER DENSITY: 16.08
DEGREES OF FREEDOM = 8
CHISQUARE = 144.99
ST.DEVIATION = 8.54
MPD UPPER 0.95 CONF LIMIT = 18.84
MPD LOWER 0.95 CONF LIMIT = 13.32
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 9
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

LAB,301B556RF190
POWER SPECTRUM

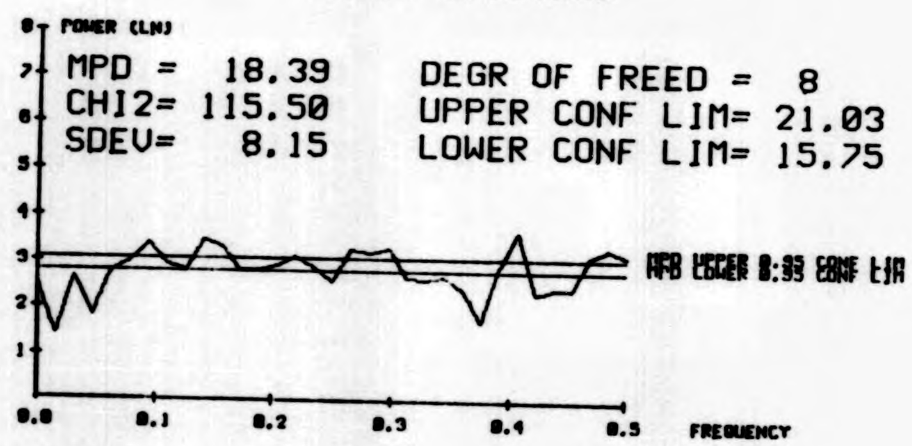


LAB,301B556RF190 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	15.4								
0.016	8.4	0.031	16.6	0.047	11.3	0.063	9.3	0.078	7.7
0.094	8.8	0.109	14.4	0.125	20.4	0.141	6.1	0.156	19.3
0.172	4.0	0.188	22.3	0.203	11.9	0.219	10.9	0.234	21.3
0.250	11.4	0.266	9.4	0.281	9.4	0.297	12.3	0.313	15.1
0.328	25.0	0.344	13.6	0.359	30.1	0.375	30.5	0.391	13.1
0.406	31.8	0.422	11.9	0.438	10.6	0.453	23.2	0.469	23.0
0.484	34.7	0.500	9.0						

MEAN POWER DENSITY: 15.82
DEGREES OF FREEDOM = 8
CHISQUARE = 129.68
ST.DEVIATION = 8.01
MPD UPPER 0.95 CONF LIMIT = 18.41
MPD LOWER 0.95 CONF LIMIT = 13.23
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 17
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 28

BRU,301B556RF200
POWER SPECTRUM

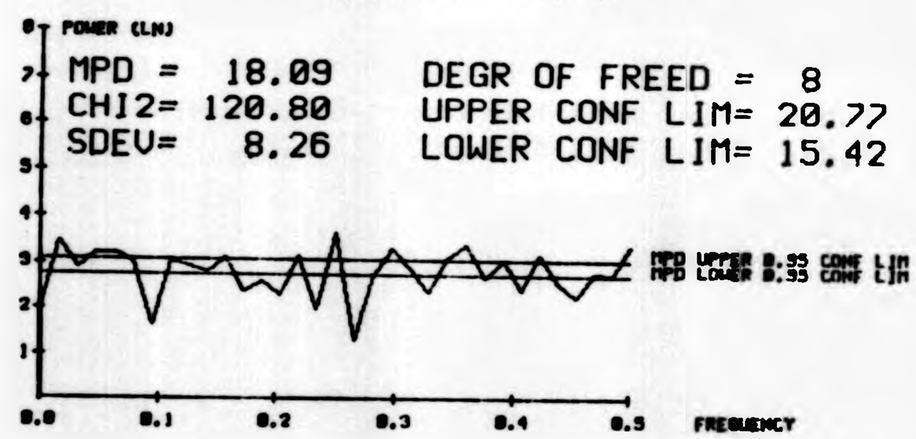


BRU,301B556RF200 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	11.8								
0.016	4.1	0.031	14.1	0.047	6.1	0.063	15.8	0.078	20.2
0.094	30.2	0.109	18.4	0.125	16.3	0.141	32.1	0.156	28.0
0.172	16.5	0.188	16.4	0.203	18.4	0.219	22.7	0.234	17.9
0.250	13.2	0.266	26.2	0.281	24.9	0.297	27.8	0.313	13.8
0.328	13.7	0.344	14.9	0.359	11.2	0.375	5.5	0.391	18.9
0.406	39.3	0.422	10.0	0.438	11.5	0.453	11.4	0.469	23.8
0.484	28.0	0.500	23.7						

MEAN POWER DENSITY: 18.39
DEGREES OF FREEDOM = 8
CHISQUARE = 115.50
ST.DEVIATION = 8.15
MPD UPPER 0.95 CONF LIMIT = 21.03
MPD LOWER 0.95 CONF LIMIT = 15.75
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

CHOM,301B556RF82
POWER SPECTRUM

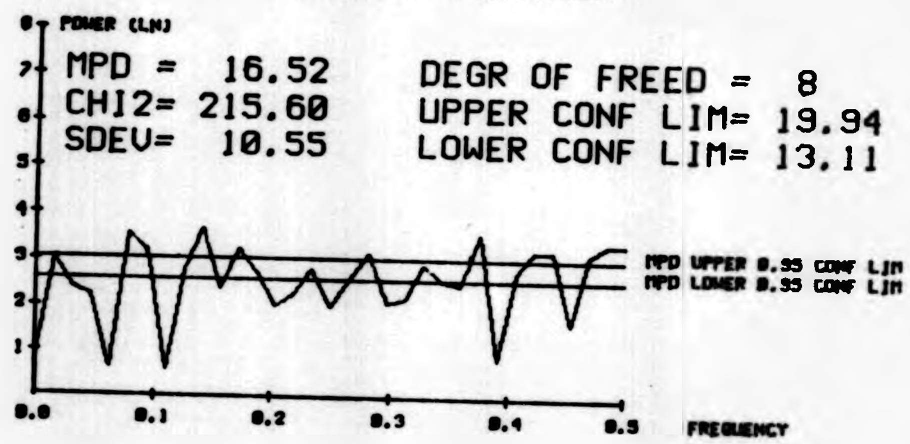


CHOM,301B556RF82 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.3								
0.016	30.7	0.031	17.8	0.047	24.7	0.063	24.6	0.078	20.1
0.094	5.0	0.109	20.7	0.125	18.2	0.141	16.6	0.156	22.8
0.172	10.6	0.188	13.5	0.203	9.7	0.219	23.6	0.234	7.1
0.250	38.5	0.266	3.6	0.281	15.6	0.297	27.1	0.313	17.6
0.328	10.7	0.344	22.7	0.359	30.0	0.375	14.7	0.391	22.0
0.406	11.2	0.422	24.6	0.438	13.1	0.453	9.3	0.469	16.7
0.484	16.0	0.500	30.6						

MEAN POWER DENSITY: 18.09
DEGREES OF FREEDOM = 8
CHISQUARE = 120.80
ST.DEVIATION = 8.26
MPD UPPER 0.95 CONF LIMIT = 20.77
MPD LOWER 0.95 CONF LIMIT = 15.42
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

1REC,401B656RF368
POWER SPECTRUM

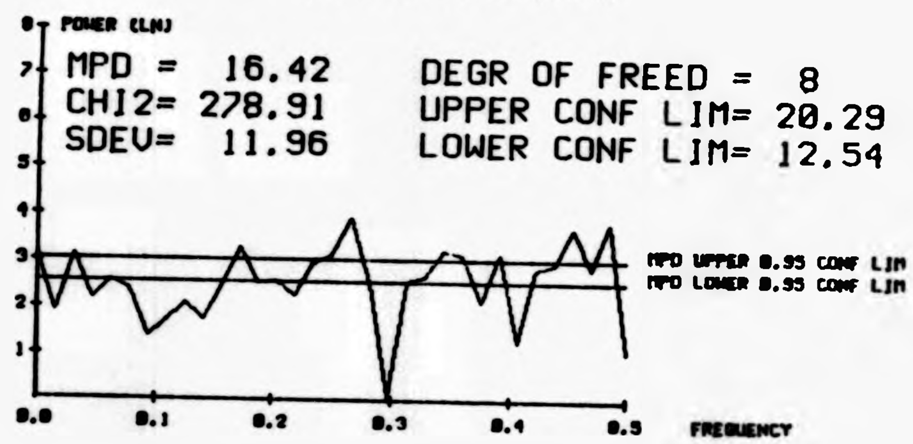


1REC,401B656RF368 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	2.3								
0.016	20.4	0.031	10.4	0.047	9.0	0.063	1.8	0.078	34.5
0.094	23.9	0.109	1.8	0.125	15.7	0.141	39.2	0.156	10.4
0.172	25.8	0.188	15.3	0.203	7.3	0.219	9.9	0.234	16.6
0.250	7.4	0.266	13.4	0.281	23.8	0.297	7.9	0.313	9.1
0.328	18.6	0.344	12.8	0.359	11.7	0.375	37.3	0.391	2.3
0.406	15.9	0.422	25.8	0.438	25.6	0.453	5.1	0.469	23.6
0.484	30.3	0.500	29.9						

MEAN POWER DENSITY: 16.52
DEGREES OF FREEDOM = 8
CHISQUARE = 215.60
ST.DEVIATION = 10.55
MPD UPPER 0.95 CONF LIMIT = 19.94
MPD LOWER 0.95 CONF LIMIT = 13.11
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

2REC,301B556RF207
POWER SPECTRUM

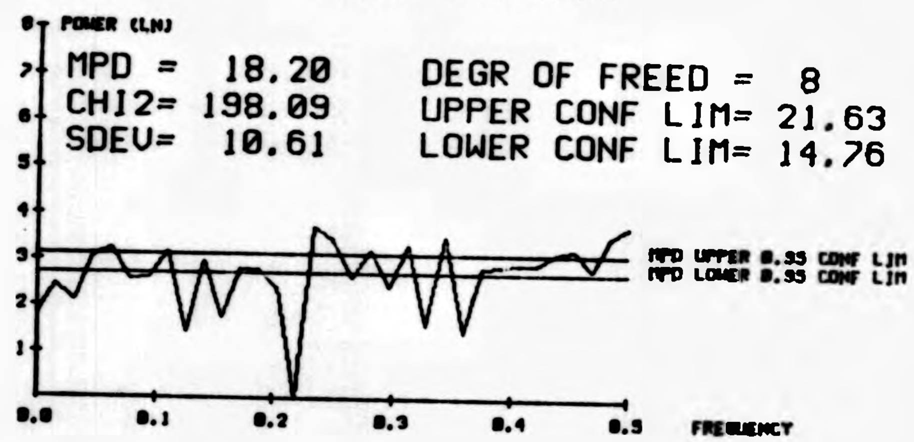


2REC,301B556RF207 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	23.0								
0.016	6.5	0.031	23.0	0.047	8.8	0.063	13.0	0.078	10.8
0.094	3.9	0.109	5.7	0.125	8.0	0.141	5.6	0.156	11.7
0.172	26.2	0.188	12.3	0.203	13.0	0.219	9.3	0.234	19.5
0.250	22.3	0.266	51.2	0.281	12.2	0.297	1.1	0.313	13.1
0.328	14.8	0.344	25.4	0.359	22.3	0.375	8.4	0.391	23.4
0.406	3.5	0.422	17.0	0.438	19.2	0.453	40.9	0.469	17.0
0.484	46.9	0.500	2.9						

MEAN POWER DENSITY: 16.42
DEGREES OF FREEDOM = 8
CHISQUARE = 278.91
ST.DEVIATION = 11.96
MPD UPPER 0.95 CONF LIMIT = 20.29
MPD LOWER 0.95 CONF LIMIT = 12.54
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 10
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

MAIL,401B656RF346
POWER SPECTRUM

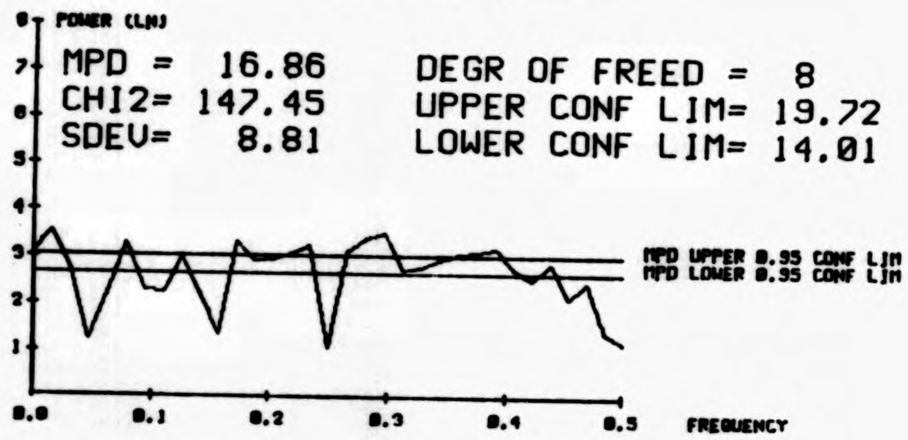


MAIL,401B656RF346 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.1								
0.016	11.3	0.031	8.0	0.047	22.1	0.063	25.2	0.078	13.1
0.094	13.2	0.109	23.2	0.125	4.0	0.141	19.4	0.156	5.5
0.172	16.6	0.188	15.7	0.203	10.8	0.219	0.9	0.234	40.7
0.250	30.8	0.266	13.2	0.281	24.8	0.297	11.1	0.313	27.8
0.328	4.7	0.344	33.9	0.359	4.0	0.375	17.2	0.391	18.0
0.406	18.7	0.422	18.3	0.438	23.4	0.453	25.9	0.469	16.7
0.484	33.1	0.500	43.1						

MEAN POWER DENSITY: 18.20
DEGREES OF FREEDOM = 8
CHISQUARE = 198.09
ST.DEVIATION = 10.61
MPD UPPER 0.95 CONF LIMIT = 21.63
MPD LOWER 0.95 CONF LIMIT = 14.76
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 12
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

HRLD,301B556RF200
POWER SPECTRUM

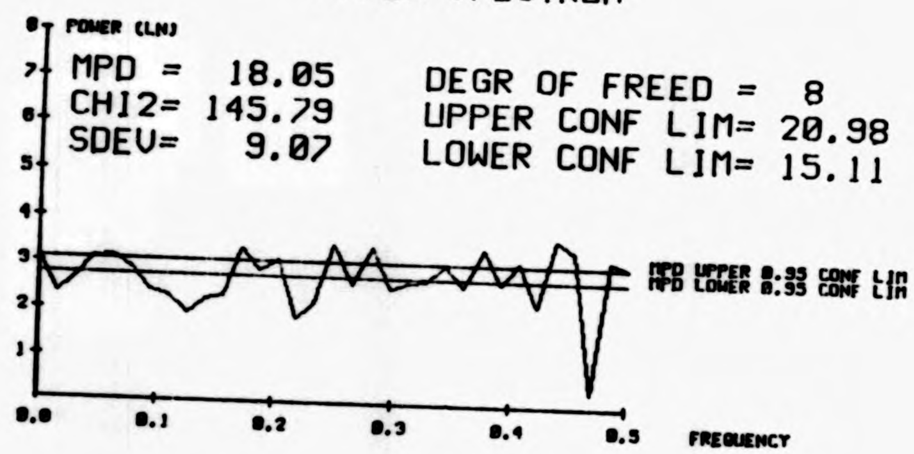


HRLD,301B556RF200 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	21.9								
0.016	33.1	0.031	14.5	0.047	3.3	0.063	8.9	0.078	26.9
0.094	9.9	0.109	9.5	0.125	20.3	0.141	9.1	0.156	3.8
0.172	27.7	0.188	18.3	0.203	19.0	0.219	21.9	0.234	25.8
0.250	2.8	0.266	22.5	0.281	29.8	0.297	33.4	0.313	15.1
0.328	16.6	0.344	19.5	0.359	21.9	0.375	22.5	0.391	24.6
0.406	16.0	0.422	12.3	0.438	17.9	0.453	8.5	0.469	12.0
0.484	4.0	0.500	3.1						

MEAN POWER DENSITY: 16.86
DEGREES OF FREEDOM = 8
CHISQUARE = 147.45
ST.DEVIATION = 8.81
MPD UPPER 0.95 CONF LIMIT = 19.72
MPD LOWER 0.95 CONF LIMIT = 14.01
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 25

GUAR,301B556RF140
POWER SPECTRUM

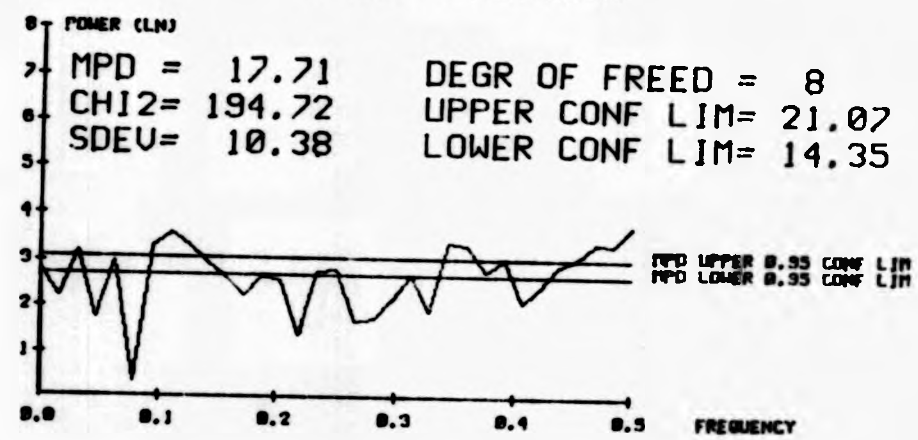


GUAR,301B556RF140 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	22.4								
0.016	10.1	0.031	14.8	0.047	22.4	0.063	23.8	0.078	17.8
0.094	11.2	0.109	9.9	0.125	6.8	0.141	9.3	0.156	10.0
0.172	28.8	0.188	17.5	0.203	23.0	0.219	6.3	0.234	9.2
0.250	32.9	0.266	13.4	0.281	30.6	0.297	12.6	0.313	14.4
0.328	15.3	0.344	21.5	0.359	13.4	0.375	31.3	0.391	14.8
0.406	23.9	0.422	9.2	0.438	39.5	0.453	30.1	0.469	1.4
0.484	25.9	0.500	22.0						

MEAN POWER DENSITY: 18.05
DEGREES OF FREEDOM = 8
CHISQUARE = 145.79
ST.DEVIATION = 9.07
MPD UPPER 0.95 CONF LIMIT = 20.98
MPD LOWER 0.95 CONF LIMIT = 15.11
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 14
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 16
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 30

PAD1,301B556RF147
POWER SPECTRUM

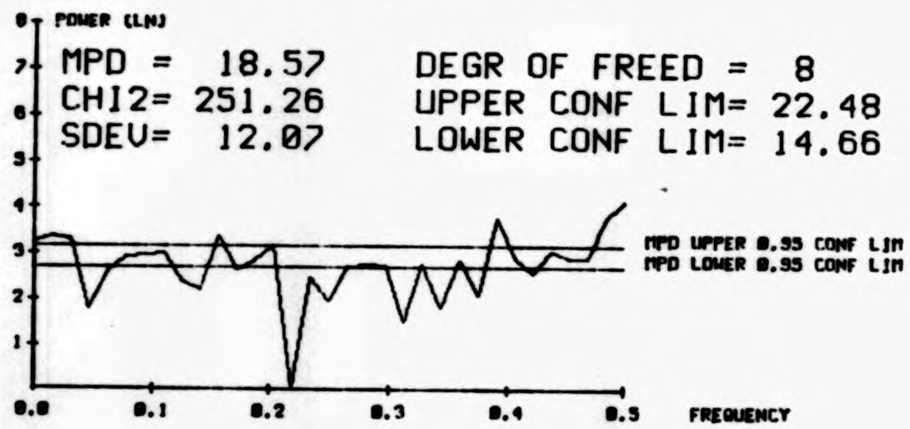


PAD1,301B556RF147 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	16.2								
0.016	9.0	0.031	24.6	0.047	5.6	0.063	19.8	0.078	1.4
0.094	28.0	0.109	37.2	0.125	28.2	0.141	19.4	0.156	13.9
0.172	9.4	0.188	14.4	0.203	12.9	0.219	3.9	0.234	16.4
0.250	17.1	0.266	5.3	0.281	5.7	0.297	9.0	0.313	15.0
0.328	6.9	0.344	30.8	0.359	29.2	0.375	16.5	0.391	21.9
0.406	8.4	0.422	12.0	0.438	18.9	0.453	22.2	0.469	31.2
0.484	29.4	0.500	44.5						

MEAN POWER DENSITY: 17.71
DEGREES OF FREEDOM = 8
CHISQUARE = 194.72
ST.DEVIATION = 10.38
MPD UPPER 0.95 CONF LIMIT = 21.07
MPD LOWER 0.95 CONF LIMIT = 14.35
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 13
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 24

PAD2,301B556RF217
POWER SPECTRUM

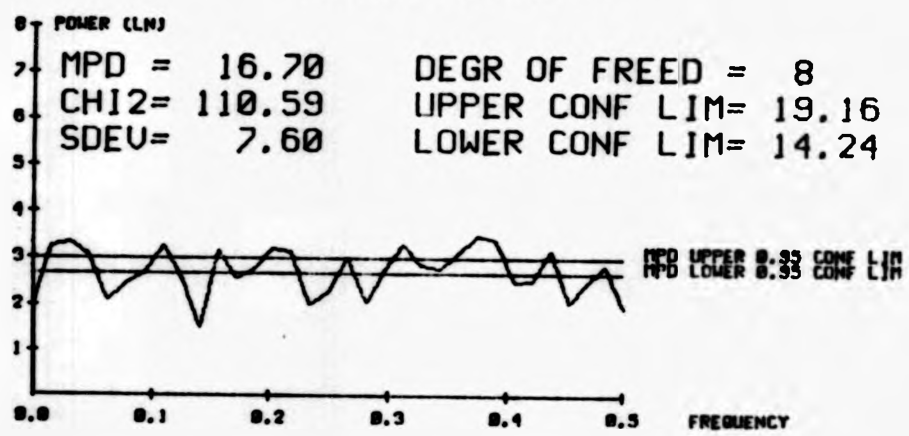


PAD2,301B556RF217 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	25.7								
0.016	29.0	0.031	26.6	0.047	5.7	0.063	13.5	0.078	18.8
0.094	19.0	0.109	20.3	0.125	10.5	0.141	9.1	0.156	28.8
0.172	14.2	0.188	17.3	0.203	23.7	0.219	0.9	0.234	12.2
0.250	7.0	0.266	14.9	0.281	15.5	0.297	15.4	0.313	4.4
0.328	15.5	0.344	6.1	0.359	17.1	0.375	8.1	0.391	43.1
0.406	17.7	0.422	13.0	0.438	21.0	0.453	18.0	0.469	17.9
0.484	42.2	0.500	60.4						

MEAN POWER DENSITY: 18.57
DEGREES OF FREEDOM = 8
CHISQUARE = 251.26
ST.DEVIATION = 12.07
MPD UPPER 0.95 CONF LIMIT = 22.48
MPD LOWER 0.95 CONF LIMIT = 14.66
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

PAD3,301B556RF164
POWER SPECTRUM

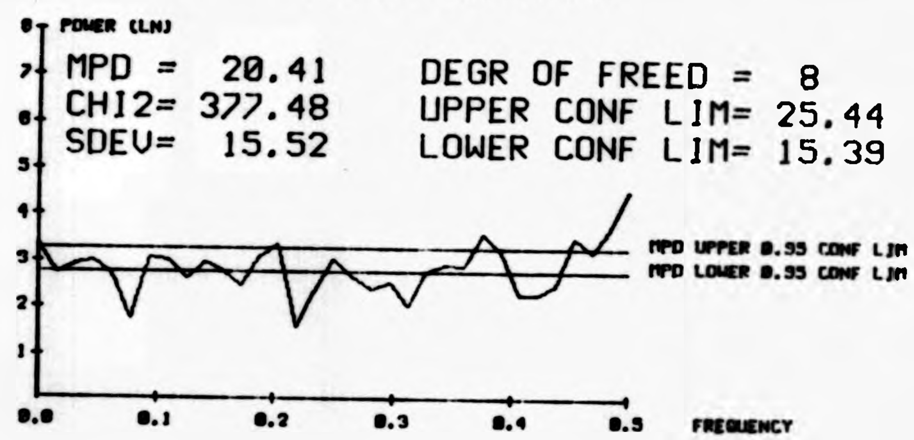


PAD3,301B556RF164 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.4								
0.016	25.7	0.031	27.3	0.047	20.7	0.063	7.9	0.078	11.4
0.094	14.3	0.109	25.4	0.125	12.6	0.141	4.4	0.156	23.3
0.172	13.1	0.188	16.0	0.203	24.3	0.219	22.8	0.234	7.4
0.250	9.7	0.266	20.0	0.281	7.8	0.297	15.6	0.313	26.1
0.328	17.1	0.344	15.5	0.359	23.0	0.375	32.1	0.391	29.2
0.406	11.7	0.422	12.5	0.438	23.5	0.453	7.7	0.469	11.8
0.484	16.9	0.500	6.7						

MEAN POWER DENSITY: 16.70
DEGREES OF FREEDOM = 8
CHISQUARE = 110.59
ST.DEVIATION = 7.60
MPD UPPER 0.95 CONF LIMIT = 19.16
MPD LOWER 0.95 CONF LIMIT = 14.24
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 13
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 27

PAD4,301B556RF144
POWER SPECTRUM

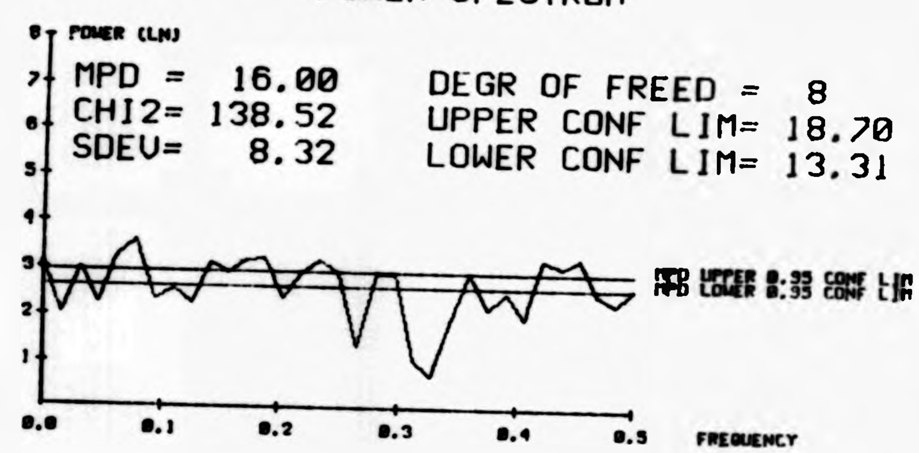


PAD4,301B556RF144 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	28.7								
0.016	15.3	0.031	18.8	0.047	20.4	0.063	14.7	0.078	5.6
0.094	21.4	0.109	20.5	0.125	13.6	0.141	19.6	0.156	15.5
0.172	11.5	0.188	22.2	0.203	28.3	0.219	4.7	0.234	10.2
0.250	20.9	0.266	14.2	0.281	10.4	0.297	12.4	0.313	7.3
0.328	16.1	0.344	18.5	0.359	18.1	0.375	37.0	0.391	24.8
0.406	9.4	0.422	9.5	0.438	11.8	0.453	34.4	0.469	24.7
0.484	41.2	0.500	92.0						

MEAN POWER DENSITY: 20.41
DEGREES OF FREEDOM = 8
CHISQUARE = 377.48
ST.DEVIATION = 15.52
MPD UPPER 0.95 CONF LIMIT = 25.44
MPD LOWER 0.95 CONF LIMIT = 15.39
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 6
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 14
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 20

POOH,301B556RF87
POWER SPECTRUM

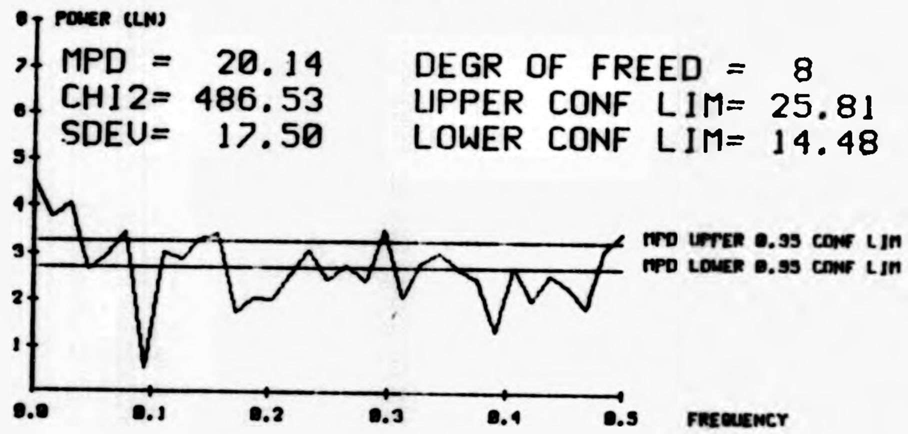


POOH,301B556RF87 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	22.8								
0.016	7.3	0.031	20.1	0.047	9.2	0.063	26.9	0.078	36.2
0.094	10.3	0.109	13.0	0.125	9.4	0.141	22.5	0.156	18.8
0.172	24.3	0.188	25.9	0.203	10.4	0.219	18.5	0.234	24.7
0.250	18.6	0.266	3.8	0.281	18.6	0.297	18.9	0.313	2.8
0.328	2.0	0.344	6.4	0.359	18.7	0.375	8.8	0.391	12.2
0.406	7.1	0.422	26.0	0.438	21.7	0.453	26.5	0.469	11.7
0.484	9.7	0.500	14.2						

MEAN POWER DENSITY: 16.00
DEGREES OF FREEDOM = 8
CHISQUARE = 138.52
ST.DEVIATION = 8.32
MPD UPPER 0.95 CONF LIMIT = 18.70
MPD LOWER 0.95 CONF LIMIT = 13.31
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 14
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 29

ALIB,301B556RF62
POWER SPECTRUM

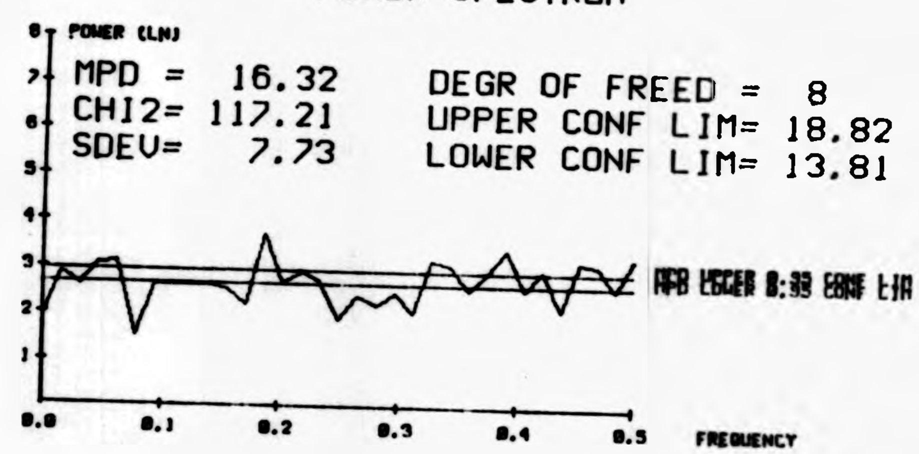


ALIB,301B556RF62 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	91.3								
0.016	43.4	0.031	56.8	0.047	14.2	0.063	19.1	0.078	31.3
0.094	1.6	0.109	20.5	0.125	18.0	0.141	27.2	0.156	31.6
0.172	5.6	0.188	7.6	0.203	7.5	0.219	12.9	0.234	22.1
0.250	11.6	0.266	16.1	0.281	11.1	0.297	33.9	0.313	7.7
0.328	16.4	0.344	20.8	0.359	14.6	0.375	11.3	0.391	3.8
0.406	15.5	0.422	7.5	0.438	13.0	0.453	9.9	0.469	6.4
0.484	22.5	0.500	31.9						

MEAN POWER DENSITY: 20.14
DEGREES OF FREEDOM = 8
CHISQUARE = 486.53
ST.DEVIATION = 17.50
MPD UPPER 0.95 CONF LIMIT = 25.81
MPD LOWER 0.95 CONF LIMIT = 14.48
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 8
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 23

ALIL,301B556RF108
POWER SPECTRUM

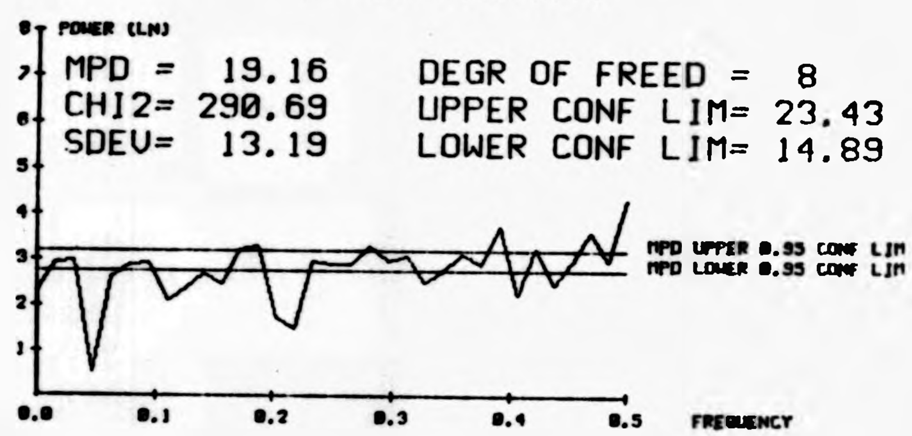


ALIL,301B556RF108 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	6.5								
0.016	17.7	0.031	13.7	0.047	22.1	0.063	22.9	0.078	4.4
0.094	13.8	0.109	14.2	0.125	13.7	0.141	14.3	0.156	12.5
0.172	9.1	0.188	40.5	0.203	14.7	0.219	18.8	0.234	15.4
0.250	6.6	0.266	11.1	0.281	9.1	0.297	12.0	0.313	7.7
0.328	24.8	0.344	21.5	0.359	12.7	0.375	19.2	0.391	31.1
0.406	12.8	0.422	20.5	0.438	8.5	0.453	24.2	0.469	22.5
0.484	13.4	0.500	26.4						

MEAN POWER DENSITY: 16.32
DEGREES OF FREEDOM = 8
CHISQUARE = 117.21
ST.DEVIATION = 7.73
MPD UPPER 0.95 CONF LIMIT = 18.82
MPD LOWER 0.95 CONF LIMIT = 13.81
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 11
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 15
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 26

GULL,301B556RF136
POWER SPECTRUM



GULL,301B556RF136 POWER DENSITY IN FREQUENCY POINTS:

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	9.8								
0.016	18.2	0.031	19.6	0.047	1.6	0.063	13.3	0.078	17.5
0.094	18.6	0.109	8.1	0.125	10.7	0.141	14.3	0.156	11.6
0.172	24.6	0.188	26.3	0.203	5.5	0.219	4.4	0.234	19.3
0.250	17.7	0.266	17.9	0.281	26.5	0.297	19.6	0.313	21.9
0.328	11.9	0.344	15.8	0.359	22.4	0.375	17.8	0.391	40.8
0.406	9.1	0.422	25.2	0.438	11.3	0.453	19.2	0.469	35.9
0.484	19.2	0.500	76.5						

MEAN POWER DENSITY: 19.16
DEGREES OF FREEDOM = 8
CHISQUARE = 290.69
ST.DEVIATION = 13.19
MPD UPPER 0.95 CONF LIMIT = 23.43
MPD LOWER 0.95 CONF LIMIT = 14.89
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 7
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 12
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 19

APPENDIX TO CHAPTER 12.

Grammatical coding.

Index.

PAD2,201B600RF185 POWER DENSITY IN FREQUENCY POINTS: TIMESERIES

FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:
0.008	17	0.016	35	0.023	9	0.031	26	0.039	17
0.047	15	0.055	7	0.063	7	0.070	15	0.078	36
0.086	26	0.094	1	0.102	20	0.109	25	0.117	12
0.125	8	0.133	2	0.141	11	0.148	9	0.156	27
0.164	40	0.172	6	0.180	11	0.188	7	0.195	28
0.203	18	0.211	9	0.219	14	0.227	2	0.234	7
0.242	8	0.250	14	0.258	1	0.266	35	0.273	19
0.281	17	0.289	17	0.297	9	0.305	10	0.313	11
0.320	17	0.328	20	0.336	10	0.344	4	0.352	6
0.359	27	0.367	6	0.375	11	0.383	22	0.391	35
0.398	39	0.406	4	0.414	31	0.422	15	0.430	26
0.438	22	0.445	23	0.453	15	0.461	29	0.469	16
0.477	6	0.484	35	0.492	29	0.500	23		

MEAN POWER DENSITY: 17.63

PAD2,201B600RF185 POWER DENSITY IN FREQUENCY POINTS: FFT

FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:
0.008	24	0.016	30	0.023	16	0.031	22	0.039	14
0.047	14	0.055	13	0.063	11	0.070	12	0.078	23
0.086	21	0.094	11	0.102	15	0.109	24	0.117	15
0.125	11	0.133	8	0.141	10	0.148	10	0.156	16
0.164	30	0.172	18	0.180	13	0.188	15	0.195	18
0.203	25	0.211	16	0.219	16	0.227	16	0.234	13
0.242	14	0.250	16	0.258	13	0.266	29	0.273	16
0.281	18	0.289	10	0.297	13	0.305	11	0.313	12
0.320	15	0.328	20	0.336	17	0.344	11	0.352	17
0.359	27	0.367	4	0.375	14	0.383	28	0.391	35
0.398	9	0.406	7	0.414	12	0.422	18	0.430	21
0.438	13	0.445	20	0.453	15	0.461	28	0.469	19
0.477	14	0.484	24	0.492	24	0.500	90		

MEAN POWER DENSITY: 18.34

PAD2,201B600RF185 POWER DENSITY IN FREQUENCY POINTS: SMOOTHED FFT

FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:
0.008	35	0.016	37	0.023	31	0.031	27	0.039	23
0.047	21	0.055	19	0.063	17	0.070	21	0.078	29
0.086	28	0.094	21	0.102	24	0.109	29	0.117	24
0.125	17	0.133	14	0.141	14	0.148	17	0.156	27
0.164	35	0.172	29	0.180	22	0.188	23	0.195	28
0.203	32	0.211	28	0.219	24	0.227	23	0.234	21
0.242	21	0.250	21	0.258	26	0.266	32	0.273	30
0.281	23	0.289	19	0.297	18	0.305	18	0.313	19
0.320	23	0.328	27	0.336	24	0.344	21	0.352	27
0.359	27	0.367	18	0.375	22	0.383	39	0.391	40
0.398	22	0.406	13	0.414	18	0.422	26	0.430	27
0.438	25	0.445	25	0.453	28	0.461	33	0.469	29
0.477	26	0.484	32	0.492	60	0.500	73		

MEAN POWER DENSITY: 26.45

PAD2,201B600RF185 POWER DENSITY IN FREQUENCY POINTS: RAW FFT

FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:	FREQ:	POW:
0.008	24	0.016	30	0.023	16	0.031	22	0.039	14
0.047	14	0.055	13	0.063	11	0.070	12	0.078	23
0.086	21	0.094	11	0.102	15	0.109	24	0.117	15
0.125	11	0.133	8	0.141	10	0.148	10	0.156	16
0.164	30	0.172	18	0.180	13	0.188	15	0.195	18
0.203	25	0.211	16	0.219	16	0.227	16	0.234	13
0.242	14	0.250	16	0.258	13	0.266	29	0.273	16
0.281	18	0.289	10	0.297	13	0.305	11	0.313	12
0.320	15	0.328	20	0.336	17	0.344	11	0.352	17
0.359	27	0.367	4	0.375	14	0.383	28	0.391	35
0.398	9	0.406	7	0.414	12	0.422	18	0.430	21
0.438	13	0.445	20	0.453	15	0.461	28	0.469	19
0.477	14	0.484	24	0.492	24	0.500	90		

MEAN POWER DENSITY: 18.34

PAD2

NOUNS WEIGHT

THE OLD 8BOXROOM WAS FINISHED AT LAST AND 8EVERYONE INCLUDING
8PADDINGTON AGREED THAT 8HE WAS A VERY LUCKY 8BEAR TO
MOVE INTO SUCH A NICE 8ROOM NOT ONLY WAS THE
8PAINTWORK A GLEAMING WHITE SO THAT 8HE COULD ALMOST SEE
HIS 8FACE IN 8IT BUT THE 8WALLS WERE GAILY PAPERED
AND 8HE EVEN HAD NEW 8FURNITURE OF HIS OWN AS
WELL IN FOR A 8PENNY IN FOR A 8POUND 8MR
8BROWN HAD SAID AND 8HE HAD BOUGHT 8PADDINGTON A BRAND
NEW 8BED WITH SPECIAL SHORT 8LEGS A 8SPRING 8MATTRESS AND
A 8CUPBOARD FOR HIS 8ODDS AND 8ENDS 8THERE WERE SEVERAL
OTHER 8PIECES OF 8FURNITURE AND 8MRS 8BROWN HAD BEEN EXTRAVAGANT
AND BOUGHT A THICK 8PILE 8CARPET FOR THE 8FLOOR 8PADDINGTON
WAS VERY PROUD OF HIS 8CARPET AND 8HE HAD CAREFULLY
SPREAD SOME OLD 8NEWSPAPERS OVER THE 8PARTS WHERE 8HE WALKED
SO THAT HIS 8PAWS WOULD NOT MAKE 8IT DIRTY MRS
BIRDS 8CONTRIBUTION HAD BEEN SOME BRIGHT NEW 8CURTAINS FOR THE
8WINDOWS 8WHICH 8PADDINGTON LIKED VERY MUCH IN FACT THE FIRST
8NIGHT 8HE SPENT IN HIS NEW 8ROOM 8HE COULD NOT
MAKE UP HIS 8MIND WHETHER TO HAVE 8THEM DRAWN TOGETHER
SO THAT 8HE COULD ADMIRE 8THEM OR LEFT APART SO
THAT 8HE COULD SEE THE 8VIEW 8HE GOT OUT OF
8BED SEVERAL 8TIMES AND EVENTUALLY DECIDED TO HAVE 8ONE DRAWN
AND THE 8OTHER LEFT BACK SO THAT 8HE COULD HAVE
THE 8BEST OF BOTH 8WORLDS THEN 8SOMETHING STRANGE CAUGHT HIS
8EYE 8PADDINGTON MADE A 8POINT OF KEEPING A 8TORCH BY
THE 8SIDE OF HIS 8BED IN 8CASE 8THERE WAS AN
8EMERGENCY DURING THE 8NIGHT AND 8IT WAS WHILE 8HE WAS
FLASHING 8IT ON AND OFF TO ADMIRE THE DRAWN 8CURTAIN
THAT 8HE NOTICED 8IT EACH 8TIME 8HE FLASHED THE 8TORCH
8THERE WAS AN ANSWERING 8FLICKER OF 8LIGHT FROM 8SOMEWHERE OUTSIDE
8HE SAT UP IN 8BED RUBBING HIS 8EYES AND STARED
IN THE 8DIRECTION OF THE 8WINDOW 8HE DECIDED TO TRY
A MORE COMPLICATED 8SIGNAL TWO SHORT 8FLASHES FOLLOWED BY SEVERAL
LONG 8ONES WHEN 8HE DID SO 8HE NEARLY FELL OUT
OF 8BED WITH 8SURPRISE FOR EACH 8TIME 8HE SENT A
8SIGNAL 8IT WAS REPEATED IN EXACTLY THE SAME 8WAY THROUGH
THE 8GLASS 8PADDINGTON JUMPED OUT OF 8BED AND RUSHED TO
THE 8WIMDOW 8HE STAYED THERE FOR A LONG 8WHILE PEERING
OUT AT THE 8GARDEN BUT 8HE COULD NOT SEE 8ANYTHING
AT ALL HAVING MADE SURE THE 8WINDOW WAS TIGHTLY SHUT
8HE DREW BOTH 8CURTAINS AND HURRIED BACK TO 8BED PULLING
THE 8CLOTHES OVER HIS 8HEAD A LITTLE FARTHER THAN USUAL
8IT WAS ALL VERY MYSTERIOUS AND 8PADDINGTON DID NOT BELIEVE
IN TAKING ANY 8CHANCES 8IT WAS 8MR 8BROWN AT 8BREAKFAST
THE NEXT 8MORNING 8WHO GAVE 8HIM HIS FIRST 8CLUE 8SOMEONE
HAS STOLEN MY PRIZE 8MARROW 8HE ANNOUNCED CROSSLY 8THEY MUST
HAVE GOT IN DURING THE 8NIGHT FOR SOME 8WEEKS PAST
8MR 8BROWN HAD BEEN CAREFULLY NURSING A HUGE 8MARROW WHICH
8HE INTENDED TO ENTER FOR A VEGETABLE 8SHOW 8HE WATERED
8IT 8MORNING AND 8EVENING AND MEASURED 8IT EVERY 8NIGHT BEFORE
GOING TO 8BED 8MRS 8BROWN EXCHANGED A 8GLANCE WITH 8MRS
8BIRD NEVER MIND 8HENRY 8DEAR 8SHE SAID 8YOU HAVE GOT
SEVERAL 8OTHERS ALMOST AS GOOD 8I DO MIND GRUMBLED 8MR
8BROWN AND THE 8OTHERS WILL NEVER BE AS GOOD NOT

PAD2 cont   NOUNS WEIGHT.

IN 8TIME FOR THE 8SHOW PERHAPS 8IT WAS ONE OF
THE OTHER 8COMPETITORS 8DAD SAID 8JONATHAN PERHAPS 8THEY DID NOT
WANT 8YOU TO WIN 8IT WAS A JOLLY GOOD 8MARROW
8THAT IS QUITE POSSIBLE SAID 8MR 8BROWN LOOKING MORE PLEASED
AT THE 8THOUGHT 8I HAVE A GOOD 8MIND TO OFFER
A SMALL 8REWARD 8MRS 8BIRD HASTILY POURED OUT SOME MORE
8TEA BOTH 8SHE AND 8MRS 8BROWN APPEARED ANXIOUS TO CHANGE
THE 8SUBJECT BUT 8PADDINGTON PRICKED UP HIS 8EARS AT THE
8MENTION OF A 8REWARD

Nou

PAD2 cont NOUNS WEIGHT.

IN 8TIME FOR THE 8SHOW PERHAPS 8IT WAS ONE OF
THE OTHER 8COMPETITORS 8DAD SAID 8JONATHAN PERHAPS 8THEY DID NOT
WANT 8YOU TO WIN 8IT WAS A JOLLY GOOD 8MARROW
8THAT IS QUITE POSSIBLE SAID 8MR 8BROWN LOOKING MORE PLEASED
AT THE 8THOUGHT 8I HAVE A GOOD 8MIND TO OFFER
A SMALL 8REWARD 8MRS 8BIRD HASTILY POURED OUT SOME MORE
8TEA BOTH 8SHE AND 8MRS 8BROWN APPEARED ANXIOUS TO CHANGE
THE 8SUBJECT BUT 8PADDINGTON PRICKED UP HIS 8EARS AT THE
8MENTION OF A 8REWARD

Noun

PAD2,201A600RF185 POWER DENSITY IN FREQUENCY POINTS: PAD2 NOUNS WEIGHT.

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	7.0								
0.008	25.0	0.016	40.1	0.023	32.4	0.031	25.8	0.039	27.8
0.047	24.0	0.055	22.9	0.063	25.1	0.070	25.4	0.078	24.2
0.086	20.1	0.094	20.4	0.102	28.2	0.109	29.8	0.117	21.2
0.125	17.2	0.133	17.7	0.141	16.4	0.148	18.7	0.156	22.4
0.164	25.8	0.172	34.2	0.180	34.3	0.188	24.5	0.195	24.6
0.203	28.7	0.211	27.6	0.219	26.1	0.227	27.1	0.234	27.2
0.242	26.6	0.250	24.6	0.258	22.5	0.266	25.8	0.273	31.6
0.281	39.9	0.289	37.2	0.297	26.4	0.305	29.4	0.313	35.8
0.320	31.9	0.328	28.5	0.336	31.9	0.344	39.5	0.352	39.7
0.359	25.8	0.367	19.2	0.375	20.4	0.383	21.5	0.391	25.2
0.398	22.9	0.406	19.5	0.414	23.1	0.422	24.5	0.430	20.6
0.438	19.2	0.445	22.3	0.453	25.6	0.461	24.7	0.469	20.7
0.477	21.1	0.484	24.7	0.492	36.5	0.500	36.5		

MEAN POWER DENSITY: 26.11
DEGREES OF FREEDOM = 6
CHISQUARE = 101.04
ST.DEVIATION = 6.42
MPD UPPER 0.95 CONF LIMIT = 27.66
MPD LOWER 0.95 CONF LIMIT = 24.57
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 20
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 26
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 46

1RUS NOUNS WEIGHT.
THE CONCEPTIONS OF LIFE AND THE WORLD WHICH WE CALL
PHILOSOPHICAL ARE A PRODUCT OF TWO FACTORS ONE INHERITED RELIGIOUS
AND ETHICAL CONCEPTIONS THE OTHER THE SORT OF INVESTIGATION WHICH
MAY BE CALLED SCIENTIFIC USING THIS WORD IN ITS BROADEST
SENSE INDIVIDUAL PHILOSOPHERS HAVE DIFFERED WIDELY IN REGARD TO THE
PROPORTIONS IN WHICH THESE TWO FACTORS ENTERED INTO THEIR SYSTEMS
BUT IT IS THE PRESENCE OF BOTH IN SOME DEGREE
THAT CHARACTERIZES PHILOSOPHY PHILOSOPHY IS A WORD WHICH HAS BEEN
USED IN MANY WAYS SOME WIDER SOME NARROWER I PROPOSE
TO USE IT IN A VERY WIDE SENSE WHICH I
WILL NOW TRY TO EXPLAIN 8PHILOSOPHY AS 8I SHALL UNDERSTAND
THE 8WORD IS 8SOMETHING INTERMEDIATE BETWEEN 8THEOLOGY AND 8SCIENCE LIKE
8THEOLOGY 8IT CONSISTS OF 8SPECULATIONS ON 8MATTERS AS TO WHICH
DEFINITE 8KNOWLEDGE HAS SO FAR BEEN UNASCERTAINABLE BUT LIKE 8SCIENCE
8IT APPEALS TO HUMAN 8REASON RATHER THAN TO 8AUTHORITY WHETHER
8THAT OF 8TRADITION OR 8THAT OF 8REVELATION ALL DEFINITE 8KNOWLEDGE
SO 8I SHOULD CONTEND BELONGS TO 8SCIENCE ALL 8DOGMA AS
TO 8WHAT SURPASSES DEFINITE
8KNOWLEDGE BELONGS TO 8THEOLOGY BUT BETWEEN
8THEOLOGY AND 8SCIENCE 8THERE IS A 8NO 8MANS 8LAND EXPOSED
TO ATTACK FROM BOTH 8SIDES 8THIS 8NO 8MANS 8LAND IS
8PHILOSOPHY ALMOST ALL THE 8QUESTIONS OF MOST 8INTEREST TO SPECULATIVE
8MINDS ARE SUCH AS 8SCIENCE CANNOT ANSWER AND THE CONFIDENT
8ANSWERS OF 8THEOLOGIANS NO LONGER SEEM SO CONVINCING AS 8THEY
DID IN FORMER 8CENTURIES IS THE 8WORLD DIVIDED INTO 8MIND
AND 8MATTER AND IF SO 8WHAT IS 8MIND AND 8WHAT
IS 8MATTER IS 8MIND 8SUBJECT TO 8MATTER OR IS 8IT
POSSESSED OF INDEPENDENT 8POWERS HAS THE 8UNIVERSE ANY 8UNITY OR
8PURPOSE IS 8IT EVOLVING TOWARDS SOME 8GOAL ARE 8THERE REALLY
8LAWS OF 8NATURE OR DO 8WE BELIEVE IN 8THEM ONLY
BECAUSE OF OUR INNATE 8LOVE OF 8ORDER IS 8MAN 8WHAT
8HE SEEMS TO THE 8ASTRONOMER A TINY 8LUMP OF IMPURE
8CARBON AND 8WATER IMPOTENTLY CRAWLING ON A SMALL AND UNIMPORTANT
8PLANET OR IS 8HE 8WHAT 8HE APPEARS TO 8HAMLET IS
8HE PERHAPS 8BOTH AT ONCE IS 8THERE A 8WAY OF
LIVING 8THAT IS NOBLE AND 8ANOTHER 8THAT IS BASE OR
ARE ALL 8WAYS OF 8LIVING MERELY FUTILE IF 8THERE IS
A 8WAY OF 8LIVING 8THAT IS NOBLE IN 8WHAT DOES
8IT CONSIST AND HOW SHALL 8WE ACHIEVE 8IT MUST THE
8GOOD BE ETERNAL IN ORDER TO DESERVE TO BE VALUED
OR IS 8IT WORTH SEEKING EVEN IF THE 8UNIVERSE IS
INEXORABLY MOVING TOWARDS 8DEATH IS 8THERE SUCH A 8THING AS
8WISDOM OR IS 8WHAT SEEMS 8SUCH MERELY THE ULTIMATE 8REFINEMENT
OF 8FOLLY TO SUCH 8QUESTIONS NO 8ANSWER CAN BE FOUND
IN THE 8LABORATORY 8THEOLOGIES HAVE PROFESSED TO GIVE 8ANSWERS ALL
TOO DEFINITE BUT THEIR VERY 8DEFINITENESS CAUSES MODERN 8MINDS TO
VIEW 8THEM WITH 8SUSPICION THE 8STUDYING OF THESE 8QUESTIONS IF
NOT THE 8ANSWERING OF 8THEM IS THE 8BUSINESS OF 8PHILOSOPHY
WHY THEN 8YOU MAY ASK WASTE 8TIME ON SUCH INSOLUBLE
8PROBLEMS TO 8THIS 8ONE MAY ANSWER AS A 8HISTORIAN OR
AS AN 8INDIVIDUAL FACING THE 8TERROR OF COSMIC 8LONELINESS THE
8ANSWER OF THE 8HISTORIAN IN SO FAR AS 8I AM
CAPABLE OF GIVING 8IT WILL APPEAR IN THE 8COURSE OF
THIS 8WORK EVER SINCE 8MEN BECAME CAPABLE OF FREE 8SPECULATION

RUS1 cont Nouns WEIGHT.

THEIR 8ACTIONS IN INNUMERABLE
IMPORTANT 8RESPECTS HAVE DEPENDED UPON THEIR
8THEORIES AS TO THE 8WORLD AND HUMAN 8LIFE AS TO
8WHAT IS GOOD AND 8WHAT IS EVIL 8THIS IS AS
TRUE IN THE PRESENT 8DAY AS AT ANY FORMER 8TIME
TO UNDERSTAND AN 8AGE OR A 8NATION 8WE MUST UNDERSTAND
ITS 8PHILOSOPHY AND TO UNDERSTAND ITS 8PHILOSOPHY 8WE MUST 8OURSELVES
BE IN SOME DEGREE 8PHILOSOPHERS 8THERE IS HERE A RECIPROCAL
8CAUSATION THE 8CIRCUMSTANCES OF MENS 8LIVES DO MUCH TO DETERMINE
THEIR 8PHILOSOPHY BUT CONVERSELY
THEIR 8PHILOSOPHY DOES MUCH TO DETERMINE
THEIR 8CIRCUMSTANCES THIS 8INTERACTION
THROUGHOUT THE 8CENTURIES WILL BE THE
8TOPIC OF THE FOLLOWING 8PAGES 8THERE IS ALSO HOWEVER A
MORE PERSONAL 8ANSWER 8SCIENCE TELLS US 8WHAT 8WE CAN KNOW
BUT 8WHAT 8WE CAN KNOW IS LITTLE AND IF 8WE
FORGET HOW MUCH 8WE CANNOT KNOW 8WE BECOME INSENSITIVE TO
MANY 8THINGS OF GREAT 8IMPORTANCE 8THEOLOGY ON THE OTHER HAND
INDUCES A DOGMATIC 8BELIEF THAT 8WE HAVE KNOWLEDGE WHERE IN
FACT 8WE HAVE 8IGNORANCE AND BY DOING SO GENERATES A
8KIND OF IMPERTINENT 8INSOLENCE
TOWARDS THE 8UNIVERSE 8UNCERTAINTY IN THE

Rus1 cont Norris Wright.

THEIR 8ACTIONS IN INNUMERABLE
IMPORTANT 8RESPECTS HAVE DEPENDED UPON THEIR
8THEORIES AS TO THE 8WORLD AND HUMAN 8LIFE AS TO
8WHAT IS GOOD AND 8WHAT IS EVIL 8THIS IS AS
TRUE IN THE PRESENT 8DAY AS AT ANY FORMER 8TIME
TO UNDERSTAND AN 8AGE OR A 8NATION 8WE MUST UNDERSTAND
ITS 8PHILOSOPHY AND TO UNDERSTAND ITS 8PHILOSOPHY 8WE MUST 8OURSELVES
BE IN SOME DEGREE 8PHILOSOPHERS 8THERE IS HERE A RECIPROCAL
8CAUSATION THE 8CIRCUMSTANCES OF MENS 8LIVES DO MUCH TO DETERMINE
THEIR 8PHILOSOPHY BUT CONVERSELY
THEIR 8PHILOSOPHY DOES MUCH TO DETERMINE
THEIR 8CIRCUMSTANCES THIS 8INTERACTION
THROUGHOUT THE 8CENTURIES WILL BE THE
8TOPIC OF THE FOLLOWING 8PAGES 8THERE IS ALSO HOWEVER A
MORE PERSONAL 8ANSWER 8SCIENCE TELLS US 8WHAT 8WE CAN KNOW
BUT 8WHAT 8WE CAN KNOW IS LITTLE AND IF 8WE
FORGET HOW MUCH 8WE CANNOT KNOW 8WE BECOME INSENSITIVE TO
MANY 8THINGS OF GREAT 8IMPORTANCE 8THEOLOGY ON THE OTHER HAND
INDUCES A DOGMATIC 8BELIEF THAT 8WE HAVE KNOWLEDGE WHERE IN
FACT 8WE HAVE 8IGNORANCE AND BY DOING SO GENERATES A
8KIND OF IMPERTINENT 8INSOLENCE
TOWARDS THE 8UNIVERSE 8UNCERTAINTY IN THE

Rus1 No

1RUS,301A700RF162   POWER DENSITY IN FREQUENCY POINTS: Russia <u>DOLLARS</u> WEIGHT.

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	13.2								
0.008	27.3	0.016	23.8	0.023	20.9	0.031	26.6	0.039	26.8
0.047	19.0	0.055	17.5	0.063	24.9	0.070	25.8	0.078	20.3
0.086	17.5	0.094	18.3	0.102	20.7	0.109	18.0	0.117	16.0
0.125	19.8	0.133	23.2	0.141	25.8	0.148	24.6	0.156	22.7
0.164	26.6	0.172	25.4	0.180	18.1	0.188	16.5	0.195	16.9
0.203	14.8	0.211	13.5	0.219	17.3	0.227	23.4	0.234	26.9
0.242	27.6	0.250	20.3	0.258	13.4	0.266	20.3	0.273	27.1
0.281	27.7	0.289	28.0	0.297	28.7	0.305	37.1	0.313	42.8
0.320	35.4	0.328	24.1	0.336	22.2	0.344	30.9	0.352	31.5
0.359	25.9	0.367	29.3	0.375	41.0	0.383	46.4	0.391	35.0
0.398	22.7	0.406	19.2	0.414	24.9	0.422	31.2	0.430	32.4
0.438	39.4	0.445	37.2	0.453	27.8	0.461	25.5	0.469	22.6
0.477	23.4	0.484	25.6	0.492	24.7	0.500	17.1		

MEAN POWER DENSITY: 24.93
DEGREES OF FREEDOM = 6
CHISQUARE = 133.73
ST.DEVIATION = 7.22
MPD UPPER 0.95 CONF LIMIT = 26.67
MPD LOWER 0.95 CONF LIMIT = 23.19
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 22
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 26
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 48

PAD2 Very weight.

THE OLD BOXROOM 8WAS 8FINISHED AT LAST AND EVERYONE INCLUDING
PADDINGTON 8AGREED THAT HE 8WAS A VERY LUCKY BEAR 8TO
8MOVE INTO SUCH A NICE ROOM NOT ONLY 8WAS THE
PAINTWORK A GLEAMING WHITE SO THAT HE 8COULD ALMOST 8SEE
HIS FACE IN IT BUT THE WALLS 8WERE GAILY 8PAPERED
AND HE EVEN 8HAD NEW FURNITURE OF HIS OWN AS
WELL IN FOR A PENNY IN FOR A POUND MR
BROWN 8HAD 8SAID AND HE 8HAD 8BOUGHT PADDINGTON A BRAND
NEW BED WITH SPECIAL SHORT LEGS A SPRING MATTRESS AND
A CUPBOARD FOR HIS ODDS AND ENDS THERE 8WERE SEVERAL
OTHER PIECES OF FURNITURE AND MRS BROWN 8HAD 8BEEN EXTRAVAGANT
AND 8BOUGHT A THICK PILE CARPET FOR THE FLOOR PADDINGTON
8WAS VERY 8PROUD OF HIS CARPET AND HE 8HAD CAREFULLY
8SPREAD SOME OLD NEWSPAPERS OVER THE PARTS WHERE HE 8WALKED
SO THAT HIS PAWS 8WOULD NOT 8MAKE IT DIRTY MRS
BIRDS CONTRIBUTION 8HAD 8BEEN SOME BRIGHT NEW CURTAINS FOR THE
WINDOWS WHICH PADDINGTON 8LIKED VERY MUCH IN FACT THE FIRST
NIGHT HE 8SPENT IN HIS NEW ROOM HE 8COULD NOT
8MAKE UP HIS MIND WHETHER 8TO 8HAVE THEM 8DRAWN TOGETHER
SO THAT HE 8COULD 8ADMIRE THEM OR 8LEFT APART SO
THAT HE 8COULD 8SEE THE VIEW HE 8GOT OUT OF
BED SEVERAL TIMES AND EVENTUALLY 8DECIDED 8TO 8HAVE ONE 8DRAWN
AND THE OTHER 8LEFT BACK SO THAT HE 8COULD 8HAVE
THE BEST OF BOTH WORLDS THEN SOMETHING STRANGE 8CAUGHT HIS
EYE PADDINGTON 8MADE A POINT OF 8KEEPING A TORCH BY
THE SIDE OF HIS BED IN CASE THERE 8WAS AN
EMERGENCY DURING THE NIGHT AND IT 8WAS WHILE HE 8WAS
8FLASHING IT ON AND OFF 8TO 8ADMIRE THE 8DRAWN CURTAIN
THAT HE 8NOTICED IT EACH TIME HE 8FLASHED THE TORCH
THERE 8WAS AN ANSWERING FLICKER OF LIGHT FROM SOMEWHERE OUTSIDE
HE 8SAT UP IN BED 8RUBBING HIS EYES AND 8STARED
IN THE DIRECTION OF THE WINDOW HE 8DECIDED 8TO 8TRY
A MORE COMPLICATED SIGNAL TWO SHORT FLASHES 8FOLLOWED BY SEVERAL
LONG ONES WHEN HE 8DID SO HE NEARLY 8FELL OUT
OF BED WITH SURPRISE FOR EACH TIME HE 8SENT A
SIGNAL IT 8WAS 8REPEATED IN EXACTLY THE SAME WAY THROUGH
THE GLASS PADDINGTON 8JUMPED OUT OF BED AND 8RUSHED TO
THE WIMDOW HE 8STAYED THERE FOR A LONG WHILE 8PEERING
OUT AT THE GARDEN BUT HE 8COULD NOT 8SEE ANYTHING
AT ALL 8HAVING 8MADE SURE THE WINDOW 8WAS TIGHTLY 8SHUT
HE 8DREW BOTH CURTAINS AND 8HURRIED BACK TO BED 8PULLING
THE CLOTHES OVER HIS HEAD A LITTLE FARTHER THAN USUAL
IT 8WAS ALL VERY MYSTERIOUS AND PADDINGTON 8DID NOT 8BELIEVE
IN 8TAKING ANY CHANCES IT 8WAS MR BROWN AT BREAKFAST
THE NEXT MORNING WHO 8GAVE HIM HIS FIRST CLUE SOMEONE
8HAS 8STOLEN MY PRIZE MARROW HE 8ANNOUNCED CROSSLY THEY MUST
8HAVE 8GOT IN DURING THE NIGHT FOR SOME WEEKS PAST
MR BROWN 8HAD 8BEEN CAREFULLY 8NURSING A HUGE MARROW WHICH
HE 8INTENDED 8TO 8ENTER FOR A VEGETABLE SHOW HE 8WATERED
IT MORNING AND EVENING AND 8MEASURED IT EVERY NIGHT BEFORE
8GOING TO BED MRS BROWN 8EXCHANGED A GLANCE WITH MRS
BIRD NEVER MIND HENRY DEAR SHE 8SAID YOU 8HAVE 8GOT
SEVERAL OTHERS ALMOST AS GOOD I 8DO 8MIND 8GRUMBLED MR
BROWN AND THE OTHERS 8WILL NEVER 8BE AS GOOD NOT

?A02 cont Verbs weight.

IN TIME FOR THE SHOW PERHAPS IT 8WAS ONE OF
THE OTHER COMPETITORS DAD 8SAID JONATHAN PERHAPS THEY 8DID NOT
8WANT YOU 8TO 8WIN IT 8WAS A JOLLY GOOD MARROW
THAT 8IS QUITE POSSIBLE 8SAID MR BROWN 8LOOKING MORE PLEASED
AT THE THOUGHT I 8HAVE A GOOD MIND 8TO 8OFFER
A SMALL REWARD MRS BIRD HASTILY 8POURED OUT SOME MORE
TEA BOTH SHE AND MRS BROWN 8APPEARED ANXIOUS 8TO 8CHANGE
THE SUBJECT BUT PADDINGTON 8PRICKED UP HIS EARS AT THE
MENTION OF A REWARD

all ✓

PAD2,201A600RF185 POWER DENSITY IN FREQUENCY POINTS: PA2 VERBS WEIGHT.

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	18.3								
0.008	24.2	0.016	25.6	0.023	30.3	0.031	31.4	0.039	26.4
0.047	19.1	0.055	17.6	0.063	21.0	0.070	22.7	0.078	23.7
0.086	27.4	0.094	28.1	0.102	27.2	0.109	31.7	0.117	30.9
0.125	30.8	0.133	31.0	0.141	20.5	0.148	21.7	0.156	32.4
0.164	31.1	0.172	33.1	0.180	38.4	0.188	38.6	0.195	40.7
0.203	31.2	0.211	20.8	0.219	20.9	0.227	19.5	0.234	18.5
0.242	22.1	0.250	25.9	0.258	26.5	0.266	31.9	0.273	32.8
0.281	24.6	0.289	19.3	0.297	16.1	0.305	17.1	0.313	20.9
0.320	19.7	0.328	18.2	0.336	21.0	0.344	25.0	0.352	27.5
0.359	29.1	0.367	26.2	0.375	27.5	0.383	33.6	0.391	25.3
0.398	19.0	0.406	25.5	0.414	26.3	0.422	22.5	0.430	21.2
0.438	21.3	0.445	20.0	0.453	26.0	0.461	33.4	0.469	27.7
0.477	24.4	0.484	35.1	0.492	50.9	0.500	40.2		

MEAN POWER DENSITY: 26.44
DEGREES OF FREEDOM = 6
CHISQUARE = 109.49
ST.DEVIATION = 6.73
MPD UPPER 0.95 CONF LIMIT = 28.06
MPD LOWER 0.95 CONF LIMIT = 24.82
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 22
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 28
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 50

Verbs weight.

1RUS
THE CONCEPTIONS OF LIFE AND THE WORLD WHICH WE CALL
PHILOSOPHICAL ARE A PRODUCT OF TWO FACTORS ONE INHERITED RELIGIOUS
AND ETHICAL CONCEPTIONS THE OTHER THE SORT OF INVESTIGATION WHICH
MAY BE CALLED SCIENTIFIC USING THIS WORD IN ITS BROADEST
SENSE INDIVIDUAL PHILOSOPHERS HAVE DIFFERED WIDELY IN REGARD TO THE
PROPORTIONS IN WHICH THESE TWO FACTORS ENTERED INTO THEIR SYSTEMS
BUT IT IS THE PRESENCE OF BOTH IN SOME DEGREE
THAT CHARACTERIZES PHILOSOPHY PHILOSOPHY IS A WORD WHICH HAS BEEN
USED IN MANY WAYS SOME WIDER SOME NARROWER I PROPOSE
TO USE IT IN A VERY WIDE SENSE WHICH I
8WILL NOW 8TRY 8TO 8EXPLAIN PHILOSOPHY AS I 8SHALL 8UNDERSTAND
THE WORD 8IS SOMETHING INTERMEDIATE BETWEEN THEOLOGY AND SCIENCE LIKE
THEOLOGY IT 8CONSISTS OF SPECULATIONS ON MATTERS AS TO WHICH
DEFINITE KNOWLEDGE 8HAS SO FAR 8BEEN UNASCERTAINABLE BUT LIKE SCIENCE
IT 8APPEALS TO HUMAN REASON RATHER THAN TO AUTHORITY WHETHER
THAT OF TRADITION OR THAT OF REVELATION ALL DEFINITE KNOWLEDGE
SO I 8SHOULD 8CONTEND 8BELONGS TO SCIENCE ALL DOGMA AS
TO WHAT 8SURPASSES DEFINITE KNOWLEDGE 8BELONGS TO THEOLOGY BUT BETWEEN
THEOLOGY AND SCIENCE THERE 8IS A NO MANS LAND 8EXPOSED
TO ATTACK FROM BOTH SIDES THIS NO MANS LAND 8IS
PHILOSOPHY ALMOST ALL THE QUESTIONS OF MOST INTEREST TO SPECULATIVE
MINDS 8ARE SUCH AS SCIENCE 8CANNOT ANSWER AND THE CONFIDENT
ANSWERS OF THEOLOGIANS NO LONGER 8SEEM SO CONVINCING AS THEY
8DID IN FORMER CENTURIES 8IS THE WORLD 8DIVIDED INTO MIND
AND MATTER AND IF SO WHAT 8IS MIND AND WHAT
8IS MATTER 8IS MIND SUBJECT TO MATTER OR 8IS IT
8POSSESSED OF INDEPENDENT POWERS 8HAS THE UNIVERSE ANY UNITY OR
PURPOSE 8IS IT EVOLVING TOWARDS SOME GOAL 8ARE THERE REALLY
LAWS OF NATURE OR 8DO WE 8BELIEVE IN THEM ONLY
BECAUSE OF OUR INNATE LOVE OF ORDER 8IS MAN WHAT
HE 8SEEMS TO THE ASTRONOMER A TINY LUMP OF IMPURE
CARBON AND WATER IMPOTENTLY 8CRAWLING ON A SMALL AND UNIMPORTANT
PLANET OR 8IS HE WHAT HE 8APPEARS TO HAMLET 8IS
HE PERHAPS BOTH AT ONCE 8IS THERE A WAY OF
LIVING THAT 8IS NOBLE AND ANOTHER THAT 8IS BASE OR
8ARE ALL WAYS OF LIVING MERELY FUTILE IF THERE 8IS
A WAY OF LIVING THAT 8IS NOBLE IN WHAT 8DOES
IT 8CONSIST AND HOW 8SHALL WE 8ACHIEVE IT 8MUST THE
GOOD 8BE ETERNAL IN ORDER 8TO 8DESERVE 8TO 8BE 8VALUED
OR 8IS IT WORTH 8SEEKING EVEN IF THE UNIVERSE 8IS
INEXORABLY 8MOVING TOWARDS DEATH 8IS THERE SUCH A THING AS
WISDOM OR 8IS WHAT 8SEEMS SUCH MERELY THE ULTIMATE REFINEMENT
OF FOLLY TO SUCH QUESTIONS NO ANSWER 8CAN 8BE 8FOUND
IN THE LABORATORY THEOLOGIES 8HAVE 8PROFESSED 8TO 8GIVE ANSWERS ALL
TOO DEFINITE BUT THEIR VERY DEFINITENESS 8CAUSES MODERN MINDS 8TO
8VIEW THEM WITH SUSPICION THE STUDYING OF THESE QUESTIONS IF
NOT THE ANSWERING OF THEM 8IS THE BUSINESS OF PHILOSOPHY
WHY THEN YOU 8MAY 8ASK WASTE TIME ON SUCH INSOLUBLE
PROBLEMS TO THIS ONE 8MAY 8ANSWER AS A HISTORIAN OR
AS AN INDIVIDUAL 8FACING THE TERROR OF COSMIC LONELINESS THE
ANSWER OF THE HISTORIAN IN SO FAR AS I 8AM
8CAPABLE OF 8GIVING IT 8WILL 8APPEAR IN THE COURSE OF
THIS WORK EVER SINCE MEN 8BECAME CAPABLE OF FREE SPECULATION
THEIR ACTIONS IN INNUMERABLE IMPORTANT

Russ1 cont varies weight.

RESPECTS 8HAVE 8DEPENDED UPON THEIR
THEORIES AS TO THE WORLD AND HUMAN LIFE AS TO
WHAT 8IS GOOD AND WHAT 8IS EVIL THIS 8IS AS
TRUE IN THE PRESENT DAY AS AT ANY FORMER TIME
8TO 8UNDERSTAND AN AGE OR A NATION WE 8MUST 8UNDERSTAND
ITS PHILOSOPHY AND 8TO 8UNDERSTAND ITS PHILOSOPHY WE 8MUST OURSELVES
8BE IN SOME DEGREE PHILOSOPHERS THERE 8IS HERE A RECIPROCAL
CAUSATION THE CIRCUMSTANCES OF MENS LIVES 8DO MUCH 8TO 8DETERMINE
THEIR PHILOSOPHY BUT CONVERSELY THEIR
PHILOSOPHY 8DOES MUCH 8TO 8DETERMINE
THEIR CIRCUMSTANCES THIS INTERACTION
THROUGHOUT THE CENTURIES 8WILL BE THE
TOPIC OF THE FOLLOWING PAGES THERE 8IS ALSO HOWEVER A
MORE PERSONAL ANSWER SCIENCE 8TELLS US WHAT WE 8CAN 8KNOW
BUT WHAT WE 8CAN 8KNOW 8IS LITTLE AND IF WE
8FORGET HOW MUCH WE 8CANNOT 8KNOW WE 8BECOME INSENSITIVE TO
MANY THINGS OF GREAT IMPORTANCE THEOLOGY ON THE OTHER HAND
8INDUCES A DOGMATIC BELIEF THAT WE 8HAVE KNOWLEDGE WHERE IN
FACT WE 8HAVE IGNORANCE AND BY 8DOING SO 8GENERATES A
KIND OF IMPERTINENT INSOLENCE TOWARDS THE UNIVERSE UNCERTAINTY IN THE

1RUS,301A700RF162 POWER DENSITY IN FREQUENCY POINTS: Russi VERES WEIGHT.

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	4.0								
0.008	19.4	0.016	40.7	0.023	48.1	0.031	38.6	0.039	29.6
0.047	28.6	0.055	26.7	0.063	21.1	0.070	20.3	0.078	21.3
0.086	16.9	0.094	16.0	0.102	19.9	0.109	20.0	0.117	21.9
0.125	23.2	0.133	19.4	0.141	19.9	0.148	21.7	0.156	21.7
0.164	23.5	0.172	22.3	0.180	20.2	0.188	22.0	0.195	23.6
0.203	23.1	0.211	21.0	0.219	19.5	0.227	21.2	0.234	24.8
0.242	39.5	0.250	53.8	0.258	43.2	0.266	27.8	0.273	23.4
0.281	23.1	0.289	23.2	0.297	24.6	0.305	27.9	0.313	26.4
0.320	21.4	0.328	15.8	0.336	13.6	0.344	16.0	0.352	19.0
0.359	19.5	0.367	23.1	0.375	27.7	0.383	27.3	0.391	32.0
0.398	34.0	0.406	32.0	0.414	35.6	0.422	35.8	0.430	34.9
0.438	33.6	0.445	29.0	0.453	25.2	0.461	25.5	0.469	26.4
0.477	22.1	0.484	18.6	0.492	18.9	0.500	15.2		

MEAN POWER DENSITY: 25.16
DEGREES OF FREEDOM = 6
CHISQUARE = 178.42
ST.DEVIATION = 8.37
MPD UPPER 0.95 CONF LIMIT = 27.17
MPD LOWER 0.95 CONF LIMIT = 23.14
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 20
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 31
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 51

PAD2 SUBJ. WEIGHT

8THE 8OLD 8BOXROOM WAS FINISHED AT LAST AND 8EVERYONE 8INCLUDING
8PADDINGTON AGREED THAT 8HE WAS A VERY LUCKY BEAR TO
MOVE INTO SUCH A NICE ROOM NOT ONLY WAS 8THE
8PAINTWORK A GLEAMING WHITE SO THAT 8HE COULD ALMOST SEE
HIS FACE IN IT BUT 8THE 8WALLS WERE GAILY PAPERED
AND 8HE EVEN HAD NEW FURNITURE OF HIS OWN AS
WELL IN FOR A PENNY IN FOR A POUND 8MR
8BROWN HAD SAID AND 8HE HAD BOUGHT PADDINGTON A BRAND
NEW BED WITH SPECIAL SHORT LEGS A SPRING MATTRESS AND
A CUPBOARD FOR HIS ODDS AND ENDS THERE WERE 8SEVERAL
8OTHER 8PIECES 8OF 8FURNITURE AND 8MRS 8BROWN HAD BEEN EXTRAVAGANT
AND BOUGHT A THICK PILE CARPET FOR THE FLOOR 8PADDINGTON
WAS VERY PROUD OF HIS CARPET AND 8HE HAD CAREFULLY
SPREAD SOME OLD NEWSPAPERS OVER THE PARTS WHERE 8HE WALKED
SO THAT 8HIS 8PAWS WOULD NOT MAKE IT DIRTY 8MRS
8BIRDS 8CONTRIBUTION HAD BEEN SOME BRIGHT NEW CURTAINS FOR THE
WINDOWS WHICH 8PADDINGTON LIKED VERY MUCH IN FACT THE FIRST
NIGHT 8HE SPENT IN HIS NEW ROOM 8HE COULD NOT
MAKE UP HIS MIND WHETHER TO HAVE THEM DRAWN TOGETHER
SO THAT 8HE COULD ADMIRE THEM OR LEFT APART SO
THAT 8HE COULD SEE THE VIEW 8HE GOT OUT OF
BED SEVERAL TIMES AND EVENTUALLY DECIDED TO HAVE ONE DRAWN
AND THE OTHER LEFT BACK SO THAT 8HE COULD HAVE
THE BEST OF BOTH WORLDS THEN 8SOMETHING 8STRANGE CAUGHT HIS
EYE 8PADDINGTON MADE A POINT OF KEEPING A TORCH BY
THE SIDE OF HIS BED IN CASE THERE WAS 8AN
8EMERGENCY DURING THE NIGHT AND 8IT WAS WHILE 8HE WAS
FLASHING IT ON AND OFF TO ADMIRE THE DRAWN CURTAIN
THAT 8HE NOTICED IT EACH TIME 8HE FLASHED THE TORCH
THERE WAS 8AN 8ANSWERING 8FLICKER 8OF 8LIGHT FROM SOMEWHERE OUTSIDE
8HE SAT UP IN BED RUBBING HIS EYES AND STARED
IN THE DIRECTION OF THE WINDOW 8HE DECIDED TO TRY
A MORE COMPLICATED SIGNAL TWO SHORT FLASHES FOLLOWED BY SEVERAL
LONG ONES WHEN 8HE DID SO 8HE NEARLY FELL OUT
OF BED WITH SURPRISE FOR EACH TIME 8HE SENT A
SIGNAL 8IT WAS REPEATED IN EXACTLY THE SAME WAY THROUGH
THE GLASS 8PADDINGTON JUMPED OUT OF BED AND RUSHED TO
THE WIMDOW 8HE STAYED THERE FOR A LONG WHILE PEERING
OUT AT THE GARDEN BUT 8HE COULD NOT SEE ANYTHING
AT ALL HAVING MADE SURE 8THE 8WINDOW WAS TIGHTLY SHUT
8HE DREW BOTH CURTAINS AND HURRIED BACK TO BED PULLING
THE CLOTHES OVER HIS HEAD A LITTLE FARTHER THAN USUAL
8IT WAS ALL VERY MYSTERIOUS AND 8PADDINGTON DID NOT BELIEVE
IN TAKING ANY CHANCES IT WAS 8MR 8BROWN AT BREAKFAST
THE NEXT MORNING 8WHO GAVE HIM HIS FIRST CLUE 8SOMEONE
HAS STOLEN MY PRIZE MARROW 8HE ANNOUNCED CROSSLY 8THEY MUST
HAVE GOT IN DURING THE NIGHT FOR SOME WEEKS PAST
8MR 8BROWN HAD BEEN CAREFULLY NURSING A HUGE MARROW WHICH
8HE INTENDED TO ENTER FOR A VEGETABLE SHOW 8HE WATERED
IT MORNING AND EVENING AND MEASURED IT EVERY NIGHT BEFORE
GOING TO BED 8MRS 8BROWN EXCHANGED A GLANCE WITH MRS
BIRD NEVER MIND HENRY DEAR 8SHE SAID 8YOU HAVE GOT
SEVERAL OTHERS ALMOST AS GOOD 8I DO MIND GRUMBLED 8MR
8BROWN AND 8THE 8OTHERS WILL NEVER BE AS GOOD NOT

PAD2 cont Subj. weight.

IN TIME FOR THE SHOW PERHAPS IT WAS BONE BOF
BTHE BOTHER BCOMPETITORS DAD SAID BJONATHAN PERHAPS BTHEY DID NOT
WANT YOU TO WIN GBIT WAS BA BJOLLY BGOOD BMARROW
BTHAT IS QUITE POSSIBLE SAID BMR BBROWN LOOKING MORE PLEASED
AT THE THOUGHT BI HAVE A GOOD MIND TO OFFER
A SMALL REWARD BMRS BBIRD HASTILY POURED OUT SOME MORE
TEA BBOTH BSHE BAND BMRS BBROWN APPEARED ANXIOUS TO CHANGE
THE SUBJECT BUT BPADDINGTON PRICKED UP HIS EARS AT THE
MENTION OF A REWARD

Sula

PAD2 cont Subj. weight.

IN TIME FOR THE SHOW PERHAPS IT WAS 8ONE 8OF
8THE 8OTHER 8COMPETITORS DAD SAID 8JONATHAN PERHAPS 8THEY DID NOT
WANT YOU TO WIN G8IT WAS 8A 8JOLLY 8GOOD 8MARROW
8THAT IS QUITE POSSIBLE SAID 8MR 8BROWN LOOKING MORE PLEASED
AT THE THOUGHT 8I HAVE A GOOD MIND TO OFFER
A SMALL REWARD 8MRS 8BIRD HASTILY POURED OUT SOME MORE
TEA 8BOTH 8SHE 8AND 8MRS 8BROWN APPEARED ANXIOUS TO CHANGE
THE SUBJECT BUT 8PADDINGTON PRICKED UP HIS EARS AT THE
MENTION OF A REWARD

Sculn

PAD2,201A600RF185 POWER DENSITY IN FREQUENCY POINTS: PAD2 SUBJECTS WEIGH

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	33.4								
0.008	50.7	0.016	42.4	0.023	30.3	0.031	30.4	0.039	35.6
0.047	38.8	0.055	42.0	0.063	42.1	0.070	38.7	0.078	33.6
0.086	31.3	0.094	34.1	0.102	35.9	0.109	36.4	0.117	33.0
0.125	27.8	0.133	30.2	0.141	33.5	0.148	29.1	0.156	22.0
0.164	21.9	0.172	29.7	0.180	32.1	0.188	25.9	0.195	20.8
0.203	19.3	0.211	19.0	0.219	22.2	0.227	25.2	0.234	23.6
0.242	22.9	0.250	22.2	0.258	25.4	0.266	29.0	0.273	21.9
0.281	17.4	0.289	21.2	0.297	22.1	0.305	23.0	0.313	28.6
0.320	32.8	0.328	29.3	0.336	21.6	0.344	20.9	0.352	25.5
0.359	22.4	0.367	16.8	0.375	16.5	0.383	17.1	0.391	16.4
0.398	15.8	0.406	16.3	0.414	16.8	0.422	19.7	0.430	19.8
0.438	18.5	0.445	20.7	0.453	20.4	0.461	17.6	0.469	15.8
0.477	15.3	0.484	17.6	0.492	26.8	0.500	26.7		

MEAN POWER DENSITY: 26.03
DEGREES OF FREEDOM = 6
CHISQUARE = 157.53
ST.DEVIATION = 8.00
MPD UPPER 0.95 CONF LIMIT = 27.95
MPD LOWER 0.95 CONF LIMIT = 24.10
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 25
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 33
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 58

1RUS

subj. weight.

THE CONCEPTIONS OF LIFE AND THE WORLD WHICH WE CALL
PHILOSOPHICAL ARE A PRODUCT OF TWO FACTORS ONE INHERITED RELIGIOUS
AND ETHICAL CONCEPTIONS THE OTHER THE SORT OF INVESTIGATION WHICH
MAY BE CALLED SCIENTIFIC USING THIS WORD IN ITS BROADEST
SENSE INDIVIDUAL PHILOSOPHERS HAVE DIFFERED WIDELY IN REGARD TO THE
PROPORTIONS IN WHICH THESE TWO FACTORS ENTERED INTO THEIR SYSTEMS
BUT IT IS THE PRESENCE OF BOTH IN SOME DEGREE
THAT CHARACTERIZES PHILOSOPHY PHILOSOPHY IS A WORD WHICH HAS BEEN
USED IN MANY WAYS SOME WIDER SOME NARROWER I PROPOSE
TO USE IT IN A VERY WIDE SENSE WHICH 8I
WILL NOW TRY TO EXPLAIN 8PHILOSOPHY 8AS 8I SHALL 8UNDERSTAND
8THE 8WORD IS SOMETHING INTERMEDIATE BETWEEN THEOLOGY AND SCIENCE LIKE
THEOLOGY 8IT CONSISTS OF SPECULATIONS ON MATTERS AS TO 8WHICH
8DEFINITE 8KNOWLEDGE HAS SO FAR BEEN UNASCERTAINABLE BUT LIKE SCIENCE
8IT APPEALS TO HUMAN REASON RATHER THAN TO AUTHORITY WHETHER
THAT OF TRADITION OR THAT OF REVELATION 8ALL 8DEFINITE 8KNOWLEDGE
SO 8I SHOULD CONTEND BELONGS TO SCIENCE 8ALL 8DOGMA 8AS
8TO 8WHAT 8SURPASSES 8DEFINITE 8KNOWLEDGE
BELONGS TO THEOLOGY BUT BETWEEN
THEOLOGY AND SCIENCE THERE IS 8A 8NO 8MANS 8LAND EXPOSED
TO ATTACK FROM BOTH SIDES 8THIS 8NO 8MANS 8LAND IS
PHILOSOPHY 8ALMOST 8ALL 8THE
8QUESTIONS 8OF 8MOST 8INTEREST 8TO 8SPECULATIVE
8MINDS ARE SUCH AS 8SCIENCE CANNOT ANSWER AND 8THE 8CONFIDENT
8ANSWERS 8OF 8THEOLOGIANS NO LONGER SEEM SO CONVINCING AS 8THEY
DID IN FORMER CENTURIES IS 8THE 8WORLD DIVIDED INTO MIND
AND MATTER AND IF SO WHAT IS 8MIND AND WHAT
IS 8MATTER IS 8MIND SUBJECT TO MATTER OR IS 8IT
POSSESSED OF INDEPENDENT POWERS HAS 8THE 8UNIVERSE ANY UNITY OR
PURPOSE IS 8IT EVOLVING TOWARDS SOME GOAL ARE THERE REALLY
8LAWS 8OF 8NATURE OR DO 8WE BELIEVE IN THEM ONLY
BECAUSE OF OUR INNATE LOVE OF ORDER IS 8MAN WHAT
8HE SEEMS TO THE ASTRONOMER A TINY LUMP OF IMPURE
CARBON AND WATER IMPOTENTLY CRAWLING ON A SMALL AND UNIMPORTANT
PLANET OR IS 8HE WHAT 8HE APPEARS TO HAMLET IS
8HE PERHAPS BOTH AT ONCE IS THERE 8A 8WAY 8OF
8LIVING THAT IS NOBLE AND 8ANOTHER THAT IS BASE OR
ARE 8ALL 8WAYS 8OF 8LIVING MERELY FUTILE IF THERE IS
8A 8WAY 8OF 8LIVING THAT IS NOBLE IN WHAT DOES
8IT CONSIST AND HOW SHALL 8WE ACHIEVE IT MUST 8THE
8GOOD BE ETERNAL IN ORDER TO DESERVE TO BE VALUED
OR IS 8IT WORTH SEEKING EVEN IF 8THE 8UNIVERSE IS
INEXORABLY MOVING TOWARDS DEATH IS THERE 8SUCH 8A 8THING 8AS
8WISDOM OR IS 8WHAT SEEMS SUCH 8MERELY 8THE 8ULTIMATE 8REFINEMENT
8OF 8FOLLY TO SUCH QUESTIONS 8NO 8ANSWER CAN BE FOUND
IN THE LABORATORY 8THEOLOGIES HAVE PROFESSED TO GIVE ANSWERS ALL
TOO DEFINITE BUT 8THEIR 8VERY 8DEFINITENESS CAUSES MODERN MINDS TO
VIEW THEM WITH SUSPICION 8THE 8STUDYING 8OF 8THESE 8QUESTIONS 8IF
8NOT 8THE 8ANSWERING 8OF 8THEM IS THE BUSINESS OF PHILOSOPHY
WHY THEN 8YOU MAY ASK WASTE TIME ON SUCH INSOLUBLE
PROBLEMS TO THIS 8ONE MAY ANSWER AS A HISTORIAN OR
AS AN INDIVIDUAL FACING THE TERROR OF COSMIC LONELINESS 8THE
8ANSWER 8OF 8THE 8HISTORIAN IN SO FAR AS 8I AM
CAPABLE OF GIVING IT WILL APPEAR IN THE COURSE OF

Russ cont. subj. weight.

THIS WORK EVER SINCE 8MEN BECAME CAPABLE OF FREE SPECULATION
8THEIR 8ACTIONS 8IN 8INNUMERABLE
8IMPORTANT 8RESPECTS HAVE DEPENDED UPON THEIR
THEORIES AS TO THE WORLD AND HUMAN LIFE AS TO
WHAT IS 8GOOD AND WHAT IS 8EVIL 8THIS IS AS
TRUE IN THE PRESENT DAY AS AT ANY FORMER TIME
TO UNDERSTAND AN AGE OR A NATION 8WE MUST UNDERSTAND
ITS PHILOSOPHY AND TO UNDERSTAND ITS PHILOSOPHY 8WE MUST OURSELVES
BE IN SOME DEGREE PHILOSOPHERS THERE IS HERE 8A 8RECIPROCAL
8CAUSATION 8THE 8CIRCUMSTANCES 8OF 8MENS 8LIVES DO MUCH TO DETERMINE
THEIR PHILOSOPHY BUT CONVERSELY
8THEIR 8PHILOSOPHY DOES MUCH TO DETERMINE
THEIR CIRCUMSTANCES 8THIS 8INTERACTION
8THROUGHOUT 8THE 8CENTURIES WILL BE THE
TOPIC OF THE FOLLOWING PAGES THERE IS ALSO HOWEVER A
8MORE 8PERSONAL 8ANSWER 8SCIENCE TELLS US WHAT 8WE CAN KNOW
BUT 8WHAT 8WE 8CAN 8KNOW IS LITTLE AND IF 8WE
FORGET HOW MUCH 8WE CANNOT KNOW 8WE BECOME INSENSITIVE TO
MANY THINGS OF GREAT IMPORTANCE 8THEOLOGY ON THE OTHER HAND
INDUCES A DOGMATIC BELIEF THAT 8WE HAVE KNOWLEDGE WHERE IN
FACT 8WE HAVE IGNORANCE AND BY DOING SO GENERATES A
KIND OF IMPERTINENT INSOLENCE TOWARDS THE UNIVERSE UNCERTAINTY IN THE

Sub

1RUS,301A600RF162 POWER DENSITY IN FREQUENCY POINTS: Russ1 SUBJECTS WEIGHT

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	20.0								
0.008	55.9	0.016	63.0	0.023	50.6	0.031	38.6	0.039	39.1
0.047	43.0	0.055	38.1	0.063	29.4	0.070	33.3	0.078	43.5
0.086	37.4	0.094	30.1	0.102	28.6	0.109	22.7	0.117	20.7
0.125	27.9	0.133	29.6	0.141	27.2	0.148	27.5	0.156	23.5
0.164	22.4	0.172	22.2	0.180	22.1	0.188	24.4	0.195	27.1
0.203	30.2	0.211	24.2	0.219	16.7	0.227	16.8	0.234	22.9
0.242	27.4	0.250	22.7	0.258	18.4	0.266	19.9	0.273	24.6
0.281	28.7	0.289	25.2	0.297	19.3	0.305	23.9	0.313	30.0
0.320	24.7	0.328	19.9	0.336	19.5	0.344	18.8	0.352	18.4
0.359	17.7	0.367	15.0	0.375	11.4	0.383	19.9	0.391	33.3
0.398	31.8	0.406	29.4	0.414	31.9	0.422	29.8	0.430	31.3
0.438	33.3	0.445	29.8	0.453	27.4	0.461	25.0	0.469	23.6
0.477	26.1	0.484	23.9	0.492	17.3	0.500	9.8		

MEAN POWER DENSITY: 27.20
DEGREES OF FREEDOM = 4
CHISQUARE = 213.92
ST.DEVIATION = 9.53
MPD UPPER 0.95 CONF LIMIT = 29.72
MPD LOWER 0.95 CONF LIMIT = 24.68
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 20
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 30
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 50

PAD2,201B600RF185 POWER DENSITY IN FREQUENCY POINTS: PAD2 NO WEIGHTING

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	18.6								
0.008	35.2	0.016	37.3	0.023	31.2	0.031	27.1	0.039	23.5
0.047	20.5	0.055	18.9	0.063	17.1	0.070	21.2	0.078	29.3
0.086	28.2	0.094	21.3	0.102	23.7	0.109	28.7	0.117	24.3
0.125	16.7	0.133	13.6	0.141	14.1	0.148	17.0	0.156	26.6
0.164	34.9	0.172	29.3	0.180	21.9	0.188	22.7	0.195	28.4
0.203	31.6	0.211	27.6	0.219	24.2	0.227	23.1	0.234	21.1
0.242	20.9	0.250	21.4	0.258	26.1	0.266	32.4	0.273	29.5
0.281	23.3	0.289	19.5	0.297	18.0	0.305	17.9	0.313	19.0
0.320	23.3	0.328	26.8	0.336	24.3	0.344	21.1	0.352	26.8
0.359	27.4	0.367	17.7	0.375	22.3	0.383	39.3	0.391	39.8
0.398	21.9	0.406	12.6	0.414	18.2	0.422	25.9	0.430	27.3
0.438	24.8	0.445	24.8	0.453	28.5	0.461	32.9	0.469	29.1
0.477	25.8	0.484	31.6	0.492	60.2	0.500	73.2		

MEAN POWER DENSITY: 26.04
DEGREES OF FREEDOM = 6
CHISQUARE = 221.43
ST.DEVIATION = 9.49
MPD UPPER 0.95 CONF LIMIT = 28.33
MPD LOWER 0.95 CONF LIMIT = 23.75
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 19
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 30
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 49

1RUS.301B700RF162 POWER DENSITY IN FREQUENCY POINTS: Russ1 NO WEIGHTING

FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:	FREQ:	POWER:
0.000	5.6								
0.008	22.1	0.016	29.3	0.023	38.6	0.031	46.3	0.039	33.5
0.047	19.4	0.055	20.1	0.063	26.4	0.070	29.7	0.078	28.8
0.086	23.5	0.094	18.5	0.102	20.9	0.109	25.2	0.117	29.9
0.125	34.8	0.133	28.2	0.141	22.2	0.148	24.3	0.156	23.1
0.164	19.9	0.172	17.2	0.180	16.0	0.188	14.3	0.195	12.7
0.203	15.7	0.211	21.1	0.219	26.7	0.227	33.3	0.234	34.6
0.242	30.3	0.250	32.4	0.258	36.0	0.266	30.1	0.273	23.1
0.281	22.7	0.289	25.6	0.297	28.5	0.305	33.0	0.313	33.7
0.320	27.1	0.328	20.2	0.336	15.2	0.344	19.0	0.352	25.1
0.359	24.6	0.367	30.6	0.375	38.8	0.383	35.1	0.391	25.0
0.398	18.5	0.406	19.6	0.414	32.4	0.422	44.6	0.430	35.3
0.438	20.1	0.445	15.8	0.453	22.6	0.461	31.9	0.469	27.6
0.477	19.2	0.484	17.4	0.492	17.7	0.500	13.3		

MEAN POWER DENSITY: 25.45
DEGREES OF FREEDOM = 6
CHISQUARE = 158.71
ST.DEVIATION = 7.94
MPD UPPER 0.95 CONF LIMIT = 27.36
MPD LOWER 0.95 CONF LIMIT = 23.53
NUMBER OF SPECTRAL POINTS ABOVE UPPER LIMIT: 26
NUMBER OF SPECTRAL POINTS BELOW LOWER LIMIT: 30
TOTAL NUMBER OF SIGNIFICANT SPECTRAL POINTS: 56