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THE EFFECT OF INTERTRIAL DEPENDENCE ON SOME SENSITIVITY AND BIAS STATISTICS

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CONTENTS

SUMMARY

An investigation of the intertrial dependencies in detection and recognition tasks was undertaken at different levels of a priori stimulus probability, intertrial interval, feedback, and task difficulty in a number of experiments. The effects of these experimental variables on the data are reported.

After preliminary tests for stationarity the dependences were characterised using 0, 1st and 2nd order manifest Markov processes, an autoregressive process and a latent Markov process. Although none of the models described all the data it appeared that the autoregressive process was the least helpful and that to obtain a reasonable fit of the latent Markov model a numerical minimum χ^2 estimation procedure had to be employed.

Estimates of the parameters of various detection and recognition models were found based on all the data and based on data which was preceded by a particular type of trial. From such evidence it appeared that the value of these estimates depended on the state on the last trial. In particular the bias statistics were dependent on the immediately preceding response and the sensitivity statistics appeared dependent on whether the immediately preceding trial was correct or wrong. Neither Atkinson's (1965) model nor the model proposed by Tanner Rauk & Atkinson (1971) was found to adequately describe the observed dependences.

Statistical tests have been developed for a number of the detection and recognition models used in the above study. These tests assume intertrial dependence. Simulations of the Markov process estimated from the experiments were used to examine the robustness of such tests against violations of the independence assumption. The tests were found to be relatively robust but large biases were found when the test statistics were based on small samples. This effect was shown to be able to account for some of the earlier findings.

1. INTRODUCTION

The aim of this project was to examine the effects of the trial by trial dependences on various signal detection and recognition models (Tanner Swets Green Peterson Birdsall Treisman Luce Atkinson, etc.). Most of the models assume independence although some e.g. Atkinson Kinchla, postulate some dependences on certain types in certain situations. Here an attempt is made to discover the extent of the dependences in the usual types of psychophysical experiments, how they vary with experimental conditions, and what effects they have on the models. To do this several experiments will be described involving detection and recognition tasks in which the variables stimulus probability feedback intertrial interval and task difficulty were systematically varied. Estimation of the dependences in each of these conditions was then undertaken. An attempt to measure the robustness of the recognition and detection models could then be attempted by simulating experiments with the observed amounts of dependence and observing the effects on the models. In short the aim was to characterise the intertrial dependence in this situation and examine the effect of this on the detection and recognition models.

Thus the review will consist of five sections. The first dealing with existing models, methods of estimation of their parameters and statistical tests which have been derived on the basis of some of the models.

After this there follows a discussion on models for describing a series of discrete events in time which are dependent. These models will be used to show what the nature of the dependences is in the situations we shall be examining. Having a model which describes such a time series enables similar series to be simulated on a computer. The differences between signal detection models applied to such series and to independent series can be examined. The models discussed for this purpose include an information theory approach, observable and latent Markov models and autoregressive processes.

An attempt will be made to review the main effects of varying the experimental conditions as have been reported in the literature for comparison at a qualitative level with the present investigation. Findings from reaction time studies will also be included since a choice reaction time experiment is a very easy recognition situation.

Up to this point the main emphasis is on the Yes/No experimental situation. A further discussion of Rating scale task will be given and results from the technique examined and compared with RTROC curves (Meyers 1970), so that the effect of latency dependencies can also be examined.

(1) The Basic Experiments

Before examining some different classes of models it might be useful to describe the sort of data to which they have been applied.

In the Yes/No detection situation a subject S is presented with a stimulus which could be either a burst of white noise (N) or a burst of white noise into which a signal (S) has been added. The subject's task is to indicate the presence or absence of a stimulus by responding R_S or R_N respectively. When this is repeated a number of times the results can be summarised by the conditional probabilities of the subjects response given what the stimulus was on that trial. The table of these figures is often referred to as a confusion matrix.

		Stimulus Presented	
		Noise	Stimulus
Subj.Resp.	R_S	$p(R_S\|N)$	$p(R_S\|S)$
	R_N	$p(R_N\|N)$	$p(R_N\|S)$

Often the models used in this situation can be used on recognition data. Here the S is required to respond R_{S_1} or R_{S_2} depending on whether he was presented with stimulus 1 or 2 rather than detecting the presence of a stimulus.

Other sorts of experimental techniques can be used than the Yes/No situation. In the Forced Choice experiment the subject is presented with two stimuli at known times. In the detection situation he must state which of the two contained the signal and in the recognition task the subject is required to state which stimulus was which. In a Rating procedure with the detection task the subject not only responds indicating the presence or absence of a signal he indicates his degree of certainty on a n point scale.

These three methods are the standard psychophysical techniques that have been used in experimental work in signal detection (Green and Swets 1966). In all but one of the experiments undertaken in this project the set up was the Yes/No design. The subject was presented with one of two known stimuli and required to say which it was the cycle being repeated for several hundred times.

2. SIGNAL DETECTION AND RECOGNITION MODELS

(a) Preamble

Different types of models have appeared from time to time in the literature over the last 20 years (Peterson Birdsall Fox, 1954; Green & Swets, 1966; Krantz, 1969; Atkinson, 1963; Luce, 1963; Thomas, 1970, etc.)

Attempts have been made to formalise the statistical properties of these models (Gourevitch & Galanter, 1967; Abrahamson Levitt & Landgraf, 1967; Dorfman & Alf, 1968; Abrahamson & Levitt, 1968 & 1969; Bush, 1963). Other recent developments in this area include the postulation of a memory recognition model (Tanner Rauk & Atkinson, 1971), and several attempts to produce a nonparametric analysis of signal detection and recognition data (Pollack and Hsieh (1969), Hodos (1970).

The following section will attempt to summarise the above models and methods of analysis.

(b) Parametric Models of Signal Detection and Recognition

In the basic model of Swets Tanner & Birdsall (1961) an observer is required to distinguish between being presented with a signal in a background of noise (S + N) or with noise alone (N). They assume that repeated presentation of the same stimulus gives rise to a distribution of values f(x) on the subject on some psychological continuum, i.e. $f(x|N)$ or $f(x|S + N)$ depending whether the signal was added to the noise or not. The subject uses his knowledge of $f(x|N)$ and $f(x|S + N)$ to decide from which of the distributions the stimulus has arisen. Indeed, in this model it is supposed that the subject decides to respond.

$$R_N \qquad \text{if the likelihood ratio } x < C$$

$$\text{and} \quad R_{S+N} \qquad \text{if the likelihood ratio } x > C$$

In the normal equal variance case when

$$f(x|N) = N(\mu_N\sigma^2) \text{ and } f(x|SN) = N(\mu_{S_N}\sigma^2)$$

the likelihood ratio of SN as opposed to N is

$$\ell(x) = \frac{\frac{1}{2\pi\sigma^2} \exp \frac{1}{2\sigma^2} (X-\mu_{SN})^2}{\frac{1}{2\pi\sigma^2} \exp \frac{1}{2\sigma^2} (X-\hat{\mu}_N)^2}$$

$$= \exp \frac{1}{2\sigma^2} \quad (2\mu_{SN} - 2\mu_N)x$$

$$- (\mu_{SN}^2 - \mu_S^2)$$

as the units and location are arbitrary we can put $\sigma = 1$ and let

$$\mu_{SN} = \frac{d'}{2} \qquad \mu_N = -\frac{d'}{2}$$

When

$$\ell(x) = \exp(d'x)$$

thus $\ell(x)$ and x are monotonically related and we can use an equivalent decision rule to describe S's behaviour

$$\text{respond } R_{SN} \text{ if } f(x) = \frac{(x|SN)}{(x|N)} > K$$

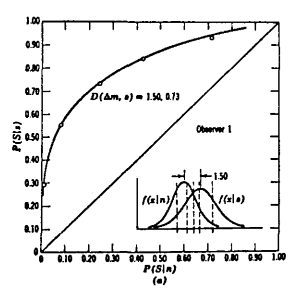
$$\text{or } R_{SN} \text{ if } f(x) = \quad x \quad > C$$

if C and K are chosen appropriately.

If in experiments (e.g. Tanner, Swets, Green 1956) we induce the subject to vary k, we obtain different estimates of k but $E(x|S + N) - E(x|N)$ usually called d' when expressed in units corresponding to the variance of the underlying distributions should be constant. If we were to plot $P(R_S|S)$ V $P(R_S|N)$ we obtain a curve characteristic of the subject, i.e. for each value of d' there is one such curve. If all the above assumptions are met. When plotted on double probability graph paper $P(R_S|S)$ V $P(R_S|N)$ should give a straight line slope.

This basic formalisation was developed by its originators (Green & Swets 1966) to include a number of variations on the original theme.

(1) They considered the case of unequal variance. This no longer results in a monotonic ROC curve if $\sigma_S > \sigma_N$ (σ_{S+N} is sd. of $f(x|S+N)$ then the ROC curve is like:



To detect this difference however is very difficult, e.g. Swets & Green claim if σ_S/σ_N = 2:1 then to detect the rapid acceleration at the top of the curve requires at least 3 place accuracy.

If the assumptions of the above model hold except $\sigma_{S+N} \neq \sigma_N$ then the effect is more easily measured using double probability paper.

$$Z_Y \text{ is now } (k - E(x|S+N))/\sigma_S \;\&\; k = \sigma_S Z_Y + \mu_S$$

$$\text{and} \quad Z_X = (k - E(x|N))/\sigma_N \;\&\; k = \sigma_N Z_X + \mu_N$$

$$Z_x = \frac{\sigma_S Z_Y + \mu_S - \mu_N}{\sigma_N}$$

i.e. the slope of the line is σ_S/σ_N and its intercept with the y axis is $\frac{\mu_S - \mu_N}{\sigma_N}$. We can thus estimate the ratio of standard deviations from the slope of the ROC curve. However, the model as it now stands begs the question that if the decision axis is no longer monotonic to the likelihood ratio the observer should be able to learn two criteria so that he restores signal to very low values of x.

(2) An alternative way of describing the data is to assume an exponential distribution.

$$f(x|N) = e^{-x}$$

$$f(x|S+N) = a\ e^{-ax}$$

$$P(R_S|N) = \int_k^\infty e^{-x} = e^{-k}$$

$$P(R_S|S) = \int_k^\infty a\ e^{-ax}\ e^{-ka} = (e^{-k})^a$$

$$P(R_S|N) = P(R_S|S)^{1/a} \qquad (\dot{X})$$

i.e. the ROC curve is given in equation ($\dot{X}$). This gives the freedom of another parameter and implies that the slope decreases with increasing k.

(3) By assuming $f(x|N) = \frac{1}{(1+x)^2}$

$$f(x|SN) = \frac{1/\eta}{(1/\eta+x)^2} \qquad \eta < 1 \qquad (X)$$

Swets and Green produce identical results as those obtained by Luce's choice model (Luce 1963a).

i.e. in $P(R_S|N) = \frac{1}{k+1}$ in a Yes/No experiment $P(R_S|S) = \frac{1/\eta}{1/\eta+k}$.
The above equation can be solved for η and k. (η being the sensitivity parameter). In fact this model differs from the choice model in that eq. (X) although giving equivalent Yes/No predictions does not also predict the forced choice equation as choice theory.

Other models with different premises are:

Luce's Choice model (1963)a

He assumes that two ratio scales η_1 and η_2 exist defined on the set of all stimuli used in the experiment ϕ (in the detection case S and N) and b is a ratio scale defined on the set of all responses in experiment ψ. He then assumes

$$p(R|S) = \frac{\eta(S, S(R))\ b(R)}{\forall \sum_{R' \varepsilon R} \eta(S,\ S(R')\ b(R')}$$

where η is the similarity between the presented stimulus S and the one S(R) for which R is the correct response. He also assumes

$$\eta(S_1 S_2) = \eta(S_2 S_1) \text{ for } \quad S_1 + S_2 \ \varepsilon\ \phi$$

$$\eta(S_1 S_1) = 1 \qquad S_1 \ \varepsilon\ \phi$$

$$\eta(S_1 S_3) \geqslant \eta(S_1 S_2) \times \eta(S_2 S_3)$$

Consider the Yes/No detection situation. Let $\eta(S, N) = \eta(N, S) = \eta$ and $b(R_S)/b(R_S) = b$, then the confusion matrix is

$$\begin{array}{ccc} & \multicolumn{2}{c}{\text{Resp.}} \\ & R_S & R_N \\ N & \dfrac{\eta(N_S)\ b(R_S)}{\eta(N_S)\ b(R_S) + \eta(N,N)\ b(R_N)} & \dfrac{\eta(N,N)\ b(R_N)}{\eta(N_S)\ b(R_S) + \eta(N,N)\ b(R_N)} \\ S & \dfrac{\eta(S,S)\ b(R_S)}{\eta(S,S)\ b(R_S) + \eta(S,N)\ b(R_N)} & \dfrac{\eta(S,N)\ b(R_N)}{\eta(S,S)\ b(R_S) + \eta(S,N)\ b(R_N)} \end{array}$$

by appropriate division of the numerators and denominators we reduce the above to

$$\begin{array}{ccc} & R_S & R_N \\ N & \dfrac{1}{1 + \eta b} & \dfrac{b}{\eta b + 1} \\ S & \dfrac{\eta}{\eta + b} & \dfrac{b}{b + \eta} \end{array}$$

η and b can then be found directly from the confusion matrix i.e. $$\eta = \left(\frac{P(R_N|S)}{P(R_S|S)} \quad \frac{P(R_S|N)}{P(R_N|N)}\right)^{\frac{1}{2}}$$

and $$b = \left(\frac{P(R_N|S)}{P(R_S|S)} \quad \frac{P(R_N|N)}{P(R_S|N)}\right)^{\frac{1}{2}}$$

<u>Threshold theories</u>

<u>Classical</u>:- This assumes that there exists some cut-off level of sensory excitation. If this is excluded the subject 'detects' a stimulus. In practice it is noticed that the same stimuli repeatedly presented to the subject may sometimes be detected and sometimes not. This can be explained by proposing that the sensory effect produced by the same stimulus varies or that the cut-off value (threshold) varies. For any stimulus S however there is a fixed probability p(s) of detecting it. If however the signal is not detected the subject may guess that it was presented with a probability g, i.e. we can characterise the situation in two matrices.

Stim. State

	D	$\bar{D}$
S	p(s)	1-p(s)
N	0	1

	R_S	R_N
D	1	0
$\bar{D}$	g	1-g

thus the resulting confusion matrix is the product of the two above.

	R_S	R_N
S	p(s) + (1-p(s))g	(1-p(s))(1-g)
N	g	(1-g)

We can thus estimate g from $p(R_S|N)$ and then find p(s)

$$p(R_S|S) = p(S) + (1 - p(S))p(R_S|N)$$

i.e. $$p(S) = \frac{p(R_S|S) - p(R_S|N)}{1 - p(R_S|N)}$$

Another performance measure used classically in the probability of being correct statistic p(c). If the number of response alternatives is m then

$$p(c) = p(c)^* + \frac{1}{m}(1 - p(c)^*)$$

where $p(c)^*$ is the underlying probability of being correct once the effect of guessing on the observed probability has been removed

$$p(c)^* = \frac{p(c) - 1/m}{1 - 1/m}$$

Luce's two state threshold analysis:- Luce modified the above formulation to make it symmetric. He assumes an activation matrix, one of two decision matrices (Luce 1963).

	D	$\bar{D}$		R_S	R_N		R_S	R_N
S	p(s)	1-p(s)	D	1	0	or	1-g	g
N	p(n)	1-p(n)	$\bar{D}$	g	1-g		0	1

This relaxes two assumptions of classical theory as there is a possibility of going into either state if noise alone is presented and, depending on whether the subject wishes to reduce his miss rate or his false alarm rate, he would choose decision matrix 1 or 2, thereby producing a confusion matrix of

	R_S	R_N	or	R_S	R_N
S	p(s)+(1-p(s))g	(1-p(s))(1-g)		p(s)(1-g)	p(s)g + (1-p(s))
N	p(n)+(1-p(n))g	(1-p(n))(1-g)		p(n)(1-g)	p(n)g + (1-p(n))

As there are three parameters in this model, ηs, ηn and y the model is not immediately testable from two independent probabilities.

Atkinson (1963):- Further extended threshold theory by postulating detection states corresponding to each stimulus condition. The probability of entering either of these states given signal or noise is specified by an activation matrix

	D_S	D_0	D_N
S	σ	$1-\sigma$	0
N	0	$1-\sigma$	σ

Thus σ is a measure of the subjects sensitivity and a decision matrix depending on trial n

	R_S	R_N
D_S	1	0
D_0	ρn	$1-\rho_n$
D_N	0	1

Thus ρ_n is an estimate of the bias on trial n.
So the resulting confusion matrix is the product of the activation and decision matrices

	R_S	R_N
S	$\sigma + \rho_n(1-\sigma)$	$(1-\sigma)(1-\rho_n)$
N	$(1-\sigma)\rho_n$	$\sigma + (1-\sigma)(1-\rho_n)$

This is the only model so far considered which allows for non independence between trials. As Atkinson in Atkinson, Bower & Crothers, 1965 postulates that

$$\rho n + 1 \begin{cases} = \rho n + \theta(1-\rho n) & \text{if } D_0 \text{ and feedback } S\_ \\ = (1-\theta')\rho n & \text{if } D_0 \text{ and feedback N} \\ = \rho n & \text{otherwise} \end{cases}$$

ρn changes only with feedback. It is shown (Atkinson, Bower & Crothers, 1965)

$$\underset{n\to\infty}{L}(\rho_n) \to \rho_\infty = \frac{\gamma}{\gamma + (1-\gamma)\phi}$$

where $\gamma = P(S)$

and $\phi = \frac{\theta'}{\theta}$

Thus ϕ and σ can be estimated from the confusion matrix.

Sandusky (1966) and (1971), proposed a model with a similar activation and decision matrix. In this model if neither signal is recognised on a trial the response depends on the sensory state on the immediately preceding trial. If the signal was not recognised on the preceding trial then the subject repeats his last response with a probability v. If the last signal was recognised he assumes a change has occurred and modifies his strategy in favour of response alternation, i.e. he repeats his last response with a probability w where w < v. Thus ρ_n is independent of n and if the probability of a true recognition is a constant α for each of the stimuli

$$\rho_n = \rho = \frac{\gamma\alpha v + (1-\gamma)\alpha(1-v) + (1-\alpha)(1-w)}{1 - (1-\alpha)(2w-1)}$$

To estimate the parameters Sandusky uses a numerical technique.

Krantz (1969) postulated a non-symmetric decision model for detection experiments. His activation matrix was

		D_2	D_1	D_0
A	S_n	η_2	η_1	η_0
	N	0	q_1	q_0

and decision matrices depending on the point on ROC curve were:-

		Y	N			Y	N
P_{neg}	D_2	1	0	P_{pos}	D_2	1	0
	D_1	b	1-b		D_1	1	0
	D_0	0	1		D_0	a	1-a

and the response matrices R = AD

are R_{neg} and R_{pos}

$$R_{neg}: \begin{array}{ccc} & Y & N \\ SN & \eta_2 + b\eta_1 & 1-\eta_2-b\eta_1 \\ N & bq_1 & 1-bq_1 \end{array} \qquad R_{pos}: \begin{array}{ccc} & Y & N \\ SN & 1-\eta_0(1-a) & \eta_0(1-a) \\ N & q_1+a(1-q_1) & (1-q_1)(1-a) \end{array}$$

and the ROC curve is

lower level $$P(R_S|S) = \frac{\eta_1}{q_1} P(S|S_N) + \eta_2$$

and

higher level $$P(R_S|S) = \frac{\eta_0}{q_0} P(S|S_N) + 1 - \frac{\eta_0}{q_0}$$

Thomas and Legge (1970) have proposed a different approach to signal detection. Following Parks (1966) the basic proposition is the subject responds so that $P(R_S)$ the probability that the subject responds S is given by

$$P(R_S) = \text{minimum } (kq,1)$$

where k is a constant depending on the payoff matrix and q is the probability of (S). It is thus assumed

$$kq \doteq qP(R_S|S) + (1-q)\ P(R_S|N)$$

$$P(R_S|S) = k - \frac{1-q}{q} P(R_S|N)$$

so that if q is fixed for all data points over generation on an ROC curve, then these points should lie on a straight line through (0, k) with slope $-(1-q)/_q$. Given two points on this line the point closer to (0, k) corresponds to a larger hit and smaller false alarm rate and this reflects more sensitivity. However, the model does not yield a measure of sensitivity on an interval scale.

(c) Theoretical Variances of Parameters

Some of the above models to be considered can be conceived as producing a number of independent binomial processes. Let there be J such processes. Bush (1963) considers some of the estimation problems involved. Let p_j and n_j be the probability of success and the number of trials on the jth process respectively. Finally let X_{ij} be a random indicator variable showing the state on the ith trial of the jth process. Thus the likelihood of a set of observations is given by

$$L = \prod_{j=1}^{J} \prod_{i=1}^{n_j} p_j^{\,X_{ij}} (1-p_j)^{1-X_{ij}}$$

and $\ln L = \sum_j \sum_i X_{ij} \ln p_j + (1-X_{ij}) \ln(1-p_j)$. Thus to find the ML estimate of a parameter (θ) where p_j is a function of θ we differentiate lnL with respect to θ and set it equal to 0.

$$\text{i.e.} \quad \frac{\partial \ln L}{\partial \theta} = \frac{\partial \ln L}{\partial p_j} \frac{\partial p_j}{\partial \theta} = 0$$

$$= \sum_j \sum_i \left(\frac{X_{ij}}{p_j} - \frac{1 - X_{ij}}{1 - p_j} \right) \frac{\partial p_j}{\partial \theta}$$

$$= \sum_j \sum_i \left(\frac{X_{ij} - p_j}{p_j(1-p_j)} \right) \frac{p_j}{\partial \theta}$$

$$= \sum_j \frac{\sum_i X_{ij} - n_i p_j}{n_j(1-p_j)} \frac{\partial p_j}{\partial \theta}$$

$$\sum_j \frac{\bar{X}_j - p_j}{n_j(1-p_j)} \frac{\partial p_j}{\partial \theta} = 0$$

$$\text{where } \bar{X}_j = \sum_i \frac{X_{ij}}{n_i}$$

A solution is $p_{.j} = \bar{X}_{.j}$ and as $p_{.j} = f(\theta)$ the ML estimate of θ is $f^{-1}(X_{.j})$

Note: $$E\left(\sum_i \frac{X_{ij}}{n_{.j}}\right) = \sum_i \frac{E(X_{ij})}{n_{.j}} = \frac{p_{.j}n_{.j}}{n_{.j}} = p_{.j}$$

It can be shown (Kendall & Stewart (1963)) that ML estimations are best asymptotically normal (BAN) with an asymptotic variance equal to the Minimum Variance Bound (MVB). The MVB is established by the Cramer Rao Inequality (Kendall & Stewart, vol.2, p.13).

$$\text{var } t < \frac{1}{-E\,\dfrac{\partial^2 \ln L}{\partial\theta^2}} \quad \text{or} \quad \frac{1}{E\left(\dfrac{\partial \ln L}{\partial\theta}\right)^2}$$

where t is the estimate of a population parameter θ and L is the likelihood function of observation made on the population. In this case therefore the asymptotic variance of θ is

$$A\text{ var }(\hat{\theta}) = \frac{1}{-E\,\dfrac{\partial^2 \ln L}{\partial\theta^2}} = \frac{1}{\sum \dfrac{n_{.j}}{p_{.j}(1-p_{.j})}\left(\dfrac{\partial p_{.j}}{\partial\theta}\right)^2}$$

$$E\,\frac{\partial^2 \ln L}{\partial\theta^2} = E\,\frac{\partial \sum\limits_j\sum\limits_i \dfrac{X_{ij} - p_{.j}}{p_{.j}(1-p_{.j})}\dfrac{\partial p_{.j}}{\partial\theta}}{\partial p_{.j}}\;\frac{\partial p_{.j}}{\partial\theta}$$

$$= E\sum_j\sum_i \frac{p_{.j}(1-p_{.j}) - (X_{ij}-p_{.j})(1-2p_{.j})}{p_{.j}^2(1-p_{.j})^2}\left(\frac{\partial p_{.j}}{\partial\theta}\right)^2$$

$$= E\sum_j\sum_i \frac{-X_{ij} + 2p_{.j}X_{ij} - 3p_j^2 + 2p_j}{pj^2(1-p_{.j})^2}\left(\frac{\partial p_{.j}}{\partial\theta}\right)^2$$

as $E(X_{ij}) = p_j$ we have

$$\frac{\partial^2 \ln L}{\partial^2 \theta} = \sum\sum_{ji} \frac{-p_j(1-p_j)}{-p_j^2(1-p_j)^2} \frac{\partial p_j}{\partial \theta}^2$$

$$= -\sum\sum \frac{1}{p_j(1-p_j)} \frac{\partial p_j}{\partial \theta}^2$$

$$= -\sum_j \frac{n_j}{p_j(1-p_j)} \frac{\partial p_j}{\partial \theta}^2$$

Thus

$$A \text{ var } (\hat{\theta}) = \frac{1}{\sum_j \frac{n_j}{p_j(1-p_j)} \frac{\partial p_j}{\partial \theta}^2}$$

<u>Luce's Choice Model</u>

Here we have two processes operating one when a signal is present and the other when the stimulus is noise alone. A solution to the ML estimation equation is

$$P(R_S|S) = \frac{1}{\eta b + 1} = \bar{X}_S \quad \therefore \quad \frac{\partial P(R_S|S)}{\partial \eta} = \frac{1}{\eta} P(R_S|S)(1-P(R_S|S))$$

$$P(R_S|N) = \frac{\eta}{\eta + b} = \bar{X}_N$$

and the ML estimates of η and b

$$\hat{\eta} = \sqrt{(1 - \bar{X}_S)/\bar{X}_S \quad \bar{X}_N/(1 - \bar{X}_N)} = \sqrt{\frac{P(R_N|S)P(R_S|N)}{P(R_S|S)P(R_N|N)}}$$

$$\hat{b} = \sqrt{(1 - \bar{X}_S)/\bar{X}_S \quad (1 - \bar{X}_N)/\bar{X}_N} = \sqrt{\frac{P(R_N|S)P(R_N|N)}{P(R_S|S)P(R_S|N)}}$$

Their asymptotic variances are

$$A\ V\ (\hat{\eta}) = \frac{\eta^2}{N(P(R_S|S)(1-P(R_S|S)) + P(R_S|N)(1-P(R_S|N))}$$

$$A\ V\ (\hat{b}) = \frac{b^2}{N(P(R_S|S)(1-P(R_S|S)) + P(R_S|N)(1-P(R_S|N))}$$

In the threshold model we have as a solution of the ML estimation equation:

$$P(R_N|S) = (1 - p(s))(1-g) = \bar{X}_S \quad \frac{\partial P(R_N|S)}{\partial p(s)} = -P(R_N|N)$$

$$P(R_N|N) = 1 - g \qquad = \bar{X}_N$$

$$g = 1 - \bar{X}_N$$

$$\text{and } p(s) = 1 - \frac{\bar{X}_S}{\bar{X}_N}$$

are the required ML estimations and

$$A\ V\ (p(s)) = \frac{\dfrac{1}{N\ P(R_N|N)^2}}{P(R_S|S)(1-P(R_S|S))}$$

is the asymptotic variance of the threshold p(s).

We can also use the probability of being correct as an index of sensitivity. The equation for the observed probability of being correct is

$$P(c) = P(c)^* + \tfrac{1}{2}\{1 - P(c)\}$$

where $P^*(c)$ is the true probability; of being correct and the other responses are guesses from m alternatives.

Thus $$P(c)^* = \frac{P(c) - 1/m}{1 - 1/m}$$

Assuming independence of trials then from the binomial distribution

$$A \text{ var } (P(c)) = P(c)(1-P(c)) / N$$

$$A \text{ var } (P(c)^*) = (1-P(c))P(c)/(1-1/m)^2 N$$

In Luce's threshold model there are as we saw three parameters to be estimated. We therefore need more data than is in one confusion matrix to estimate these parameters. However, it is possible to obtain two confusion matrices differing only in g, i.e. the subject is required to detect the same signal in two situations where experimental conditions are arranged to make the subject change his bias parameter. Let the two bias parameters and let the variables in the second situation be denoted by a prime. Then the estimation equations are:

$$P(R_N|N) = (1 - p_n)(1 - g)$$
$$P(R_N|S) = (1 - p_s)(1 - g)$$
$$P(R_N|N)' = (1 - p_n)(1 - g')$$
$$P(R_N|S)' = (1 - p_s)(1 - g')$$

Gourevitch and Galanter (1967) derived an approximation to the sampling distribution of d' when

$$f(x|N) = (\mu_N, \sigma^2) \quad \text{and}$$

$$f(x|SN) = N(\mu_{SN}, \sigma^2).$$

Let

$$p_1 = P(R_N|N) = \int_{-\infty}^{c} f(x|N)dx$$

$$p_2 = P(R_N|SN) = \int_{\infty}^{c} f(x|SN)dx$$

Normally we estimate p_1 and p_2 empirically i.e. obtain $\hat{p}_1$ and $\hat{p}_2$ and then convert these to z scores using a table of areas under a ND curve to give z_1 and z_2. The estimate of $d' = \mu_{sn} - \mu_n$ is $d_1 = z_1 - z_2 = est(c - \mu_N) - est(c - \mu_{SN})$. If $\sigma = 1$ we can write

$$p_i = \int_{-\infty}^{c} \frac{1}{\sqrt{2\pi}} e^{\frac{-(x - \mu_i)^2}{2}} dx$$

$$= \int_{-\infty}^{c} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$= \int_{-\infty}^{z_i} \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}} dx$$

i.e. $p_i = \phi(z_i)$

$$z_i = \phi^{-1}(p_i) = g(p_i)$$

Now expanding $g(\hat{p})$ about the point $\hat{p} = p$

$$g(\hat{p}) = g(p) + (\hat{p} - p)g'(p) + \ldots\ldots \qquad *$$

Differentiating * we have

$$\frac{dp}{dz} = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} = \text{ord } z$$

where ord z means the ordinate of the normal curve at standard score z.

$$g'(p) = \frac{dz}{dp} = \frac{1}{\text{ord } z}$$

$$\hat{z} = z + \frac{\hat{p} - p}{\text{ord } z}$$ substituting into equation *.

Thus $\hat{d} = \hat{z}_1 - \hat{z}_2 = z_1 - z_2 + \dfrac{\hat{p}_1 - p_1}{\text{ord } z_1} - \dfrac{\hat{p}_2 - p_2}{\text{ord } z_2}$ and

$$\text{var}(\hat{d}) = \frac{\text{var } \hat{p}_1}{(\text{ord } z_1)^2} + \frac{\text{var } \hat{p}_2}{(\text{ord } z_2)^2}$$

as p_1, p_2, z_1 and z_2 are constant.

We assume p_j is estimated from n_i independent observations distributed binomally.

Thus $$\text{var}(d) = \frac{p_1(1-p_1)}{n_1(\text{ord } z_1)^2} + \frac{p_2(1-p_2)}{n_2(\text{ord } z_2)^2}$$

$$\text{var }(\hat{d}) = \frac{\hat{p}_1(1-\hat{p}_1)}{n_1(\text{ord } \hat{z}_1)^2} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2(\text{ord } \hat{z}_2)^2}$$

we can thus test H_o: $\hat{d}_1 - \hat{d}_2 = 0$ using

$$Z = \frac{\hat{d}_1 - \hat{d}_2}{\sqrt{\dfrac{\hat{p}_1(1-\hat{p}_1)}{n_1(\text{ord } z_1)^2} + \dfrac{\hat{p}_2(1-\hat{p}_2)}{n_2(\text{ord } z_2)^2}}}$$

when the Z distribution is N(0, 1).

Recently Abrahamson & Levitt (1969) have extended this approach to an examination of a number of different points on the same ROC curve. They define

$$F(x|N) = \int_{-\infty}^{x} f(t|N)dt \text{ and } F(x|SN) = \int_{-\infty}^{x} f(t|SN)dt$$

These have inverses $F^{-1}{}_N$ and $F^{-1}{}_{SN}$ respectively.

$$P(R_S|SN) = P(\text{hit}) = 1 - F_{SN}(c) = P(c)$$

$$P(R_S|N) = P(\text{false alarm}) = 1 - F_N(c) = p(c)$$

thus eliminating c we have the equation for the ROC curve

$$F^{-1}{}_N(1-p) = F^{-1}{}_{SN}(1-P)$$

if we assume $\quad f(x|N) = \frac{1}{\sigma} f(\frac{x}{\sigma})$

and $\quad f(x|SN) = \frac{1}{\sigma_s} f\,(\frac{x-s}{\sigma_s})$

where σ^2 is the variance of the noise distribution and $\sigma_s{}^2$ the variance of the signal plus noise distribution. Note how much less restrictive this is than the equal variance normal condition previously considered,

$$P(c) = 1 - F(\frac{c-s}{\sigma_s}) \quad p(c) = 1 - F(\frac{c}{\sigma})$$

and the ROC curve

$$F^{-1}(1-P) = \frac{\sigma}{\sigma_s} F^{-1}(1-p) - \frac{s}{\sigma_s}$$

if $\sigma = \sigma_s$ this depends only on s/σ which we call d'.

By changing the probability of the signal P(S) on the rewards the estimate of (c) and P(c) can be obtained for several values of c. Suppose n_i trials are made at c_i. For $i = 1....N$ we can estimate

$$\hat{p}(c_i) = \hat{p}_i = \frac{\text{no } R_s \text{ given SN}}{P(S_i)n_i}$$

$$\hat{P}(c_i) = \hat{P}_i = \frac{\text{no } R_s \text{ given S}}{(1-P(S_i))n_i}$$

where $P(S_i)$ is the a priori probability of a signal being presented and asymptotically

$$(n_i)^{\frac{1}{2}} \begin{pmatrix} \hat{p}_i - p_i \\ \hat{P}_i - P_i \end{pmatrix} \sim N \left(\begin{matrix} 0 \\ 0 \end{matrix} \, , \; \begin{matrix} \frac{p_i(1-p_i)}{1-P(S_i)} & 0 \\ 0 & \frac{P_i(1-P_i)}{P(S_i)} \end{matrix} \right)$$

now if $\quad X_i = F^{-1}(1 - \hat{p}_i) \quad \xi_i = F^{-1}(1 - p_i)$

$$Y_i = F^{-1}(1 - \hat{P}_i) \quad \eta_i = F^{-1}(1 - P_i)$$

and $\quad \gamma_i = \frac{p_i(1 - p_i)}{(1-P(S))f(\xi_i)} \qquad \delta_i = \frac{P_i(1 - P_i)}{P(S_i)f(\eta_i)}$

If $f(\xi_i)$ and $f(\eta_i)$ are normal γ_i and δ_i are probit weights (Finney 1952)

$$X_i - \xi_i = \frac{\hat{P}_i - P_i}{f(\xi_i)}$$

$$Y_i - \eta_i = \frac{\hat{P}_i - P_i}{f(\eta_i)}$$

and asymptotically

$$(n_i)^{\frac{1}{2}} \begin{matrix} X_i - \xi_i \\ Y_i - \eta_i \end{matrix} \sim N \begin{matrix} 0 \\ 0 \end{matrix}, \begin{matrix} \gamma_i 0 \\ 0\ \delta_i \end{matrix}$$

if $\quad z_i = X_i - Y_i$

$$n^{\frac{1}{2}}(z_i - \frac{s}{\sigma}) \sim N(0, \tau_i)$$

where $\quad \tau_i = \gamma_i + \delta_i$

note: $X \sim N(\mu,\Sigma)$ means vector X is multivariate normal will mean vector μ and covariance matrix Σ.

They then considered an estimate of $d'(\frac{S}{\sigma})$ from a number of estimates from different points on the ROC curve $(\hat{d}'_i)$. They obtain a solution which they claim is asymptotically unbiased and efficient:-

$$\hat{d}' = \Sigma n_i \hat{d}'_i/\text{var}\ \hat{d}'_i \quad \Sigma n_i/\text{var}\ \hat{d}'_i{}^{-1}$$

with variance

$$\text{var}\ \hat{d}' = \Sigma n_i/\text{var}\ \hat{d}'_i{}^{-1}$$

where n_i are the number of observations for each data point. The estimates of the individual cutoffs are found from the maximum likelihood equation

$$\ell(d', \frac{c_i}{\sigma}) = \prod_i \left(1 - F(\frac{c_i}{\sigma} - \frac{S}{\sigma})\right)^{n_i(S|S)} F(\frac{c_i}{\sigma} - \frac{S}{\sigma}) \qquad \times$$

$$\left(1 - F(\frac{c_i}{\sigma})\right)^{n_i(S|NS)} \quad F(\frac{c_i}{\sigma})^{n_i(NS|NS)}$$

$n_i(S|S)$ is the number of hits in condition i.

$$K_1 = \sum_{1}^{N} \frac{p_i - (1 - F(\hat{c}_i/\hat{\sigma}))^{\;2}}{F((\hat{c}_i - S)/\hat{\sigma})\ 1 - F((\hat{c}_i - S)/\hat{\sigma})} n_i(1 - P(S_i))$$

$$+ \sum_{1}^{N} \frac{P_i - -1 - F((\hat{c}_i - S)\hat{\sigma})^{\;2}}{F((\hat{c}_i - S)/\hat{\sigma})\ 1 - F((\hat{c}_i - S)/\hat{\sigma})} n_i P(S_i)$$

where $\hat{\sigma} \doteq S(S/\hat{\sigma})$ and $c_i = \hat{\sigma}(\frac{c_i}{\sigma})$

K_1 is distributed as χ^2 with N-1 degrees of freedom.

If the n_i's are allowed to increase so that $n_i/\sum_j n_j \to$ a limit v_i and the models assumptions hold then $K_1/\sum_j n_j$ will converge to 0. Otherwise it will reach a minimum for some values σ^o and C^o $(C_1^o \ldots C_N^o)$. In such a case K_1 is roughly distributed as $A^{-1}\chi^2_{2N}(\Delta^2)$ where A is a constant

$$A = M \qquad M \frac{p_i{}^o(1 - p_i{}^o)}{p_i(1 - p_i)} , \frac{P_i{}^o(1 - P_i{}^o)}{P_i(1 - P_i)}$$

$\chi^2_{2B}(\Delta)$ is a non central chi square with 2N degrees of freedom and non centrality parameter Δ

$$\Delta = \sum n_i \frac{(p_i - p_i{}^o)^2}{p_i(1 - p_i)}(1 - P(S_i)) + \frac{(P_i - P_i{}^o)^2}{P_i(1 - P_i)} P(S_i)$$

To achieve a power of at least β against a specified set of p_i's and P_i's n_i should be large enough to satisfy

$$P(\chi^2_{2N}(\Delta) > A\ \chi^2_{N-1}) \doteq \beta$$

From this they showed that to test the goodness of fit of a logistic model against a normal one with power .5 and significance level .05 well over 5,000 observations would be required. They also considered the case where $\sigma_s \neq \sigma$ and showed estimates for σ/σ_s, S/σ_s, c_i/σ_s and the covariance matrix of these parameters could be found from the maximum likelihood equation

$$\ell(\frac{\sigma}{\sigma},\frac{S}{\sigma_s},\frac{c}{\sigma_s}) = \prod_i \quad 1 - F(\frac{\sigma}{\sigma_s}\,\frac{c}{\sigma_s} - \frac{S}{\sigma_s})^{\,n_i(S|S)} \times$$

$$F(\frac{\sigma}{\sigma_s}\,\frac{c}{\sigma_s} - \frac{S}{\sigma_s})^{\,n_i(NS|S)} \times \qquad 1 - F(\frac{c}{\sigma_s})^{\,n_i(S|NS)} \times$$

$$F(\frac{c}{\sigma_s})^{\,n_i(NS|NS)}$$

Unfortunately there is no explicit solution to this equation and solutions have to be generated numerically.

In, however, the case where $\sigma = \sigma_s$ they reach the same solutions as Gourevitch and Galanter using different notation.

(d) <u>The Memory Recognition Model</u>

Tanner Rauk and Atkinson (1970) proposed a model of signal amplitude recognition which predicts sequential dependences and the effect of feedback.

The model supposes two signals S_o and S_1 are presented to a subject in a Yes/No signal recognition, experiment. γ is the a priori probability of S_1 and A_0 and A_1 are the responses corresponding to S_0 and S_1.

When a stimulus S is presented to a subject an image I of it is set up. I is normally distributed $I_o \sim N(s_o, \sigma_I^2)$ $I_1 \sim N(s_1, \sigma_I^2)$. For scaling purposes s_o is set equal to 0 and s_1 to 1. At the end of the trial I is stored and becomes trace T. $T_o \sim N(t_o, \sigma_T^2)$ $T_1 \sim N(t_1, \sigma_T^2)$.

The relation postulated between s and t is linear and depends on γ i.e. $t_1 = \alpha + (1 + \alpha)\gamma$

$$t_0 = (1 + \alpha)\gamma$$

where α is a const.

Let $S_\ell{}^j$ be the presentation of stimulus ℓ on trial j. When $S_\ell{}^j$ occurs $I_\ell{}^j$ is set up and compared with $t_m{}^{j-1}$ the trace of the stimulus S_m presented on the last trial. The decision on what to respond depends on $d_{j\ j-1} = S_\ell{}^j - t_m{}^{j-1}$.

The decision process may be specified thus

	$d_{j\ j-1} > \delta_0$		Respond A_1
if	$d_{j\ j-1} < \delta_1$	then	Respond A_0
	other		Repeat last response.

Thus

$$P(A_1^j | S_\ell^j A_m^{j-1} S_n^{j-1}) = \Phi \frac{s_\ell - t_n - s_m}{\sigma D}$$

where $\Phi(x)$ is the integral of the unit normal density function

$$\text{i.e. } \Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-(\frac{1}{2})y^2}\, dy$$

If feedback is present then the decision process becomes

$$\text{if}\quad \begin{array}{lll} d_{j\ j-1} > \delta_0 & & \text{Respond } A_1 \\ d_{j\ j-1} < \delta_1 & \text{then} & \text{Respond } A_0 \\ \text{other} & & \text{Repeat last stimulus} \end{array}$$

Thus $P(A_1^j | S_\ell^j A_m^{j-1} S_n^{j-1}) = \phi \dfrac{s_\ell - t_n - \delta_m}{\sigma D}$

Tanner <u>et</u> <u>al</u>. propose when feedback is present the actual process is a weighted average of the two decisions i.e. Subjects do not make full use of feedback in this case

$$P(A_1^j | S_\ell^j A_m^{j-1} S_n^{j-1}) = w\phi\left(\frac{s_\ell - t_n - \delta_n}{\sigma D}\right)$$

$$+ (1 - w)\phi\left(\frac{s_\ell - t_n - \delta_m}{\sigma D}\right)$$

Thus there are five unknowns σ_D δ_0 δ_1 w and α.

(e) <u>Non-Parametric Approaches to Signal Detection</u>

Recently attempts have been made to overcome the difficulty of having to choose which model you must use to obtain a measure of a subject's sensitivity. The solution for psychologists less interested in examining the models than in using them was to develop simple statistics which approximated to estimates of the various models.

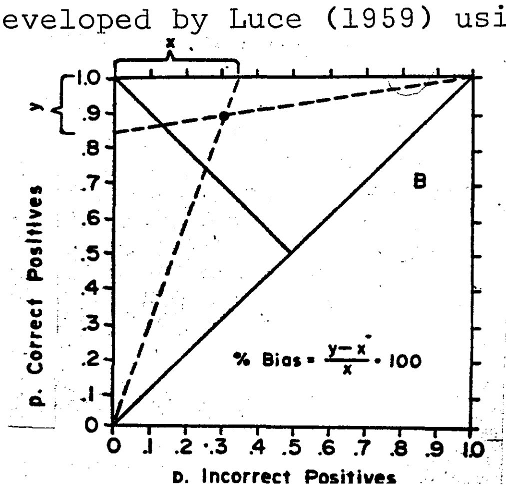
The sampling distribution of these measures provides a fairly intractible analytic problem. Pollack & Hsieh (1969) attempted to find it empirically by simulating a forced choice experiment on a computer. They specified the distribution of noise f(N) and signal + noise f(S + N) and calculated $P(f(N) < x)$ and $P(f(S + N) < x)$ for all values of x. From this they obtained the area under the ROC curve (A_g). They found that for a given value of d' varying the σ_{SN}/σ_N ratio affected A_g

and σ_{Ag}. For a value of A_g however σ_{Ag} was relatively constant with an underlying normal distribution. Analogous results were obtained using uniform and negative exponential underlying distributions for noise and signal + noise. Correlating the samples from f(N) and f(NS) did not appear to affect A_g or σ_{Ag}. That is to say they found that the sampling variability of the area measure was dependent on its mean value and relatively independent of the complex conditions which led to the given mean value.

They also attempted to use the intersection of the ROC curve with the negative diagonal P(I) as a measure of performance similar to A_g or d'. Again for a given value of d' the parameters P(I) and $\sigma_{P(I)}$ are related to σ_{SN}/σ_N. However the sampling variability of Ag is less than the sampling variability of P(I).

Pollack and Norman (1964) suggested a model-free analysis of a subject sensitivity based on a single point $P(R_S|S)$, $P(R_S|N)$ on a ROC curve. The straight line from the point (0,0) and (1,1) to $P(R_S|S)$, $P(R_S|N)$ divides the ROC curve into four regions (see diagram).

According to all models discussed points in the area I represent inferior performance that the point $P(R_S|S)$, $P(R_S|N)$. Similarly the area S contains only the points representing superior performance. Points lying in other areas are ambiguous. Thus, Pollack and Norman (1964) suggested the measure A' equal to the area I plus half the ambiguous area as a measure of performance. A non-parametric measure of bias was introduced by Hodos (1970). Using the same diagram as Pollack he suggested a percentage bias parameter equal to one hundred (y - x)/y where x is the intercept on the y axis of the line passing through the point (1,1). Isobias lines based on this assumption appear similar to those developed by Luce (1959) using his model.



(f) Extension to Rating Experiments

Although originally developed for the Yes/No experimental set up signal detection models were soon applied to the results of rating scale experiments (e.g. Watson Rilling and Bourbon (1964)), as this procedure enables more information about subjects ROC curves to be obtained from a similar amount of experimental effort. The rating task implies that the subject must use several decision criteria simultaneously. He must place each observation in a category that corresponds to his degree of certainty as to which stimuli had occurred. The probabilities of $P(R_S|S)$ and $P(R_S|N)$ can be found assuming that the subjects responds signal present only when he was most certain that it was present or when he is most and second most certain that the signal is present, etc. Thus for n categories n - 1 data points on a ROC curve can be derived.

Abrahamson and Levitt (1969) have studied the statistical properties of a Tanner Swets Green type model in this situation. The degrees of certainty are $c_1, c_2 \ldots\ldots c_k$. The subject responds c_r when the psychological representation of the stimulus lies between c_r and c_{r+1} on the decision axis where $c_1 = -\propto$ and $c_{r+1} = \propto$.

$$P(c_i|SN) = Q_i = \int_{c_i}^{c_{i+1}} f_{SN}(x)dx$$

$$P(c_i|N) = q_i = \int_{c_i}^{c_{i+1}} f_N(x)dx$$

Again, estimates of Q_i and q_i are easily obtained, and the random vector $(Q_1 \ldots\ldots Q_k)$ and $(q_1 \ldots\ldots q_k)$ are independent estimates of a multinomial process. The hit probabilities if the subject uses criterion c_i are

$$P_i \simeq f_{SN}(x)dx = \sum_{j \geq i} Q_j = 1 - F\frac{(c_i - s)}{\sigma}$$

and the corresponding false alarm probabilities are

$$p_i = \sum_{j>i} q_j = 1 - F(\frac{c_i}{\sigma})$$

Therefore the ROC curve is as before

$$F^{-1}(1-P_i) = \frac{\sigma}{\sigma_s} F^{-1}(1-p_i) - \frac{s}{\sigma_s}$$

Under the assumption $\sigma_s = \sigma$ they define an approximation to the minimum variance estimator of s and its variance

$$\frac{\tilde{s}}{\sigma} = \sum_{ij} \hat{\tau}^{ij} Z_j / \sum_{ij} \hat{\tau}^{ij}$$

$$\text{where } \tau^{ij} = \frac{\hat{p}_i(1 - \hat{p}_j)}{(1 - P(S))f(F^{-1}(1 - p_i))} + \frac{\hat{P}_i(1 - \hat{P}_j)}{P(S)f(F^{-1}(1-P_i))}$$

and by approximating to a solution of the maximum likelihood equation they derive a goodness of fit statistic. They state that in the case of $\sigma_s = \sigma$ is intractible.

Meyers (1970) suggested defining the categories $c_1 \ldots . c_k$ in a Yes/No experiment in terms of the latencies. That is to say the frequency of the same responses at different latencies are grouped together and ordered from fast Yes to slow Yes to slow No to fast No and treated as if they were Yes certain Yes uncertain No uncertain No certain. Meyers then proposed a model similar to that of Krantz (1969) be applied to data in this situation.

(3) Experimental Variables

The main independent variables that have been investigated in detection or recognition systems are stimulus probability, payoffs, instructions, inter response time, feedback, stimulus difficulty and the nature of the stimuli. Some of these variables may very well effect the nature of the sequential effects.

(a) Stimulus Probability

This is one of the most common independent variables to be studied as the subject's sensitivity as measured by most models is assumed independent of this variable. For example, Tanner Swets and Green (1956) varied the a priori stimulus probabilities using values of .1, .3, .5, 1.7, and 1.9. They then obtained an ROC curve as described in Chapter 1. Some observers in this situation did not produce ROC curves which were symmetrical about the negative diagonal and their data was better fitted when the assumption $\sigma_N = \sigma_{SN}$ is not made. In general, however, it was found that increasing the a priori stimulus probability had the effect of raising the point representing the subject's performance on the ROC curve. That is to say it increased simultaneously both the probability of a hit and a false alarm.

Recently Tanner Haller and Atkinson (1967) and Parducci and Sandusky (1965) in auditory and visual recognition studies produced rather contradictory results. Tanner et al. experimental situation involved a auditory amplitude recognition task. Subjects were run for 400 trials at each stimulus probability on each of three sessions. The order for presentation of each session was determined randomly. In this case subjects were given no feedback and were not informed of the a priori probabilities. The results are shown in the diagram below.

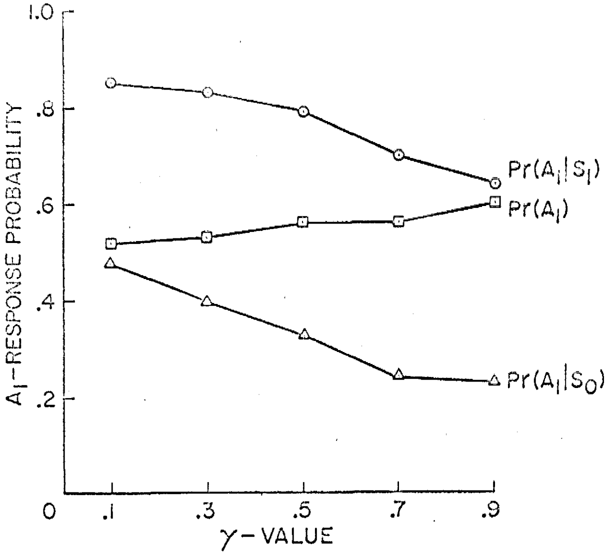


Fig. 1. Probability of hits, false alarms, and the A_1 response averaged over observers.

They found that the probability of a hit $P(R_1|S_1)$ and false alarms $P(R_1|S_2)$ decreased as the probability of stimulus 1 $P(S_1)$. The probability of response 1 $P(R_1)$ only increased largely with $P(S_1)$. Summarising the results of the two experimental situations one can say that increasing a priori stimulus probability has its greatest effect on the bias of the subject. The direction of the effect is determined by the amount of information the subject has of the value of $P(S_1)$.

(b) Feedback

Green and Swets (1966) state that trial by trial feedback helps to bring about a rapid approach to asymptotic behaviour. This effect however is small when presession training is given. This was demonstrated by Grundy (1961). Kinchla and Atkinson (1964) varied the probability of giving feedback in a Yes/No detection situation. They found that this had an effect on the subject's bias parameter but not on the sensitivity one. They used an Atkinson type model, see section on signal detection models.

Kinchla (1966) and Tanner et al (1967) showed that feedback effects the relationship between the relationship between the a priori stimulus probability and the hit and false alarm probabilities. That is to say subjects have a greater tendency to probability match when they have feedback. The difference between the feedback and non-feedback condition is even more noticeable in the case where subjects have no information about the a priori stimulus probabilities

(Tanner Rauk and Atkinson (1970)). The effect of feedback on sequential dependencies in pooled data was also studied in the above paper. They predicted and found that in the no feedback condition the sequential dependencies would affect only the bias of the subject and not his sensitivity i.e. the points $(P(R_1|S_1R_1S_1), P(R_1|S_2R_1S_1))$, $(P(R_1|S_1R_1S_2), P(R_1|S_2R_1S_2))$, $(P(R_1|S_1R_1S_2)$, $P(R_1|S_2R_1S_2))$, $(P(R_1|S_1R_2S_2), P(R_2|S_2R_2S_2))$, all lie on the same ROC curve. While if feedback is presented they predict that only the points $P(R_1|S_1R_jS_j)$, $P(R_1|S_2R_jS_k)$ where $j = k$ lie on the curve. They claim that the data generally bears out their predictions. Although a glance at the graphs suggests that the points $P(R_1|S_1R_jS_k)$, $P(R_1|S_2R_jS_k)$ where $j = k$ appear if anything to be on a more sensitive ROC curve than the others. They also found that feedback reduced the total amount of dependence on the last trial.

(c) Stimulus difficulty

McGill (1957) used a four signal auditory frequency recognition task and varied the difficulty by varying the intensities of the signals against a background of white noise. He used an information theory analysis and found that as the task became easier the information shared between a response and a stimulus which evoked it increased while the information shared between this response and the response on the immediately succeeding trial decreases. This is really saying that as the probability of the correct response increases the other factors affecting the response must simultaneously decrease.

(d) Payoffs and instructions

It was discovered early that payoffs could influence the bias of the subject without affecting his sensitivity. E.g. Tanner Swets and Green (1956) show that a subject can be made to change the value of his bias parameter by varying the payoffs dependent on the outcomes of each trial. The extent to which the subject does this is smaller than would be predicted by a normative Bayesian type analysis. This however is a common enough finding in decision making, c.f. Peterson and Beach (1968). The same effect can be observed by varying the instructions to a subject. Egan Schulman & Greenberg1959 instructed subjects to use a "strict", "medium" and "lax" criteria. Feedback was given to subjects if the criterion they were using fell outwith a specified range. Again the sensitivity was found to remain constant while the bias changed.

(e) Sequential effects

This is the area in which this project is mainly interested. Fechner (1860) found a "negative time error" in his experiment on lifted weights. That is to say if two equal weights are presented to a subject then the second weight is judged greater than the first. Fechner postulated a fading memory trace to account for this mechanism. Thus when a subject lifted the first weight he formed an image which was then compared to the second. As this trace fades so the second is judged as heavier. Contemporary introspectionists did not like this idea. Thus Kohler (1923) postulated a hypothetical physiological process as an explanation instead.

Postman (1946) studied this effect for tones differing in either pitch or intensity. He found little time error for pitch but with the intensity variable he found a time error the nature of which depended on the interstimulus interval (ISI). Averaging over subjects and frequencies he obtained the following graph for intensity judgments and

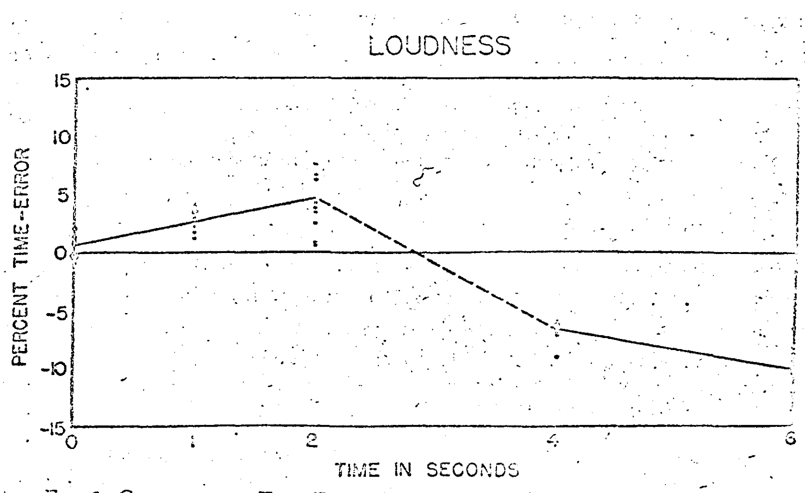
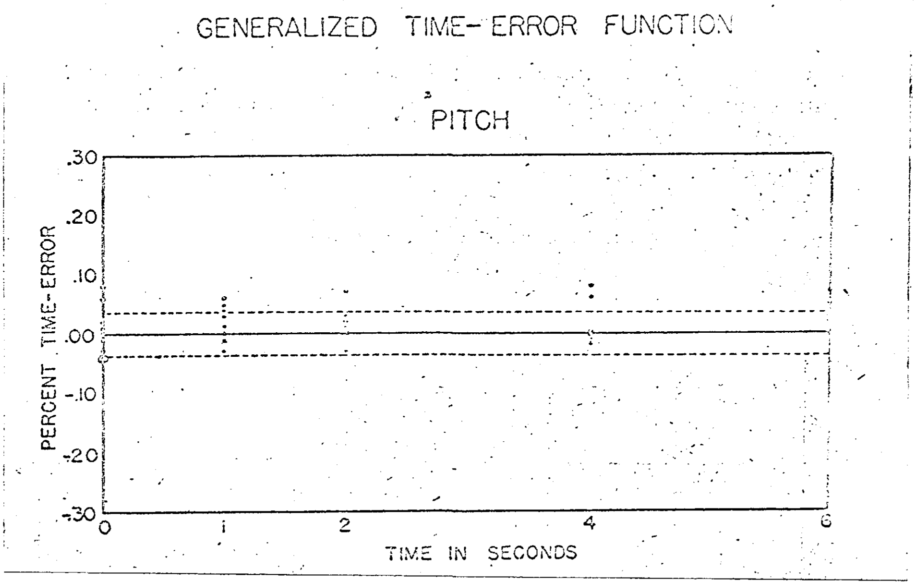


FIG. 8. GENERALIZED TIME-ERROR FUNCTIONS FOR PITCH AND LOUDNESS
Each point on the graph represents the average time-error for an *O* at a given time-interval.

a straight line for pitch judgment



A distinction is made by Stevens (1939) between discriminations which depend on the addition of excitation to excitation (e.g. intensity judgment) and those which depend on differential patterns of excitation. The former appeared to lead to systematic time errors while the latter do not.

Needham (1934) found that the time error reversed itself after extensive practice becoming negative after a short interval and positive after a longer one. Similar after effects are common in visual studies.

In the 1950's some work was carried out into sequential effects by presenting a constant stimulus around threshold to a subject for a large number of trials and asking the subject to detect the presence of the stimulus, e.g. Verplank, Collier and Cotton (1952) used a light at the 50% threshold.

This stimulus was presented to sixteen subjects on 300 successive trials during four separate sessions. They found significant auto correlations up to about lag 11 (representing about one minute real time) and no significant dependence over lag 20. Day (1956) presented a continuous 1000 cps tone to the right ear of each of five subjects at a sensation level of 70 db. Subjects were instructed to respond by pressing a key whenever they could detect an increment in the loudness of the tone. From 300 to 600 increments in intensity each 0.1 second in duration were added regularly to the tone at a fixed interstimulus interval. A response of Yes or No was recorded for each increment. Day varied the interstimulus interval and found that the subjects' responses did not conform to a random series as measured using a runs test (see Siegel (1956)). He also found that as the interstimulus interval increased so the departure from randomness decreased, although some subjects showed marked degrees of non-randomness even at the longest interstimulus intervals.

Other experimenters (Senders and Sowards (1952), Senders (1953) and Wagnaar (1968)) presented a constant stimulus to a subject asking him to respond as to whether it fell into one of two categories. Wagenaar states that in these experiments no real pressure was involved as the subjects' task was to state which of two stimuli presented came first. As both stimuli were presented simultaneously the author claimed that threshold fluctuations could not serve as an explanation for the strong response dependencies found in all cases. He preferred to postulate a sequential response bias to account for the response dependencies which in most cases corresponded to a tendency to repeat the same response on the part of the subject. The main findings were that strong dependencies existed together with wide individual subject differences.

Wertheimer (1953) took successive measurements of auditory visual and pain thresholds on a series of three subjects. These were obtained at 6 second, 1 minute, 3 minute and 1 day intervals. An analysis of the data revealed significant auto correlation between successive measures of thresholds. An analysis of variance showed that in the last experimental condition where the inter threshold determination time was one day, this variable the inter thresh old determination time was found to have a significant effect on the threshold obtained.

Matrices used

$$A \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .5 & .5 \\ S_2 & .5 & .5 \end{array} \qquad B \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .8 & .2 \\ S_2 & .8 & .2 \end{array} \qquad C \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .2 & .8 \\ S_2 & .2 & .8 \end{array}$$

$$D \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .8 & .2 \\ S_2 & .2 & .8 \end{array} \qquad E \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .2 & .8 \\ S_2 & .8 & .2 \end{array} \qquad F \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .8 & .2 \\ S_2 & .8 & .8 \end{array}$$

$$G \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .2 & .8 \\ S_2 & .5 & .5 \end{array} \qquad H \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .5 & .5 \\ S_2 & .8 & .2 \end{array} \qquad I \quad \begin{array}{ccc} & \multicolumn{2}{c}{T_{n+1}} \\ & S_1 & S_2 \\ T_n \; S_1 & .5 & .5 \\ S_2 & .2 & .8 \end{array}$$

More recently work has concentrated on detection and recognition situations. Speeth and Mathews (1961) in a four interval forced choice signal detection experiment found that a subject's current response was effected by his immediately preceding response, his past performance level and an indication of what his last response should have been. This effect decreased as the signal increased, i.e. the task became easier. Carterette and Wyman (1962) in a Yes/No detection experiment found that the trial frequencies were not a zero order Markov process.

We shall now see how more recent studies have revealed some of the relationships between the independent variables and sequential effects. Freidman and Carterette (1964) varied the stimulus probability by making the presentation sequence of stimuli a first order Markov process. A forced choice detection task was used and subjects were not informed of the nature of the stimulus dependencies nor the purpose of the experiment. The transition matrices used are given on the following page. In A, B and C the probability of the first stimulus S_1 on trial n is independent of the stimulus on trial n - 1. In D, F and H the probability of a stimulus repetition is increased while in E, G and I the probability of a stimulus alteration is decreased. For the most part the data points were well fitted by a traditional ROC curve. The a priori probabilities appeared to effect the placing of the data points on the curve. They also examined the effect of run length on the probability of a correct response P(c) and the results are shown in the diagram below.

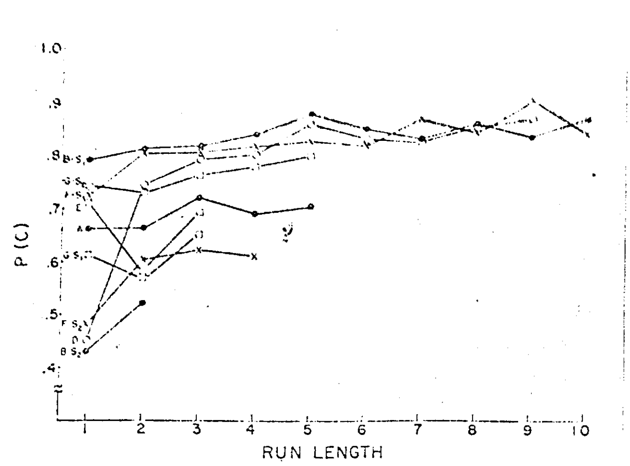


FIG. 2. Proportion of correct responses [P(C)] averaged over the three observers as a function of run length for the various Markov-chain generators.

FIG. 2. Proportion of correct responses [P(C)] averaged over the three observers as a function of run length for the various Markov-chain generators.

In experimental conditions A, B and C the probability of a correct response increased with run length. In conditions D and E which had the greatest amount of stimulus dependence run length had a dramatic effect on P(c). In condition D P(c) went from .45 on the first trial of a run to .8 on the second while in A the corresponding values were .70 and .58. The observed dependencies of responses on responses were small. The authors suggest that this was due to the provision of feedback following every trial without which more dependency on the immediately preceding response to a given trial might have been noted.

(f) The Effect of Feedback on Sequential Effects

Freidman and Carterette (1964) state that from their research feedback is an important determiner of response dependencies. If feedback is given then the largest response dependencies are on the stimulus presented on the immediately preceding trial. If no feedback is given then the largest effect is of the immediately preceding response. Parducci and Sandusky (1965) in a recognition task of the special position of lights found the effect of feedback was to reduce the accuracy after a stimulus alternation but to increase it after a stimulus repetition. Both these effects cancelled each other out when the probability of a correct response was taken as a performance measure. This perhaps explained the findings of Grundy (1961) who found that the provision of feedback did not appear to effect the probability of a correct response. Also in both these studies the a priori stimulus probability was .5 . Kinchla (1966) in a signal recognition task showed that subjects in a feedback condition tended to match the probability of the responses whilst in a non-feedback condition they did not. Thus the probability of each of the responses without feedback regressed to .5 .

The effect of feedback on stimulus alternation was examined by Tanner Haller and Atkinson (1967) who found subjects were more accurate after a stimulus alteration than after a stimulus repetition in a no feedback signal recognition experiment. This is interpreted by assuming that the subject compares the stimulus on one trial with some "memory" of the stimulus on the immediately preceding trial. Thus if the subject is wrong on one trial he will compare the stimulus on the next with a wrongly labelled "memory" and thereby increasing the chances of him making a wrong response. The effect of feedback in decreasing the probability of a correct response after a stimulus alternation is less easy to explain unless it is postulated that feedback in some way interferes with the comparison process.

We can therefore conclude that sequential effects are observable over a wide variety of detection and recognition tasks. As the task becomes easier so these effects decrease. The same thing happens when the interstimulus interval is increased. Feedback appears to increase the probability of a correct response after a stimulus repetition but has the opposite effect after a stimulus alternation.

4. RELEVANT REACTION TIME FINDINGS

(a) Experimental Results

The literature on reaction time is of direct relevance to the task we are considering as the task facing a subject in a Yes/No recognition situation is very similar to that in a choice reaction time experiment.

Smith (1968) has reviewed the literature of choice reaction time and defines a choice reaction time experiment as follows:-

(a) The stimulus and responses are known at the start of the experiment.

(b) The error rate is low - less than 10% wrong responses occur and no comparison stimuli are presented.

(c) Latency is the major dependent variable.

In the signal recognition task used in the current investigation the error rate was often higher than the 10% stipulated by Smith as characteristic of the reaction time experiment. It is usually more difficult and the experimenter is interested in other dependent variables than latency. There is also a difference in the instruction normally given to the subjects. The similarity of the two experimental procedures however makes the findings of choice reaction time experiments of direct relevance to those interested in signal recognition.

The major variables found to effect the choice reaction time (CRT) experiment are given below.

(i) CRT and stimulus uncertainty.

The relation choice reaction time is proportional to stimulus uncertainty has been found to hold good whether stimulus uncertainty is varied by changing the number of equiprobable alternatives or varying the probability of occurrence of individual stimuli Hick (1952) and Hyman (1953) and subsequent studies. This is in cases where the task is one one i.e. there is one and only one distinguishable response for each stimuli. Whether this relationship still holds when the one : one relationship is altered is open to question, e.g. Rabbitt (1959) and Pollack (1963). Stimulus uncertainty however cannot entirely explain the finding of Broadbent and Gregory (1965) who showed that the CRT's to a stimulus that occurred on 75% of the trials were longer when this stimulus was part of a four alternative choice reaction time experiment than a two choice task. Thus the number of stimuli has an effect on the latency which is independent of the probability of that stimulus.

(ii) CRT and payoff.

Fitts (in Smith (1968)) showed that where payoffs were greater to the subject following fast accurate responses to some stimuli choice reaction times were shorter to the more highly valued stimuli. Laberge (1964) also found that the effect of increasing the payoff associated with the particular response had the effect of decreasing the latency of that response.

(iii) CRT and sequential effects.

Bertleson (1961) showed that the choice reaction time to a stimulus increase is the number of intervening trials since the last occurrence of the stimuli. Although data produced by Hyman (1953) do not appear to confirm this in a two choice reaction time experiment they do with four, six or eight choices. Bertleson and Rankin (1966) found the effect reversed when the interval between the stimulus was long, i.e. 12 - 15 seconds.

Laming (1968) studied sequential dependencies in reaction time experiments. He used the multiple regression analysis technique whose basic equation is as below.

$$E_i = e + a_0(S_i - \tfrac{1}{2}) + \Sigma a_j(Q_{ij} - \tfrac{1}{2}) +$$

$$\sum_k a_{0k}(S_i - \tfrac{1}{2})(Q_{ik} - \tfrac{1}{2}) +$$

$$\sum_j \sum_{k<j} a_{jk}(Q_{ij} - \tfrac{1}{2}) + \sum_j b_j E_{i-j}\left[Q_{ij} + 1\right] +$$

$$\sum_j c_j E_{i-j} Q_{ij} + \varepsilon_i$$

S_i equals 1 if stimulus 2 is presented on the trial otherwise zero.

R_i equals 1 if response 2 is made on the trial otherwise zero.

$_i$ equals $|S_i + R_i|$.

Q_{ij} equals $|S_i + S_{i-j}|$.

a_0 is the effect of the stimuli on the current trial on the error rate.

a_j is the effect of the stimulus on trial i-j.

a_{ij} is the effect of the combination of stimuli on trials i and j.

b_j is the effect of a mistake of the same sort on trial i-j.

c_j is the effect of a mistake of a different sort on trial i-j.

The values of a, b and c are the regression coefficients and provide some measure of the sequential effects. If the coefficient of a similar regression analysis using the response of the dependent variable was also performed. Also the latencies were analysed using the regression equation

$$
\begin{aligned}
T_i = t &+ \sum_j h_j T_{i-j} + \sum_j \{ f_j([R_i + R_{i-j}] - \tfrac{1}{2})(T_{i-j} - \mu) \\
&+ g_j(Q_{ij} - \tfrac{1}{2})(T_{i-j} - \mu)\} \\
&+ s_0 E_i + s_1(S_i - \tfrac{1}{2}) + s_2(R_i - \tfrac{1}{2}) \\
&+ \sum_j U_j(Q_{ij} - \tfrac{1}{2}) + \sum_j \sum_{j>k} u_{jk}(Q_{ij} - \tfrac{1}{2})(Q_{ik} - \tfrac{1}{2}) \\
&+ \sum_j v_j E_{i-j} Q_{ij} + \sum_j w_j E_{i-j}[Q_{ij} + 1] + \tau_i
\end{aligned}
$$

t is the average reaction time.

k_j gives the effect of times on preceding trials.

f_j gives the effect of times of responses for R_i and R_{i-j} being equal or not.

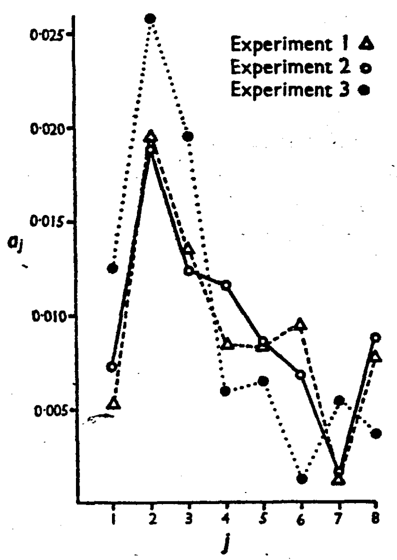
u_j gives the effect of the difference in reaction time between the events S_{i-j} is not equal to S_i and S_{i-j} equals S_i.

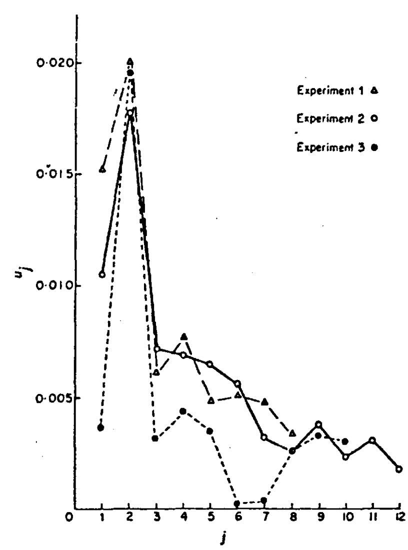
u_{jk} gives the effect of the events Q_{ij} and Q_{ik} which are not included in the u_j.

w_j - this represents the increase in reaction time on a trial when the signal involved in an error on trial i - j is presented again.

v_j represents the increase in reaction time when the alternative signal is presented.

Laming estimated the above regression equation using data from several experiments in the same analysis. He reported where the regression coefficients differed depending on the conditions. One of his findings was that the order in which subjects were run in different experimental conditions was important. Analysing the effects of run length he found that during a run of one of the stimuli S_A the reaction time and probability of an error both decreased. While during a run of the other stimuli, however, the opposite happened. Laming postulated a random walk model to explain the latencies construed that this effect was due to a shift in the starting point of the random walk. The effect of adding a bias parameter to the regression equation was to reduce the difference between the constants in the regression equation. From the regression coefficient our general finding is that a_2 and u_2 are greater than a_1 and u_1. The graph showing how the coefficients vary with distance from the current trial is shown below.





Median values of the a_j regression coefficients in Experiments 1, 2 and 3.

Another find is the importance of the inter-trial interval on the sequential dependencies. He found that the interaction regression coefficients became more important as the inter-trial interval decreased below .5 of a second. He interprets this by claiming that the speed of extraction of information is less after an alternating sequence of signals than after a run during short inter-trial interval conditions. Too much weight however must not be placed on the absolute value of the regression coefficients since they may be serving to suppress some variation in another dependent variable rather than to predict the dependent variable directly.

Bertleson (1963) used an experimental situation involving four stimuli in which two were associated with each response. In this way it was possible for him to study the effect of stimulus and response repetition on reaction time independently. He concluded that response repetition led to the greatest effect on latency. It could also be argued that this effect can explain the results showing that stimulus uncertainty is proportional to latency. The more probable a stimulus is the more repetitions of the response to it will be involved. This however cannot account for all of the experimental findings.

(iv) CRT and discriminability.

Increased discriminability decreases CRT for a given number of stimuli Sternberg (1964). However it appears that the way the changes in discriminability occur changes the effect of varying the number of stimuli. In Sternberg's task the stimulus was changed by the addition of noise to it. If the relation between reaction time and number of stimuli (s) is CRT = k(s) + c where k and c are constants then decreasing discriminability by the addition of noise has the effect of altering c. Crossman (1955) and Thrumound and Alluisi (1963) varied the similarity of the stimuli directly and found that they changed the slope of this function i.e. k.

(v) CRT and compatibility.

Fitts (1959) found that the "naturalness" of SR relations e.g. spacial orientation were related to CRT. This stimulated attempts to see if the effects of the number of stimuli disappeared with very compatible stimulus-response relations. Leonard (1959) found that when the stimuli where the tactile vibration of the fingers and the response was depression of the stimulated finger that the number of stimuli had no effect on the response time.

(vi) CRT and Intertrial Interval.

The effect of intertrial interval on the intertrial dependence has been studied by a number of investigators. The experimental findings, however, lead to rather unclear conclusions. Bertleson (1961), Bertleson and Rankin (1966), and Hale (1967) found that introducing a delay between trials of more than a second had the effect of reducing or abolishing the "repetition" effect. Indeed Hale (1967) showed a transition from positive to negative recency as the intertrial interval was increased. This finding was replicated by Williams (1966). Keele (1969) found no change in the repetition effect over intertrial intervals of 2, 4 and 8 seconds in a six-choice lights-buttons task and no effect of interpolated arithmetic tasks in the 4-second intertrial interval. Schvaneveldt and Chase (1969) found a negative recency effect occurred in both 2 and 4 choice (S-R) compatible tasks and the negative recency increased as the intertrial interval decreased. With less compatible S-R tasks a positive repetition effect was found and the intertrial interval did not appear to affect it.

(vii) CRT and practice.

Some studies e.g. Mowbray and Rhoades (1959) and Davis Moray and Treisman (1961) found that practice could eventually reduce the effect of increasing the number of stimuli to the subject. The two studies combined, however, used only four subjects in total.

(viii) CRT and instructions.

It is possible to reduce the latency at the expense of accuracy by varying the instructions e.g. Fitts (1966) and Hick (1952).

(b) Reaction Time Theories

Theoretical analysis of such studies has developed along a number of different lines. There is the "psychological model" of Selfridge, Neisser etc. who are concerned with the nature of the psychological process rather than developing parametric models. There are mathematical models of the reaction time process e.g. Hick Luce Falmange Laberge Stone Laming etc. In these cases the psychological process is formalised into a mathematical model. Finally there is the approach of McGill who seems concerned mainly with specifying the reaction time distribution statistically and who pays less attention to the psychological process.

Smith (1968) provides a comprehensive verbal review of the cognitive approaches starting with Donders and leading to an extended discussion of the differences between feature testing versus template matching models. Since this approach is not particularly relevant to the present topic the interested reader is referred to this review for a summary of the above work.

Recently the use of Markov chains and random walks came to the notice of psychologists and they have been applied to a number of different situations. A distinction should be made between the "Macro" Markov models discussed in the section on characterising dependencies where each event is a trial i.e. the process continues throughout the whole experiment without absorption, and the more common "micro" model in which each trial is represented by an absorption of a Markov process i.e. the process starts and absorbs during each trial. Looking at the micro model first we see that this was originally applied to choice theory. The unobservable events being referred to as "implicit processes" or some similar concept. If the events are seen as corresponding to observable responses then these criteria for reaching the absorbing state can be studied. Bower (1959) and Estes (1960) considered two successive events corresponding to the same response and Audley (1960) extended this from two to k. Bower also considered using as an absorption criteria the number of events corresponding to one of two responses being greater than k. While Laberge (1962) considered using the criterion k not necessarily successive events corresponding to each course. Although mainly concerned with the response probability such models can equally be made to have latency applications if one postulates the distribution of events in time.

Probably the first application of Markov models to the study of response latencies was by Stone (1960). He made use of the sequential probability ratio test developed by Wald (1947) to relate the mean and variance of the latencies to the error rates and the relative frequencies of the stimulus presentation. Stone postulated that the subject is operating on a stream of random variables $x_1, x_2 \ldots x_n$ separated by a constant time t. $p_0(x)$ and $p_1(x)$ are the probabilities of the random variable taking the value x when the stimulus s_0 and s_1 respectively have been presented. The probabilities are assumed to be constant for all observations. The subject transforms each observation x to c(x) and cumulates the transformed observation over the decision period to give a total c_T.

Constants log A and log B are chosen where $A > B$, so that the subject decides s_1 is present when $c_T > \log A$ and s_0 when $c_T < \log B$. Wald's sequential probability ratio test shows that the optimum choice for c(x) is

$$c(x) = \log p_1(x) - \log p_0(x)$$

This implies that the subject is familiar with $p_0(x)$ and $p_1(x)$.

Less restrictive assumptions were used by Stone in the formulation of his model. He postulated that the subject only assumed symmetry of the probability distributions, i.e. that $p_1(x)/p_0(x)$ when x is distributed as $p_0(x)$ has the same distribution as $p_0(x)/p_1(x)$ when x is distributed as $p_1(x)$. If n_i and v_i are the mean and variance of the sample size of observations necessary to decide s_i is present then Stone showed

$$\frac{\bar{n}_1}{\bar{n}_0} = J(\beta,\alpha)/J(\alpha,\beta)$$

and $$J(\alpha,\beta)v_1 - J(\beta,\alpha)v_0 =$$

$$\frac{4\ J(\alpha,\beta)\alpha(1-\alpha)\bar{n}_1{}^2 - J(\alpha,\beta)\beta(1-\beta)\bar{n}_2{}^2}{(1-\alpha-\beta)}$$

$$J(\alpha,\beta) = \alpha \log \alpha/(1-\beta) + (1-\alpha)\log(1-\alpha)/\beta$$

and α and β are the probabilities of s_0 and s_1 respectively. If the pure decision time T_d can be measured directly then T_{di} can be substituted for n_i and var T_{di} for v_i in the above equations.

Stone's model did not specify the distribution of the small x's. However Laming (1968) extended this by postulating the distribution for the x given S_0.

$$f(x|S_0) = N(\mu_0\sigma^2)$$

and $$f(x|S_1) = N(\mu_1\sigma^2)$$

i.e. they are both normally distributed with equal variances.

In applying his model to the 2 choice situation Laming denotes the a priori information

I_{AP} where

$$I_{AP} = \log \frac{P(S_1)}{P(S_0)}$$

The information obtained by the rth observation

$$\delta Ir = \log \frac{x_r|S_1}{x_r|S_0}$$

and the total information cumulated after n observations

$$I_n = I_{AP} + \sum_{1}^{n} \delta I_n = \log \frac{P(S_1)P(x_i \ldots x_n|S_1)}{P(S_0)P(x_i \ldots x_n|S_0)}$$

As soon as $I_n = I_i$ when i = 0 or 1 response R_i is made. Thus:-

$$I_0 = \log \frac{P(S_1)}{P(S_0)} \frac{P(R_1|S_1)}{P(R_0|S_0)}$$

and

$$I_1 = \log \frac{P(S_1)}{P(S_0)} \frac{P(R_1|S_1)}{P(R_0|S_0)}$$

If n is the number of responses before a response is made then the expectation of n is

$$E(n) = P(S_0)E(n|S_0) + P(S_1)E(n|S_1)$$

Using the properties of the normal distribution Laming is able to derive an explicit solution for both $E(n|S_0)$ and $E(n|S_1)$.

In this model it is assumed that the subject minimises the latency subject to a minimum error rate. This is to say he minimises E(n) subject to the condition.

$$P(S_0)\,P(R_1|S_0) + P(S_1)P(R_0|S_1) < \varepsilon$$

We see that the minimum is obtained when

$$I_0 = \log \frac{\varepsilon}{1 - \varepsilon} \quad \text{and}$$

$$I_1 = \log ((1 - \varepsilon)/\varepsilon)$$

but $I_0 = \log \dfrac{P(S_1)P(R_0|S_1)}{P(S_0)P(R_0|S_0)} - \log \dfrac{P(S_1|R_0)}{P(S_0|R_0)}$

$$\varepsilon = P(S_1|R_0)$$

similarly it can be shown

$$\varepsilon = P(S_0|R_1)$$

Laming derives the following main consequences for this model:-

1. The ratio of the errors given S_1 as opposed to S_0 approaches an optimal value $(P(S_1) - \varepsilon)/(P(S_0) - \varepsilon)$.
2. The signal that elicits the faster reaction has the smaller probability of error.
3. For a given response the distribution of reaction times is the same whether the response is correct or not.

Predictions 1 and 2 were borne out in a series of experiments, Laming (1968). Prediction 3 however was demonstratably found not to be true. Laming therefore modified the models so that the subject begins sampling the information from the blank display at some time before the signal is presented. The information so sampled is irrelevant to the discrimination between the signals. This leads to the prediction that in a two choice reaction time the errors are faster than the same response made correctly.

Falmagne (1965) developed a choice reaction time model which is an interesting special case of the latent class Markov models discussed in the next section. He postulated that a subject is either in a state of preparedness or not for each stimulus for each trial. If the stimulus presented on one trial was in the prepared state then it remains in the subject's prepared state for the next trial. However, if the stimulus in the prepared state was not presented on a trial then it goes into the unprepared state with the probability I - c' and the stimulus in the unprepared state goes into a prepared state with a probability of c. When a subject is in a prepared state his reaction time distribution is K(x) and in the unprepared state it is $\bar{K}(x)$. This model is in fact a latent Markov process with the states of preparedness being the latent states.

Falmagne's model postulates that $S_n(S)$ is a random variable defined for each trial n. The reaction time to stimulus j depends on K_{in}. At trial n the state of the subject can be represented by a vector

$$K_n(s) = \begin{pmatrix} K_1(s) \\ \cdot \\ K_r(s) \end{pmatrix}$$

If the subject is prepared his reaction time distribution is K(x) otherwise $\bar{K}(x)$. He also postulated a random indicator variable $E_{in}(s) = 1$ if stimulus i has been presented to subject s on trial n or 0 if i has not been presented to subject s on trial n. So the stimuli presented to the subject can be represented by a vector

$$E_n(s) = \begin{pmatrix} E_{1n}(s) \\ \\ E_{rn}(s) \end{pmatrix}$$

W_n is the outcome to trial n.

$$W_n = \langle E_n(s)K_n(s), \ldots E_2(s)K_2(s), E_1(s)K_1(s) \rangle$$

The theoretical cumulative distributions of RT to stimulus i at trial n, given the state the subject is in are given below.

$$J(x_n | E_{in} = 1, \quad K_{in} = 1, \ W_{n-1}) = K(x)$$

$$J(x_n | E_{in} = 1, \quad K_{in} = 0, \ W_{n-1}) = \bar{K}(x)$$

Transitions between states for all i and n are described by:-

$$P|K_{in+1}(s)|E_n(s),\ K_n(s),\ W_{n-1}| = f(E_{i,n}(s),\ K_{in}(s))$$

and the values of f are given in the table below

$K_{in}(s) \backslash E_{in}(s)$	1	0
1	1	$1 - c'$
0	c	0

let $P_{in}(s) = P(K_{in} = 1|W_{n-1})$

$\pi_i = P(E_{in} = 1)$

The theoretical cumulative distributions of RT on trial n given the presentation of stimulus i is

$$J_{in}(x) = \sum_{W_{n-1}} J(x_n|E_{in} = 1, W_{n-1})\ P(W_{n-1})$$

$$= P_{in}K(x) + (1 - P_{in})\bar{K}(x)$$

Falmagne shows

(1) $P_{in+1} = (1-c)P_{in} + c$

$P_{in+1} = (1-c')P_{in}$

(2) The transition of the Markov chain latent states

$K_{in} \backslash K_{in+1}$	1	0
1	$1 - (1-\pi_i)c'$	$(1-\pi_i)c'$
0	$\pi_i c$	$1-\pi_i c$

$$P_i = \lim_{n\to\infty} P_{in} = \frac{\pi_i c}{\pi_i c + (1-\pi_i)c'}$$

(3) If $E_{in}(s) = 1$

$J_{in+1}(x) = (1-c)\ J_{in}(x) + cK(x)$

if $E_{in}(s) = 0$. $J_{in+1}(x) = (1-c')J_{in}(x) + c'\bar{K}(x)$.

We also find a number of implications, e.g. sequential effects on moments.

Let $$E(X^v_{in}) = \int x^v J_{in}(x)$$

$$E(X^v_k) = \int x^v k(x) \text{ and } E(X^v_{\bar{k}}) = \int x^v \bar{k}(x)$$

then

$$E(X^v_{in+1} \mid E_{in} = 1) = (1-c)E(X^v_{in}) + cE(X^v_k)$$

$$= (1-c')E(X^v_{in}) + c'E(X^v_{\bar{k}})$$

this can be estimated also can use different

Falmagne also postulates a linear model.

(1) $$P(K_{in+1}(s) = 1 | E_{in}(s) = 1,\ K_{in}(s) = 1,\ W_{n-1}) =$$

$$(1-c)P(K_{in}(s) = 1 | W_{n-1}) + C$$

(2) $$P(K_{in+1}(s) = 1 | E_{in}(s) = 0,\ K_{in}(s),\ W_{n-1}) =$$

$$(1-c')P(K_{in}(s) = 1 | W_{n-1})$$

Falmagne also reported experimental data from R/T studies which are generally in accord with his main predictions. The fit is less good as the predictions get smaller.

Since much work has been done on reaction time studies it would be useful to see if we can find anything in the literature relevant to detection and recognition situations. However, the reaction time experiment is a recognition task where subjects make few mistakes we should find a relationship between such work and that under present consideration.

McGill (1963) reviewed the nature of a probability mechanism for generating latencies (L). The probability density function of the latencies is f(t) ($P(t_1 < L < t_2) = \int_{t_1}^{t_2} f(t)dt = F(t_2) - F(t_1)$ where F(t) is the cumulative density.

Of the possible densities he considers

1. Exponential distribution. Random events occurring in time with an equal probability will produce an exponential distribution

$$f(t) = \lambda e^{-\lambda t}$$

2. Geometric. If we have a device making two responses A with probability p and $\bar{A}$ with probability $q = 1 - p$ then the probability of a run of k A responses is given by

$$p(k) = q^k p$$

which is a geometric distribution with moment generating function

$$m_k(\theta) = \int_o^\infty e^{\theta t} q^k p = \frac{p}{1-qe^\theta}$$

Suppose each response takes time δt and as δt decreases then the number of $\bar{A}$ increases as δt decreases. We assume

$$\lim_{\delta t \to 0} \frac{p}{\delta t} \to \lambda \quad \text{(a constant)}$$

Let $\quad t = k\delta t$

$$M_t(\theta) = \frac{p}{1-pe^{\theta\delta t}}$$

$$\lim_{\delta t \to 0} M_t(\theta) = \frac{\lambda\delta t}{1 - (1-\lambda\delta t+\theta\delta t)}$$

$$= \frac{\lambda}{\lambda - \theta}$$

This is the moment generating function of the exponential distribution. However most reaction time studies have yielded data which shows systematic departures from the constant probability functions of McGill (1961). McGill went on to consider that the response latency was the sum of a number of different components. He postulated that the response latency t equals $\sum_1^N t$ in which t_k is a random variable which is exponentially distributed

$$f(t_k) = e^{-\lambda tk}$$

$$M_{tk}(\theta) = (1 - \theta/\lambda)^{-1}$$

$$M_t(\theta) = (1 - \theta/\lambda)^{-n}$$

which turns out to be the moment generating function of a gamma distribution.

$$f(t) = \frac{\lambda^n}{(\lambda \ \theta)^n} \int_o^\infty \frac{1}{(n-1)!} \mu^{n-1} e^{-\mu}$$

Thus for any given k number of elemental responses we can generate a gamma distribution. Suppose k is distributed geometrically

$$M_t(\theta) = \Sigma q^k p(1-\theta/\lambda)^{-k+1}$$

$$= \frac{p}{1-\theta/\lambda} \sum_{k=o}^{\infty} \left(\frac{q}{(1-\theta/\lambda}\right)^k$$

$$= \frac{p}{1-\theta/\lambda} \quad \frac{1}{1-q/(1-\theta/\lambda)}$$

$$= 1/(1 - (\theta/\lambda) p)$$

This still gives an exponential distribution of t and is apparently insensitive to the random duration of the sub-response elements.

If we consider the latency has two elements t_1 and t_2

$$f(t_1) = \beta e^{-\beta t_1}$$

$$f(t_2) = \alpha e^{-\alpha t_2}$$

$$m_t(\theta) = \frac{\alpha\beta}{(\alpha-\theta)(\beta-\theta)}$$

The function

$$f(t) = \frac{\alpha\beta}{(\beta-\alpha)} \quad e^{-\alpha t} - e^{-\beta t}$$

has the above mg.f.

McGill (1965) went on to extend this approach to k elements.

5. Methods of characterisation of the dependencies

(a) Preamble

As this project is an attempt to study the effect of dependencies on some standard models a major problem consists in adequately describing the dependencies. For this purpose each trial can be considered as a discrete event in time. For most purposes each trial can be classified by $R_i\ S_j$ i.e. on this trial the subject responded R_i to stimulus S_j. In the two stimulus Yes/No situation there are only four types of trial R_1S_1, R_2S_2, R_1S_2, and R_2S_2. Each trial may yield more information - latencies confidence ratings etc. but can still be approximated to using discrete states.

(b) Manifest Markov models

Probably the most obvious method of describing such data is using a manifest Markov chain cf. Carterette and Wyman (1962) and Macdonald (1968). Let the state on the j trial be S_j and let A equal $(a_1 a_2 \ldots a_n)$ be the set of all possible outcomes on a particular trial. The results of an experiment of n trials are therefore W equal to $(X_1, X_2 \ldots X_n)$. We can now classify different properties of the outcome of such experiments regarded as stochastic processes.

(i) W is an independent process if for all j equal to 1 .... n and k equal to 1 .... n

$$P(X_j = a_k | X_{j-1} \ \ldots \ X_1) = P(X_j = a_k)$$

i.e. the probability that $X_j = a_k$ is unrelated to the observed states on the previous trials.

(ii) W is a Markov chain of order c if for all j equal to 1 ..... n and for all small k equal to 1 ..... n

$$P(X_j = a_k | X_{j-1}\ X_{j-2} \ \ldots \ X_1) = P(X_j = a_k | X_{j-1} \ldots X_{j-c})$$

i.e. the probability that $X_j = a_k$ given the observed states $X_{j-1} \ldots X_{j-c}$ is independent of all states earlier in the process.

(iii) W is a stationary Markov chain of order e if for all k and e

$$P(X_1 X_2 \ \ldots \ X_e) = P(X_{k+1}, X_{k+2} \ \ldots \ X_{k+e})$$

i.e. the probability of a trial being in a particular state is independent of the trial number.

A higher order Markov chain can be transformed into a first order one of many more states. For example if we have a chain $(X_1 \dots X_n)$ of order c we can define a constant state b_k as the ordered c tuple $(X_k \dots X_{k-c+1})$. Thus if Y_j is the outcome of trials $X_j, X_{j-1} \dots X_{j-c+1}$ then

$$P(Y_j = b_k | Y_{j-1}, Y_{j-2} \dots Y_1) = P(Y_j = b_k | Y_{j-1})$$

and $Y_1 \dots Y_{n-c}$ is a first order Markov chain. We can test to see how the data conformed to this stationarity assumption and the assumption of different orders using a χ^2 analysis. If the stationarity assumption is broken then the proportion of trials in different states should depend on which section of the data we are looking at. Let us break the data down into T sections when $p_{ij}(t)$ is the observed probability of being in state i on one trial and j on the succeeding trial in section t. To test the stationarity assumption we assume $p_{ij}(t)$ is independent of t equal to p_{ij} the same probability as measured over all the sections. If there are $n_i(t)$ trials on state i and section t, the stationarity assumption is tested by

$$\chi^2 = \sum_i \sum_j \sum_t n(t-1)(p_{ij}(t) - p_{ij})^2 / p_{ij}$$

With degrees of freedom equal to n(n-1)(t-1).

Let n_{ijk} be the number of times a trial is in state k when it was in state j on the immediately preceding trial and state i on the trial before that. Let $n_{ij} = \sum_k n_{ijk}$ and $n_i = \sum_j n_{ij}$. The n_{ijk} are sufficient statistics for estimating p_{ijk} (the maximum likelihood estimate is n_{ijk} divided by n_{ij}) in a second order Markov chain and the n_{ij} are sufficient for estimating the p_{ij} in a first order one, cf. Anderson and Goodman (1954). We may test to see whether a chain corresponds to first or second order by

$$\chi^2 = \sum_i \sum_j n_i (p_{ij} - p_j)^2 / p_j$$

$$df = (n-1)^2$$

or whether a chain is second or third order by

$$\chi^2 = \sum_i \sum_j \sum_k n_{ij} (p_{ijk} - p_{jk})^2 / p_{ik}$$

$$df = n(n-1)^2$$

Indeed the test can be extended to find whether a chain is adequately described by a cth or a c+1th order one. This test does not require the stationarity assumption to be upheld. This technique will enable us to completely characterize the process by a cth order Markov chain if the χ^2 for the cth versus higher order is not significant. The problem here is obtaining enough data to obtain accurate estimates of the higher order transition probability. To test the hypothesis of third versus fourth order we require to have 256 probabilitie to estimate and it is difficult to make a subject perform more than 1000 trials in one session. In order to estimate the above probabilities therefore one would be forced either to average over sessions or subjects.

(c) Information theory analysis

Information theory analysis enables one to measure the absolute size of the sort of dependencies which we are considering. The theory on which it is based is much the same as the Markovian analysis (see Garner (1962) and Attneave (1959)). Let us again assume we have a series of trials $(X_1 \ldots X_n)$ each resulting in one of n discrete states $(a_1 \ldots\ldots a_n)$. Making the stationarity assumption as defined in the last section implies that $p_i = P(X_j = a_i)$ is independent of j. Having made this assumption the amount of information given when we know $X_j = a_i$ is defined as $-\log_2 p_i$ and the expected value of the information on any trial j - $E(H_j)$ is simply

$$E(H_j) = - \sum_{1}^{N} p_i \log_2 p_i$$

This is estimated by

$$- \Sigma \hat{p}_i \log_2 \hat{p}_1$$

where

$$p_i = \frac{n_i}{n}$$

Another name for this statistic is entropy or uncertainty.

A value of this approach is that it enables us to examine the extent to which different events are independent of each other. Supposing we consider another series $(Y_1 \ldots . Y_N)$ when Y can assume any one of the states $(b_1 \ldots b_n)$ and $q_i = p(Y_j = b_i)$ which does not depend on j. We now find

$$(H_X) = - p_i \sum_1^N \log_2 p_i$$

$$(H_Y) = - q_i \sum_1^N \log_2 q_i$$

We can also consider the series $(X_1 Y_1 X_2 Y_2 \ldots X_n Y_n)$ and define $p_{ij} = p((X = a_i)\ (Y = b_j))$. If X and Y are independent then

$$p_{ij} = p_i q_j$$

$$(H_{XY}) = (H_X) + (H_Y)$$

which is easily verified. However, we can find H_{XY} by considering the composite series

$$\hat{H}_{XY} = \sum_{ij} p_{ij} \log_2 p_{ij}$$

and can estimate the information shared between X and Y in the statistic T_{XY}

$$\hat{T}_{XY} = \hat{H}_X + \hat{H}_Y - \hat{H}_{XY}$$

This shows the proportion of the entropy that is shared between the two series. This idea is easily extendable to a three simultaneous series case where we can specify all the dependencies by estimating the statistics $\hat{H}_X, \hat{H}_Y, \hat{H}_Z, \hat{T}_{XY}, \hat{T}_{XZ}, \hat{T}_{YZ}$ and $\hat{T}_{XYZ}$. There is a simple relation between T and the equivalent χ^2 in the Markovian analysis. Attneave (1959) stated the relationship as

$$\chi^2 = (\log_2 2) n\hat{T}$$

However, this is only an approximation to the χ^2 analysis discussed above. The former method is preferable for significance testing as informations statistics are biased, see MacRae (1970).

(d) Latent Markov models

Both the above techniques are descriptive of any series of events in time and do not really form an analogue of any psychological process. If it were possible to show that data from the sorts of experiments we have been discussing could be fitted by a latent state Markov model then this result would tell us something about the processes involved. Such models have been used mainly by sociologists looking at a large number of a few repeated observations rather than small numbers of long series of observations.

Wiggins (1955) was the first to use such models and Coleman (1964a), (1964b) used latent Markov models during studies of attitude change. A comprehensive text on this and related classes of models was written by Lazarsfeld and Henry (1968).

Let us examine in more detail the latent model used in subsequent analyses. Let us assume that on any trial a subject is in one of n latent classes ($\alpha, \beta, \ldots$). The states that a subject enters on each trial form a first order Markov process specified by the transition matrix $M = |m_{\alpha,\beta}|$ where $m_{\alpha,\beta}$ is the probability of the state α on trial n and β on trial n + 1. Corresponding to each state there is a response vector giving the probability of responding in each of n response categories ($R_1 \ldots R_n$). This can be summarised in a response matrix Q equal to $|q_{\alpha i}|$ where $q_{\alpha i}$ is the probability of the subject responding R_i on a trial when he was in state α. At each trial t there is a row vector V(p) equal to $v_\alpha(p)$ where $v_\alpha(t)$ is the probability of being in state α at time t. We define V(t) as the diagonal matrix whose diagonal elements are the elements of $V(t)$. As the process is ergodic then $\lim_{t\to\infty} v_\alpha(t)$ exists and is denoted by v_α and similarly $\lim_{t\to\infty} V(t)$ is denoted by V. We denote the observed probabilities by $P(t)$ equal to $p_i(t)$, $P(t,s) = p_{ij}(t,s)$ etc. where $p_{ij}(t,s)$ is the probability of responding R_i on trial t and R_j on trial s. Similarly $p_i(t)$ is the probability of responding R_i on trial t.

We now have the first order probabilities defined as

$$P(1) = V(1)Q \quad \text{i.e. } p_i(1) = \sum_\alpha v_\alpha(1)\, p_{\alpha i}$$

$$P(2) = V(2)Q = V(1)MQ \text{ i.e. } p_i(2) = \sum_\beta\sum_\alpha v_\alpha(1) m_{\alpha\beta} p_{\beta i}$$

$$P(t) = V(t)Q = V(1)M^{t-1}Q$$

We will see that it is very useful if Q is square and has an inverse in each case

$$P(t) = V(1)\; Q\; Q^{-1}\; M^{t-1}\; Q$$

$$= P(1)\; R^{t-1} \text{ where } R = Q^{-1}\; MQ^2$$

Similarly the second order probabilities

$$P(12) = Q'V(1)MQ \text{ i.e. } p_{ij}(12) = \quad q_{\alpha i} v_\alpha(i) m_{\alpha\beta} q_{\beta j}$$

$$P(1t) = Q'V(1)\; M^{t-1}Q$$

and $P(t\;\, t+n) = Q'V(1)\; M^N Q = Q'V(1)QQ^{-1}M^N Q$

$$= Q'V(1)QR^N$$

$$P(13) = QV(1)MQQ^{-1}MQ \quad = P(12)R$$

$$R = P(12)^{-1}\; P(13)$$

To find the third and higher order probabilities we introduce the diagonal matrix X_k which has as its diagonal elements the kth column of Q, and the notation $P_k(13;2) = |p_k(i,j)|$ where $p_k(i,j)$ is the probability of responding i at time 1 and j at time 3 having responded k at time 2.

$$P_k(13;2) = Q'VMX_kQ$$

And in a similar way we can obtain the higher order probabilities

$$P_{k\ell}(14;23) = Q'VMX_kMX_\ell MQ$$

It should now be possible given enough data to obtain estimates of QV & M. However in practice an analytic solution may prove slightly intractible. In the case where Q is square and has an inverse a solution does exist

$$P_k(13;2) = Q'VMQQ^{-1}X_kQQ^{-1}MQ$$

but $R = Q^{-1}MQ = P(12)^{-1}P(13)$

and $Q'VMQ = P(12)$

we have $P_k(13;2) = P(12)Q^{-1}X_kQP(12)^{-1}P(13)$

$$Q^{-1}X_kQ = P(12)^{-1}P_k(13;2)P(13)^{-1}P(12)$$

As X_k is diagonal its elements are the latent roots of the right hand side of the above equation. The other columns of Q can be found from the corresponding characteristic column vectors or by using other values of k.

The two response two latent state case is therefore immediately solvable. However psychologically speaking restricting the number of latent states to the number of responses does not appear particularly meaningful.

We should be able to start with two states and then if the model does not fit be able to extend this number. It is also useful if the model places no restrictions on the number of responses in the system under examination. One way this might be circumvented would be by considering different partitions of the total response set. For example, suppose there are n responses. We can now divide the n responses into a two response set, e.g. (R_1) and $(R_2 \dots R_n)$ and we can estimate q_{11} and $1-q_{11}$. Similarly we may estimate q_{1i} and $1-q_{1i}$. By different partitions we should be able to obtain estimates of $(q_{1i} + q_{1j})$ which should be consistent with q_{1i} and q_{1j}. This approach of reducing the number of response categories equal to the number of latent states should work for any number of latent states m in a situation with n observable responses where n is greater than m.

(e) Autoregressive processes

Autoregressive functions cf. Cox and Miller (1965) provide an alternative way of characterising a stationary time series. Suppose (X_n) is a discrete Gaussian process, i.e. one for which the distribution of $X_{n1} \ldots X_{nc}$ is multi variate normal. Then the process is stationary if (1) $E(X_j) = U$ a constant for all j and (2) the covariance matrix $\gamma(n_1 n_2)$ equal $C(X_{n1}, X_{n2})$ is a function of $n_1 - n_2$ only, i.e. $C(X_{n+h}, X_n) = \gamma(h)$. $\gamma(h)$ is the autoregressive function where $\gamma(0)$ = the variance of X_n and $\rho(h)/\gamma(0)$ is the auto covariance function.

Cox and Miller describe a class of such stationary processes which might prove useful in describing subjects' response sequences. Let $X_{(n)}$ be a discrete time series. $Z_{(n)}$ be a series of uncorrelated random variables such that $E(Z_n) = 0$ and $Var(Z_n) = \sigma_z$. We assume $E(X_n) = 0$. In this case a finite moving average series (X_n) is defined as the process

$$X_n = a_o Z_n + \ldots + a_r Z_{n-r}$$

If we introduce the further restriction that $Za = 1$ then $(a_o \ldots a_r)$ are the weighting constants.

$$E(X_n) = 0$$

$$Var(X_n) = (a_o^2 + \ldots a_r^2)\sigma_z^2$$

$$\sum_{s=o}^{r-h} a_s a_{s+h} \sigma_z \quad (\text{for } 0 < h < r)$$

$$0 \qquad (\text{for } h > r)$$

If $\Sigma a = 1$ we could solve the above for the a's and σ_z.

An ith order autoregressive process is defined by the relation

$$X_n = \lambda_1 X_{n-1} + \dots \lambda_i X_{n-i} + Z_n$$

Multiplying throughout by X_{n-1} we have

$$X_n X_{n-1} = \lambda_1 X_{n-1}^2 + \dots \lambda_i X_{n-1} X_{n-i} + Z_n X_{n-i}$$

and taking expectations

$$\gamma(1) = \lambda_1 \gamma(0) + \dots \lambda_i \gamma(n-1) \text{ as } (X_{n-1} Z_n) = 0$$

Multiplying by X_{n-h} we have

$$\gamma(h) = \lambda_1 \gamma(h-1) + \dots \lambda_i \gamma(h-i)$$

and dividing by $\gamma(0)$

$$\rho(h) = \lambda_1 \rho(h-1) + \dots + \lambda_i \rho(h-i)$$

This gives a set of equations which can be solved for $\lambda_1 \dots \lambda_i$ from the autocorrelation coefficients. In the special case of the first order autoregressive process we see

$$\rho(0) = \frac{\gamma(0)}{\gamma(0)} = 1$$

$$\rho(h) = \lambda_1^h$$

A common modification mentioned by Cox and Miller is to have a random term superimposed at each trial e.g. an error of observation. If $X_{(n)}$ is an ith order autoregressive process we can produce (Y_n)

$$Y_n = X_n + U_n$$

where $E(U_n) = 0$ and $Var(U_n) = \sigma_u$. Thus U_n is a series of uncorrelated random variables as

$$C(Y_n Y_{n+h}) = C(X_n X_{n+h}) \quad (h = 12 \dots)$$

we still have

$$\gamma(h) = \lambda_1\gamma(h-1) \ldots \lambda_i\gamma(h-i)$$

and $\rho(h) = \lambda_1\rho(h-1) + \ldots + \lambda_i\rho(h-i)$

the only difference being

$$Var(V_n) = \sigma_\lambda^{\ 2} + \sigma_u^{\ 2}$$

Now we have examined several ways of describing stationary discrete series which enable us later to describe the sorts of sequences of events existing in a detection or recognition experimental setup. Thus hopefully we have described at least one statistical technique capable of characterising the dependencies present in the experimental setup we are considering.

MATERIALS AND METHOD

(a) Preamble

Having reviewed the literature dealing with sequential dependencies it is now of interest to examine what data might most usefully describe this phenomenon. Of the possible paradigms the one most susceptible to dependencies is probably the Yes/No design. In this situation the subject is presented successively with one of two stimuli and each time required to state which stimulus was presented. It has been suggested by Tanner Atkinson and others (see previous section) that the subject compares what he hears on every trial with the image of the immediately preceding stimulus. This means that if feedback is not given errors will tend to be perpetuated where the same stimulus is presented following an error. Thus one might expect feedback to alter the sequential dependencies in this way. The effect of feedback can be studied where feedback is given all the time and when it is only given sometimes within the same session.

If the memory recognition process suggested by Atkinson et al. is correct one might expect that the time between successive presentations should affect the "accuracy of the image" of the stimuli on the immediately preceding trials. If correct this should have the effect of reducing the extent of the dependencies on each trial to the immediately preceding stimuli (although not necessarily the response on the inter-response dependencies). If the time between trials can be shown to be important it raises a further complication to the situation as the response latencies are subject-controlled. Thus the times between the stimuli are variable and this may interact with other experimental variables, for example if feedback is present the subject may take longer between trials as he has no information to process or, alternatively, if the a priori stimulus probabilities are unequal then one might expect differential latencies to each of the stimuli which could have quite complicated effects on the dependencies present. That this is quite likely to happen is suggested by the work in reaction time experiments.

One way of reducing the dependencies might be to present subjects with one of the stimuli before each trial. This should make the "image" of the previous stimuli less important and could remove the effect of feedback. Apart from any interference with the subject memory process of previous trials it also provides a constant stimulus for reference. The presentation of a supposed irrelevant noise, for example white noise in a signal recognition task between each trial, might enable one to study the interference effect without providing the constant standard.

In a rating experiment subjects might expect the sequential dependencies to be more complex and perhaps more pronounced. It would be interesting to examine their effects and compare them with those derived from a RTROC analysis of the data in a Yes/No situation.

(b) Experimental Method

The subjects who were students at the University of Stirling were all volunteers. If they participated in more than two sessions they were paid at the rate of 6/- (30p) per session. Each session lasted approximately for an hour. Two subjects who agreed to participate in one of the longer experiments (18 sessions) stopped attending before having completed ten sessions. They were not paid and their data is not included in the analysis.

In all sessions subjects were allowed to familiarise themselves with the signals, the response box and the response signal sequence by performing 100 practice trials with feedback before the experimental session proper started. They were also told under what conditions they would be run i.e. given information about the stimulus probability and the occurrence of feedback, but nothing about the purpose of the experiments for fear that this might influence their performance. A typical set of instructions to a subject in a recognition task without feedback was as below.

"This is an experiment in signal recognition and you will be presented successively with one of two tones. Your job is to tell me which one of the two occurred on each trial.

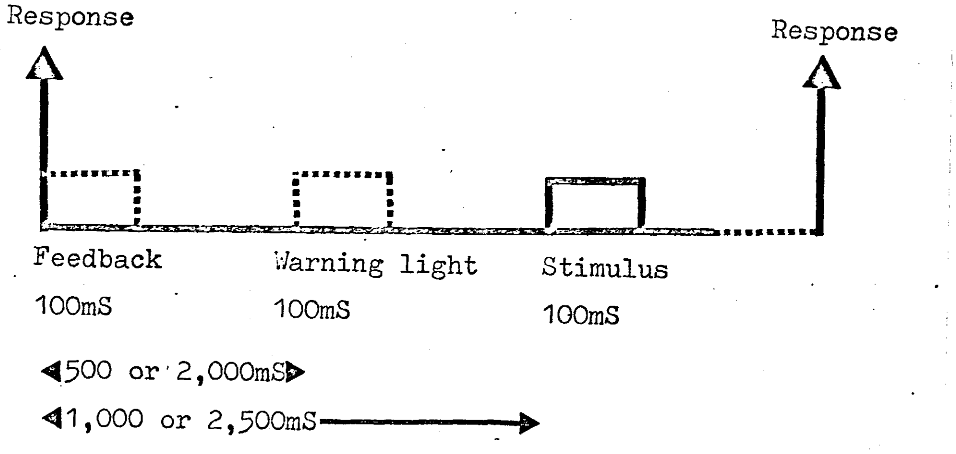
Initially in order that you can learn the tones you will be told which of the tones has appeared later it will be left to you to decide which tone has been presented. If you put the earphones on and press either of the two buttons in front of you you should hear a tone after a short delay. Now if you press either response button in front of you it will activate either light 1 or light 2 depending on which of the stimulus was presented. After a delay another stimulus will occur and again you should respond but this time press the button corresponding to the tone you think was presented. This cycling will continue for several trials to enable you to familiarise yourself with the experimental task.

After this the experiment proper will begin. Your task is then exactly the same as the practice one but this time the light will not work. That is to say, you will be given no information as to which stimulus has occurred on each trial. Each of the two signals is equally likely to occur on each trial and there are no sequences or patterns in the presentation as the order has been generated by a randomising procedure on a computer. After a few minutes I shall stop you to see if you fully understand the task. Have you any questions?"

These instructions were written out on a piece of paper and the experimenter attempted as far as possible to stick to a standard wording.

(c) The experimental design

The subjects were required to perform 100 practice trials prior to each session in the hope of reducing the amount of learning present during the session. In the session proper they performed 500 (in the first experiment) or 740 (in subsequent experiments) trials. Each trial consisted of the presentation of a stimulus to which the subject responded. This response could cause either feedback or a constant stimulus or both to be produced and always resulted in the presentation of the next stimulus (see diagram)



On each trial the stimulus response latency and presence or absence of feedback was recorded on paper tape. This raw data was subsequently fed into the computer and stored on magnetic tape. All the analyses were performed calling data from the magnetic tape.

<u>The experiments</u>

(1)

(a) In this experiment 15 subjects performed for one session each. They were given a signal recognition task in which the stimuli were two tones one of 1000 cycles per sec. and one of 1010 cycles per second. They were randomly assigned to one of three conditions in which the a priori stimulus probabilities was .25, .5 and .75. In this experiment no feedback was given.

(b) This was followed by running 10 subjects for one session each in a signal detection task with a priori signal probability .5 . This experiment was really a pilot one and was conducted while some of the control equipment used in subsequent experiments was still under development.

(2) Here five subjects performed 18 experimental sessions. The first two of which attempted rather unsuccessfully in the event using the method of constant stimuli to determine the stimulus that the subject could respond to correctly about 75% of the time. This was to reduce the colossal individual differences between subjects.

(a) The order of sessions was randomised. All subjects performed the recognition and detection task at three levels of stimulus probability (.25, .5 and .75), and with the presence and absence of feedback, making twelve sessions in all.

(b) Also randomised within these sessions subjects performed the above task at the .5 stimulus probability level with a burst of white noise being presented to the subject prior to each stimulus. This data therefore gave two different designs some of it common to both (the main effects in the first one being task stimulus probability and feedback and in the second task presence or absence of white noise and presence or absence of feedback).

(3) Here five subjects (different ones from the last experiment) performed in 19 experimental sessions. The task was a detection one in which the a priori stimulus probability was set at .5 . Each subject performed the task with 100%, 50% and 0% feedback. In the 50% feedback condition feedback was given randomly throughout the session. The task involved three levels of difficulty again chosen on the basis of the subject's performance to a constant stimulus psychophysical task on the first two sessions and at two levels of delay before the presentation of the stimulus following a response. This made 18 conditions in all the order of which was randomised. In the 50% feedback condition the occurrence of feedback was randomised within the session. Again the first two sessions were attempts to obtain psychometric functions for the subjects to determine stimuli they would get correct 60% and 85% of the time. In the very easy condition the stimuli were set so far apart that the difficulty of the task was similar to that in a choice reaction time experiment.

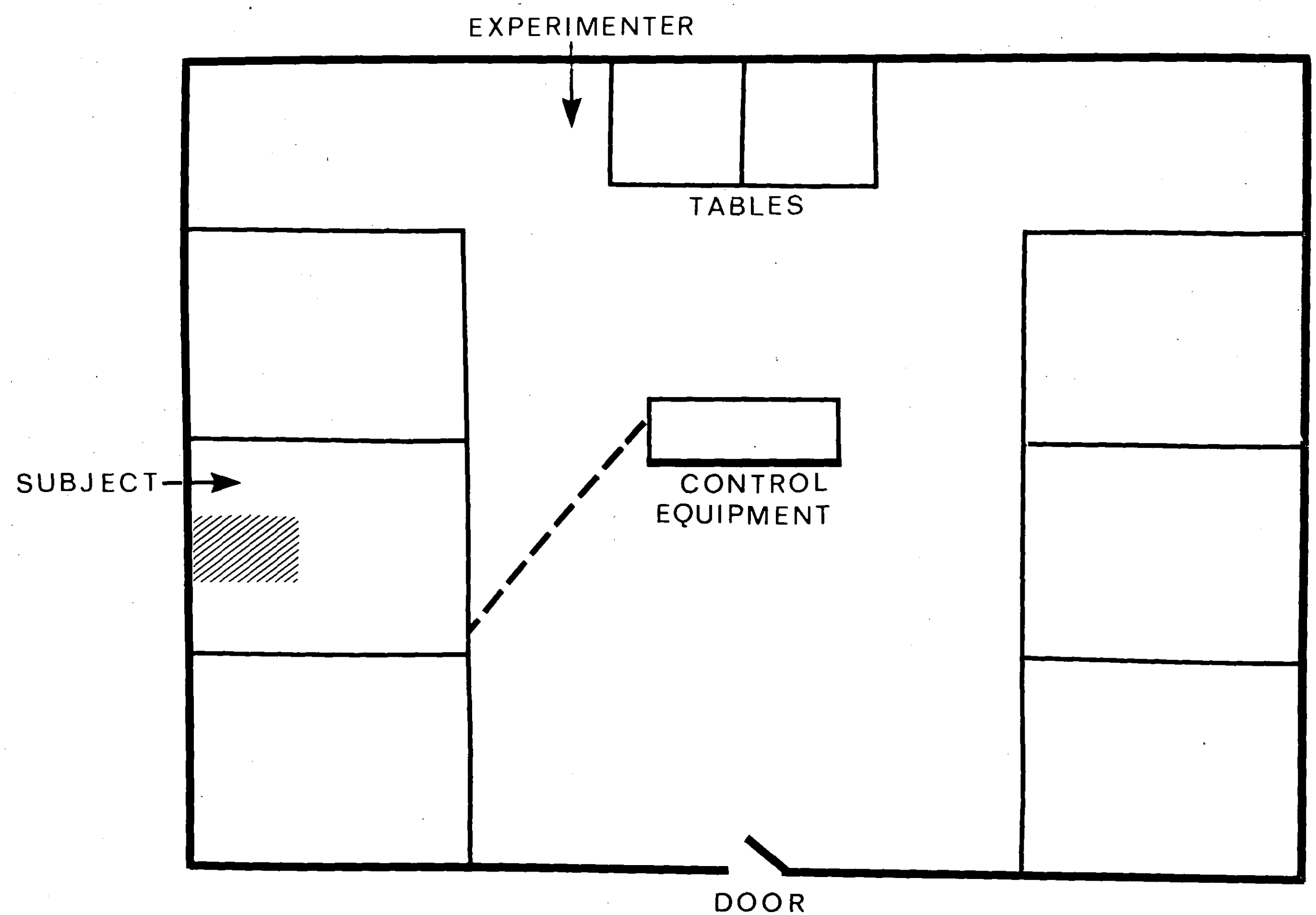
(4) In this experiment a detection task with a priori signal probability of .5 was used. 15 subjects were allocated to each of three experimental conditions, 100%, 50% and 0% feedback with short delay. The difference in this case was that subjects were asked to respond on a 5 point scale which stimulus they thought had occurred. The responses were labelled as sure signal, think signal, do not know, think noise, sure noise.

A summary of these experiments is given in the table below.

EXPERIMENTAL DESIGNS

Exp																				No. Subject	No. Sessions
1	TASK						R	R	R	D											
	STIM PROB						.25	.5	.75	.5										25	25
2	TASK	R	R	R	R	R	R	R	R	D	D	D	D	D	D	D	D				
	STIM PROB	.25	.5	.25	.5	.5	.5	.75	.75	.25	.5	.25	.5	.5	.5	.75	.75			5	80
	FEEDBACK %	0	0	100	0	100	100	0	100	0	0	100	0	100	100	0	100				
	NOISE BURST		B				B				B				B						
3	FEEDBACK %	100	100	100	100	100	100	50	50	50	50	50	50	0	0	0	0	0	0		
	DIFFICULTY	VE	VE	E	E	D	D	VE	VE	E	E	D	D	VE	VE	E	E	D	D	5	90
	DELAY	S	L	S	L	S	L	S	L	S	L	S	L	S	L	S	L	S	L		
4	FEEDBACK %						100	50	0											15	15

LAB IN WHICH THE EXPERIMENTS WERE CONDUCTED



(d) Experimental layout

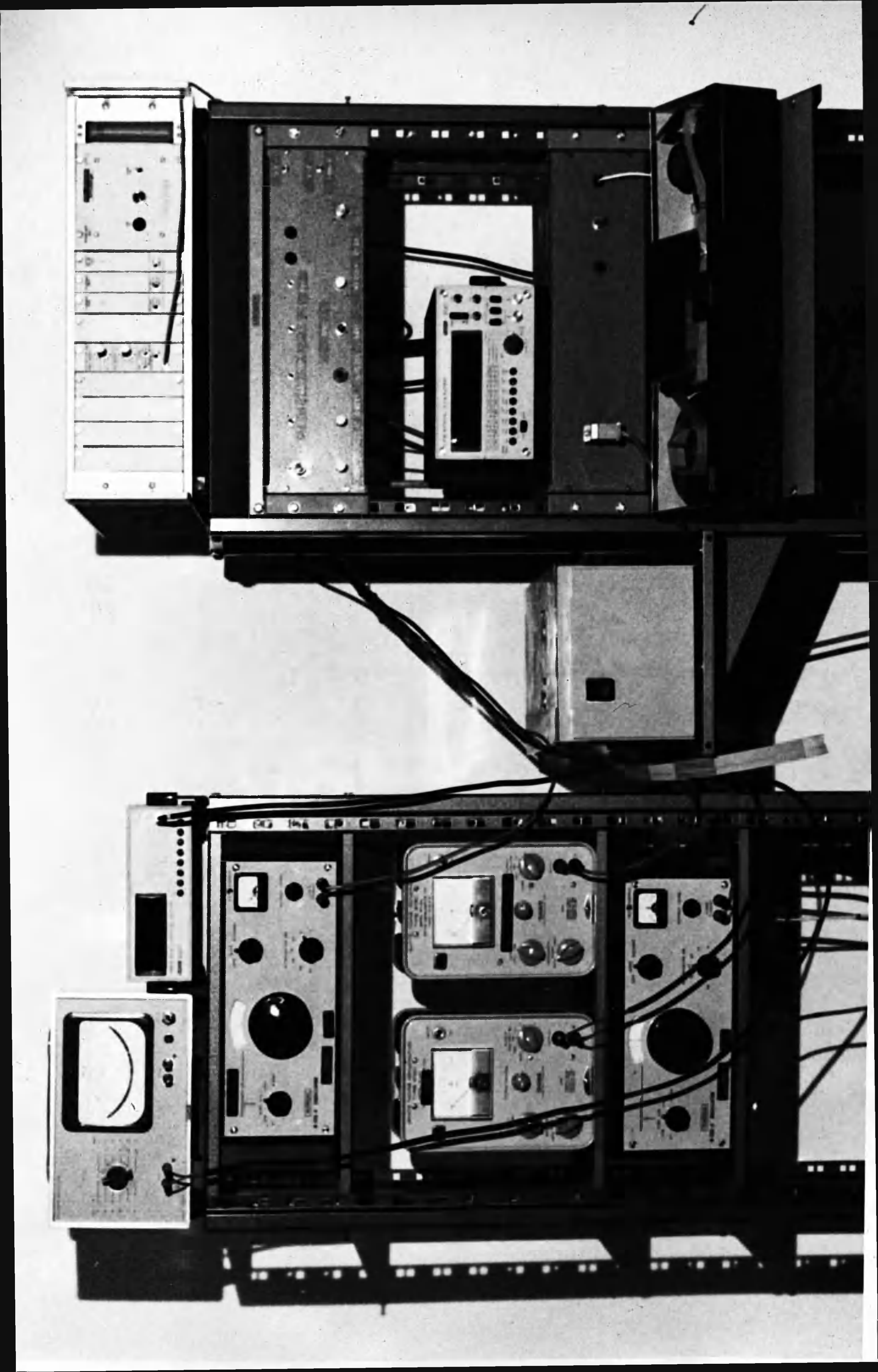
The experiment was conducted in a laboratory designed for communications experiments. The plan of the room is given below (figure 1). The cubicles in which the subjects were seated were semi-soundproof. The control equipment was placed in the centre of the laboratory as it could not be placed in another cubicle for reasons of temperature control. The noise from the paper tape punch was just audible to the subjects. The ambient sound level was 29 db in the cubicle and 33 db in the lab.

(e) Apparatus

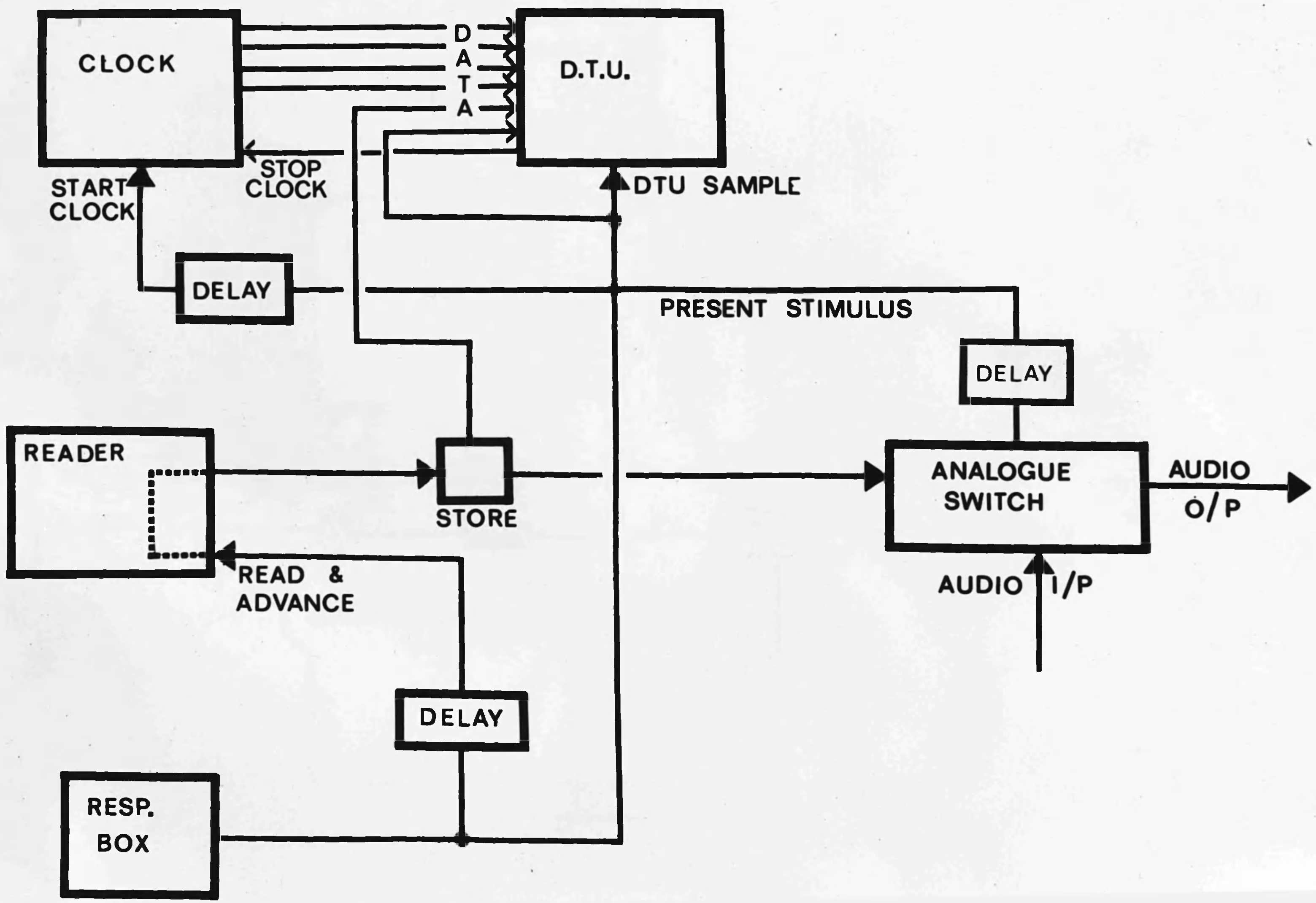
Basically the equipment consisted of four audio sources:- two signal generators (Muirhead 205A) and two white noise generators (Dawes 419C), a paper tape reader (GNT24), a 6-digit timer counter (Racal 835), a data transfer unit (hereafter referred to as DTU) (Solatron) a 80-character/second paper tape punch (Facit), a response box and control logic. The signals were standardised using a frequency meter (Racal 9520) and a valve sensitive voltmeter (TF 2600).

The cycle of operations was initiated by a response which is stored and sends a signal to the DTU which stops the timer counter (clock), inputs all the information on its register and outputs it on paper tape via the punch. This signal also initiates a delay which produces a signal from the reader to read a character and advance. Depending on which character has been read one of two audio outputs is presented to the subject (see figure 2).

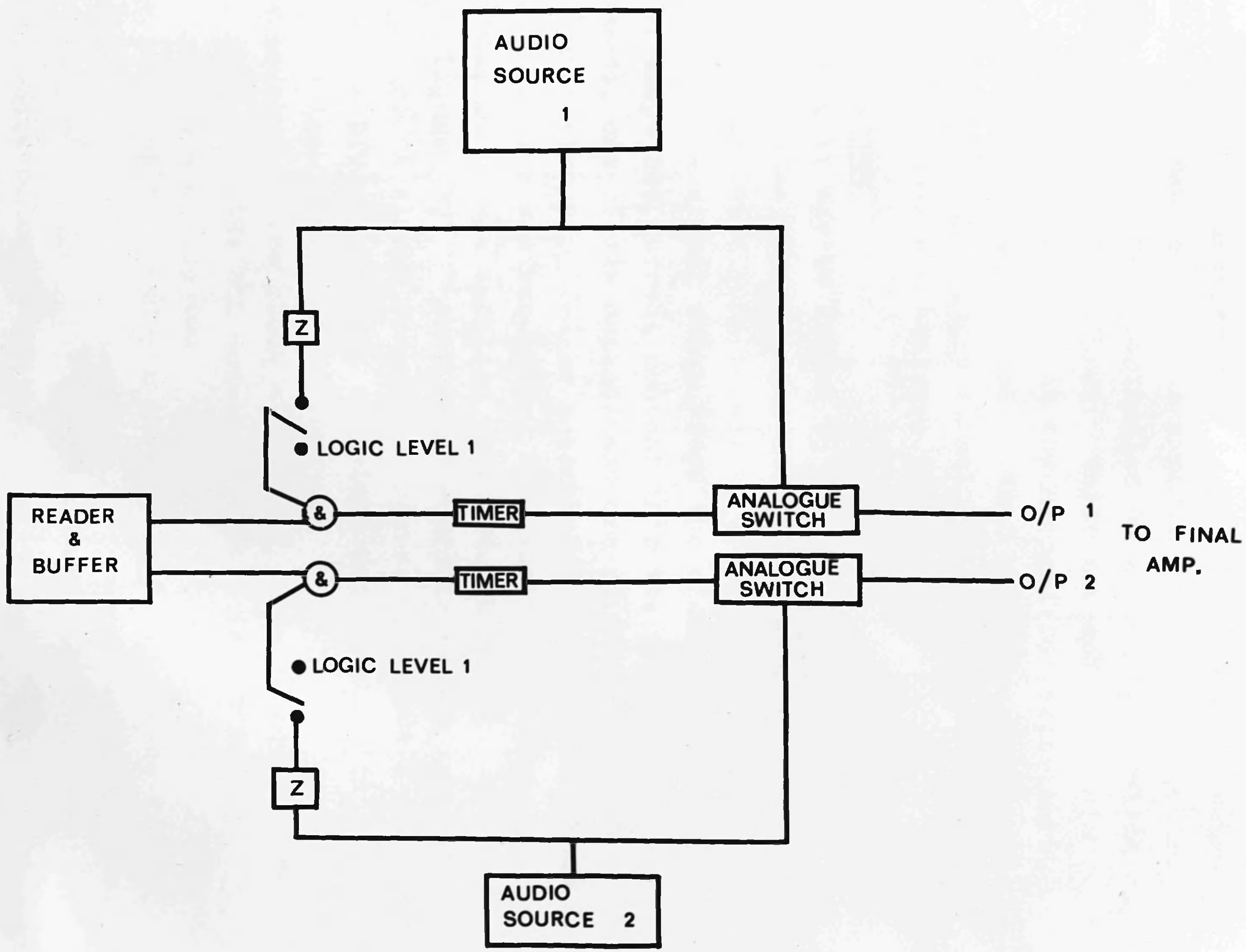
Different aspects of the control logic will now be examined in more detail.



SIMPLIFIED OVERALL SYSTEM



STIMULUS CONTROL



1. Stimulus control (see figure 3)

When a subject responds this starts a delayed unit which after some time (the size of the delay was an experimental variable) produces a signal which reads in advance of the paper tape reader. The character read is then stored and depending on which of the two used in the experiment it was activates one of two audio channels controlled by an analogue switch and a timer set at 100 milliseconds. While the audio signals contain no white noise, i.e. in the recognition experiment, zero detectors were used to ensure that both signals started in phase. These give a logic signal one when there is an input which is audio and has zero phase.

Record data system

Here it may be useful to explain the function of the DTU. This has nine binary coded decimal (BCD) i. e. 8-4-2-1 codes decodes as input. On receiving a sample instruction the DTU outputs a signal which stops the clock at its next count and dumps the current content into the paper tape punch in two words, one of six decades and one of four. The DTU and the punch were supplied as a package from the manufacturers and no interfacing was required. The Racal timer which was the experimental clock was supplied with the BCD output.

Figure 4 shows the recording system and noise control logic. A signal from the response box sends a sample signal to the DTU which stops the clock and samples its current inputs. The inputs to the DTU are

(1) the content of the clock - word one - six decades

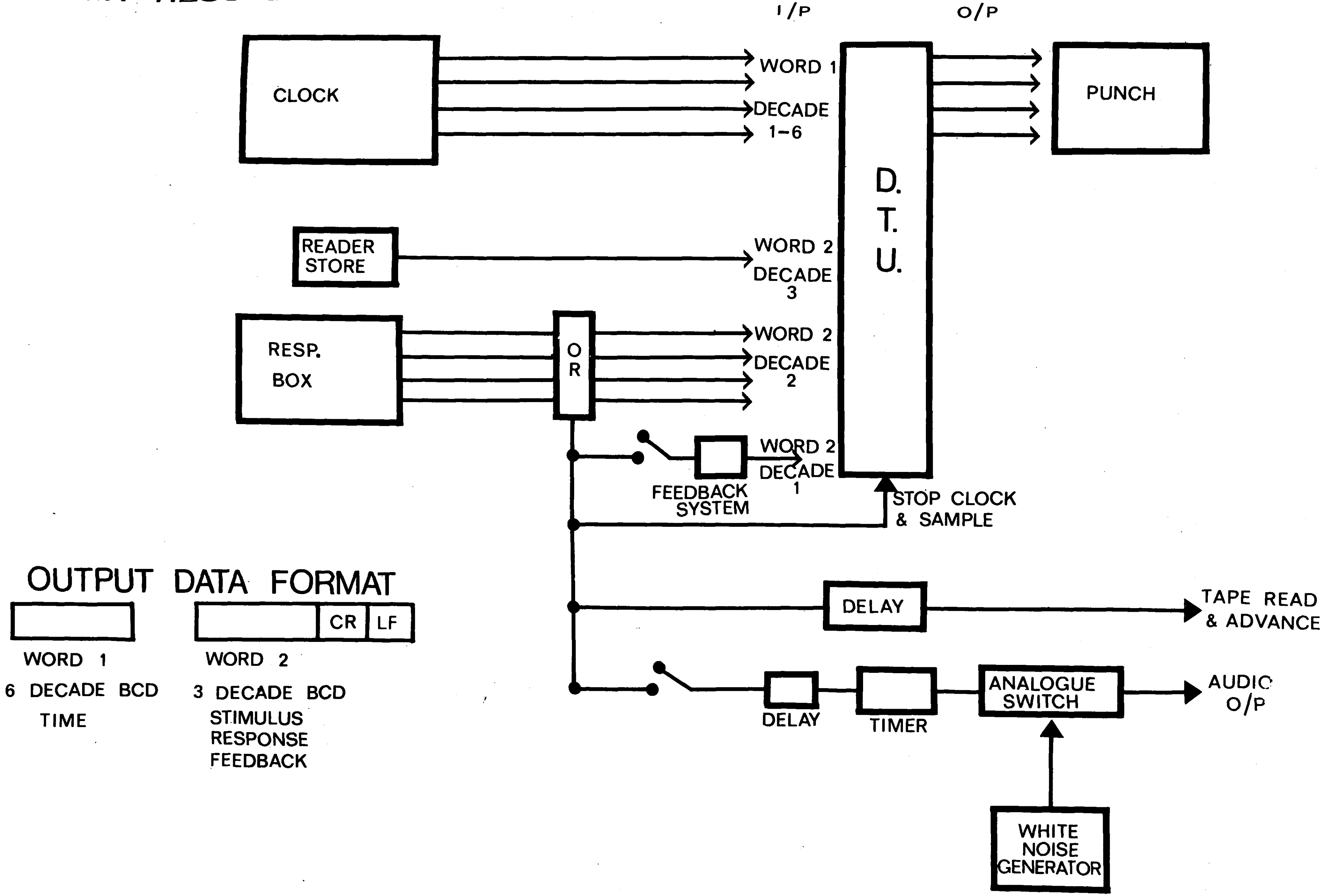
(2) the response (the BCD conversion logic is not shown) word two - decade two

(3) the state of the reader's store - word two decade three

(4) whether feedback is present or not - word two decade one.

After a short delay provision was made to present a burst of white noise to the subject (see experiment 2) after a longer delay a signal was given to the tape reader to read, advance and channel input to the DTU.

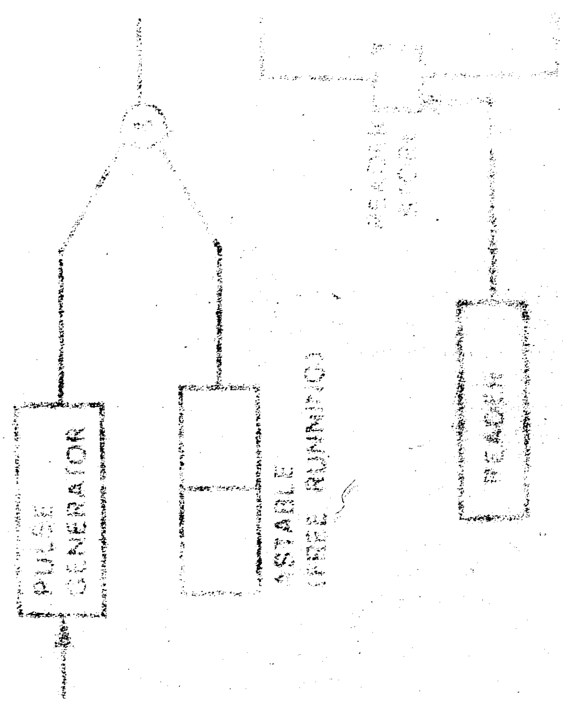
DATA RECORDING SYSTEM



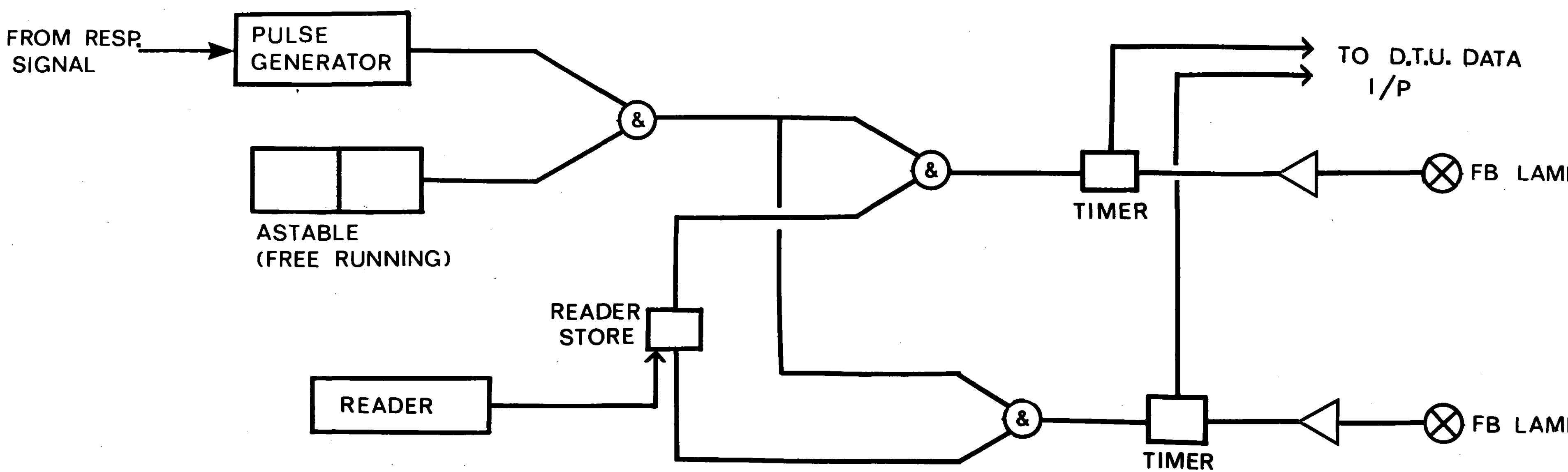
Feedback system (see figure 5)

Here a trigger pulse from the response line (see figure 5) is gated with a free running astable. When the astable is in one state the response is able to produce feedback while in the other state it is not because of the AND gate. The appropriate feedback light is selected by gating the feedback pulse from the output from the reader store.

The signals were subject to some drift due to temperature and because of this stimulus frequency and intensity values were checked before and after each session. Providing the equipment had been switched on for two hours prior to the experiment any drift was below the level that could be detected by a human subject. The frequency drift was of the order of + or - .1 cycles per second. The intensities were checked on a valve sensitive voltmeter. This means that the intensity cannot be quoted in absolute units however the drift appeared to be small relative to the differential threshold.



FEEDBACK SYSTEM



RESULTS

Introduction

The computation following the experiments described above can be broken down into roughly three major headings. The first is descriptive, the second estimation of detection and recognition models, and the third simulation.

The descriptive section involves the calculation of summary statistics from the data and analyses of variance on the summary statistics to see if the experimental conditions had any effect on that aspect of the data. Most of the procedures used in this section were incorporated in a program which was given the name OVERALL.

The second section estimated the parameters of five different detection models for each session and for each session given the state on the immediately preceding and the immediately preceding two trials. Another program determined whether the parameters were affected by any of the experimental conditions or whether the dependence of the parameters on the preceding trials were affected by the experimental conditions. The programe in this section were called ESTIMATE and SEST.

In the final section a program called SIMLUC simulated experimental data with different degrees of dependence, depending on the model used to measure the inter-trial dependence. The procedures from ESTIMATE were then applied to the simulated data. It was therefore possible to measure the effect the dependencies had on the detection and recognition models. In particular the sampling distributions of the estimates of the model's parameters were examined to see how they compared with the same sampling distributions when more dependencies existed in the data.

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Descriptive Results

The first thing a researcher should do with a set of data is to examine the raw data rather than fit preconceived models. This prevents one from ignoring important though unexpected aspects of the data. A print-out of all the data corrected in all the experiments was obtained. The first 740 numbers are latencies of each of the trials in one particular session. The next 740 are the stimuli presented while the next indicate the responses made to the stimuli and the final 740 numbers indicate the presence or absence of feedback. As there were 185 experimental sessions similar to the above and 25 more on which only 500 trials were given a print-out of all the raw data would be far too large to include even in an appendix. The raw data, however, still exists in this form on four I.B.M. compatible magnetic tapes.

Let us consider the analysis of the experiments as output by the OVERALL program.

(a) Tests for Stationarity

One of the first things to be tested was whether a subject's performance had remained constant throughout each session. The data was grouped into five equal sections and the number of correct responses in successive blocks of ten trials was obtained. An analysis of variance was then performed on this data and a value of F obtained for each session. The table below gives the number of wrong responses in successive blocks of 100 trials for each of the 25 sessions of experiment 1, together with the F value testing the stationarity assumption. Out of 25 sessions only four showed significant amounts of non-stationarity on the F test at the .05 level.

A similar analysis was performed on the number of R1 responses in each of the five successive blocks of trials. A significant F in this case would imply some change in the bias of the subject throughout the experimental session. The table giving the F values calculated for each experimental session is given below. Also included are F values testing the stationarity of the sequences of latencies generated by each subject on each trial. Each session was broken down into five equal parts and an analysis of variance performed on the latencies generated in each of the parts to see whether the trial number had a significant effect on the latencies generated by the subjects. If, for example, a subject had got progressively faster throughout the session then this would have resulted in a significant F value. This process was repeated after the first 100 trials had been discarded and again after the first 200 trials had been discarded to eliminate the possibility of early learning.

We can conclude from the above table that by far the greatest indication of non-stationarity lies in the latency sequences and that even removing the first few hundred trials there still remains a significant degree of non-stationarity. Little evidence of non-stationarity was found in the analysis of correct wrong sequences although

Number of X responses in successive blocks of 100 trials

Condition	Subject	1-100	101-200	201-300	301-400	401-500	F
	1	28	20	12	22	25	1.3
	2	41	41	36	44	40	.3
.25R	3	43	22	34	33	27	2.3
	4	49	70	25	57	63	4.8
	5	33	33	41	51	44	1.4
	6	36	32	45	44	39	.9
	7	56	52	50	36	44	1.7
.5R	8	15	18	19	16	9	.6
	9	50	46	50	38	46	1.1
	10	50	45	45	46	33	1.4
	11	36	37	44	48	50	1.1
	12	45	45	53	41	31	1.7
.75R	13	14	12	11	13	12	.1
	14	25	24	11	14	22	1.6
	15	24	18	25	14	21	1.3
	16	12	15	13	11	17	.5
	17	48	56	53	53	48	.6
	18	19	9	9	13	4	2.9
	19	47	49	27	24	12	10.7
.5D	20	39	48	50	39	43	.8
	21	53	48	38	29	32	4.2
	22	39	44	41	57	41	2.0
	23	40	39	45	32	26	1.7
	24	26	28	20	17	16	1.1
	25	54	42	40	46	35	1.2
	df						4,45

X = Wrong

F values testing stationarity of error and latency.

Condition	Subject	Errors	Response	L	L - 100	1 - 200
	1	1.3	1.7	6.5	.7	.8
	2	.3	2.0	45.0	21.5	24.6
.25R	3	2.3	2.9	25.6	6.1	3.9
	4	4.8	2.8	20.5	3.3	2.1
	5	1.4	1.0	24.6	14.7	6.8
	6	.9	5.2	3.0	1.3	2.0
	7	1.7	1.3	45.3	6.3	4.0
.5R	8	.6	.7	7.5	1.4	1.6
	9	1.1	.6	2.6	3.5	1.2
	10	1.4	5.4	26.0	13.0	5.6
	11	1.1	1.1	8.8	11.3	6.6
	12	1.7	2.3	16.0	1.1	1.1
.75R	13	.1	1.2	1.1	22.2	13.0
	14	1.6	4.4	11.1	15.5	10.6
	15	1.3	.6	20.7	6.0	5.6
	16	.5	1.2	1.0	5.6	7.1
	17	.6	2.6	2.8	2.0	3.8
	18	2.9	.7	1.9	1.6	1.8
	19	10.7	3.3	3.2	3.8	3.6
.5D	20	.8	.7	7.3	4.5	3.6
	21	4.2	2.0	1.3	15.6	3.0
	22	2.0	2.8	5.3	12.8	17.0
	23	1.7	.9	.5	1.2	2.8
	24	1.2	2.0	6.9	6.4	2.6
	25	1.2	.6	5.8	.9	1.0
	df.	4/45	4/45	4/495	4/395	4/295

from subsequent analysis it will be found that many subjects were not discriminating very well between the stimuli. In these cases the correct wrong sequences should approximate to random binary sequences. That significant response sequences should be obtained may be in part due to subjects responding equally to the two stimuli presented as the session wears on. The subject is informed that stimulus 1 appears 75% of the time and stimulus 2 25% of the time. However, no feedback is given in the experiments and as time wears on the effect of the initial instruction may decrease.

Turning again to the latency data the table below gives the mean latency in the five equal parts of the session for each subject. A Kruskal Wallis non-parametric analysis of variance was performed on this data and a significant value of H equal to 45.8 was obtained on the differences between the five blocks. However, when the first block was ignored and the analysis repeated on the last four this H value was no longer significant. Thus, it appears that in the first 100 trials subjects take longer to respond than in subsequent trials but that the changes in latency with trial number which occur after the first 100 trials vary with the different subjects and there appears to be no consistent pattern of increasing or decreasing latencies.

Thus, although we have shown that there are significant differences between blocks even if the first 200 trials are ignored these differences are not consistent across sessions. Looking at data from all the sessions (i.e. different subjects) the only significant consistency in the latencies for the different blocks is that the first 100 trials had longer latencies.

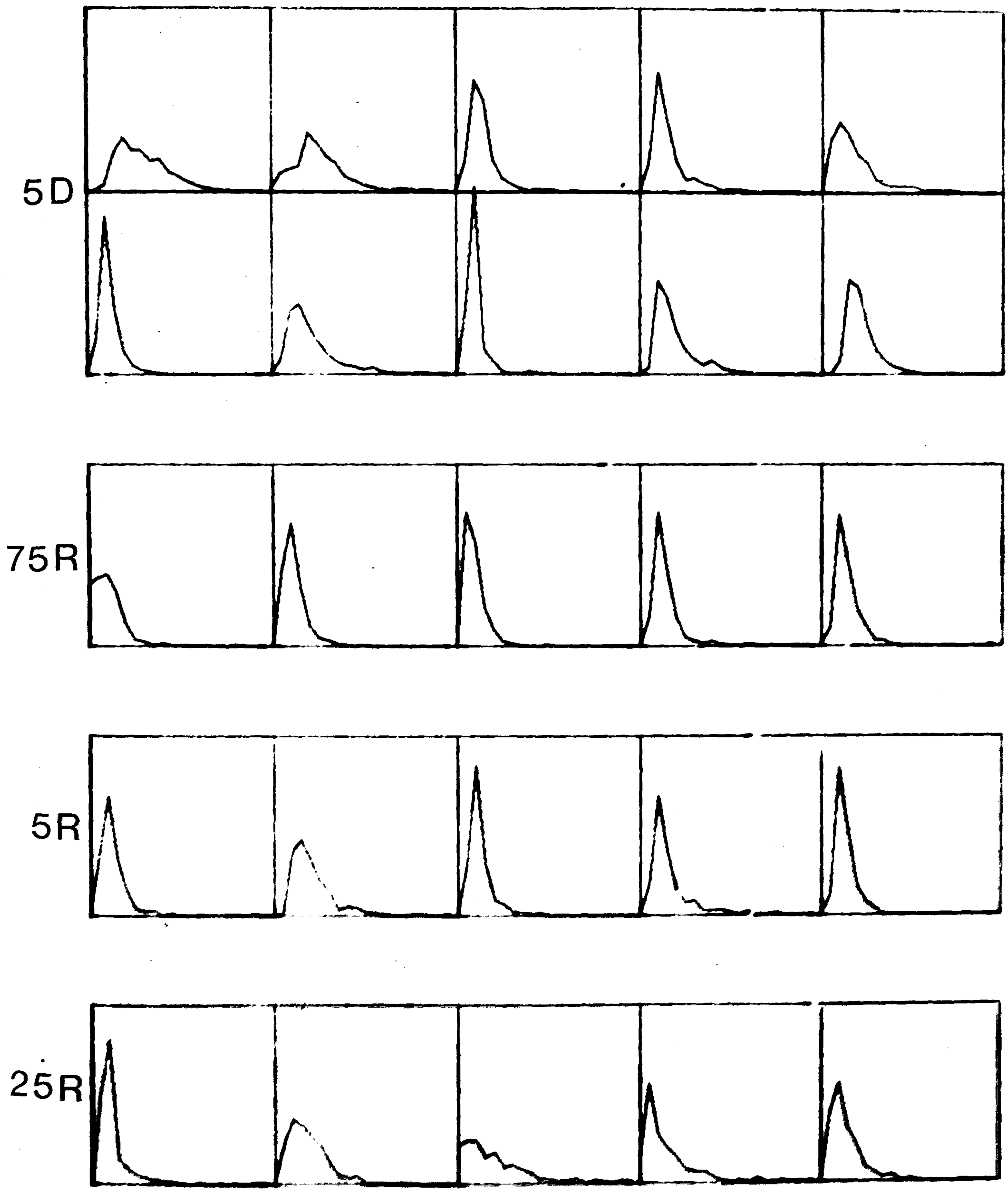
The same type of analysis was performed on the subsequent experiments. A summary of all these analyses is presented in the table below which gives the number of significant F ratios for each experiment for each type of sequence. In the case of Experiment 4 where the subject had five responses available to him in order to make the results

Mean Latencies for Experiment 1 (seconds).

Condition	Session	Block 1	Block 2	Block 3	Block 4	Block 5
	1	.95	.64	.62	.69	.61
	2	1.58	1.12	1.05	.75	.64
.25R	3	3.49	.86	1.06	1.36	1.46
	4	1.87	.52	.69	.72	.98
	5	1.08	.96	.85	.51	.71
	6	1.38	.87	.90	.84	.94
	7	1.90	.93	1.22	.99	1.03
.5R	8	1.15	.73	.75	.71	.69
	9	1.81	.85	1.14	.85	.89
	10	.99	.73	.70	.77	.72
	11	1.29	.64	.49	.41	.87
	12	1.29	.67	.54	.59	.74
.75R	13	3.08	.47	.71	.53	.52
	14	3.03	.80	.76	.70	.57
	15	1.12	.80	.82	.79	.70
	16	1.23	.75	.81	.75	.70
	17	2.50	1.22	1.07	1.08	1.39
	18	.87	.58	.59	.66	.68
	19	1.41	1.19	1.03	1.16	.89
.5D	20	2.09	1.13	1.17	1.14	1.00
	21	3.46	2.01	1.70	1.48	1.44
	22	1.71	1.69	1.21	1.59	2.07
	23	1.18	1.42	.83	.92	1.19
	24	1.68	.74	.88	.79	.71
	25	2.19	.98	1.26	.72	.84

No. of F values significant at the .05 level (see appendix).

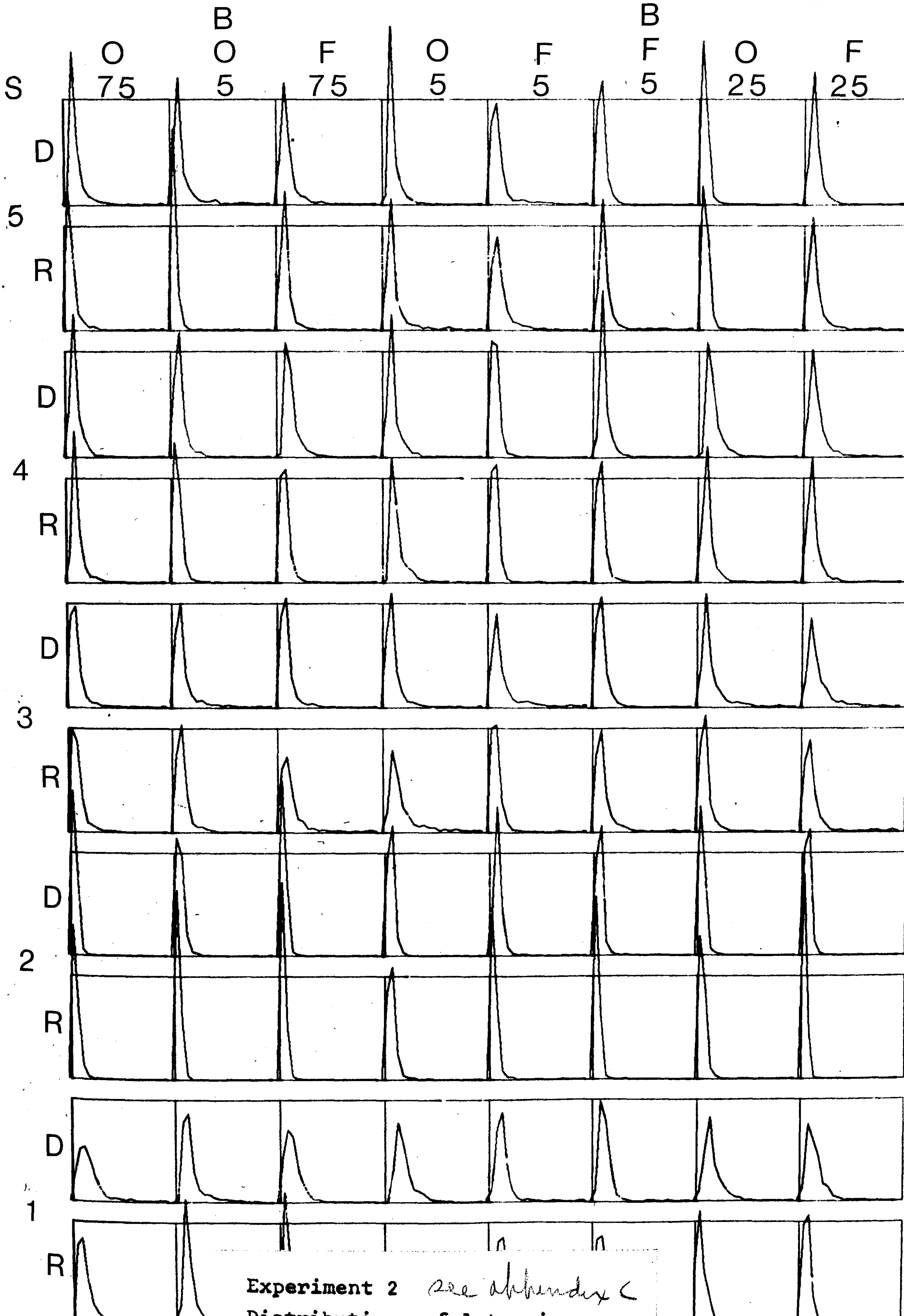
Experiment	No.sess.	Correct W	Response	L	L-100	L-200
1	25	4	8	20	17	17
2	80	17	13	43	53	55
3	90	19	11	44	71	55
4	15	3	5	8	11	10



Experiment 1

Distributions of latencies

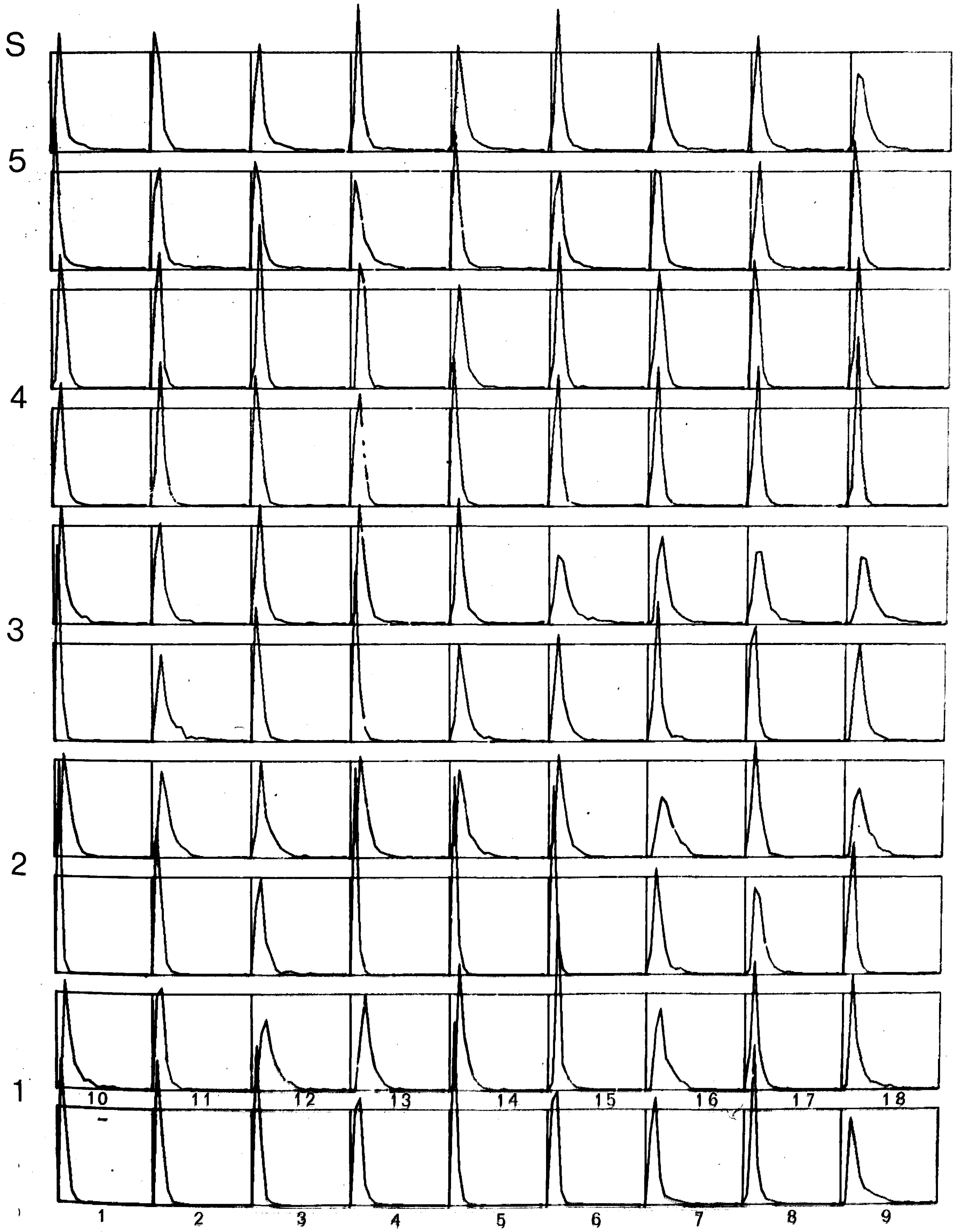
Y axis frequency 0-300
X axis latency 0-5 sec



Experiment 2 see appendix C

Distributions of latencies

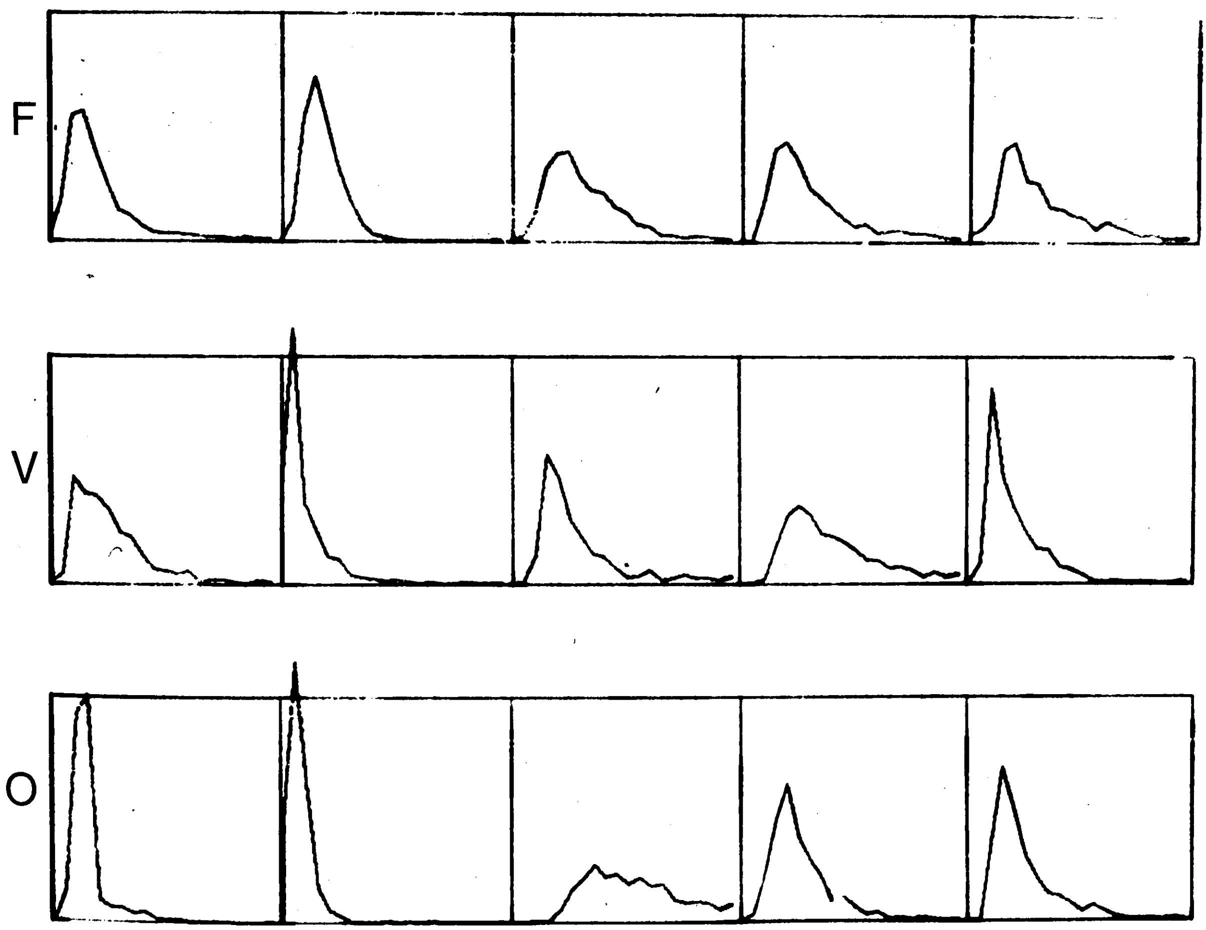
Y axis frequency 0-300
X axis latency 0-5 sec



Experiment 3

Distributions of latencies

Y axis frequency 0-300
X axis latency 0-5 sec



Experiment 4

Distributions of latencies

Y axis frequency 0-300
X axis latency 0-5 sec

comparable response 1 and 2 was treated as response 1 and 3, 4 and 5 as being response 2. Approximately the same amount of non-stationarity appears in the correct wrong sequences in all of the experiments. In Experiments 1 and 4 where naive subjects were used the amount of non-stationality in the response sequences appears to be somewhat greater than for the practice subjects. Perhaps the most unusual finding is that the number of significant non-stationary latency sequences are increased if the first hundred trials is ignored in experiments 2, 3 and 4. This result seems very strange when we consider the evidence presented for Experiment 1 that in the first 100 trials the subjects are taking significantly longer than in the later part of the experiment. This finding appears replicated in Experiments 2, 3 and 4. The result can be more easily understood when one examines the summary tables of each of the individual analysis of variance. It appears here that the within mean square is greater in the total analysis than when the first 100 trials have been dropped. In Experiment 3, for example, the mean square within groups for the analysis ignoring the first 100 trials is less than the equivalent statistic for the analysis over all the data in 69 out of 90 sessions. This indicates that during the first trial not only is there a longer main latency but there is also a greater variability in the latencies produced by the subject. This greater within block variance appears to have the effect of reducing the number of significant between block effects, thereby accounting for the proportionately fewer non-stationary sequences including the first 100 trials than when the first 100 trials has been dropped.

Analyses of variance were performed on these F statistics to test whether the experimental conditions manipulated in the different experiments had any effect on the degree of non-stationarity.

(b) Information Theory Statistics

In an attempt to study the nature of the interrelation of the three measures taken at each trial, namely, stimulus, response and latency, the latencies were divided into quartiles and an information theory analysis was undertaken. This meant the calculation of the average information at each trial given by the response, stimulus and latency, together with the shared information between each pair of these measures, and finally the shared information between all of these measures. The results are shown in the accompanying table.

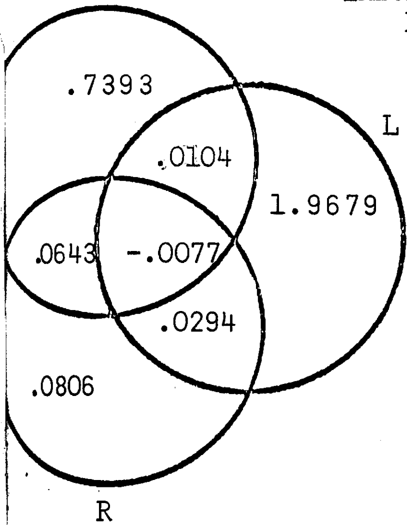
These results may be more easily comprehended by averaging the information over sessions. A diagram is drawn for each of the experimental conditions used in the first session. This is a diagram of overlapping circles where each circle represents one of the measures and the numbers in the shared areas represent the shared information between these measures. The value of the information theory analysis of the data is that it shows the proportion of information in the measure that is shared between it and another.

The same analysis was performed on the results of Experiments 2, 3 and 4. A detailed table of the average information contained on each trial by the various measures was circulated as before. There is little point in producing all that information here, however. It will probably suffice to reproduce the diagrams giving the average information contained in the measures stimulus, response and latency, and how it is shared between them for each of the subsequent experiments. In Experiment 2 the main analysis was performed on the data including the bursts and the data not including bursts, accordingly the average information is given for each of these two analyses (see section on effect of experimental variables). The only comments that may be made from these diagrams is that in experiments 2 and 3 the subject's performance is much better than on experiments 1 and 4 where the subjects were naive. This can be seen from the

Average Information Experiment No. 1

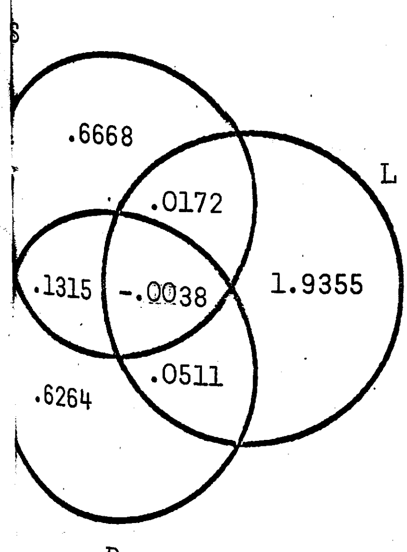
Session	Latency(L)	Stimulus(S)	Response(R)	LS	LR	SR	LSR
1	2.00	.83	.98	.03	.08	.24	.00
2	2.00	.79	.93	.00	.00	.00	.00
3	2.00	.84	.90	.00	.04	.04	-.01
4	2.00	.77	.89	.02	.03	-.03	-.03
5	2.00	.80	.98	.01	.00	.01	.00
6	2.00	1.00	.99	.00	.01	.03	.00
7	2.00	1.00	1.00	.01	.01	.00	.00
8	2.00	1.00	.98	.02	.02	.38	-.01
9	2.00	1.00	.90	.00	.01	.01	-.01
10	2.00	.99	.99	.00	.01	.01	-.01
11	2.00	.80	.98	.00	.07	.00	-.01
12	2.00	.85	1.00	.00	.02	.02	-.01
13	2.00	.78	.52	.07	.16	.25	.07
14	2.00	.86	.82	.01	.01	.18	-.04
15	2.00	.77	.93	.00	.01	.20	-.03
16	2.00	1.00	.99	.08	.09	.43	.02
17	2.00	1.00	.77	.00	.01	.00	.00
18	2.00	1.00	1.00	.01	.01	.51	-.02
19	2.00	1.00	1.00	.01	.01	.10	-.03
20	2.00	1.00	.99	.00	.01	.01	.00
21	2.00	.99	1.00	.01	.00	.03	-.03
22	2.00	1.00	.93	.00	.01	.01	.00
23	2.00	1.00	.97	.00	.05	.06	-.01
24	2.00	1.00	1.00	.05	.04	.25	.00
25	2.00	1.00	1.00	.00	.00	.01	-.02

Information Analysis
Experiment 1

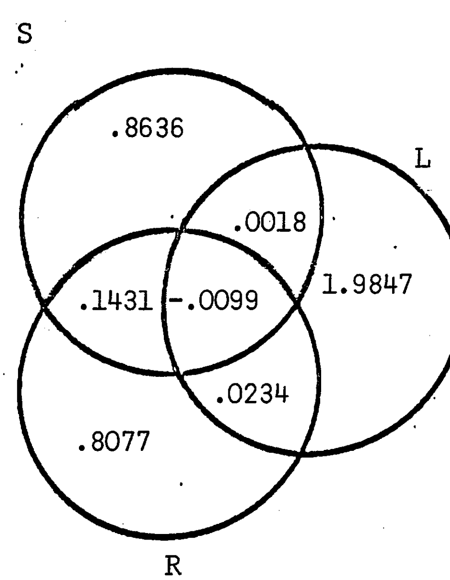


ecognition Stimulus
robability .25

Recognition Stimulus
Probability .5

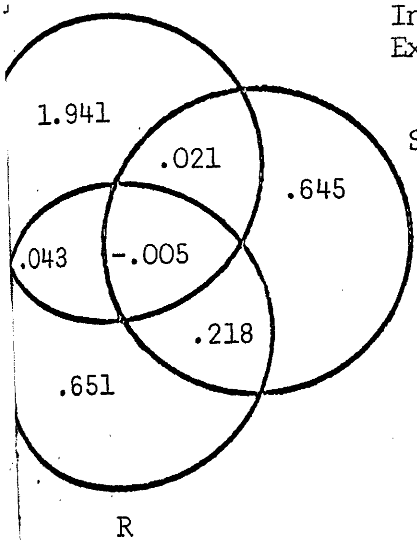


ecognition Stimulus
obability .75

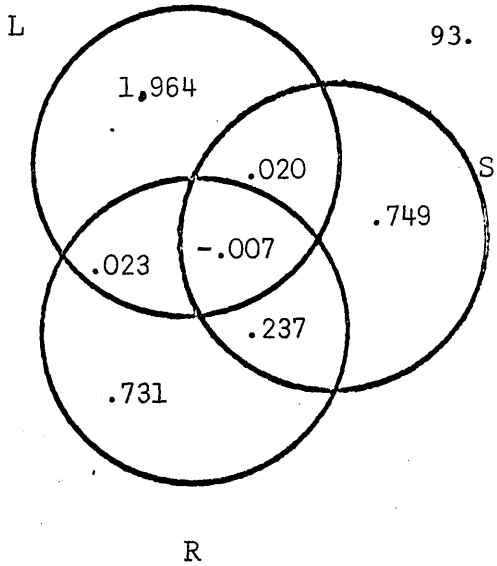


Recognition Stimulus
Probability .5

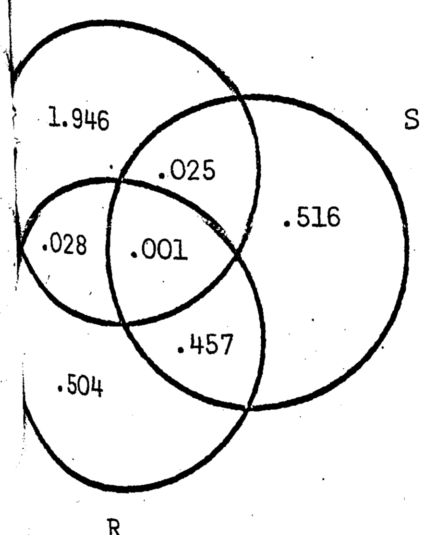
Information Analysis
Experiments 2, 3 & 4.



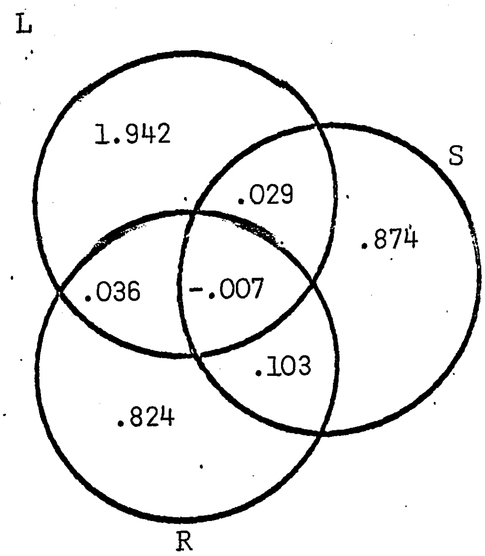
Experiment 2
(ignoring Burst Data)



Experiment 2
(ignoring data where a priori stimulus probability ≠ .5)



Experiment 3



Experiment 4

amount of shared information between the S and R measures. It also appears that the amount of information shared between the response and the latency is greater than that between the stimulus and the latency. This is what we would expect as both response and latency are subject controlled.

(c) χ^2 analysis of dependencies between stimulus, response and latencies

An equivalent χ^2 analysis was also performed on the same data and the values of χ^2 on the independence of the different sequence measures are given in the table below.

From the above data we can see that in eight of the sessions there is a significant relationship between the stimulus and the latency. On 14 of the sessions there is a significant relationship between the response and the latency and on 21 of the sessions there is a significant relationship between stimulus and response. On 11 of the sessions there is a significant interaction between all three measures. Thus, we can conclude that four subjects showed no significant relationship between stimulus and response and were therefore not discriminating significantly better than chance. On examining the results for these four subjects the only significant relationship is one significant χ^2 between response and time. These results agree with the information theory statistics suggesting that the biggest relation is between stimulus and response followed by between response and latency followed by that between stimulus and latency. In the information analysis the stimulus by response by latency information statistic was a composite of two factors, (1) the shared information between the three measures, and (2) the interaction term. There would be a significant interaction if, say, subjects responded faster when the responses were correct than when the responses were wrong. An examination of the histograms of latencies of correct and wrong responses revealed that in fact such a relation existed. The same analysis was repeated on the data from Experiments 2, 3 and 4, and the number of significant χ^2 in each of the conditions is given in the table below. This table reveals that the pattern is similar in all the different experiments. In Experiment 2 one subject did not discriminate significantly on eight of the sessions. In Experiment 3 in only one session did a subject not discriminate significantly. The relationship between the response and latency appears greater than that between the stimulus and the latency as one might expect, and both these dependencies appear greater in Experiment 2 where a priori stimulus probability was an experimental variable, than in Experiment 3 where the a priori stimulus probability was .5 throughout the experiment. The significant SRL χ^2 is presumably an indication that correct responses have a shorter latency than incorrect ones.

χ^2 testing relationship between following measures.

Condition	Subject	LS	LR	SR	LSR
	1	21.2	54.4	157.7	9.76
	2	2.00	2.9	.7	1.17
.25R	3	4.7	28.4	28.5	6.38
	4	3.1	10.5	19.0	17.30
	5	5.9	1.6	7.7	2.05
	6	.8	8.4	23.6	1.35
	7	4.1	5.9	1.2	2.36
.5R	8	13.8	11.6	240.1	4.82
	9	2.9	8.2	3.9	8.66
	10	1.6	4.2	8.7	9.10
	11	1.8	33.3	2.7	6.80
	12	2.4	11.2	14.6	7.43
.75R	13	54.1	119.4	198.1	259.48
	14	4.1	3.9	132.2	11.61
	15	.3	3.5	142.6	14.73
	16	54.8	57.6	268.9	9.27
	17	3.0	3.7	.7	1.75
	18	8.3	10.2	310.4	7.69
	19	8.4	7.5	69.0	18.70
.5D	20	2.9	6.6	7.2	1.01
	21	8.2	.8	21.6	20.54
	22	2.6	5.4	6.1	.12
	23	1.1	35.2	43.0	5.59
	24	33.1	24.6	165.8	14.98
	25	2.0	4.1	8.8	11.18
	df.	3	3	1	3

<u>Number of Significant χ^2</u>

Experiment	No.Sessions	SR	RL	SL	SRL
1	25	21	14	8	11
2	80	72	61	47	43
3	90	89	50	17	26
4	15	12	9	7	8
	df	1	3	3	3

Characterising dependences

(a) Manifest Markov Processes

As mentioned in the Introduction the inter-trial dependences can be measured by fitting Markov processes of different orders to the stimulus, response sequences. The depth of the dependences are measured by the highest Markov process necessary to describe the sequence. As χ^2 statistic tests the hypothesis of a nth order Markov process versus a n + 1 th or higher order. Owing to the data available it was only practical to test the hypothesis of a zero versus a first order dependence and a first order dependence versus a second or higher order dependence. To test the hypothesis of a second versus a third order dependence would involve determining the relative frequency of four successive events. Even if the probability of occurrence of the least likely event was .1 then the probability of four successive of these events would be of the order .0001. This could be expected to occur once in a session of ten thousand trials and to obtain an estimate of this probability accurately should therefore involve several tends of thousand trials. To run a subject in a session lasting this length of time is really impractical. Such a process would have to be estimated by averaging over sessions.

In the analysis of the first experiment there appears to be a great deal of inter-trial dependence in the sequences. All of the latency data when discretised into four quartiles shows a significant Markov dependency higher than first order. While this is true in all but one of the SR response sequences this appears mainly attributable to dependences in the response sequences rather than in the correct wrong sequences. The Markov analysis was performed on the latencies discretised into quartiles, the SR sequences, the R sequences, and the correct wrong sequences. The stimulus sequences from a zero order Markov process as they were generated by a pseudo random number generator which was tested for randomness using various tests such as runs test, χ^2 test, autocorrelations, etc. The number of significant χ^2 is shown in the table below. The suffixes indicate the hypothesis being tested, for example, R2 indicates

χ^2 testing and zero and first order dependences

Condition	Session	Latency 1	Latency 2	SR 1	SR 2	Response 1	Response 2	Correct Wrong 1	Correct Wrong 2
	1	61	41	38	34	9	4	18	3
	2	278	102	32	30	25	1	1	2
.25R	3	188	84	32	882	25	2	3	3
	4	303	87	159	94	125	37	55	10
	5	190	125	211	45	201	2	21	5
	6	36	37	38	61	61	42	5	4
	7	139	74	46	54	34	15	4	1
.5R	8	77	45	101	19	19	2	30	1
	9	168	74	221	29	212	2	1	2
	10	119	54	8	44	0	9	1	8
	11	196	73	29	35	23	8	2	2
	12	149	113	84	63	75	12	8	14
.75R	13	118	57	18	25	3	1	1	8
	14	128	86	40	39	0	8	4	6
	15	119	72	40	29	11	1	3	1

table continued:

Table continued:

Condition	Session	Latency 1	Latency 2	SR 1	SR 2	Response 1	Response 2	Correct Wrong 1	Correct Wrong 2
	16	17	51	90	29	0	4	1	2
	17	29	43	110	34	186	1	0	2
	18	47	64	13	23	19	3	1	0
	19	116	69	24	40	0	9	13	6
.5D	20	79	91	20	52	4	21	1	0
	21	52	52	11	46	1	0	0	2
	22	113	71	44	54	34	11	1	1
	23	119	57	103	37	79	4	6	0
	24	63	94	11	57	0	17	3	4
	25	182	19	106	24	100	1	3	0

(.5)

	df.	9	36	9	36	1	2	1	2

No. Sig χ^2 testing   1st and 2nd order Dependence
Experiment 1.

	L_1	L_2	R_1	R_2	C_1	C_2	SR_1	SR_2
No. Sig (·05)	24	21	18	11	9	5	21	8
Total No.	25	25	25	25	25	25	25	25

No. Sig χ^2 testing 1st and 2nd order dependence SEE APPENDIX
Experiment 2.

	L_1	L_2	R_1	R_2	C_1	C_2	SR_1	SR_2
S_1	14	14	14	10	6	5	15	7
S_2	14	5	4	2	4	1	8	4
S_3	15	7	7	4	5	6	9	6
S_4	6	5	2	1	1	1	1	0
S_5	16	11	5	3	2	2	3	5
No. Sig (.05)	65	42	32	20	18	15	36	22
Total No.	80	80	80	80	80	80	80	80

No. Sig χ^2 testing 1st and 2nd order dependence SEE APPENDIX B
Experiment 3.

	L_1	L_2	R_1	R_2	C_1	C_2	SR_1	SR_2
S_1	17	8	5	5	1	1	8	-
S_2	17	14	5	2	1	1	8	-
S_3	17	13	3	0	4	1	5	1
S_4	18	14	3	2	4	2	7	2
S_5	17	9	4	3	5	3	10	3
No. Sig (·05)	86	58	20	12	15	8	38	6
Total No.	90	90	90	90	90	90	90	90

No. Sig χ^2 testing 1st and 2nd order dependence
Experiment 4.

	L_1	L_2	R_1	R_2	C_1	C_2	SR_1	SR_2
No. Sig (.05)	13	9	7	5	2	1	1	3
Total No.	15	15	15	15	15	15	15	15

χ^2 testing the hypothesis of a zero versus a second or higher order process on the 25 response sequences. We can thus see that the greatest dependencies exist in the latencies and that 20 of the SR sequences are first order dependent while 8 are second order or higher dependent. It also appears that the observed dependence in the SR sequences are attributable to dependencies in the response rather than in the correct wrong although significant dependencies do exist even in the correct wrong sequences.

The same analysis was performed on the data obtained in Experiments 2, 3 and 4. The following tables show the number of significant χ^2 obtained in each of the experiments. For Experiments 2 and 3 these are displayed for each subject as well as over all sessions. From this it appears that there are marked differences between the dependencies produced by different subjects. The pattern that emerges is fairly consistent through the experiment. The sequence of latencies is by far the most dependent although large numbers of the SR sequences also exhibit first order dependence. Only about 20% of these sequences, however, show significant dependence of a second or greater order. We also find that the dependences that exist in the response sequences are greater than the dependences existing in the correct wrong sequences, although significant dependencies occur in both cases.

(b) Autocorrelations and autoregressive processes

Another method of characterizing the dependences was using autocorrelation. The first 20 autocorrelations were calculated for the latencies in each session and the results are shown graphically in the accompanying diagrams which plot autocorrelation against lag. Attempt to obtain similar diagrams for the response and correct wrong sequences used an estimate of the tetrachoric coefficient, namely, $r_{\cos\pi}$. Following the discussion on autoregression processes a first and second order regression analysis was undertaken on the autocorrelation coefficients where the latency data and the results are given in the table below. In some cases the multiple correlation coefficient on one variable is greater than when two variables are used. This appears self-contradictory. However, the analysis of one variable is based on a slightly different sample. Thirty autocorrelations being used in the first analysis while only 29 were available for use in the second.

A similar analysis was performed on the sequences of responses and on the sequences of correct wrongs. Estimates of the autocorrelations were obtained and a regression analysis performed on these autocorrelation coefficients. The results of this analysis are given below.

As most of these multiple correlation coefficients are not perfect or anything like it we cannot really say that the sequences have adequately been described by the autoregressive process.

These statistics, however, do show up some of the features of the data, for example the dependencies in the latency sequences appear much greater than in the correct wrong sequences as we have seen already in the χ^2 analysis. This is hardly surprising since for at least part of the time some of the subjects are responding at little better than chance level. The subject is not discriminating the correct wrong sequence must be random by definition. On looking at

Coefficients of Multiple Regression on Latency Data

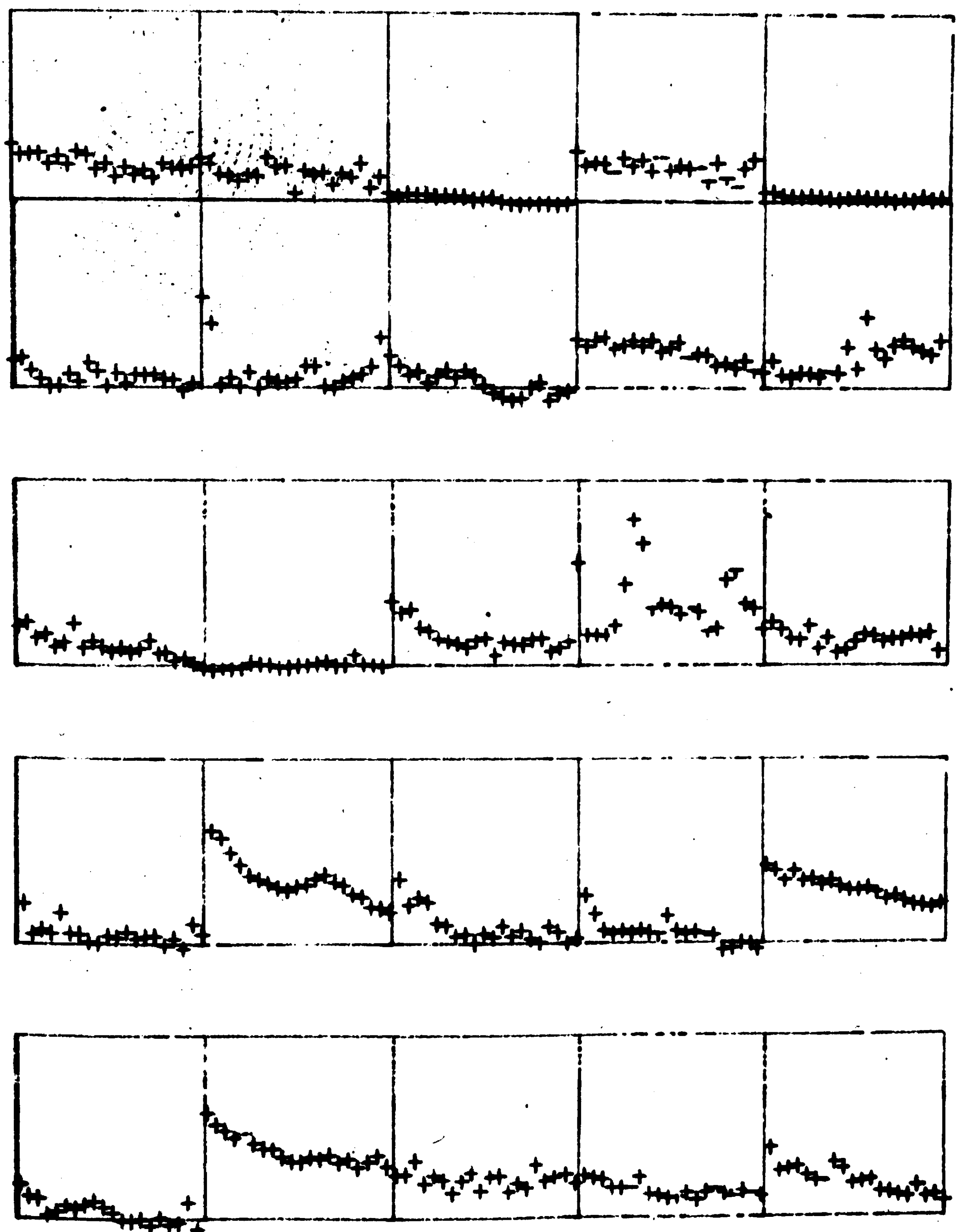
Subject	Condition	First order Analysis	Second order Analysis
1		.49	.58
2		.93	.93
3	.25R	.07	.26
4		.60	.66
5		.84	.86
6		.26	.30
7		.97	.97
8	.5R	.86	.86
9		.62	.66
10		.93	.95
11		.58	.62
12		.50	.55
13	.75R	.65	.76
14		.66	.66
15		.37	.38
16		.60	.59
17		.58	.56
18		.77	.78
19		.84	.87
20	.5D	.46	.54
21		.64	.73
22		.21	.34
23		.99	.91
24		.16	.30
25		.70	.70

Coefficients of Multiple Regression on Response and Correct Wrong Data

Session	Condition	Response 1st Order Analysis	Response 2nd Order Analysis	Correct Wrong 1st Order Analysis	Correct Wrong 2nd Order Analysis
1		.55	.59	.39	.40
2		.42	.44	.16	.52
3	.25R	.69	.67	.02	.13
4		.96	.96	.87	.87
5		.89	.89	.54	.61
6		.62	.67	.30	.45
7		.84	.85	.27	.29
8	.5R	.60	.61	.56	.57
9		.97	.97	.16	.27
10		.47	.42	.15	.20
11		.45	.45	.56	.57
12		.94	.94	.46	.51
13	.75R	.36	.42	.21	.25
14		.19	.20	.22	.32
15		.41	.42	.29	.29
16		.17	.22	.24	.25
17		.92	.93	.13	.17
18		.46	.49	.24	.30
19		.24	.23	.21	.37
20	.5D	.79	.81	.32	.34
21		.18	.34	.28	.30
22		.66	.73	.26	.32
23		.86	.86	.22	.23
24		.53	.56	.35	.35
25		.90	.91	.39	.40

the graphs of the autocorrelations it is clear that the autocorrelations are positive and decrease with order except in the response case where some subjects appear to show a negative relationship between responses differing by about ten trials. This suggests that they tend to maintain responding on the same button for five or six trials and then switch to responding on the other. While this effect is noticeable the size of it is very small.

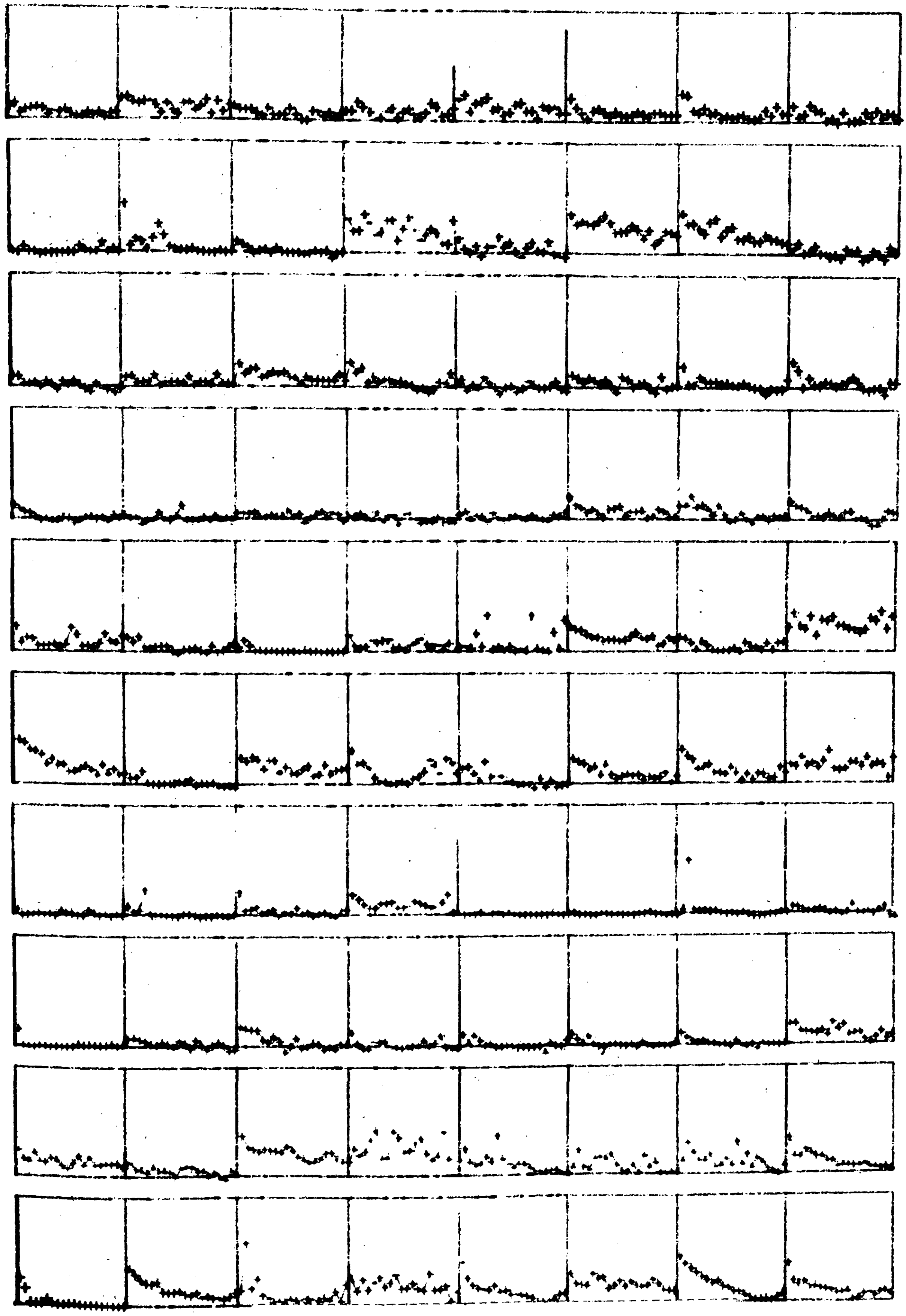
Finally, the effect of the second order regression analysis, i.e. taking into consideration the two previous correlations, does not appear to affect the predictive value of the model except in perhaps a few cases of correct wrong sequences. Thus, the more complicated analysis did not explain very much more of the data. It could be seen from looking at the graphs of the autocorrelations that the autoregressive process was not likely to describe the data particularly well. We have shown this to be the case for the data in Experiment 1. Subsequent analyses were performed on Experiments 2, 3 and 4 and similar results were found. However, we shall confine ourselves here to including only the graphs of the autocorrelation for each session in each of the experiments from which it can be seen that consideration of the autoregressive process is not likely to prove very fruitful.



Experiment 1 see p88 for conditions

Plot of Autocorrelations of latencies

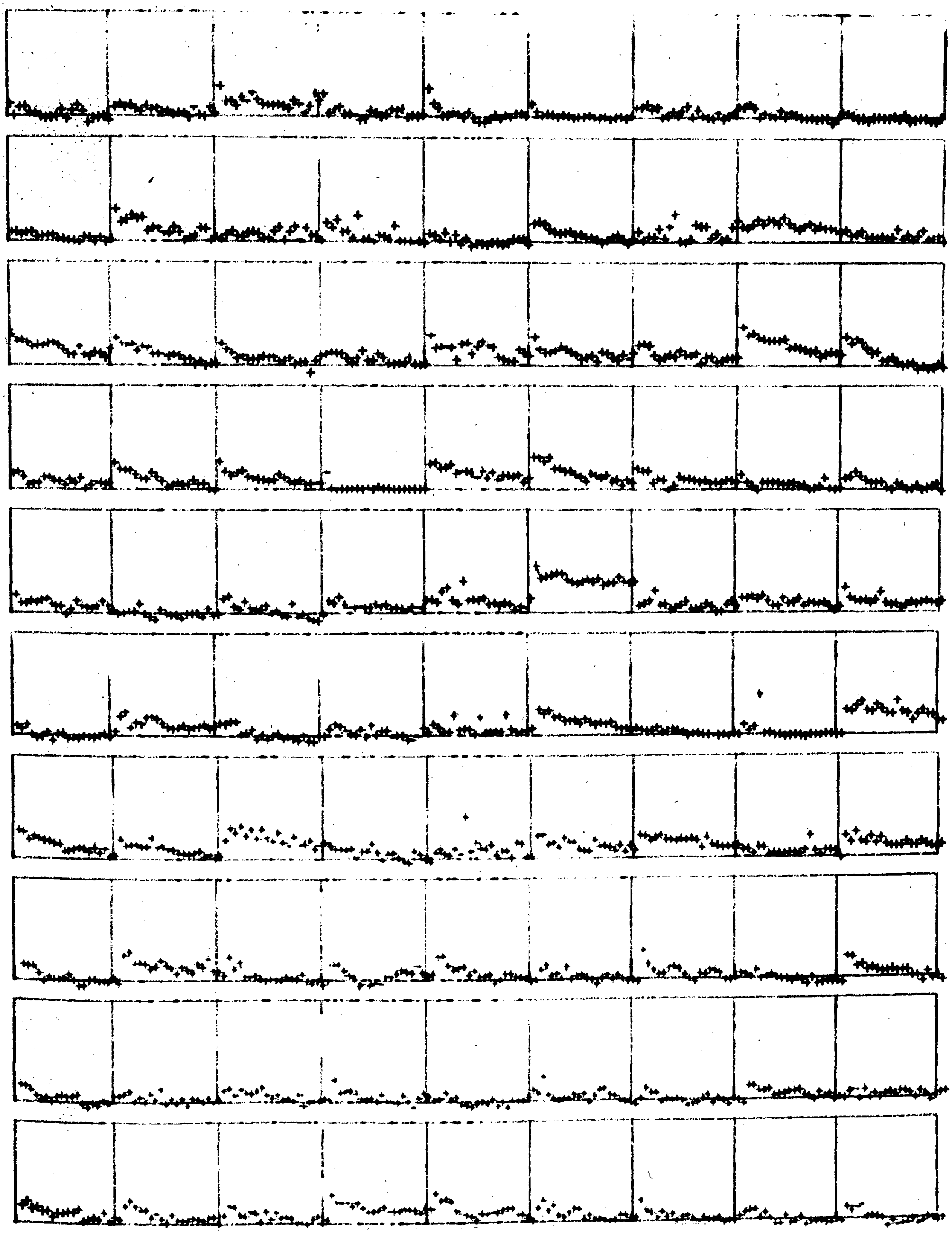
Y axis autocorrelation 0-1
X axis lag 1-20



Experiment 2

Plot of Autocorrelations of latencies

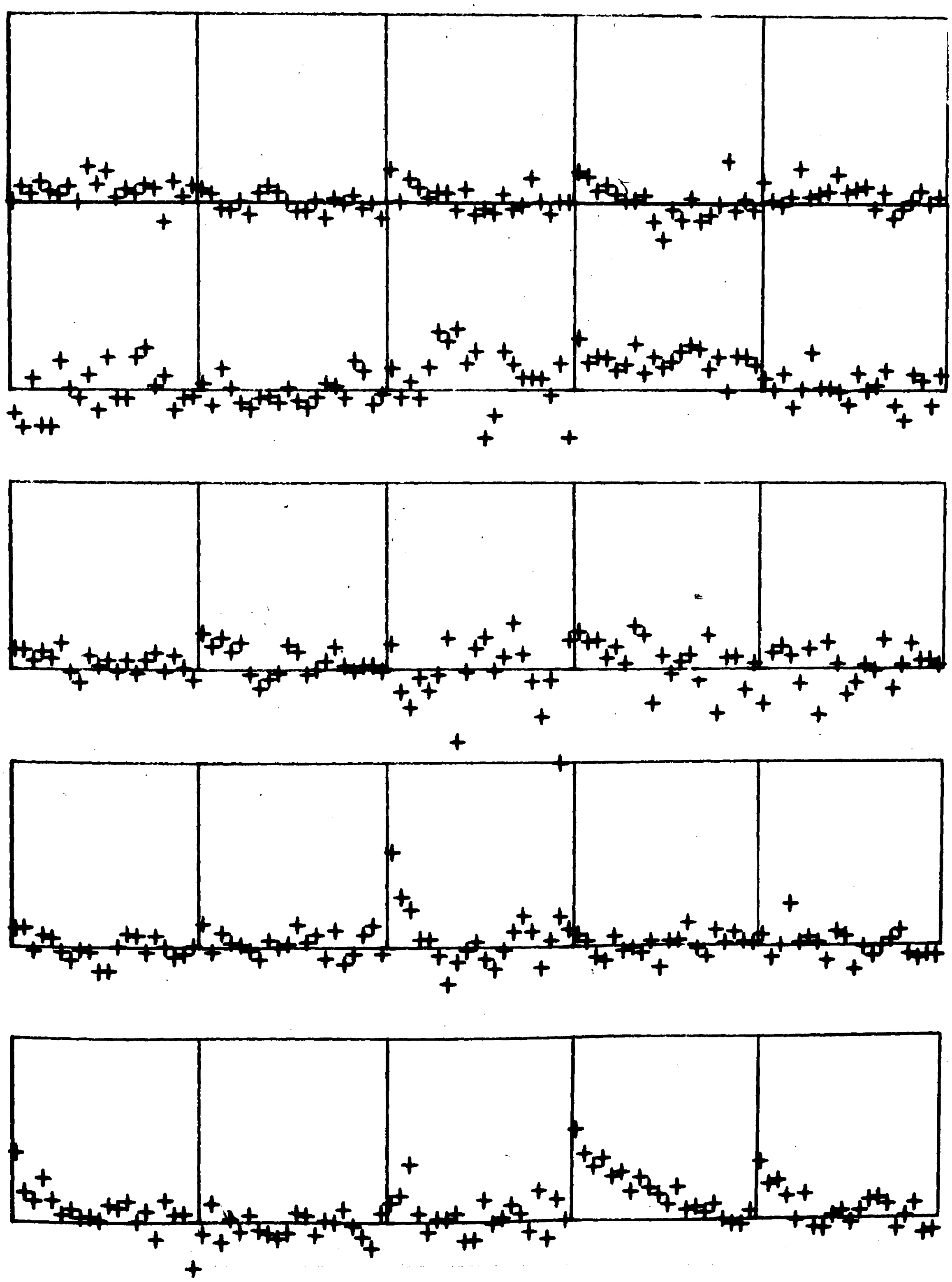
Y axis autocorrelation 0-1
X axis lag 1-20



Experiment 3

Plot of Autocorrelations of latencies

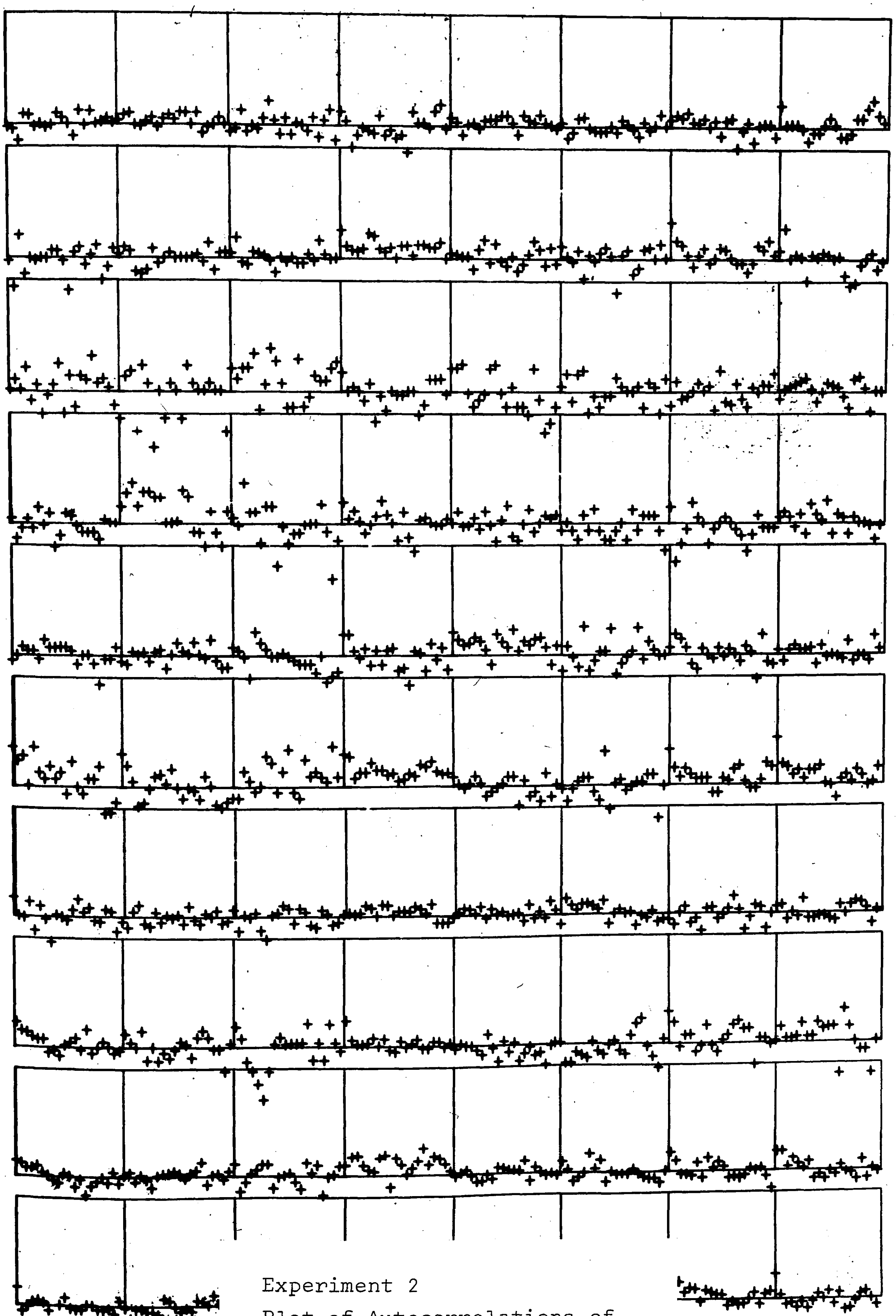
Y axis autocorrelation 0-1
X axis lag 1-20



Experiment 1

Plot of Autocorrelations of
Correct Wrongs

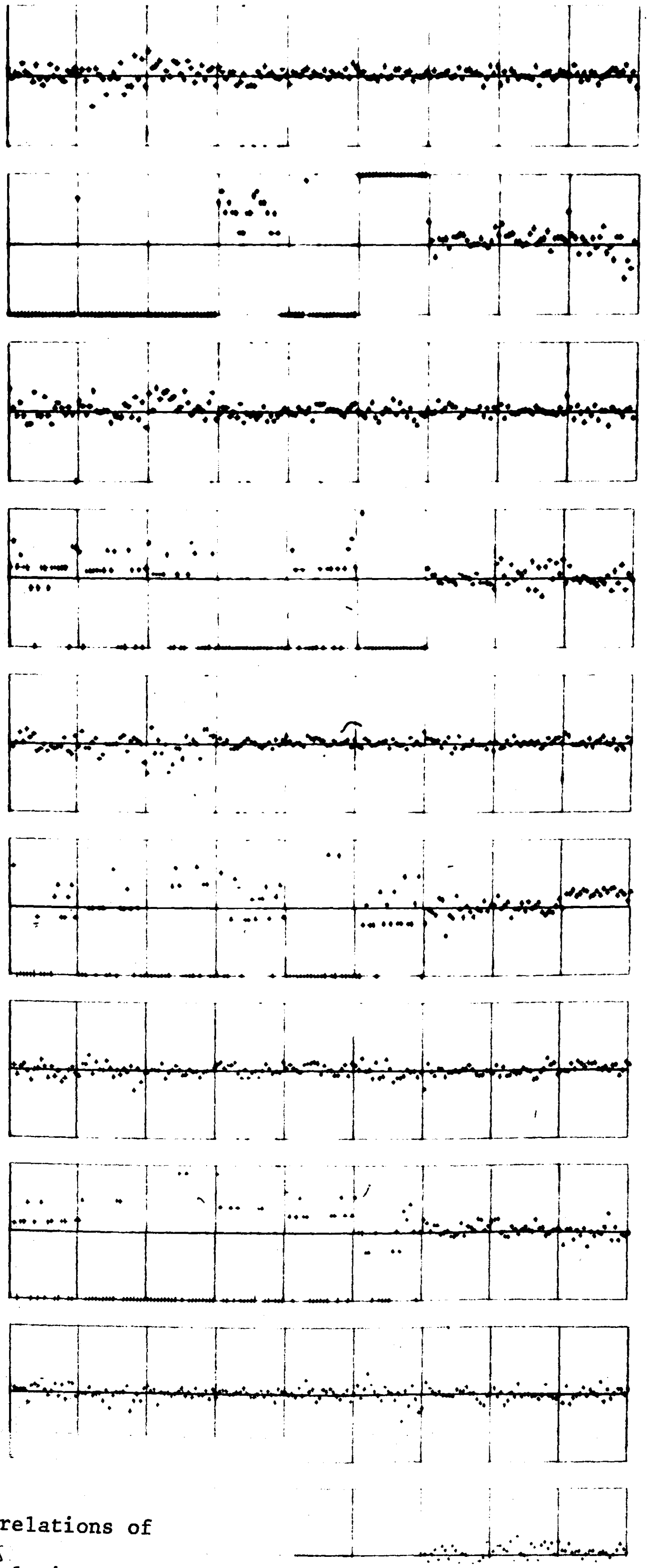
Y axis autocorrelations 0-1
X axis lag 1-20



Experiment 2

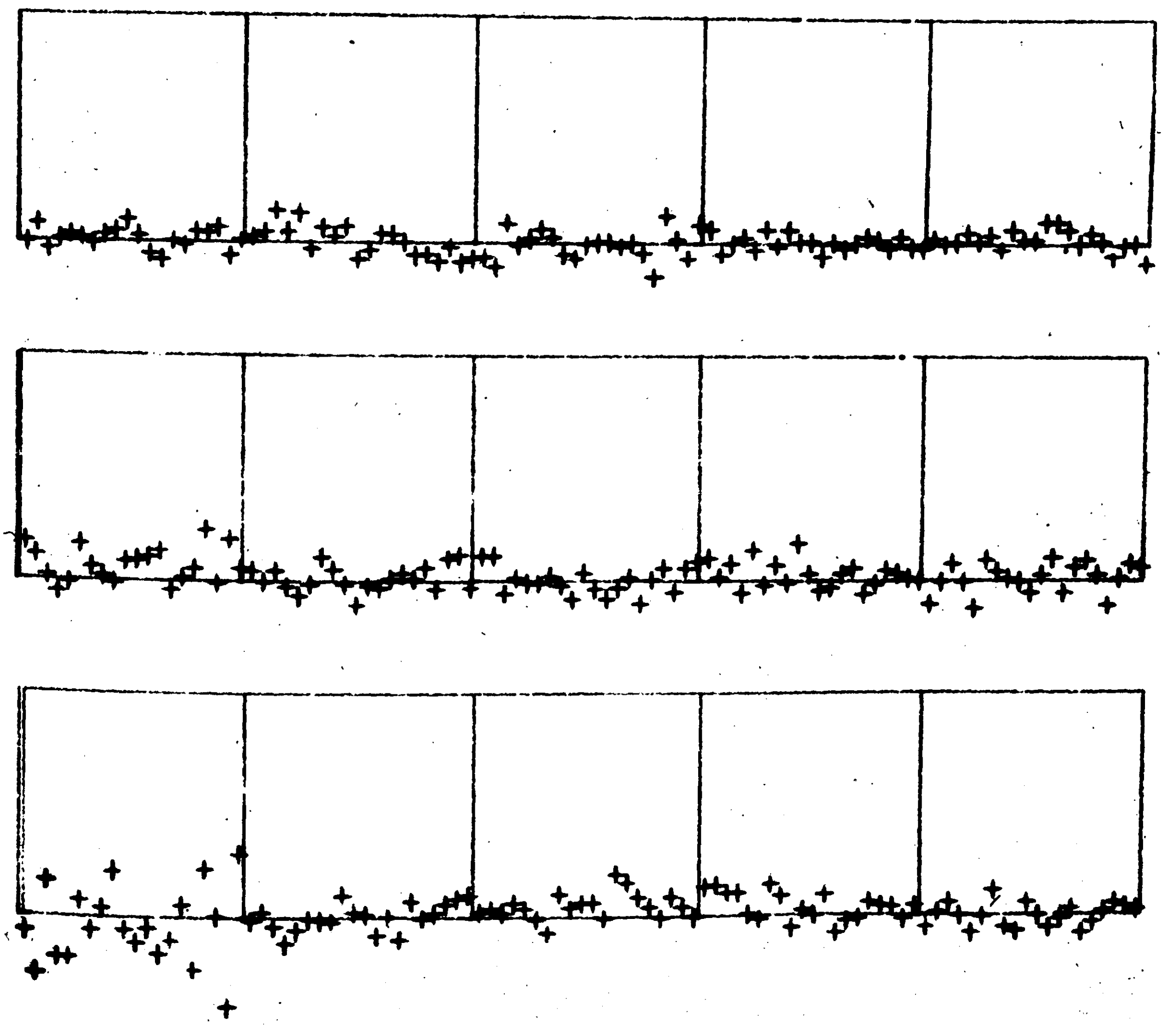
Plot of Autocorrelations of Correct Wrongs

Y axis autocorrelations 0-1
X axis lag 1-20



EXPERIMENT 3

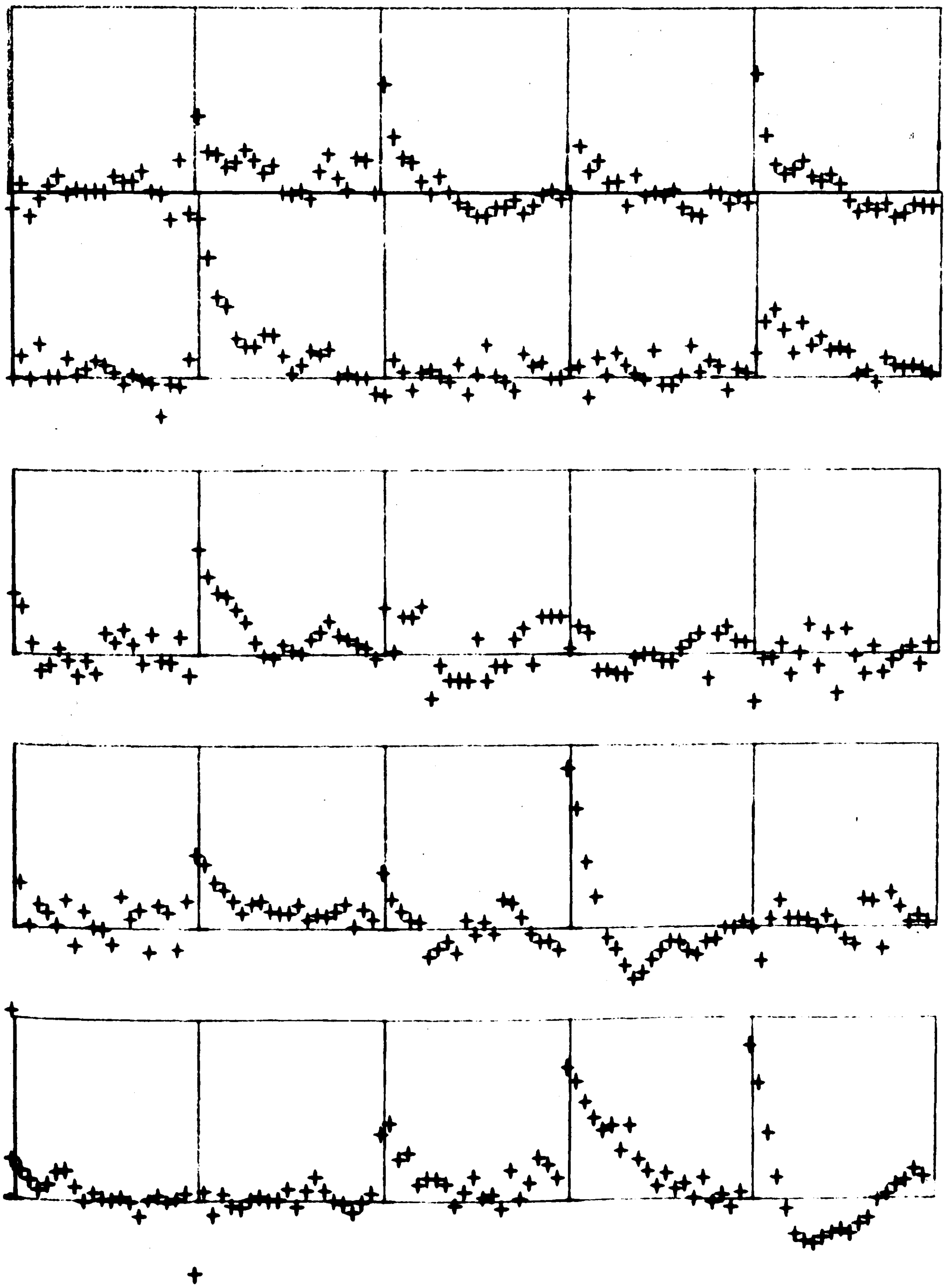
Plot of Autocorrelations of
correct wrongs
Y axis autocorrelation -1→+ 1
X axis lag 1-20



Experiment 4

Plot of Autocorrelations of
Correct Wrongs

Y axis autocorrelations 0-1
X axis lag 1-20



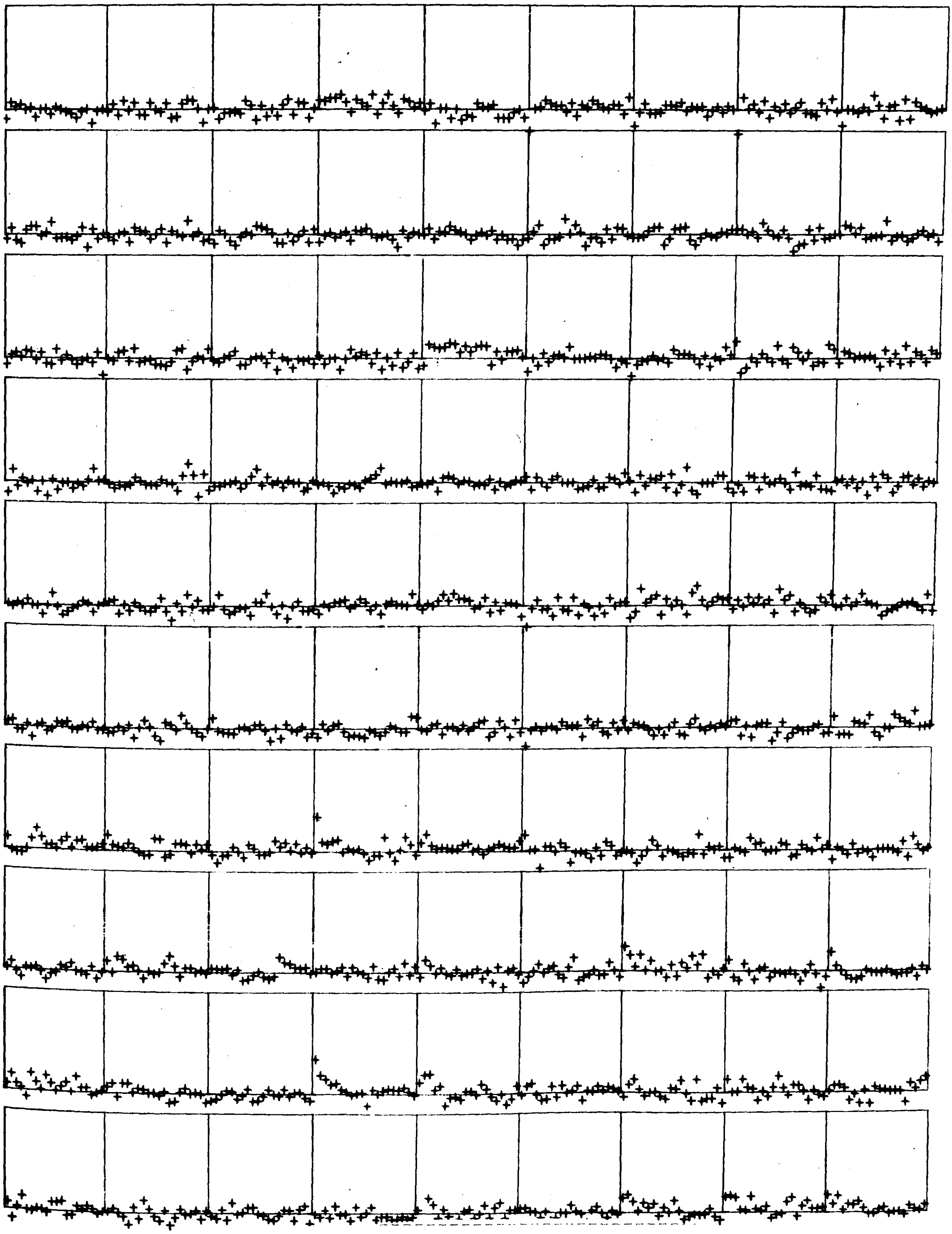
Experiment 1

Plot of Autocorrelations of Responses

Y axis autocorrelations 0-1
X axis lag 1-20

Experiment 2

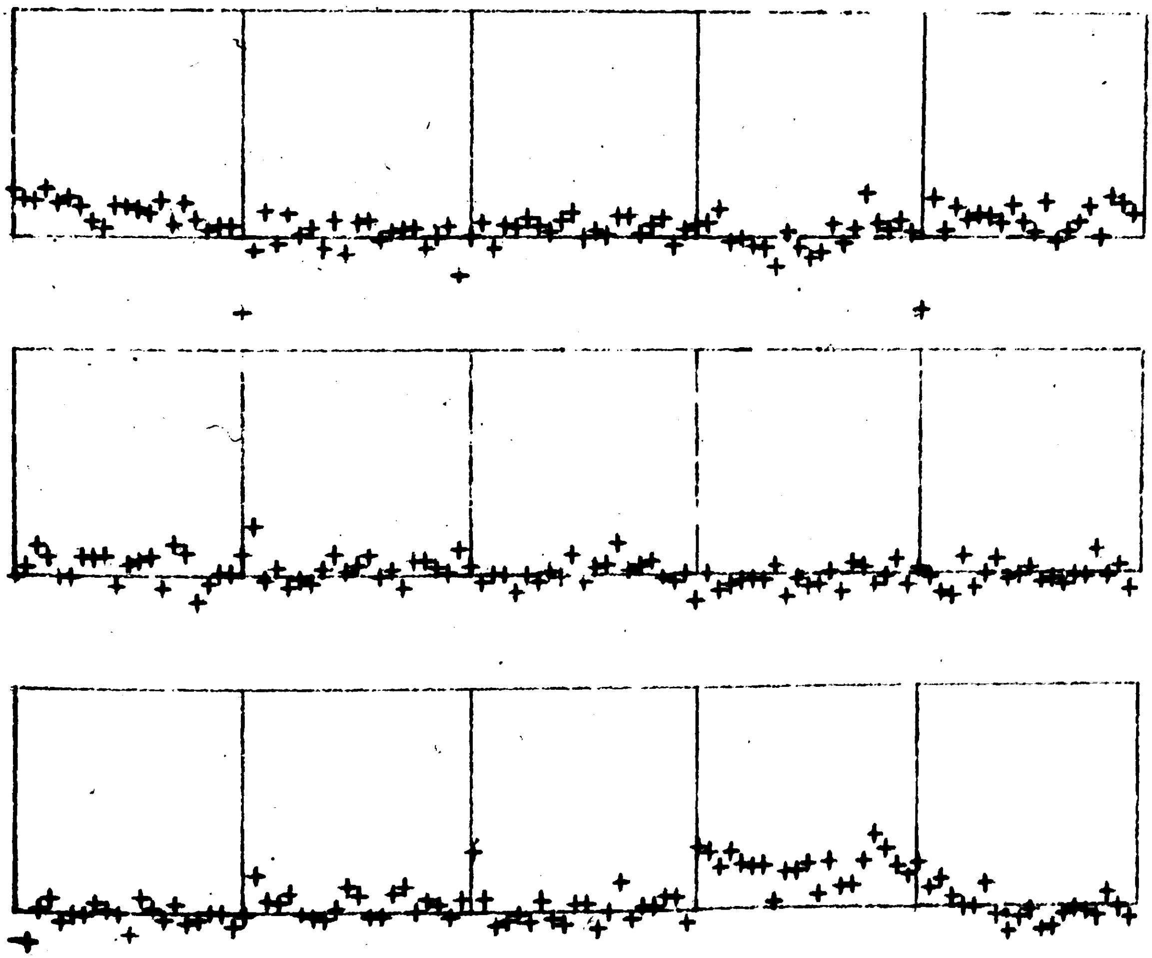
Plot of Autocorrelations of
Responses
Y axis autocorrelations 0-1



Experiment 3

Plot of Autocorrelations of Responses

Y axis autocorrelations 0-1
X axis lag 1-20



Experiment 4

Plot of Autocorrelations of Responses

Y axis autocorrelations 0-1
X axis lag 1-20

(c)Latent Markov Analysis

A number of analyses of the dependences using a latent Markov model as a base were undertaken (see Introduction). The two latent state Markov process was fitted to sequences of respknses and to sequences of correct wrong trials. This method of estimation is as given in the Introduction. The results of this analysis produced in certain cases values of parameters supposedly representing probabilities outwith the bounds of zero to one. When this occurred the program was made to substitute the probability of zero or one depending on which was nearest the estimate of that probability. The results, using the same terminology as in the Introduction, are given in the table below for the analysis of responses and correct wrong sequences.

As can be seen from these results there are a number of occasions where impossible parameter values were obtained. In an attempt to provide an alternative method of fitting the model to the data a numerical hill-climbing procedure was adopted. From the initial estimation procedure values of parameters M(1,1), M(2,2), Q(1,1) and Q(2,2). From these values the other elements of the M and Q matrices and the values of the V matrix could be determined. With these values a χ^2 measure of goodness of fit with the observed third order conditional probabilities was obtained. The four original parameters were then modified systematically by adding or subtracting an increment of .1 and after each transformation another χ^2 goodness of fit statistic was determined and the parameter was changed back to its initial state. After this had been done to all the parameters the change which resulted in the greatest improvement in the goodness of fit statistic was adopted and the procedure was then repeated. The process was then continued until the χ^2 statistic did not improve after any of the transformations. The size of the increment added or subtracted from each of the parameters at each iteration was then changed from .1 to .01 and the process again repeated until no more improvement

EXPERIMENT NO 1

LATENT MARKOV ANALYSIS ON RESPONSES AND CORRECT WRONG SEQUENCES

M				Q				V	CH	M				Q				V	CH
.80	.20	.08	.92	.77	.23	.28	.72	.27	.02	.73	.27	.35	.65	1.0	.00	.51	.49	.57	3.0
.21	.79	.35	.65	1.0	.00	.07	.93	.30	15	.50	.50	1.0	.00	.63	.37	.43	.57	.81	7.7
1.0	.00	.00	1.0	.61	.39	.18	.82	.33	3.0	1.0	.00	.00	1.0	.77	.23	.57	.43	.56	1.0
.95	.05	.08	.92	.95	.05	.22	.78	.65	.00	.85	.15	.14	.86	.82	.18	.13	.87	.50	.00
.81	.19	.13	.87	.98	.02	.02	.98	.41	.00	.76	.24	.17	.83	.94	.06	.36	.64	.41	.02
.46	.54	.98	.02	.84	.16	.07	.93	.64	.02	1.0	.00	.00	1.0	1.0	.00	.58	.42	.08	.30
.94	.06	.06	.94	.77	.23	.23	.77	.48	.00	.00	1.0	.00	1.0	1.0	.00	.61	.39	.00	69
.81	.19	.30	.70	.84	.16	.22	.78	.62	.01	.92	.08	.48	.52	.95	.05	.16	.84	.86	.00
.89	.11	.24	.76	.99	.01	.00	1.0	.69	2.6	.49	.51	.02	.98	1.0	.00	.52	.48	.03	2.7
1.0	.00	.00	1.0	.84	.16	.55	.45	.01	9.7	.00	1.0	.00	1.0	1.0	.00	.57	.43	.00	11
.90	.10	.13	.87	.80	.20	.28	.72	.57	.03	1.0	.00	.00	1.0	.69	.31	.44	.56	.53	.00
.85	.15	.13	.87	.89	.11	.15	.85	.46	.02	.97	.03	.34	.66	.62	.38	.00	1.0	.92	9.7
.32	.68	.26	.74	1.0	.00	.84	.16	.28	7.5	.00	1.0	.00	1.0	1.0	.00	.88	.12	.00	15
1.0	.00	.00	1.0	.74	.26	.14	.86	1.0	8.2	.99	.01	.26	.74	.83	.17	.00	1.0	.97	.23
.11	.89	.00	1.0	1.0	.00	1.0	.00	.00	H	.00	1.0	.46	.54	1.0	.00	.71	.29	.30	.65
.00	1.0	.00	1.0	.75	.25	.46	.54	.00	3.7	1.0	.00	.00	1.0	1.0	.00	.88	.12	.00	5.4
.91	.09	.27	.73	1.0	.00	.04	.96	.76	.06	1.0	.00	1.0	.00	.47	.53	.12	.88	1.0	3.5
.78	.22	1.0	.00	.50	.50	.10	.90	.89	9.1	.00	1.0	.00	1.0	1.0	.00	.90	.10	.00	2.1
1.0	.00	.00	1.0	.54	.46	.00	1.0	.99	7.6	.65	.35	.15	.85	1.0	.00	.55	.45	.30	4.9
1.0	.00	.00	1.0	.72	.28	.40	.60	.10	16	.17	.83	.16	.84	1.0	.00	.48	.52	.16	1.5
.00	1.0	.45	.55	.73	.27	.38	.62	.28	.68	1.0	.00	.00	1.0	.87	.13	.60	.40	.01	1.6
.80	.20	.29	.71	.59	.41	.00	1.0	.59	7.9	.72	.28	.01	.99	1.0	.00	.53	.47	.05	.58
.83	.17	.35	.65	.90	.10	.00	1.0	.67	1.9	.72	.28	.68	.32	.90	.10	.00	1.0	.71	5.6
1.0	.00	.00	1.0	.77	.23	.51	.49	.00	17	.87	.13	.03	.97	1.0	.00	.74	.26	.17	1.9
.75	.25	.30	.70	.97	.03	.00	1.0	.55	1.3	.30	.70	.17	.83	1.0	.00	.46	.54	.19	3.0

RESULTS OF FITTING 2-STATE LATENT MARKOV MODEL TO RESPONSES AND CORRECT WRONG SEQUENCES FROM EXPERIMENT 1

(after min χ^2)

M				Q				V	χ^2	M				Q				V	χ^2
.80	.20	.08	.92	.76	.24	.28	.72	.27	.01	.79	.21	.33	.67	1	0	.45	.55	.39	.27
.10	.90	.39	.61	1.0	0.0	.07	.93	.30	.65	0	1.0	1.0	0	.7	.3	.49	.51	.50	.33
1	0	0	.1	.54	.46	.1	.9	.50	3.4	1	0	0	1	.8	.2	.56	.44	.50	.22
.95	.05	.08	.92	.95	.05	.22	.78	.35	-	.85	.15	.15	.85	.82	.18	.13	.87	.50	-
.81	.19	.13	.87	.98	.02	.02	.98	.41	-	.76	.24	.17	.83	.94	.06	.36	.64	.41	.01
.46	.54	.99	.01	.84	.16	.07	.93	.65	.01	.91	.09	.01	.99	1	0	.56	.44	.11	.14
.94	.06	.06	.94	.77	.23	.23	.77	.48	-	1	0	0	1	1	0	.52	.48	.00	8.4
.81	.19	.31	.69	.84	.16	.22	.78	.62	.00	.92	.08	.48	.52	.95	.05	.16	.84	.86	.00
.90	.10	.22	.78	.99	.01	.00	1.00	.69	1.4	.77	.23	.02	.98	1.0	.0	.50	.50	.07	.61
0	1	0	1	1	0	.56	.44	.00	9.4	.69	.31	.02	.98	0	1	.60	.40	.06	7.4
.90	.10	.13	.87	.80	.20	.27	.73	.57	.01	.70	.30	.44	.56	1	0	0	1	.50	.00
.85	.15	.13	.87	.89	.11	.15	.85	.46	.02	.97	.03	.20	.80	.65	.35	0	1.0	.88	2.13
.80	.20	.18	.82	1	0	.78	.22	.48	1.2	.63	.37	0	1	0	1	.89	.11	.01	4.1
1	0	0	1	.74	.26	0	1.0	1.0	8.2	1	0	.25	.75	.83	.17	0	1.0	.97	.1
.54	.46	.72	.28	1	0	.1	.9	.61	1.1	0	1	.53	.47	1	0	.69	.31	.34	.03
1.0	.00	.00	1.0	1.0	.00	.45	.55	.02	2.1	.43	.57	.26	.74	.86	.14	.87	.13	.31	3.2
.92	.08	.27	.73	1.0	.00	.04	.96	.76	.03	.87	.13	.71	.29	.40	.60	.92	.08	.84	2.4
.32	.68	1.0	.00	.59	.41	.27	.73	.60	.81	.31	.69	.04	.96	.56	.44	.92	.08	.06	.29
1.0	.00	.00	1.0	.53	.47	.00	1.0	1.0	9.5	.75	.25	.15	.85	1.0	.00	.50	.50	.37	.56
1.0	.00	.00	1.0	.60	.40	.27	.73	.50	9.5	.36	.64	.15	.85	.99	.01	.46	.54	.19	.05
.00	1.0	.45	.55	.75	.25	.36	.64	.31	.03	1.0	.00	.00	1.0	1.0	.00	.60	.40	.00	1.8

Table continued.

	M				Q			V	χ^2		M				Q			V	χ^2
.82	.18	.22	.78	.63	.37	.00	1.0	.55	1.2	.81	.19	.01	.99	1.0	.00	.53	.47	.07	.06
.84	.16	.32	.68	.91	.09	.00	1.0	.67	.48	.72	.28	.54	.46	.90	.10	.12	.88	.66	.16
1.0	.00	.00	1.0	1.0	.00	.51	.49	.00	17	.91	.09	.03	.97	1.0	.00	.72	.28	.25	.24
.76	.24	.29	.71	.97	.03	.00	1.0	.55	.33	.47	.53	.17	.83	1.0	.00	.43	.57	.24	.15

in the value of χ^2 could be obtained. The output of this procedure is given in the table below. From the results it can be seen that this procedure has increased the goodness of fit of the model in the cases where the χ^2 values differed from zero. It should be noted that in this case the number of parameters is equal to the degrees of freedom for the χ^2 so that if the model fitted one should expect a χ^2 value of zero. Combining the two estimation methods appears to lead to sensible estimates for the parameters.

The next stage was to develop an analysis of data involving the four observable states. This is to analyse the sequences of trials each trial being denoted by the stimulus and response which occurred at that time.

An analysis of such a sequence done as per the Introduction involves a solution of a quartic equation. A computer program was written to solve such an equation however the initial values obtained as estimates of the parameters included several imaginary solutions which were very difficult to interpret. An alternative approach therefore making use of more information was used in this case.

It proved possible here to use the information available about the stimulus sequence alone. The stimulus sequence was generated by simulating the independent zero order Markov process given the a priori stimulus probability values. As mentioned before this was done using a standard pseudo random number generator. If we denote the a priori probability stimulus one as ST1 and the a priori probability stimulus two as ST2 we can use the following equation for the response matrix Q.

$$Q = \begin{pmatrix} X_1 & ST1 - X_1 & X_3 & ST2 - X_3 \\ X_2 & ST1 - X_2 & X_4 & ST2 - X_4 \end{pmatrix}$$

$$M = \begin{pmatrix} M_1 & 1 - M_1 \\ 1 - M_2 & M_2 \end{pmatrix}$$

$$V = \begin{pmatrix} V_1 & 0 \\ 0 & 1 - V_1 \end{pmatrix}$$

We denote the observed transition probability matrix between time T = 1 and time T = 2 by P(1,2) and between time T = 1 and time T = 3 as P(1,3). We will also introduce the stratified matrix $P_{k(1,3;2)}$ as being the matrix whose ijth elements are the probability of being in state i at time 1 and j at time 3, while at time 2 being in state k. We also introduce X_k as being the diagonal matrix whose diagonal elements are the kth column of Q.

Thus $X_1 = \begin{pmatrix} X_1 & 0 \\ 0 & X_2 \end{pmatrix}$ and $X_2 = \begin{pmatrix} ST1 - X_1 & 0 \\ 0 & ST1 - X_2 \end{pmatrix}$

$X_3 = \begin{pmatrix} X_3 & 0 \\ 0 & X_4 \end{pmatrix}$ $X_4 = \begin{pmatrix} ST2 - X_3 & 0 \\ 0 & ST2 - X_4 \end{pmatrix}$

We can now aake use of the theoretical relations mentioned in the Introduction.

$P(1,2) = Q'VMQ$

$P(1,3) = Q'VM^2Q$

$P_1(1,3;2) = Q'VMX_1MQ$

$P_2(1,3;2) = Q'VMX_2MQ$

$P_3(1,3;2) = Q'VMX_3MQ$

$P_4(1,3;2) = Q'VMX_4MQ$

Taking determinants we have

$$\frac{P_1(1,3;2)}{P(13)} = X_1 = X_1X_2$$

$$\frac{P_2(1,3;2)}{P(13)} = X_2 \quad (ST1 - X_1)(ST1 - X_2)$$

On rearranging the above we obtain the following quadratic equation

$$X_2{}^2 - \frac{ST1^2 + X_1 - X_2}{ST1} X_2 + X_1 = 0$$

The two values of X_1 and X_2 are therefore the two rates of the above equation. A similar analysis involving the last two states gives the following equations:-

$$\frac{P_3(1,3;2)}{P(1,3)} = X_3 = X_3X_4$$

$$\frac{P_4(1,3;2)}{P(1,3)} = X_4 = (ST2 - X_3)(ST2 - X_4)$$

And the quadratic equation

$$X_4{}^2 - \frac{ST2 + X_3 - X_4}{ST2} X_4 + X_3$$

The results of this analysis in no case produced estimates of all the probabilities within the range 0 to 1.

The minimum χ^2 procedure was therefore written analogous to the minimum χ^2 procedure used in the latent state two observable response case. However, it was found that this procedure took too long to find a solution in order that it could be used on all the individual sessions. Unfortunately all that could be done was to combine the data together and fit the model to the combined data. The original estimates of the parameters of the model are given in the table below along with the values of the parameters after using the minimum χ^2 procedure. It can be seen here that the minimum χ^2 procedure gives sensible answers for the model.

This approach for characterising the dependences was used in Experiments 2, 3 and 4. The two latent state two

ESTIMATES OF THE PARAMETERS OF THE LATENT MARKOV MODEL (ANALYTICALLY DETERMINED AND NUMERICALLY)

EXPERIMENT 1

V		Q			M	
1	0.499	0.501			1	0
0	0.499	0.501			.19	.81

$\chi^2 = 5.5 \times 10^{24}$

after min. χ^2

V		Q			M	
.56	.46	.04	.33	.17	.87	.13
.44	.21	.29	.03	.47	.16	.84

$\chi^2 = 46.5$

EXPERIMENT 2

V		Q			M	
1	0.50	0.50			1	0
0	0.50	0.50			.22	.78

$\chi^2 = 9.9 \times 10^{24}$

after min. χ^2

.92	.42	.08	.14	.36	.98	.01
.08	.07	.43	.04	.46	.11	.89

EXPERIMENT 3 $\chi^2 = 86.7$

V			Q		M	
1	21	29	0	5	1	0
0	0	5	0	5	1	0

$\chi^2 = 7.7 \times 10^{15}$

after min. χ^2

V			Q		M	
.75	.47	.03	.03	.47	.10	.10
.25	.25	.25	.25	.25	.30	.70

$\chi^2 = 7.5$

observable state model was applied directly to the response and correct wrong sequences and the results of this are given in the tables below. As in Experiment 1 if the probability parameters fall outwith the zero to 1.0 bound they were set to either zero or one. On looking at the data it can be seen that this was necessary in practically every case. These estimates should therefore be improved by using the minimum χ^2 procedure described in the analysis of Experiment 1. The above values could be taken as starting points. Unfortunately the time taken to reach a solution would make finding a minimum χ^2 190 times too expensive in computer time to be worth the effort. We would, however, imagine that the improvement resulting from the use of the minimum χ^2 technique would be of the same order as that found in the analysis of experiment 1.

Analysing the SR sequences in terms of a latent state model produced the same problem in that the time taken to run minimum χ^2 procedures which would have been necessary to obtain sensible parameter estimates would have proved prohibitive. As a result all the experimental data for each experiment was combined and the combined data was analysed using the latent Markov process described above. The results are given in the tables below.

We can thus see that the results show considerable improvement in the estimates of the parameters after the use of a minimum χ^2 procedure. Any χ^2 value at all still means that the model does not fit but at least the degree to which it does not fit is considerable improved. These estimates were then used in the simulation procedures which will be described later on.

Of the models the best fit is in Experiment No. 3.

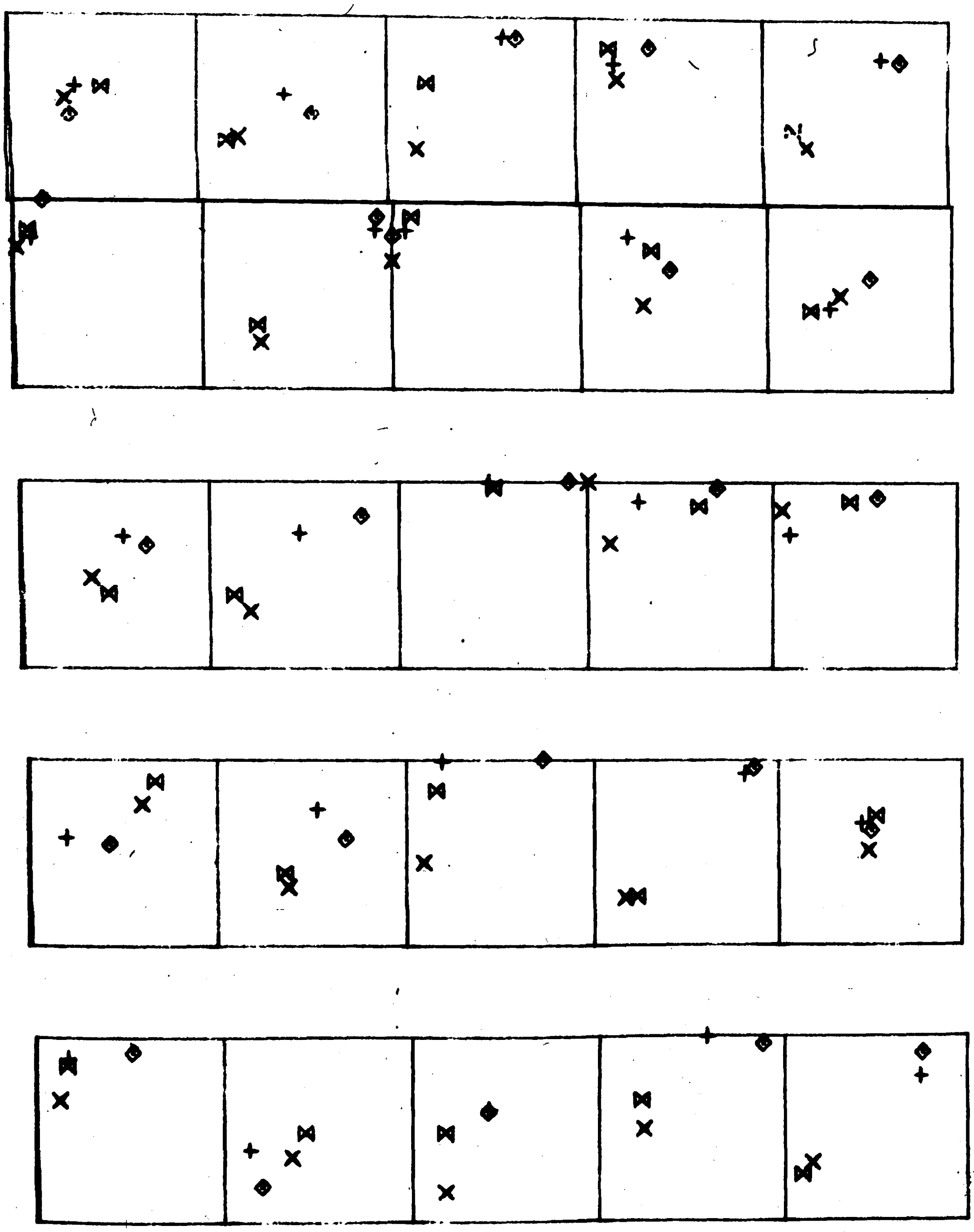
The data on Experiment 1 included much data in which the subjects were not discriminating between the stimuli as mentioned above. Experiment 2 averaging the data involved averaging the data with different a priori stimulus probabilities which would make the fitting of any statistic model difficult. Averaging the data for Experiment 3 involved averaging easy, medium and difficult discriminations. An interesting finding is the values of the parameters obtained after the minimum χ^2 analysis in Experiment 3. This is very much aligned with the Falmange model. In this model the subject alternates between two states. When the subject is in one state he discriminates well when in the other he does not. From the values found in the Q matrix it appears that the subject is doing just that. In one state the subject is equally likely to respond with either of the alternatives while in the other state he responds with the correct alternative in the ratio of 47 : 2.5. We must be careful, however, to realise that this result may be due to the averaging of easy, medium and difficult sequences of discrimination rather than the validity of the two latent state type model.

The effect of the dependencies on the signal detection models

The probabilities of the subjects responding R_1 given the stimulus presented and the SR combination on the last trial was determined and then $P(R_1|S_1S_iR_j)$ versus $P(R_1|S_2S_iR_j)$ was plotted for all i's and j's. Thus, if the commonly held independence assumption is true then these points should be independent of the SR combination on the immediately preceding trial. As no feedback was given in any of the sessions in this experiment (1) Atkinson's model (in Atkinson Bower and Crothers (1965)) also predicts that these points should be the same. While the Tanner and Rauk model predicts that the points should lie on an ROC curve. On examining the graph we see that the points do not appear to be randomly distributed around some particular value, nor do they appear to lie on ROC curve. The main effect on the points appears to be a change in bias related to the response on previous trials. This point will be more fully made when the parameters of the various signal detection models are estimated for each of these four points. Here we would expect to find the major effect on the bias parameter. The results indicate a large amount of individual variation between sessions. As different subjects performed in each session it is not possible to say whether this variability is between subjects or between sessions. If the same subjects perform on the same session twice one could say whether the effect of these dependences were relatively constant. As previously noted the main effects appear to be a change in bias depending on the preceding response. However, this effect varies from subject to subject. In the majority of cases the effect is due to an apparent increase in probability of maintaining the same response although in at least one case the opposite effect is seen and the subject tends to alternate his response from trial to trial. The other effect is that there appears to be a tendency for the sensitivity to be increased when the subject was correct on the last trial. This is the sort of result one would expect to obtain if the subject was performing as in a latent Markov state model where one of the states corresponds to a better performance level from the other. That is to say this result would be predicted if one assumed that the subject's state of performance varied throughout the trials and his performance was more likely to be like that on the immediately preceding trial than on any other trial. This effect, however, will be obscured by the fact that in some cases the subjects were only marginally responding better than chance. In such cases any effects like this would be difficult to observe.

We are mainly concerned with the effect of the dependency on the sensitivity and bias statistics of the detection and recognition models. It is therefore useful to estimate not only the overall parameter value of these models but also to estimate the parameter value looking at data following a particular trial event. The results of this analysis will be considered in the section dealing with the analyses of the detection and recognition models.

The equivalent results for experiments 2, 3 and 4 are given in the following pages. Again, changes in bias and sensitivity appear in all the experiments depending on the state on the immediately preceding trial, and it does not appear that saying the points lay on the same ROC curve is a particularly good approximation to the observed points.



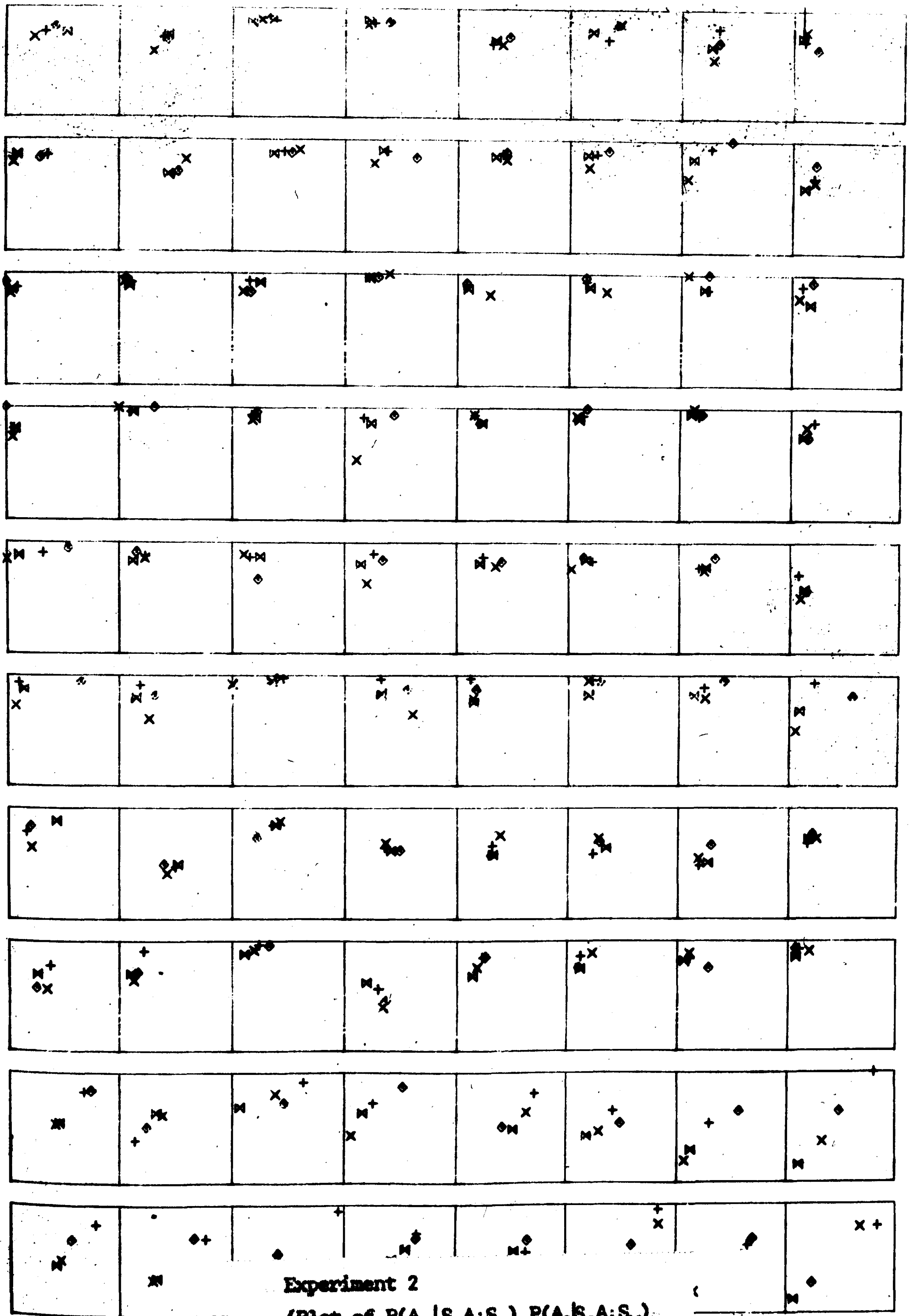
Experiment 1 SEE P88 for condition

(Plot of $P(A_1|S_1A;S_K)$ $P(A_1|S_2A;S_K)$

for preceding trials

S_1R_1 - + S_1R_2 X

S_2R_1 - ◇ S_2R_2 ⋈



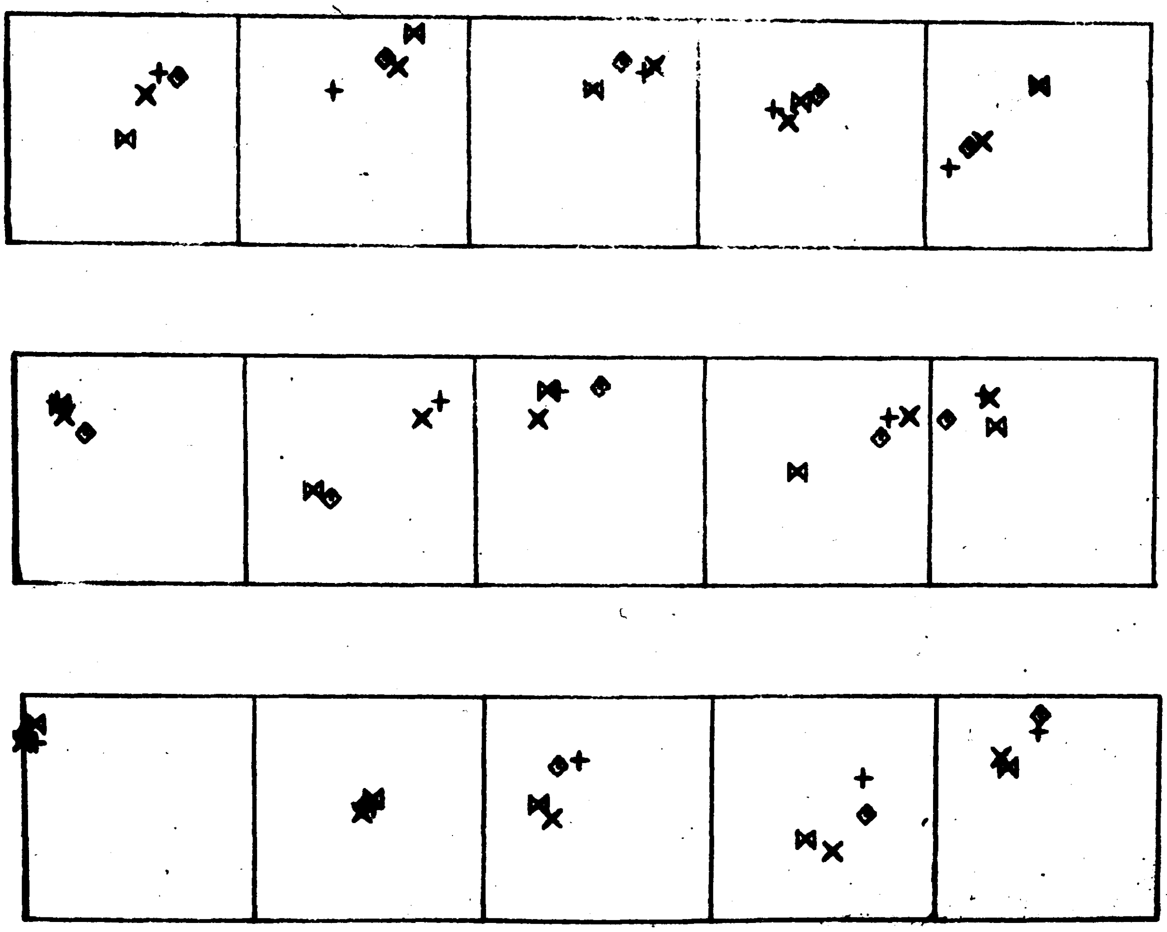
Experiment 2

(Plot of $P(A_1|S_1A;S_K)$ $P(A_1|S_2A;S_K)$

for preceding trials

S_1R_1 - + S_1R_2 X

S_2R_1 - ◇ S_2R_2 ⋈



Experiment 4

Plot of $P(A_1|S_1A;S_K)$ $P(A_1|S_2A;S_K)$

for preceding trials

S_1R_1 - + S_1R_2X

S_2R_1 - ◇ S_2R_2⋈

The effect of the experimental variables on the descriptive statistics

Much of the descriptive analysis discussed in the previous section was performed by the program OVERALL. This program derived the following statistics:-

(1) The average information in each stimulus.

(2) The average information in each response.

(3) The average information shared between latency and stimulus.

(4) The average information shared between latency and response.

(5) The average information shared between latency, stimulus and response.

(6) The χ^2 measuring relationship between latencies and stimuli.

(7) The χ^2 measuring the relation between latencies and responses.

(8) The χ^2 measuring the relationship between stimuli and responses.

(9) The χ^2 measuring relationship between stimuli responses and latencies.

(10) Variances of the total latencies in each 1/5th of the experiment.

(11) Variances of the total errors in each 1/5th of the experiment.

(12) Variances of the total responses in each 1/5th of the experiment.

(13) The χ^2 measuring the first order dependancy for the latency sequences.

(14) The χ^2 measuring the second order dependance of the latency sequences.

(15) The χ^2 measuring the first order dependancies of the response sequences.

(16) The χ^2 measuring the second order dependencies of the response sequences.

(17) The χ^2 measuring the first order dependencies of the correct wrong sequences.

(18) The χ^2 measuring the second order dependencies of the correct wrong sequences.

(19) The χ^2 measuring the first order dependencies of the SR sequences.

(20) The χ^2 measuring the second order dependencies of the SR sequences.

(21) The mean latency.

Each statistic was then used as the dependence variable in an analysis of variance to see how the experimental conditions affected each statistic. Tables of the raw data input into these analysis appear in the appendix. In the results of Experiment 1, two completely randomised designs were used. In design 1 the levels of the main effects were recognition task at probability .25, .5 and .75, and detection task at stimulis probability .5. In design 2 the levels were recognition at stimulus probabilities .25, .5 and .75. In design 2 the detection data were omitted. See table in the appendix of sample analysis. The results of this first experiment showed very little, in fact the only significant effects were:-

(1) The average information of each stimulus in both designs was significant. As this was under the control of the experimenter and deliberately manipulated in the experiment we had hoped that this result would have been obtained.

(2) The χ^2 value testing the first order dependencies of the latencies proved significant at the .05 level in design 1. This indicated that the recognition sessions showed less dependence for the latencies.

In conclusion, it appears that little was found about the effects of the experimental variables and the data in Experiment 1. A better design is required to enable one to make a precise study of the experimental effects. In particular, controlling the subject differences might be expected to increase the precision of the experiment. The analysis of the experiment No. 2 took two forms. The first form was an analysis of four factors, recognition versus detection, stimulus probability, presence or absence of feedback, and subject. While some of the same data was used in the second analysis, again using A x B x C x S design where the factors are recognition or detection task, presence or absence of burst of white noise between trials and presence or absence of feedback. The results of the first analysis on the 22 statistics mentioned above are summarised in the table below. This table shows the F statistics

F Values Computed in Experiment 2

(Ignoring Burst Data)

				EFFECT				
Stat.	Task	Stim. Prob.	Feedback	T x P	T x F	P x F	T x P x F	Subj.
Av I.S.	.00	413.34	.02	.17	.43	.35	.53	4.76
Av I.R.	3.05	36.00	26.67	.26	3.12	5.05	1.28	1.84
I.L.S.	.46	1.93	2.28	2.87	.01	1.56	.18	3.87
I.L.R.	.25	3.97	2.30	1.19	.09	2.47	6.16	3.65
I.S.R.	1.09	.91	1.27	4.34	.52	1.70	.98	36.56
I.L.S.R.	.25	2.63	14.05	1.43	.53	.78	1.30	.98
Ch.L.S.	.52	1.96	2.14	2.45	.01	1.44	.22	4.00
Ch.L.R.	.33	4.13	2.49	1.19	.06	2.97	1.30	3.49
Ch.S.R.	1.11	.32	2.07	3.79	.37	1.15	5.10	34.59
Ch.L.S.R.	2.29	7.25	.01	1.21	.38	4.00	1.30	1.04
Var. L	.00	.27	.45	2.32	.26	.59	.66	1.64
Var. E	.56	3.08	2.53	.08	.33	.99	.83	2.10
Var. R	2.20	3.69	.30	1.07	.78	2.21	.90	6.57
ChLdep.1	3.37	.81	2.62	.65	.83	.28	.55	42.55
ChLdep.2	.00	2.35	5.04	1.38	.33	.27	.49	40.09
ChRdep.1	4.53	1.76	1.43	.56	.46	.55	.76	5.81
ChRdep.2	1.62	1.52	.31	1.22	.44	1.63	1.32	4.08
ChEdep.1	6.02	1.75	7.83	1.57	5.20	1.40	.79	3.26
ChEdep.2	.00	3.07	.01	1.50	.03	.55	2.47	4.32
ChSRdep.1	3.58	1.53	.52	1.56	.50	.62	.37	32.0
ChSRdep.2	2.53	3.70	.15	.96	.18	1.65	.98	4.81
L	.41	1.06	.13	4.70	.00	4.40	2.17	8.67
DF	1,4	2,8	1,4	2,8	1,4	2,8	2,8	4,8
CritF (.05)	7.71	4.46	7.71	4.46	7.71	4.46	4.46	3.84
CritF .01	21.20	8.65	21.20	8.65	21.20	8.65	8.65	7.01

calculated and their degrees of freedom - a sample analysis appears in the appendix.

Looking at this table we find stimulus probability has an effect on the average amount of information contained in each stimulus. This result is similarly found in the first experiment, and is simply a reflection of the manipulation of the experimental variable stimulus probability. As one might expect this effect also affects the average information contained in the response to each of the stimuli. A .05 sig. effect of the S factor must be attributed to chance factors. That is to say, the maximum amount of information is obtained when the responses are equally likely. When the stimulus probabilities are not the same the responses are not equally likely. There is also a significant effect of feedback on the average information contained by a response. It appears that in both the .25 and .75 stimulus probability conditions the effect of feedback is to reduce the average information in the response. This could be attributed to the result that probability matching was greater in the presence of feedback as opposed to the no feedback condition where subjects usually show a greater tendency to respond equally to each of the two alternatives. This conclusion is supported by the presence of a significant P x F interaction, see table.

	O	F
.75	8.98	8.00
.5	9.77	9.83
.25	9.17	8.70

total average information of responses in P x F table.

A significant T x P x F interaction effect is found in the average information shared between S and R.

	R			D		
	.75	.5	.25	.75	.5	.25
O	1.0	.8	1.3	.9	1.3	.6
F	1.1	1.6	1.0	1.1	1.1	.9

total average information shared between S x R in T x P x F table.

It appears in the O feedback recognition condition subjects do better when the a priori stimulus probability are equal while the reverse is true in the detection task.

Feedback appears to affect the shared information between LS and R.

O	F
-.319	.04

total average information shared between TS and R

In the absence of feedback there appears to be an interaction effect between TS and R cancelling out any shared information, (i.e. a relation between correctness and latency.)

When the analysis is repeated on the equivalent χ^2 a significant T x P x F interaction effect was found in the SR dependence as was described above. However, on the χ^2 measuring the second order interdependence of SR and T no significant Feedback effect was found although a significant stimulus probability effect was observed, indicating a much higher inderdependence in the .75 S condition.

It is possible that the variance in total response one's errors and latencies might be related to non stationability. Accordingly this statistic was used in this analysis. The only significant experimental effect was a P x F interaction on the variance of the errors.

	O	F
.75	24	25
.5	52	29
.25	32	25

total variance of total errors in each 1/5th of the experiment

Feedback appears to reduce the variance in this .5 stimulus probability condition.

Analysis of variance were then run on χ^2 measuring first and second order markov dependence. The only significant effects were found on the correct wrong sequences where it was found that the 1st order dependence was greatest in the absence of feedback.

O	F
1 78 .8	91.4

total χ^2 df3 measuring 1st order dependence in correct wrong sequences (each figure is the total of 30 χ^2.

Finally a significant T x P interaction was found on the total latencies.

	.75	.5	.25	
R	7729	9373	6515	total latencies
D	7916	8027	9102	

It appears that the total latency in the equi-variable stimulus condition is greatest in the recognition task - this is not true in the detection task.

We shall now consider an analysis of the results of the same experiment this time ignoring the unequal stimulus probability condition. (For a sample analysis see appendix.) The table below gives the computed F values and their degrees of freedom.

On examining an analysis of the information statistics the significant (0.5) effects are:-

a T x B interaction effect on the shared information between T and S.

	R	D	
O	.13	.19	total average information
B	.12	.10	shared between S and T

It appears that the addition of a burst of white noise reduces the relation between stimulus and latency on a trial in the detection task but not in the recognition task. There is also a significant T x F interaction in the shared information between S and R.

	O	F	
R	2.03	2.92	total average information
D	2.29	1.99	shared between S and R

Feedback appears to help the recognition task but not the detection. It may be worth remembering that in this experiment some of the Detection task have bursts of white noise between trials. A significant effect of Feedback on information shared between SR and L.

O	F
-.28	-.17

total average information shared between LS and R

This is similar to the effect noted in the last analysis. When the same analysis was performed on the χ^2 equivalent to the information statistics the T x B and T x F interaction reported above were found to be significant (.05). The effect of feedback on the information shared between LS and R was not found.

The only effect of an experimental variable on the variances of the totals for each 1/5th of the sessions was in the error variance where a significant F x B effect was observed.

F Values Computed in Experiment 2

(Ignoring unequal Prob. condition)

	Task	Feedback	Burst	T x F	T x B	F x B	T x F x B	Subj
Av I.S.	.0	.1	.5	1.9	1.7	3.0	.0	1.8
Av I.R.	4.3	.0	4.5	.1	1.2	1.8	.8	5.4
I.L.S.	.3	.4	.4	.5	17.2	.1	1.5	9.8
I.L.R.	.3	.7	.1	1.8	.5	.4	.1	.9
I.S.R.	.6	1.3	.2	12.8	6.9	1.9	4.7	53.2
I.L.S.R.	.3	7.8	.3	1.5	1.8	1.6	.8	.5
Ch.L.S.	.3	.5	.4	.5	18.2	.1	1.63	10.5
Ch.L.R.	.2	.6	.1	1.6	.3	.4	.1	1.0
Ch.S.R.	.6	1.5	.2	11.8	5.0	1.8	5.0	61.2
Ch.L.S.R.	.1	1.5	.3	1.0	2.5	5.4	.2	.9
Var.L	.0	.1	.1	1.6	5.0	1.6	.0	1.7
Var.E	.2	1.0	4.8	.9	1.7	8.7	.0	9.6
Var.R	.0	.0	2.0	2.1	.4	2.1	1.8	1.6
ChLdep.1	1.9	2.0	4.0	1.4	4.6	.4	1.7	21.0
ChLdep.2	1.3	1.5	.2	3.2	1.2	.3	2.6	5.3
ChRdep.1	2.2	1.1	1.3	.7	2.2	1.0	1.1	7.6
ChRdep.2	1.6	1.8	.2	1.3	.2	.3	.0	44.8
ChEdep.1	2.7	6.4	8.7	5.4	3.6	10.5	1.4	3.8
ChEdep.2	.1	2.3	.0	3.7	3.0	.3	.5	.3
ChSRdep.1	7.2	.4	3.1	1.0	.9	.5	.6	1.8
ChSRdep.2	4.2	3.2	1.0	1.5	.1	.0	.0	4.4
L	2.3	.5	1.5	1.5	9.2	5.1	1.0	15.3
DF	1,4	1,4	1,4	1,4	1,4	1,4	1,4	1,4
CritF (.05)	7.71	7.71	7.71	7.71	7.71	7.71	7.71	6.39
CritF (.01)	21.2	21.2	21.2	21.2	21.2	21.2	21.2	15.52

	O	B	
O	22.8	52.3	variance of total errors
F	41.9	28.7	in each 1/5th of the session

This indicates that the presence of a burst decreases the error variance in the O feedback condition and increases it in the feedback condition.

In the analysis performed on χ^2 measuring markov dependence in sequences of errors responses latencies and SR combinations. The experimental variables were shown to affect dependence only in the error sequences. Here Burst has the effect of increasing first order dependence.

O	B
33.3	75.7

total $\chi^2 df_1$ measuring 1st order dependence
(20 χ^2 in each condition)

Burst x Feedback interaction is also found

	O	B
O	20.6	66.7
F	12.7	9.0

total $\chi^2 df_1$ measuring 1st order dependence

It appears feedback has the effect of reducing the dependence in the Burst condition.

A similar analysis was performed on statistics calculated from experiment three. A sample analysis is reproduced in the appendix. The F ratios and their degree of freedom are reproduced in the table below.

We find a significant effect T x D on the average information contained in each stimulus. The stimuli were randomly generated however we have performed 17 significant tests on this statistic and we might expect to get one significant (.05 level) by chance. A significant Difficulty effect was found on the average information contained in each response.

E	M	D
29.95	29.67	29.45

total average information in each response

Since in the easy condition subjects were getting almost all trials correct they had no opportunity to show response preferences. Also, a massive effect was obtained on the effect of difficulty on information shared between S and R, as one would expect.

E	M	D
25.86	11.21	4.14

The effect was reproduced in the test on the equivalent χ^2s. A significant (.05) effect was also obtained of the effect of Difficulty on χ^2 measuring the second order interaction between SR and L. It should be noted that in many cases in the easy condition there were too few frequencies for the estimated χ^2 statistic to be distributed as χ^2.

On examining the effect of experimental variables on the variances of totals for each half of a session Difficulty appeared to increase the error variance. This is probably due to the fact that it had a large effect on the total number of errors.

E	M	D
8.61	104.65	143.16

variances of total errors in each 1/5th of the session

F Values Computed in Experiment 3

	Time	Feed back	Diffi culty	T x F	T x D	F x D	T x F x D	Subj
AvI.S.	.6	.1	1.8	.5	4.9	.8	1.21	.6
AvI.R.	1.4	2.2	6.3	.4	.9	1.3	1.5	3.3
I.L.S.	3.1	1.3	1.8	.9	1.4	2.3	1.9	16.1
I.L.R.	3.8	1.2	1.4	1.7	1.2	2.3	1.5	12.1
I.S.R.	.0	.9	116.6	.4	.1	.8	1.8	3.5
I.L.S.R.	2.7	1.3	2.4	1.4	1.2	1.8	1.5	2.7
Ch.L.S.	3.2	1.3	1.8	.8	1.3	2.4	2.0	19.3
Ch.L.R.	4.0	1.1	1.4	1.7	1.1	2.3	1.5	13.1
Ch.S.R.	.0	.8	103.5	.4	.1	.8	1.7	2.2
Ch.L.S.R.	2.2	.5	6.0	.0	1.3	1.0	.1	15.8
Var.L	1.1	1.1	.2	1.8	.8	1.0	.7	1.6
Var.E	.1	.2	9.3	1.4	1.3	1.2	1.0	.6
Var.R	.5	1.7	.6	1.3	.8	4.5	1.6	.9
ChLdep.1	1.4	1.7	.4	.9	2.9	1.5	1.4	2.6
ChLdep.2	2.4	.9	1.9	.8	1.9	.7	.9	1.8
ChRdep.1	4.7	.7	7.1	1.4	6.5	.5	1.0	2.0
ChRdep.2	.0	2.1	1.9	.7	1.7	.7	1.7	1.4
ChEdep.1	.5	1.0	1.2	2.2	.6	1.2	.8	1.4
ChEdep.2	1.5	.1	.2	1.2	2.2	.5	1.1	1.6
ChSRdep.1	2.1	1.5	4.6	2.2	1.8	.2	.8	1.5
Ch SRdep.2	.2	1.0	12.3	.8	2.2	.9	1.0	2.2
L	9.3	.3	9.2	.7	1.0	.0	1.1	3.9
DF	1,4	2,8	2,8	2,8	2,8	4,16	4,16	4,16
Crit F(05)	7.71 21.20	4.46 8.65	4.46 8.65	4.46 8.65	4.46 8.65	3.01 4.77	3.01 4.77	3.01 4.77

An F x D interaction was found on the variances of the total responses.

	E	M	D
O	38	30	59
V	29	47	24
F	24	28	40

variance of total response one's in each 1/5th of the session

Variable feedback appears to increase the observed variance in the medium difficulty task and reduce it in the difficult condition.

In examining the effect of experimental variables on χ^2 measuring 0 and first order dependencies. The most important factor appears to be task difficulty. Obviously if the subject is responding 100% correctly his response sequence is an 0 order markov if the stimulus sequence is an 0 order markov. We thus find significant effects of difficulty on χ^2 measuring the first order dependencies in the response and SR sequences and in the χ^2 measuring second order dependencies in the SR sequences. There is also a significant (.05) Times x Difficulty interaction on the χ^2 measuring the first order dependencies in the response sequences.

	E	M	D
S	13.6	58.6	141.9
L	23.1	24.7	35.1

total $\chi^2 df_1$ measuring first order dependencies in response sequences (each total contain 15 χ^2s)

It seems that apart from in the easy condition a longer dead period between trials reduces the dependence in the response sequences.

Finally in the analysis of the latencies it appears that the subjects take longer if the task is more difficult

E	M	D	
18249	24005	26929	total latency

and that a longer dead period between trials increases the subjects' latency.

S	L	
31461	37722	total latency

Analysis performed on the results of experiment four showed no significant effect of the only experimental variable feedback. As there were only 15 sessions all using naive subjects it is not a very powerful test. It was again a simple randomised design as experiment one.

Since so many F tests were performed it seems likely that some apparently significant Fs are due to chance. However, bearing that in mind one can tentatively draw the conclusion that separating sequential effects into response dependencies and correct wrong dependencies is useful as difficulty and intertrial period appear to affect the former while feed-back and the introduction of a burst of noise between trials affect the latter.

Also worthy of mention is the frequency of large subjects' differences found when the MS subjects were tested against the MSA x B x C x S interaction.

Detection and Recognition Models

(a)Estimation of parameters of detection and recognition models

This analysis was performed using a program called ESTIMATE. It contained five estimation procedures. These procedures estimated the parameters for each model for all the data collected in one session. For the same data divided into four groups depending on the state on the immediately preceding trial and for all the data grouped into 16 parts depending on the state on the immediately preceding two trials. These latter estimates were not very useful since the data involved in each estimation was very small, or even non-existent. In this case it was proved possible to obtain estimates of these parameters depending on the immediately two preceding trials. The five estimation procedures were (1) Luce (this estimates the sensitivity and bias parameters of Luce's choice model),
(2) DP (this estimates the sensitivity d' and the bias parameter B for Tanner Swets and Green's model),
(3) Classical (this estimates the threshold statistic and the probability of being correct statistic),
(4) ATK (this estimates the sensitivity parameter sigma and the bias parameter of Atkinson's model), and
(5) NP (this estimates the non-parametric statistics A' and percentage bias). The results of this program on the data for Experiments 1, 2, 3 and 4 are given in the tables below.

The values given are that for each statistic for each session, together with the values of the statistic depending on the immediately preceding trial. In cases where not enough data was available to estimate the statistic in a certain condition, the value given in the table is zero. It is important to realise that these are not parameter estimates, merely blanks indicating that no estimation was possible. The values of the statistic depending on the immediately preceding two trials are not quoted for each session, however the mean values of these parameters over each experiment are available, and will appear for a different purpose in the simulation section. The program

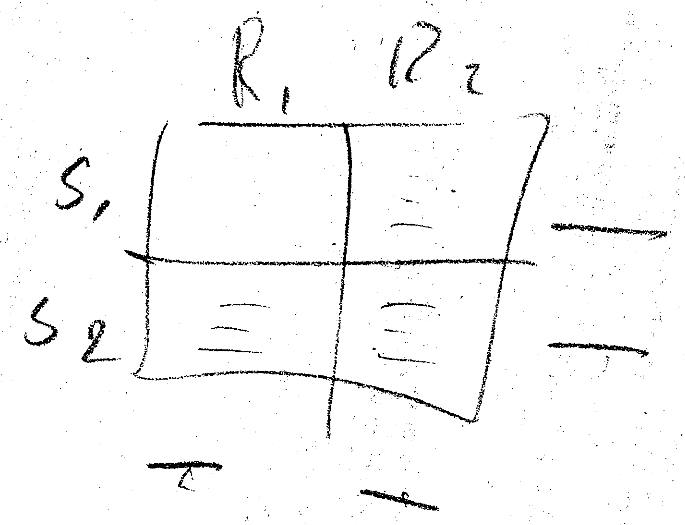
ESTIMATE also performed the Friedman two way analysis of variance on the estimates of each parameter depending on the immediately preceding trials. A significant χ^2_r value obtained in one of these analyses indicated that a particular statistic was dependent on the immediately preceding trial and that the nature of the dependency was consistent over all the subjects in that particular session. The mean value of each statistic depending on whether the last trial was S1 or S2 was calculated from the same data and again a Friedman analysis performed to see whether the stimulus on the last trial had any effect on this statistic. This method was applied to test the hypothesis at the response on the immediately preceding trial affected each statistic and that the correctness of the immediately preceding trial also affected the statistic. The results of experiment 1 are summarised in the tables below. The other experiments were analysed in the same way but the detailed results are not included for lack of space.

In Experiment 1 we find that all the sensitivity parameters were dependent on the state on the immediately preceding trial. A more detailed analysis revealed that the two threshold statistics and the non-parametric measure depended on whether the subject was correct or wrong in the immediately preceding trial. That is to say, an estimate of his sensitivity following a correct trial was higher than that following a wrong trial. The threshold value was also significantly related to what response was present on the last trial. He was more likely to be correct following a response signal present than following a response noise alone. On looking at the bias parameters we find a slightly different pattern of results. Again, all the bias parameters studied were significantly related to the state on the immediately preceding trial and they were also related to the response on that trial. This indicates an overall tendency on the part of the subjects to maintain the response on the immediately preceding trial. The Luce-bias parameter shows a significant effect relating to the stimulus on the last trial. The Tanner Swets and Green bias parameter was

EXPERIMENT NO 1
ESTIMATION 1LUCES CHOICE MODEL

STATE ON LAST TRIAL SESSION	Z OVERALL	Z S1R1	Z S1R2	Z S2R1	Z S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	.220	.171	.289	.306	.198	1.49	1.42	.577	3.83	1.13
2	.913	.500	.997	1.01	.888	.563	.333	.554	.252	.858
3	.583	.658	1.04	.679	.478	.574	1.07	.209	1.02	.442
4	.543	.000	.577	.577	.409	3.29	.000	.577	15.0	.784
5	.751	.905	.637	.559	.580	.816	3.32	.294	5.78	.198
6	.633	.428	.682	.773	.524	1.34	.594	2.20	.981	3.89
7	.905	.636	1.13	1.25	.930	.946	1.77	.529	1.67	.603
8	.168	.041	.346	.000	.192	1.88	5.71	.289	.000	.983
9	.826	.593	.758	.532	.930	2.13	7.54	.273	12.1	.338
10	.763	.658	.953	.791	.690	1.29	1.26	1.00	1.26	1.59
11	.833	.704	.794	.983	1.15	1.22	1.69	.756	2.04	.764
12	.679	.580	.779	.950	.469	.785	1.55	.347	4.21	.305
13	.074	.055	.000	.000	.169	14.2	16.2	.000	.000	5.92
14	.288	.208	.261	.258	.471	2.16	1.90	.547	9.30	3.30
15	.242	.209	.098	.333	.278	.898	.549	.600	4.00	2.62
16	.151	.169	.115	.000	.145	.725	.685	.346	.000	.765
17	1.09	1.33	1.17	1.07	.885	3.41	8.80	.389	13.0	.466
18	.118	.115	.000	.000	.104	.786	.667	.000	.000	1.24
19	.455	.272	.775	.730	.446	1.21	1.30	.671	1.31	1.41
20	.777	.809	.779	.905	.646	.758	.659	.833	1.41	.498
21	.652	.579	.588	.761	.783	.896	.933	.729	.657	1.23
22	.799	.800	.699	1.28	.603	.533	1.08	.381	1.17	.302
23	.534	.418	.676	.540	.386	1.66	3.76	.285	4.23	.707
24	.270	.288	.367	.343	.202	1.05	.923	.779	1.89	1.07
25	.764	.677	.816	.893	.533	1.13	2.67	.387	3.20	.383

FOR FIRST PARAMETER OVERALL FRIEDMAN 15.0
STIM FRIEDMAN .800RESP FRIEDMAN .800COR WR FRIEDMAN 3.20


R_1
R_2
S_1
S_2

EXPERIMENT NO 1
ESTIMATION 2TANNER SWETS GREEN MODEL

STATE ON LAST TRIAL SESSION	DPRIME OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	1.83	2.10	1.51	1.42	1.95	1.05	1.19	.583	1.09	1.02
2	.114	.857	.003	-.008	.149	.041	.223	.001	-.002	.069
3	.673	.523	-.052	.483	.913	.248	.270	-.009	.244	.289
4	.756	.000	.684	.678	1.10	.573	.000	.253	.633	.491
5	.359	.126	.561	.718	.674	.162	.097	.130	.607	.116
6	.571	1.05	.477	.323	.799	.326	.401	.327	.160	.628
7	.126	.564	-.157	-.279	.091	.061	.358	-.055	-.174	.034
8	2.11	3.38	1.29	.000	1.98	1.30	2.36	.319	.000	.985
9	.240	.647	.346	.775	.091	.163	.568	.075	.711	.023
10	.338	.522	.060	.294	.464	.190	.290	.030	.164	.285
11	.228	.439	.289	.022	-.170	.125	.276	.124	.015	-.074
12	.483	.679	.313	.064	.933	.213	.410	.081	.052	.230
13	2.72	2.96	.000	.000	2.03	2.30	2.49	.000	.000	1.62
14	1.51	1.88	1.62	1.58	.926	.994	1.17	.613	1.38	.700
15	1.72	1.88	2.68	1.33	1.55	.822	.723	1.13	1.03	1.07
16	2.24	2.11	2.48	.000	2.28	.993	.912	.819	.000	1.03
17	-.107	-.357	-.194	-.089	.154	-.083	-.320	-.055	-.083	.049
18	2.50	2.52	.000	.000	2.62	1.15	1.09	.000	.000	1.40
19	.977	1.59	.320	.393	.999	.531	.881	.129	.223	.578
20	.316	.265	.313	.126	.545	.136	.106	.142	.073	.183
21	.534	.682	.663	.342	.307	.253	.330	.281	.136	.169
22	.281	.279	.447	-.313	.629	.098	.145	.125	-.169	.149
23	.781	1.07	.489	.761	1.17	.483	.826	.110	.609	.496
24	1.59	1.52	1.24	1.31	1.93	.811	.735	.549	.834	.988
25	.337	.486	.254	.142	.780	.179	.352	.071	.108	.222

FOR FIRST PARAMETER OVERALL FRIEDMAN 15.3
STIM FRIEDMAN .200RESP FRIEDMAN .800COR WR FRIEDMAN 3.20

EXPERIMENT NO 1
ESTIMATION 3CLASSICAL THRESHOLD MODEL

STATE ON LAST TRIAL SESSION	THRESHOLD OVERALL	THRESHOLD S1R1	THRESHOLD S1R2	THRESHOLD S2R1	THRESHOLD S2R2	P(C) OVERALL	P(C) S1R1	P(C) S1R2	P(C) S2R1	P(C) S2R2
1	.829	.867	.611	.839	.818	.570	.652	.647	.200	.652
2	.063	.300	.002	-.003	.104	.189	.511	.178	.271	.100
3	.328	.351	-.014	.323	.371	.362	.194	.412	.187	.456
4	.605	.000	.333	.643	.547	-.057	.000	.375	-.417	.464
5	.227	.143	.188	.627	.169	.193	-.258	.333	-.208	.515
6	.407	.475	.408	.225	.640	.216	.370	.154	.128	.130
7	.093	.438	-.091	-.321	.053	.048	.206	-.062	-.028	.040
8	.892	.991	.400	.000	.806	.690	.830	.364	.000	.678
9	.229	.601	.113	.687	.036	.079	.169	.101	.000	.033
10	.262	.372	.047	.231	.366	.120	.197	.024	.111	.124
11	.182	.357	.180	.023	-.125	.140	.286	.033	.148	-.133
12	.289	.483	.121	.079	.307	.137	.337	-.114	.375	.044
13	.989	.994	.000	.000	.944	.752	.785	.000	.000	.607
14	.809	.862	.630	.908	.681	.613	.695	.429	.519	.494
15	.741	.693	.851	.821	.834	.591	.526	.755	.500	.674
16	.809	.779	.740	.000	.823	.731	.703	.762	.000	.738
17	-.141	-.670	-.091	-.141	.075	-.034	-.011	-.033	-.066	.019
18	.858	.841	.000	.000	.912	.787	.787	.000	.000	.807
19	.576	.767	.186	.300	.608	.369	.566	.152	.143	.373
20	.196	.155	.203	.111	.253	.129	.136	.124	.042	.178
21	.333	.411	.363	.195	.237	.205	.266	.235	.133	.141
22	.145	.207	.180	-.310	.212	.114	.104	.167	-.117	.182
23	.541	.743	.161	.628	.551	.276	.289	.172	.115	.435
24	.736	.699	.589	.747	.807	.574	.552	.462	.444	.665
25	.248	.432	.107	.158	.299	.136	.185	.057	.046	.222

FOR FIRST PARAMETER OVERALL FRIEDMAN 11.3
STIM FRIEDMAN .200RESP FRIEDMAN 5.00COR WR FRIEDMAN 7.20

EXPERIMENT NO 1
ESTIMATION 4 NONPARAMETRIC ANALYSIS

STATE ON LAST TRIAL SESSION	APRIME OVERALL	APRIME S1R1	APRIME S1R2	APRIME S2R1	APRIME S2R2	BIAS OVERALL	BIAS S1R1	BIAS S1R2	BIAS S2R1	BIAS S2R2
1	.887	.912	.849	.814	.901	-39.5	-39.2	44.9	-72.4	-15.4
2	.543	.736	.501	.497	.556	4.96	49.0	.151	.789	1.81
3	.706	.671	.480	.660	.752	24.9	-2.73	5.31	-.718	42.3
4	.714	.000	.708	.678	.794	-47.1	.000	25.0	-61.6	18.4
5	.625	.547	.672	.697	.691	5.60	-10.2	38.5	-55.4	51.2
6	.683	.782	.655	.614	.720	-12.2	33.6	-24.7	.502	-52.6
7	.546	.679	.441	.401	.535	.551	-21.9	7.44	-10.5	3.53
8	.908	.950	.800	.000	.904	-58.8	-95.4	66.7	.000	2.24
9	.586	.680	.616	.696	.535	-12.9	-54.8	27.0	-65.3	6.96
10	.618	.670	.523	.605	.654	-6.58	-9.03	-.005	-5.33	-15.5
11	.583	.647	.603	.509	.437	-3.54	-16.4	6.19	-1.19	3.57
12	.660	.708	.608	.525	.748	8.79	-20.6	21.5	-6.08	54.2
13	.868	.880	.000	.000	.858	-97.9	-98.6	.000	.000	-89.2
14	.844	.887	.861	.796	.746	-56.1	-56.1	50.0	-87.3	-54.1
15	.879	.888	.947	.800	.842	12.3	53.7	56.6	-71.0	-64.4
16	.923	.912	.922	.000	.926	37.7	41.4	80.3	.000	32.9
17	.460	.385	.429	.467	.557	-8.91	-36.5	12.7	-11.5	8.55
18	.940	.939	.000	.000	.947	31.6	47.2	.000	.000	-29.6
19	.772	.863	.612	.635	.775	-13.1	-26.1	9.51	-8.12	-22.8
20	.611	.595	.610	.548	.673	6.68	8.31	4.44	-3.33	25.0
21	.674	.711	.705	.619	.608	4.51	3.62	15.0	10.6	-4.97
22	.600	.600	.646	.389	.688	12.8	-1.75	27.2	-3.78	41.4
23	.730	.766	.654	.711	.805	-26.0	-62.1	35.1	-52.6	26.3
24	.865	.856	.815	.821	.899	-4.97	8.42	20.6	-45.4	-8.79
25	.618	.656	.590	.553	.723	-3.25	-29.6	16.4	-11.2	42.1

FOR FIRST PARAMETER OVERALL FRIEDMAN 15.3
STIM FRIEDMAN .800RESP FRIEDMAN .200COR WR FRIEDMAN 3.20

EXPERIMENT NO
ESTIMATION 5 ATKINSONS MODEL

STATE ON LAST TRIAL SESSION	SIGMA OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	.625	.697	.524	.386	.668	.189	.244	1.42	.039	.285
2	.042	.257	.001	-.002	.059	.566	1.35	.561	1.23	.365
3	.246	.206	-.012	.191	.306	.747	.328	1.72	.362	1.08
4	.217	.000	.250	.067	.414	.065	.000	.567	.012	.384
5	.141	.036	.158	.148	.152	.396	.090	1.22	.036	2.35
6	.220	.379	.163	.128	.210	.667	1.80	.376	.965	.190
7	.050	.206	-.057	-.104	.034	1.21	.596	2.07	.763	1.95
8	.678	.804	.364	.000	.678	.400	-.097	8.62	.000	1.33
9	.083	.110	.093	.093	.028	.431	.082	4.23	.054	3.02
10	.132	.203	.024	.115	.174	.622	.617	.827	.630	.509
11	.090	.163	.113	.008	-.067	2.51	1.70	4.18	1.52	4.00
12	.188	.254	.096	.016	.269	3.48	1.54	8.50	.596	12.3
13	.482	.526	.000	.000	.472	.034	-.005	.000	.000	.661
14	.499	.619	.551	.267	.266	.778	.952	3.92	.129	.495
15	.609	.622	.804	.352	.483	4.10	9.13	7.84	.790	.698
16	.729	.698	.712	.000	.740	1.68	2.14	-8.05	.000	1.08
17	-.030	-.053	-.063	-.009	.053	.305	.143	2.36	.081	2.20
18	.785	.781	.000	.000	.808	1.41	2.62	.000	.000	.523
19	.372	.566	.122	.153	.373	.725	.575	1.52	.695	.563
20	.123	.101	.123	.049	.192	1.26	1.51	1.12	.645	2.04
21	.210	.267	.254	.130	.121	1.39	1.39	1.76	2.02	.932
22	.102	.111	.142	-.124	.179	1.87	.880	2.88	.835	3.94
23	.287	.289	.135	.191	.433	.475	.139	4.05	.162	1.44
24	.574	.552	.458	.453	.664	.963	1.20	1.64	.450	.780
25	.133	.154	.081	.041	.248	.972	.349	3.16	.332	3.82

FOR FIRST PARAMETER OVERALL FRIEDMAN 20.8
STIM FRIEDMAN .800RESP FRIEDMAN .000COR WR FRIEDMAN 7.20

DEPENDENCE OF STATISTIC ON IMMEDIATELY PRECEDING TRIAL

CONDITION ALL EXPERIMENTS

	Experiment 1				Experiment 2				Experiment 3				Experiment 4			
Stat	O	S	R	CW	O	S	R	CW	O	S	R	CW	O	S	R	CW
η	X							X	X	X		X				X
d'	X							X	X	X		X				X
Th	X		X	X	X		X		X	X	X	X				X
P(c)	X			X	X			X	X	X		X				
A	X			X	X			X	X	X		X				
σ	X				X			X	X	X		X				
b(Luce)	X	X	X		X		X		X	X						
b(TSG)	X		X	X	X		X		X	X						
Bias %	X		X		X		X		X	X						
b(ATK)	X		X		X		X		X	X						

O = Overall
S = Stimulus
R = Response

CW = Correct Wrong

X = Sig at .05 level

found to be related to the correctness on the immediately preceding trial. This could have been expected in the case of this parameter as the measure of bias was taken to be the distance between the mean of the noise distribution to the cut off or criterion, and must be related to sensitivity as well as to bias.

Looking at the results of the second experiment we again have fairly clear cut results. Four of the sensitivity parameters are found to be significant though dependent on the immediately preceding trial, while five out of six of them are dependent on whether the state on the last trial was correct or not. The threshold statistic is again related to the response made by the subject on the immediately preceding trial. The bias parameters are all significantly related to the last trial, and in particular to the response made on the last trial. This indicates a tendency of subjects to maintain the response they made on the immediately preceding trial.

In Experiment No. 3 a slightly different pattern emerged. All the estimates of the parameters were found to be related to the immediately preceding trials. However, the sensitivity parameters as well as being related to the correctness of the immediately preceding trial were also found to be related to the stimulus presented on that trial. And the bias parameters were no longer related to the response on the last trial but were related to the stimulus present on that trial. In this experiment two-thirds of the conditions involve feedback and it might be that the more feedback the more the bias parameter tended to be related to the feedback (i.e. the stimulus on the immediately preceding trial) rather than the immediately preceding response.

In the final experiment No. 4 the only significant result found was that the sensitivity statistics were related to the correctness of the subject on the immediately preceding trial.

From this analysis we have now found that both sensitivity and bias statistics are affected by inter-trial dependence. In the case of the sensitivity statistic the most important effect appears to be whether the subject was correct or wrong on the immediately preceding trial. This is what was expected as if the subjects were alternating between two or more states of different performance levels then we would expect this result. More surprising result is the dependence of the sensitivity statistics on the stimulus presented on the immediately preceding trial as found in experiment No. 3. On examining the results of the bias parameter we find that they tend to be related to the response made by the immediately preceding trial but again in Experiment 3 the bias parameter is related to the stimulus present in that trial. Another difference between Experiment 3 and the others which might have been responsible for this difference is that it involved only the detection task. In Experiment 2 the only other involving large number of sessions by the same subject half the time the task was recognition and half the time it was detection.

The only other detection or recognition model applied to this data was the one by Tanner Rauk & Atkinson. A program MEMREC was written to perform a minimum χ^2 procedure and estimate the parameters of the model in the no feedback situation. As already stated (see Introduction) the prediction made by the model is that the ROC points calculated depending on the state on the immediately preceding trial should all lie on the same ROC curve. We saw in the previous section that this was not the case. It is therefore not surprising that the fits obtained by the model were not particularly good. This program took as starting values the parameter values found in the Tanner Rauk and Atkinson paper. It systematically varied each of the parameters and measured the goodness of fit of the model until no change in the parameters produced any better fit. The procedure was repeated until the χ^2 obtained did not change by more than .01 when any of the parameters were changed. The degrees of freedom in the second order probabilities from which the model's parameters were estimated are twelve. There were four

MIN. χ^2 OBTAINED FROM THE TANNER RAUK & ATKINSON MODEL.

Condition	Session	Min. χ^2
	1	166.5
	2	39.9
.25R	3	38.9
	4	91.0
	5	114.4
	6	18.2
	7	31.7
.5R	8	298.0
	9	57.2
	10	16.5
	11	37.3
	12	31.6
.75R	13	377.1
	14	185.3
	15	166.2
	16	89.3
	17	163.0
	18	203.0
	19	8.1
.5D	20	12.2
	21	25.5
	22	14.3
	23	28.4
	24	13.6
	25	36.4

parameters estimated leaving eight degrees of freedom if the parameters were all independent. Using this conservative estimate of the degrees of freedom in the situation we find that out of the 25 sessions in Experiment 1 only six are not significant at the .05 level. The Table below gives the parameter values of the model and the final minimum χ^2 for each of the 25 subjects. Unfortunately this procedure took a very long time to obtain a minimum solution. As a result of this it was impossible to use the program on the results of experiments 2, 3 and 4.

(b) <u>The Effects of Experimental Variables on the Parameters of the Detection and Recognition Models</u>

The analysis of the effects of the experimental variables on the estimates of the parameters of the models was performed using a program SEST. This program was a composite of ESTIMATE and OVERALL. In this program each of the estimates of the parameters of the model were re-derived and analyses of variance were performed on the overall estimates for each session to examine the effect of the experimental variables. In order to give an idea as to whether the dependence of the estimate on the immediately preceding trial was related to the experimental condition, an estimate of the variance of the estimated parameters was found from the statistics based on data preceded by the same trial. This variance statistic was an estimate of the standard error of the estimate of the parameter together with a sizeable component due to the fact that the estimate depended on the state on the immediately preceding trial. Differences in the variance statistic between different experimental conditions will be interpreted as implying that the dependence of the statistic on the immediately preceding trial changed as a result of the experimental conditions. The results of Experiments 1, 2, 3 and 4 are summarised in the tables below.

We see that for the results of Experiment 1 none of the analyses revealed any significant results. As before the analysis of the data in Experiment 2 was divided into two sections. One involving an analysis of task by a priori stimulus probability by feedback by subject, and the other involving an analysis of task by feedback by burst by subject. The results of the analysis of the task by probability by feedback by subject shows that there is a significant subject effect on all the sensitivity parameters and a significant task by subject interaction on four out of six of them. This indicates that the differences between subjects were not well controlled at the beginning of the experiment. It is interesting to note that both the threshold and probability correct statistics are affected by a priori stimulus probabilities. This was the original justification for signal detection models in that they enabled sensitivity statistics to be derived which were independent of the experimental conditions. Here we find that all the sensitivity parameters based on the signal detection models are unrelated to the experimental conditions ignoring subject differences while the classical ones are not. Looking at the bias statistic we find that all the statistics are affected by the stimulus probabilities. Again, this is a classical finding. For three of the parameters there are differences between subjects. There is a significant probability by feedback interaction in all the bias statistics. This shows that where no feedback is given and the stimulus probabilities are not equal subjects tend to respond more equally than when feedback is given, i.e. in the presence of feedback subjects tend to probability match and in its absence they tend to respond equally on all the different alternatives. Related to this interaction we find that for two of the estimates of the parameters there is a significant probability by feedback by subject interaction, a probability by subject interaction, a feedback by subject interaction, and one significant feedback effect on its own. The results of a task by subject interaction effect in one of the conditions.

This analysis of variance was then applied to the statistic variances which were estimates of the degree to which the statistic was dependent on the immediately preceding trial. These results showed a significant subject effect in all bar one case indicating the dependence of the bias statistic on the immediately preceding trial in all bar one case was related to the individual subject. It was also found in all bar one case that the task was related to the dependence of the sensitivity statistic. It appears that the dependence between trials is greatest in a recognition rather than a detection task. Two task by subject interactions were also observed. In the consideration of the variance of the probability correct statistic we find that the probability and probability by subject interaction effects are significant. This was one of the sensitivity statistics which were found to be related to

CONDITION EXPERIMENT NO 2

Stat.	Task	Prob	Feed back	S	TP	TF	TS	PF	PS	FS	TPF	TPS	TFS	PFS
η				X			X							
d'				X			X				X			
Th		X		X			X							
P(c)		X	X	X										
A'				X			X							
σ				X										
ην	X			X						X				
d'ν						X								
Thν														
P(c)ν	X	X		X			X		X					
A'ν	X			X						X				
σν				X		X								
b(Luce)		X						X						
b(TSG)		X		X				X						
Bias %		X		X			X	X	X	X			X	
b(ATK)		X	X	X				X	X	X			X	
b(Luce)ν														
b(TSG) ν														
Bias % ν														
b(ATK) ν														
df	1,8	2,8	1,8	4,8	2,8	1,8	4,8	2,8	8,8	4,8	2,8	8,8	4,8	8,8

X sig at 05 level

X sig at 01 level

CONDITION EXPERIMENT NO 2

Stat	Task	Feed back	Burst	S	TF	TB	TS	FB	BS	FS	TFB	TBS	TFS	FBS
η				X										
d'				X										
Th				X										
P(c)				X			X							
A'				X			X							
σ				X			X							
ην														
d'ν				X										
Thν														
P(c)ν	X	X	X	X	X	X	X	X		X	X	X		
A'ν														
σν	X	X	X	X	X		X	X		X	X			
b(Luce)														
B(TSG)				X										
Bias %			X	X								X		
b(ATK)	X			X			X					X		
b(Luce)ν														
b(TSG)ν														
Bias %ν														
b(ATK)ν														
df	1,4	1,4	1,4	4,4	1,4	1,4	4,4	1,4	4,4	4,4	1,4	4,4	4,4	4,4

X sig at 05 level

X sig at 01 level

a priori stimulus probability. As the value of the probability increases so does its variance. In Luce's model and in the non-parametric analysis a significant feedback by subject interaction was found on the variance of the sensitivity statistic and in Atkinson's model a significant task by feedback interaction was also found. To summarize then the major effect on the dependence of the sensitivity statistics of detection and recognition models are subject variables and task variables. The recognition task showed more inter-trial dependence from the detection task. When we examine the effect of experimental conditions on the dependence of the bias statistic on the immediately preceding trial no significant results were found.

The results of the second analysis performed on Experiment 2 involving the task by feedback by burst by subject design is given in the table above. We find first of all that the sensitivity parameter is dependent on the subject, thus the individual subject differences were not entirely controlled for in the setting up of the experiment. A significant task by subject interaction was found in three of the sensitivity statistics and this indicates that even within subjects performance on two tasks was not entirely standardised as had been the intention.

Looking at the bias statistics we find that for all models except Luce's there is a subject effect, i.e. the subjects have different biases. Other significant effects are less consistent. There is a significant task effect on Atkinson's bias parameter, a significant burst effect on the non-parametric bias measure, a significant task by subject effect in Atkinson's measure, and a significant task by burst effect in both Atkinson's and the non-parametric estimate of the bias parameter. On examining the raw data this appears to be due to a very small bias in the detection task when a burst is present, the other conditions being very much the same.

If we look at the variance of the sensitivity statistics confounded with the effects of the immediately

CONDITION EXPERIMENT NO 3

Stat	Task	Feed back	Diffi culty	S	TF	TD	TS	FD	FS	DS	TFD	TFS	TDS	FDS
η			X											
d'			X											
Th			X											
P(c)			X											
A'			X											
σ			X											
ην														
d'ν			X											
Thν														
P(c)ν														
A'ν														
σν														
b(Luce)			X	X										
b(TSG)			X	X						X				
Bias %			X	X										
b(ATK)			X	X										
b(Luce)ν			X											
b(TSG)ν			X											
Bias % ν	X		X	X							X			
b(ATK)ν														
df	1,16	2,16	2,16	4,16	2,16	2,16	4,16	4,16	8,16	8,16	4,16	8,16	8,16	16,16

X sig at 05 level

X sig at 01 level

preceding trial we find significant subject effects in three of the sensitivity statistics, namely, Luce's data, the probability of correct statistic and Atkinson's sigma. In both the probability of correct statistic and Atkinson's sensitivity measure a large number of significant effects were obtained. Going back to the original data we find that this is largely due to a significant three way task by feedback by burst interaction. This in turn appears to be due to the very high value for one of the conditions. In the case where the subject is given a recognition task without feedback and without a burst it appears that the dependence on the immediately preceding trial is greatest by a very large extent. The only other main effect very much larger than this is the task by feedback effect where we find that in the recognition task when no feedback is present the dependence is much larger than in any of the other conditions. The other significant effects can be traced back to these conditions. It might be advisable to put in a word of caution but perhaps it would have been more appropriate to have performed these analyses on the square root of the variants rather than on the variances themselves. No significant effects were found for the bias variances which indicated that the dependency of the bias parameter on the immediately preceding trial was not greatly related to the experimental conditions.

Looking now at the results of Experiment No. 3 we find that any differences in the sensitivity parameter have been completely swamped by the large differences due to the different levels of task difficulty.

The only significant result from the analysis of variance on the statistic variances measuring the dependence on the immediately preceding trial from the sensitivity statistics is that of d' in which the difficulty effect is insignificant. As the task difficulty is affecting the main d' value it is not surprising that it could affect the variance of the d' depending on the state on the immediately preceding trial.

This same analysis was performed on the bias statistics and here we find that the subject variable is significant in all four cases, the difficulty variable is significant in three cases, and there is one difficulty by subject interaction. We must remember here that in the easy task subjects were performing at almost the 100% correct level. Under these conditions the bias would be virtually negligible. In the last two experiments no experimental effect has found to affect the dependency of the biases on the preceding trial. Here in Experiment 3, however, we find that for three of the bias statistics the difficulty condition is significant. Again the same comment can be made here since in all of the conditions the subject is getting practically all of them correct and the measurable effect of bias is pretty small as opposed to the difficult condition when the subject may be making 20% errors. The Atkinson's bias statistic also shows a significant subject effect, a time effect, and a time by feedback by difficulty interaction. Looking at the original data we find although the situation appears complicated increasing the amount of feedback appears to have the effect of increasing the dependence in the short easy condition and decreasing the dependence in the difficult long condition. We should note that the analysis performed here differs slightly from the analysis performed by OVERALL as the extremely easy condition had to be omitted. In that particular condition not enough errors were made to enable the estimation of the detection and recognition parameters following a trial in which an error had occurred. This would have the original analysis inappropriate.

In Experiment No. 4 the only experimental condition varied was the feedback and the subject made one of five possible responses. If this response is dichotomised we complete the data as in the other experiments. Having done this we can examine the data for the effect of feedback on the statistics of the models. On so doing we find no significant differences in sensitivity bias or dependence of the bias parameters. However, in the Atkinson and the

Tanner, Swets and Green model feedback appears to have the effect of increasing the dependence of the sensitivity parameter. Looking at the original data it appears that what is happening is that the dependence is the same when feedback or no feedback is present but when variable feedback is introduced the dependence on the immediately preceding trial is increased.

(c)ROCT analyses

Following Meyer's suggestion of using the latencies to produce rating type data a ROCT analysis was performed for all the experiments. Thus for every session the latencies were divided into fast and slow depending on which side of the median they lay. The responses were then grouped as follows - fast signal present, slow signal present, slow signal absent and fast signal absent. Using a rating scale type analysis we obtained three points on a ROCT curve which can be specified by their sensitivity and bias. The results of this analysis were analysed using a Luce choice reaction time model, see tables below for Experiment 1. The same sort of results were obtained from analysis of the other experiments but the detailed reactions are not included from lack of space. The programme which performed this analysis also calculated the range of the estimates of the parameters of the models for each of the sessions. Other analyses of variance were performed on this statistic to see whether the experimental conditions affected the departures of the points from an isosensitivity curve.

On looking at the results two things appear fairly clear. Firstly, the bias increases with each of the three points as one would expect that the different cut offs should correspond to three different bias positions. Also the sensitivity of the middle point appears greater than the sensitivity of either of the other two points indicating that by using the latencies as a measure of confidence we are in fact underestimating the performance of the subject. These comments apply to the results of all experiments. Analysis of variance testing the effects of experimental variables on the range of the estimates of the sensitivities were performed. We find that in Experiment 1 there is a significant effect. Looking at the raw data this appears largely due to an increase in the range of the sensitivity values as the stimulus probability changes from .5. This suggests that the underestimation caused by using latencies as confidence ratings is least when

EXPERIMENT NO. 1

ROCT ANALYSIS USING LUCE'S MODEL

Condition	Session	Z			B		
	1	.24	.22	.27	.13	.28	2.4
	2	.85	.91	.87	.13	.32	1.8
.25R	3	.57	.58	.51	.19	.43	2.3
	4	.31	.55	1.1	.06	.21	1.6
	5	.72	.75	1.0	.13	.32	1.7
	6	.75	.64	.85	.31	.89	2.8
	7	.89	.91	.78	.34	1.1	3.6
.5R	8	.88	.17	.29	.20	.75	4.9
	9	.87	.83	.99	.29	.92	3.2
	10	.98	.76	.84	.28	.80	2.7
	11	1.3	.84	1.4	.60	3.0	8.6
	12	.81	.68	.78	.54	2.7	7.1
.75R	13	.25	.07	1.4	.15	.48	20
	14	.69	.29	.35	.46	1.7	5.0
	15	.78	.24	.17	.59	3.7	14
	16	.31	.15	.08	.39	1.2	8.9
	17	1.0	1.1	.96	.36	1.1	2.8
	18	.27	.12	.17	.28	1.1	5.5
	19	.74	.46	.47	.33	.87	2.9
.5D	20	.84	.78	.74	.32	.95	3.1
	21	1.0	.65	.58	.36	1.2	3.9
	22	.96	.79	.94	.32	1.0	3.0
	23	.89	.53	.65	.29	.78	2.9
	24	.47	.27	.31	.36	1.0	3.3
	25	.78	.76	.88	.36	1.1	3.2

the stimulus probability equals .5.

This result is confirmed in the second experiment where there appears to be a large difference in the range dependent on the a priori stimulus probability. There also appears to be a subject difference and a task by feedback interaction. Feedback also apparently has the effect of reducing the range of the sensitivity statistic. The analysis of the second experiment using the task by feedback by burst design shows that we have a significant subject effect and significant feedback by burst by subject interaction and a significant task by subject interaction. On looking at the raw data we find this is due to the fact that the range is considerably smaller than there is feedback but no burst.

Looking at the analysis of the third experiment we find that the most significant effect is that of task difficulty. The more difficult the task the larger the range of sensitivity. This may be an effect of the position on the sensitivity scale as it is much more difficult to improve the sensitivity of .01 than it is to improve on a sensitivity of .91. These results also indicate a significant difference between subjects, the results of the significant task by subject interaction and the difficulty by subject interaction.

The analysis of the third experiment revealed that the experimental conditions had no effect on the range of sensitivity values of Luce's model calculated as above.

The results of the ROCT analysis may perhaps be more easily understood if we look at them in the following way. The speed of response was the same as confidence when we should expect all the points to have the same sensitivity value. The wider the range of the sensitivity values the less the latencies related to the subject's confidence. We knew from previous analysis that latency is related to a priori stimulus probability. It would therefore appear that when the stimuli were not equiprobable the effect of the stimulus probability on the latency would obscure relationship between the latency and confidence. This would have the effect of increasing the range of the sensitivity values calculated in the ROCT analysis. This sort of reasoning may be able to explain certain of the other results post hoc. For example, time is most closely related to confidence in the feedback condition where no bursts are present which could explain the feedback by burst interaction.

It was possible to use the same program as was used in the ROCT analysis to analyse the results of the rating scale data, see Experiment No. 4. Here what was wanted was an estimate of the sensitivity and bias parameters corresponding to each of the response cut outs. The subject was in this case allowed five responses. Certain signal present, uncertain signal present, don't know, uncertain signal absent, certain signal absent. This normally gave fewer data points on an ROC curve. The sensitivity and bias parameters were calculated according to Luce's model for each of the four data points. This analysis was then repeated using data following a one or a two response with stimulus 1, a one or a two response with stimulus 2, a three, four or five response with stimulus 1, and a three, four or five response with stimulus 2. It was not possible to estimate the parameters for all possible stimulus response combinations as there were too many of them. This analysis is made more complicated by the fact that some subjects did not use all the available response alternatives. On looking at the data we notice that differences exist in the bias parameter as we would expect. The bias increases with the position on the ROC curve. If all the points lay on the same ROC curve then the sensitivity values for each of the points should be the same. A Friedman non-parametric analysis of variance was performed on sensitivity data and showed that the data value being in fact dependent upon the point being considered. The middle two points appeared to give the highest sensitivity. On looking at the frequency distribution of responses it was noticeable that subjects seemed reluctant to use the two more extreme responses. Perhaps if the subjects had not been naive this effect would not have been so marked. As it was the χ^2_r was found to be equal to 19.8.

As mentioned before the ROCT analysis was repeated following each of four types of trial. A non-parametric of variance was performed on the sensitivity value at each of the cut off points to see if there was a difference depending on the state in the last trial. None of the resulting χ^2_r values were significant. This, however, does not mean that dependences did not exist where rating scale data was used or even that dependences are less under these circumstances. It must be remembered that only fifteen sessions were analysed on naive subjects. In the analysis of the non-rating experiments the number of sessions were 25, 80 and 90 respectively. When Experiment 4 was analysed in the estimate program treating it as a non-rating scale experiment the overall effects were not significant. However, dependencies on the sensitivity parameters of a number of different models depended on the correctness of the immediately preceding trial were found.

Simulation

The final part of this work consisted in simulating sequences of SR events with the same dependences that had been observed in the aforementioned experiments. The data from the whole of Experiment 2 was averaged and zero first and second order Markov processes fitted to the SR sequences. A two-state latent Markov model was also fitted using a minimum χ^2 procedure to improve upon the initial estimates as described above. A program SIMLUC was written which simulated the SR sequences with the parameters of the zero first and second order Markov processes and the latent Markov process estimated above. SIMLUC also contained the ESTIMATE procedures and estimates of the signal detection and recognition models were determined for each of the simulated sequences. This process was repeated ten times and estimates of the parameters of the detection and recognition models discussed earlier were thereby obtained. The following table consists of the averages and variances of the estimates of the parameters of each of the models. Together with estimates of these parameters dependent on the state on the immediately preceding trial and on the immediately two trials. Finally included are the empirically obtained estimates as discussed earlier.

The differences between the real and the simulated data are due to at least two factors.

(1) Differences between the simulated performance of the subject and his real performance.

(2) Differences due to the real data being averages of several different subjects operating in several different experimental conditions.

Differences in the mean values overall are probably due to the differences in averaging every statistic of a signal detection model and finding the rated average of the probability and then calculating the same statistic. Differences in the mean values of the statistics depending on the state on the immediately preceding trial showed the differences between the simulation models used.

The empirically obtained variances, theoretical variances (where they exist) and the simulated variances for each of the ten statistics for each of the experiments are given in the tables below.

It appears that the empirical variances are by far the largest. This we would expect as we have shown before that the sessions are not homogeneous. The theoretical variances is usually the smallest.

As the simulated experiments were all based on a sample of only ten sessions the estimates of the standard errors of the statistics cannot be very accurate. Thus the conclusions drawn above can only be tentative on this data. There also is an indication that as the order of the estimated Markov process increases so does the variance of the statistics.

Another finding is that the sensitivity of the subjects as estimated from the simulated data appears better than when the estimate is derived from the mean of each of the subjects sensitivity statistics. This is probably due to the different averaging techniques. Extremely good performances of, say, ten errors out of 740 trials are less heavily weighted when all the sequences are lumped together and then the sensitivity calculated than when the sensitivity is calculated for each sequence and then the sensitivities averaged.

The dependencies observed in the simulated data do not appear to be of the same magnitude as in the real data. Increasing the order of the Markov sequences from 0 to 2 appears to have the effect of increasing the dependency of the model's statistics on the last two trials. Some dependency of the statistic on the last two trials is observed even in the zero order condition. More will be said of this effect later.

The first order Markov model gets the direction of the first order effects on the sensitivity parameters correct. If anything, however, it appears to over-estimate the effect of the immediately preceding trial on the sensitivity parameter and under-estimate the effect on bias. The second order effect again appears to over-estimate the effect of the immediately preceding trial on the sensitivity statistics. It also gets the relative order of the bias

STATISTIC EXPERIMENT 1

Variances

STATISTIC		Model simulated				
		ThV	OM	1M	2M	LM
Luce	z	.0024	.0023	.0034	.0055	.0063
	b	.0025	.0057	.0021	.0098	.0035
Non P	A'		.0011	.0012	.0016	.0009
	b%		2.3	4.7	.23	1.36
Classic	Pc	.0013	.0063	.0021	.0026	.0030
	Th	.0003	.0026	.0003	.0025	.0030
ATK	σ		.0012	.0012	.0007	.0016
	b		.0009	.0055	.0013	.0036
TSG	d'		.0045	.014	.0024	.0042
	b		.0011	.0027	.0006	.0007

STATISTIC EXPERIMENT 2

Variances

Model simulated

STATISTIC		ThV	OM	1M	2M	LM
Luce	z	.0004	.0009	.0009	.0004	.001
	b	.005	.016	.013	.004	.010
Non P	A'		.0001	.0003	.0016	.00014
	b%		69.3	49.5	47.3	54.1
Classic	Pc	.0004	.0015	.0003	.0004	.0004
	Th	.0014	.0010	.001	.004	.001
ATK	σ		.0016	.0016	.0007	.0014
	b		.0014	.006	.003	.009
TSG	d'		.009	.012	.044	.0024
	b		.003	.005	.95	.0006

STATISTIC EXPERIMENT 3

Variances

Model simulated

STATISTIC		ThV	OM	1M	2M	LM
Luce	z	.0002	.0002	.0003	.0003	.0004
	b	.005	.008	.026	.007	.007
Non P	A'		.00008	.0001	.00004	.00009
	b%		148.6	125.7	137.7	73.7
Classic	Pc	.00025	.0003	.0003	.0009	.0002
	Th	.0013	.0014	.0006	.002	.0006
ATK	σ		.0005	.001	.0007	.001
	b		.005	.009	.010	.012
TSG	d'		.011	.009	.009	.008
	b		.003	.006	.003	.003

statistics depending on the immediately preceding trial wrong.

As a result of these simulations some potentially interesting effects have become apparent. However, it is difficult to make more than tentative conclusions owing to the smallness of the number of simulated sessions. A major constraint was the amount of computing time required to perform a simulation and it was decided that it was not possible to extend the number of sessions looked at in any but one particular case. The problem was then to decide on which experiment to use as the estimates for the Markov models which were to be simulated. Experiments No. 1 and 4 were ruled out as they used naive subjects whose performance varied very greatly. Experiment No. 3 was also eliminated as it contained sequences where the subjects almost got 100% correct together with sequences where they were responding at little better than chance. This left Experiment 2 where the experimental independent variables were whether the task was detection or recognition a priori stimulus probability presence or absence of feedback and the inclusion or non-inclusion of a burst of white noise between trials. It was decided therefore to use the data from the second experiment after the sessions involving non-equal a priori stimulus probabilities had been removed, thereby hopefully producing a reasonably homogeneous selection of sequences.

From th is data, therefore, zero first second and a latent Markov model were fitted to this data as had been done to each of the experiments mentioned previously. When the latent model was fitted as had been found before probabilities outwith the range of zero to one were obtained. Again, a minimum χ^2 procedure was used to improve the estimates of the model within the usual bounds for probabilities and the results are shown in the table below. The minimum χ^2 improved to a final value of 20.29 and the values of the m, v and q matrix obtained show some evidence of a Falmange type model operating on this system. With this data, therefore, 50 sequences were simulated for each model and estimates of the

MAIN SIMULATION (MEANS)

Statistic	model 0	1	2	LM
z	.361	.359	.354	.361
b	1.188	1.208	1.18	1.20
A'	.823	.846	.821	.819
B%	-16.07	-12.86	-14.95	-14.7
P(c)	.670	.674	.669	.667
Th	.404	.412	.396	.405
σ	.466	.473	.468	.475
b(A)	.887	.889	.890	.904
d'	1.259	1.258	1.262	1.259
b(TSG)	.677	.681	.683	.678

MAIN SIMULATION (VARIANCES)

model

Statistic	Th	0	1	2	LM
z	.00045	.0010	.0010	.0009	.0010
b	.0002	.007	.0111	.009	.010
A'		.00022	.00019	.00021	.00025
B%		48. 4	72.2	41.9	50.1
P(c)	.0005	.00081	.0010	.0008	.0011
Th	.001	.0028	.0021	.0020	.0025
σ		.0009	.0009	.0010	.0010
b(A)		.002	.003	.003	.003
d'	.0087	.0113	.0085	.0108	.0111
b(TSG)		.0039	.0028	.0035	.0034

Observed Frequencies of Combination of 3 trials

0 Order Markov Simulation

	S_1R_1	S_1R_2	S_2R_1	S_2R_2
$S_1R_1S_1R_1$	58	6	23	46
$S_1R_1S_1R_2$	7	5	1	7
$S_1R_1S_2R_1$	15	8	8	8
$S_1R_1S_2R_2$	40	17	16	36
$S_1R_2S_1R_1$	12	2	3	9
$S_1R_2S_1R_2$	12	3	3	3
$S_1R_2S_2R_1$	5	3	4	8
$S_1R_2S_2R_2$	12	4	2	13
$S_2R_1S_1R_1$	8	4	4	12
$S_2R_1S_1R_2$	4	3	2	6
$S_2R_1S_2R_1$	3	3	3	6
$S_2R_1S_2R_2$	12	5	4	16
$S_2R_2S_1R_1$	41	6	9	41
$S_2R_2S_1R_2$	7	6	3	6
$S_2R_2S_2R_1$	12	10	13	7
$S_2R_2S_2R_2$	33	13	11	30

Observed Frequencies of Combination of 3 trials (continued)

1st Order Markov Simulation

	S_1R_1	S_1R_2	S_2R_1	S_2R_2
$S_1R_1S_1R_1$	47	17	23	33
$S_1R_1S_1R_2$	19	6	5	11
$S_1R_1S_2R_1$	5	3	7	17
$S_1R_1S_2R_2$	46	9	19	35
$S_1R_2S_1R_1$	18	2	7	12
$S_1R_2S_1R_2$	7	1	3	5
$S_1R_2S_2R_1$	7	2	0	5
$S_1R_2S_2R_2$	12	3	4	13
$S_2R_1S_1R_1$	12	2	2	14
$S_2R_1S_1R_2$	9	2	4	3
$S_2R_1S_2R_1$	5	1	3	4
$S_2R_1S_2R_2$	9	4	4	11
$S_2R_2S_1R_1$	42	4	17	31
$S_2R_2S_1R_2$	19	2	2	10
$S_2R_2S_2R_1$	13	5	8	11
$S_2R_2S_2R_2$	34	9	8	33

Observed Frequencies of Combination of 3 trials (continued)

2nd Order Markov Simulation

	S_1R_1	S_1R_2	S_2R_1	S_2R_2
$S_1R_1S_1R_1$	53	4	11	28
$S_1R_1S_1R_2$	7	2	3	7
$S_1R_1S_2R_1$	19	7	6	15
$S_1R_1S_2R_2$	45	12	15	44
$S_1R_2S_1R_1$	14	6	4	14
$S_1R_2S_1R_2$	2	1	2	4
$S_1R_2S_2R_1$	5	5	6	0
$S_1R_2S_2R_2$	6	7	2	9
$S_2R_1S_1R_1$	19	3	6	15
$S_2R_1S_1R_2$	4	3	0	3
$S_2R_1S_2R_1$	10	3	6	7
$S_2R_1S_2R_2$	11	5	10	7
$S_2R_2S_1R_1$	42	11	15	38
$S_2R_2S_1R_2$	8	12	1	4
$S_2R_2S_2R_1$	10	5	5	11
$S_2R_2S_2R_2$	45	10	11	33

signal detection models were obtained from these sequences. The results are comparable to those obtained in the smaller simulation.

The results indicate that the variances of the statistics are greater if dependences are assumed in the simulated data. The size of this effect, however, is relatively small. A more important difference is the extent to which the empirically obtained variances are higher than the minimum variances calculated theoretically, assuming large sample sizes, i.e. as the sample size to infinity. Surprisingly the statistic which has an empirical variance close to the asymptotic variance is d'. The main values for the parameters were calculated for each of the simulations and are given in the table below. As can be seen from th is table all the simulated data approximate reasonably well to the empirical.

As well as calculating the results for the overall parameters the value of the parameters following a specific trial and a specific two trials were calculated as in programme estimate. A very surprising finding was the results for the zero order Markov simulation, see table below. Here it appears that the values of the parameters are dependent on the immediately preceding trial even though the data was simulated according to a zero order Markov process. The programme was re-run and the sample sizes on which each of the estimates of the parameter had been calculated was obtained and the results are given in the table below. As can be seen the sizes of the samples varied tremendously, the smaller sample sizes occurring when there are more errors preceding the estimation than correct. This means that in a zero order Markov process the number of corrects followed by correct were much greater than the number of wrongs followed by wrongs. Therefore the estimate of the sensitivity following two corrects is based on a much larger sample than when you are looking at the value of the parameter following two successive wrong responses. The nett result of this is therefore to confound the state in the immediately preceding trial with any effects of biases in the estimates.

Accordingly the biases in the parameters were studied in more detail. It proves difficult to work out an explicit formula for the biases of the parameters therefore a programme bias was written to calculate numerically the expectation of each of the parameters, because the difference between the expected value of the parameter and the population parameter gives the measure of the bias of the statistic. Thus, bias works out the probability of every possible result within a sample of size N given the population parameters. For each possible result it calculates the observed value of the statistic that would be found and the product of this value and its probability summed over all the possible observations gives you the expected value of the statistic. This programme was first run using Luce's model and it gives an expectation of infinity. This is because when no observations are obtained in certain categories the estimates value of the statistic is, in fact, infinity. However, such instances were removed from the sample being considered in programme estimates. Accordingly, programme bias was amended so that the expectation of the various statistics were derived excluding outcomes which contained no observations in a particular category from the sample space. The results are given in the tables below when the probabilities of being correct are .5, .6, .7, .8 and .9. In all cases there are biases. As can be seen from the table the statistics in Luce's model are biased. This effect was very large when the sample sizes are less than ten. However, by the time sample sizes of 45 or more are obtained the statistic values have almost reached their asymptotic levels. Equivalent tables are given for the other models and these appear below.

This bias effect confounds the differences between statistics depending on data following particular sequences of trials. It is possible therefore that some of the results obtained earlier could have been the result of this bias effect. Accordingly programme estimate was re-run with a minor modification in that the estimates of the signal detection statistics were all based on samples of size 100, the rest of the data being discarded. Thus for every sequence

LUCE'S MODEL (z)

n	5	15	25	35	45	∝
Pc						
.5	1.06	1.17	1.11	1.07	1.05	1.00
.6	.99	.78	.71	.69	.69	.67
.7	.92	.51	.71	.44	.43	.43
.8	.85	.35	.27	.25	.25	.25
.9	.78	.23	.16	.13	.12	.11

Non P (A')

	5	15	25	35	∝
Pc					
.5	.5	.5	.5	.5	.5
.6	.53	.63	.65	.65	.66
.7	.55	.74	.77	.78	.79
.8	.59	.82	.86	.87	.88
.9	.62	.88	.92	.93	.94

P(c)	5	15	25	35	∝
Pc					
.5	0	0	0	0	0
.6	.04	.18	.20	.20	.20
.7	.08	.35	.39	.40	.40
.8	.12	.51	.57	.59	.60
.9	.16	.63	.73	.76	.80

Th	5	15	25	35	∝
Pc					
.5	-.06	-.18	-.11	-.07	
.6	.008	.21	.28	.30	.33
.7	.08	.17	.54	.56	.57
.8	.15	.65	.72	.74	.75
.9	.22	.76	.84	.86	.88

σ	5	15	25	35	∝
Pc					
.5	.02	.09	.10	.10	.1
.6	.04	.17	.20	.20	.2
.7	.06	.25	.29	.30	.3
.8	.08	.32	.36	.38	.4
.9					

d'*	n	5	10	∝
Pc				
.5		0	0	0
.6		.08	.34	.507
.7		.16	.66	1.05
.8		.25	.95	1.68
.9		.33	1.19	2.56

* The data for larger n was not collected as the estimation procedure took much more computer time than the others.

some data following correct trials was discarded and some sequences were discarded as they did not have 100 wrong trials. When this was done for Experiment 2 out of the 80 sessions only about 20 remained, and this was not really enough to make very powerful tests of the hypothesis that the statistics depended on the state of the immediately preceding trial. As a result the programme was again amended this time insisting that the sample sizes on which the statistics depending on the immediately preceding trial were based was 45 in all cases. Having done this 51 sessions out of the 80 remained in the sample for analysis and the reliability of the estimates had been reduced.

The results of this analysis are given in the table below. On the overall test to see whether the statistic depends on the immediately preceding trial none of the sensitivity statistic showed a significant dependence while all the bias statistics did. On the analysis to see whether they depended on the stimulus on the last trial the response on the last trial or whether the last trial was correct or wrong the only significant finding was that the bias statistic of Atkinson's model did depend on the response on the last trial. It thus appears that by ensuring equal numbers in the samples from which the statistics are calculated one is reducing the power of the test. The only conclusion that one can draw is that the bias statistics depend on the state the subject was in on the last trial and that the sensitivity statistics as calculated using all the data depend on the state in the last trial, in particular they depend on whether the correct was correct or wrong or not. This effect, however, is contaminated with a possible bias effect.

Dependence of statistics on Immediately Preceding Trial
(all based on sample size N = 45)

Statistic	Last Trial Characterised by: Overall S-R	S	R	Correct/Wrong
η				
d'				
Th				
P(c)				
A'				
σ			X	
bias(Luce)	X			
bias(TSG)				
Bias %	X		X	
bias(ATK)	X		X	

<u>Conclusions</u>

In the Introduction several signal detection models were summarised and major experimental findings in the area reported. It was also pointed out that although the phenomenon of inter-trial dependence was well established none of the models appeared adequately to account for this phenomenon. Indeed, the existence of this effect would, it was suspected, reduce the accuracy of some of the more quantitative predictions of the models.

The experiments reported were designed to estimate the effect of inter-trial dependence in a number of common types of experimental conditions. The experimental variables were chosen as those commonly varied in recognition detection and reaction time tasks. Out of the 210 sessions studied 105 showed significant first order SR dependences while 39 showed significant second order or higher dependences. On breaking the SR sequences down into sequences of responses, sequences of correct wrongs, and sequences of stimuli it was found that the response sequences showed the greatest number of dependences. The inter-trial dependences of the latencies appeared larger than those measured from the SR sequences.

On examining the sessions for non-stationality it was found that after the first 100 trials had been discarded the effect was negligible on the SR sequences although it was more apparent in the latency data. The experimental variables found most to affect the χ^2 measuring inter-trial dependence were the subject variable, task difficulty and a priori stimulus probability. Perhaps this is due to the fact that these variables also affected the total number of correct and wrong responses.

Attempts were made to describe the dependences using zero, first and second order Markov models, a two state latent Markov model, and autoregressive processes. A low order autoregressive model proved incapable of adequately describing the inter-trial dependence. None of the Markov models fitted exactly and the latent model gave a sensible approximation to the data only when its parameters were estimated using a iterative procedure.

The parameters of the signal detection models were then calculated depending on the SR state of the immediately preceding trial. This was found to affect the value of both the bias and the sensitivity parameters, the bias parameter depending particularly on the immediately preceding response while the sensitivity parameter appeared to depend on whether the immediately preceding trial was correct or wrong. As there were more correct responses than wrong ones the sample size on which the estimate was based following the correct response was greater than that following a wrong response. The estimates of the sensitivity parameters of the models were shown to be biased. This bias could account for the dependence of the sensitivity statistic on the immediately preceding trial. The significant dependences found in the sequences of correct wrongs both of first and second order indicate that at least in some cases an unbiased estimate of the sensitivity would depend on whether the last trial was correct or not. The degree of this dependence was estimated by calculating the variance of the estimates of the parameters depending on the immediately preceding trial. The major experimental variable found to affect this statistic was task difficulty, and this result could be explained by an effect of bias.

The Markov models used to characterise the dependence were then used in a large number of simulations in order to find out the effect of such dependence on the theoretical variances of the estimates of the parameters of the models. It was found that the dependence did have the effect of increasing the variances of the statistics. However, this effect was quite small when compared to the bias present in a number of the statistics due to the small sample size. When the sample sizes are larger (over 100) the bias effect disappears although the small effect of non-independence remains.

To sum up, sequential dependences were measured in a number of tasks. The most important aspect of bias on detection or recognition models assuming trial independence was dependence of a response on the immediately preceding response.

Dependence on the accuracy of the immediately preceding trial was also present. The most critical factors affecting the dependence were subject differences and task difficulty. The effect of the dependence is greater on the bias than on the sensitivity parameters. It was also shown that statistical tests developed for sensitivity statistics were robust against the observed violations of the independence assumptions.

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A P P E N D I X A

This contains the total number of errors response ones and latencies (in m.s.) occurring in 5 successive blocks of 140 trials for Experiments 2, 3 and 4.

COND	BLOCK	TOTAL ERRORS 1	2	3	4	5
0.75R		51.000000	42.000000	60.000000	54.000000	57.000000
0.50RB		69.000000	72.000000	70.000000	69.000000	72.000000
F.75R		50.000000	46.000000	63.000000	57.000000	55.000000
0.50R		71.000000	67.000000	61.000000	58.000000	66.000000
F.50R		78.000000	76.000000	78.000000	71.000000	59.000000
F.50RB		56.000000	71.000000	73.000000	70.000000	60.000000
0.25R		45.000000	52.000000	57.000000	73.000000	49.000000
F.25R		43.000000	57.000000	55.000000	45.000000	51.000000
0.75D	S 1	38.000000	63.000000	47.000000	46.000000	50.000000
0.50DB		36.000000	48.000000	57.000000	49.000000	64.000000
F.75D		34.000000	27.000000	34.000000	41.000000	30.000000
0.50D		29.000000	51.000000	43.000000	52.000000	23.000000
F.50D		72.000000	56.000000	69.000000	55.000000	76.000000
F.50DB		50.000000	60.000000	62.000000	65.000000	51.000000
0.25D		46.000000	51.000000	46.000000	41.000000	40.000000
F.25D		52.000000	55.000000	53.000000	48.000000	41.000000
0.75R		36.000000	41.000000	40.000000	51.000000	44.000000
0.50RB		24.000000	19.000000	37.000000	21.000000	31.000000
F.75R		11.000000	22.000000	10.000000	8.0000000	17.000000
0.50R		41.000000	51.000000	52.000000	63.000000	66.000000
F.50R		27.000000	33.000000	28.000000	26.000000	30.000000
F.50RB		23.000000	23.000000	27.000000	16.000000	21.000000
0.25R		25.000000	14.000000	14.000000	15.000000	16.000000
F.25R		20.000000	14.000000	9.0000000	11.000000	11.000000
0.75D	S 2	30.000000	31.000000	29.000000	33.000000	27.000000
0.50DB		78.000000	67.000000	67.000000	21.000000	72.000000
F.75D		32.000000	36.000000	34 000000	22.000000	27.000000
0.50D		40.000000	56.000000	51.000000	53.000000	63.000000
F.50D		41.000000	40.000000	44.000000	57.000000	62.000000
F.50DB		48.000000	50.000000	35.000000	31.000000	55.000000
0.25D		31.000000	43.000000	42.000000	45.000000	50.000000
F.25D		31.000000	33.000000	29.000000	26.000000	23.000000
0.75R		12.000000	22.000000	6.0000000	13.000000	15.000000
0.50RB		24.000000	30.000000	28.000000	20.000000	24.000000
F.75R		7.0000000	23.000000	16.000000	25.000000	13.000000
0.50R		24.000000	36.000000	37.000000	36.000000	53.000000
F.50R		19.000000	23.000000	22.000000	16.000000	21.000000
F.50RB		26.000000	21.000000	10.000000	26.000000	19.000000
0.25R		37.000000	37.000000	30.000000	18.000000	15.000000
F.25R	S 3	28.000000	22.000000	22.000000	26.000000	32.000000
0.75D		14.000000	19.000000	20.000000	25.000000	18.000000
0.50DB		18.000000	26.000000	20.000000	25.000000	20.000000
F.75D		19.000000	22.000000	26.000000	16.000000	21.000000
0.50D		22.000000	27.000000	30.000000	31.000000	28.000000
F.50D		27.000000	26.000000	28.000000	25.000000	47.000000
F.50DB		24.000000	19.000000	21.000000	20.000000	34.000000
0.25D		33.000000	31.000000	34.000000	29.000000	34.000000
F.25D		41.000000	30.000000	20.000000	20.000000	28.000000

COND

0.75R		17.000000	29.000000	27.000000	27.000000	19.000000
0.50RB		7.0000000	5.0000000	13.000000	21.000000	11.000000
F.75R		14.000000	9.0000000	11.000000	18.000000	19.000000
0.50R		19.000000	24.000000	28.000000	32.000000	20.000000
F.50R		23.000000	14.000000	26.000000	24.000000	18.000000
F.50RB		14.000000	14.000000	17.000000	11.000000	13.000000
0.25R	S 4	15.000000	21.000000	13.000000	14.000000	16.000000
F.25R		28.000000	20.000000	13.000000	17.000000	30.000000
0.75D		25.000000	11.000000	11.000000	20.000000	17.000000
0.50DB		13.000000	14.000000	13.000000	14.000000	14.000000
F.75D		27.000000	14.000000	10.000000	13.000000	7.0000000
0.50D		15.000000	19.000000	19.000000	25*000000	08.000000
F.50D		19.000000	18.000000	11.000000	13.000000	20.000000
F.50DB		13.000000	18.000000	26.000000	15.000000	19.000000
0.25D		26.000000	20.000000	29.000000	25.000000	28.000000
F.25D		17.000000	32.000000	24.000000	28.000000	16.000000
0.75R		31.000000	29.000000	18.000000	29.000000	24.000000
0.50RB		53.000000	43.000000	61.000000	56.000000	59.000000
F.75R		28.000000	37.000000	29.000000	22.000000	24.000000
0.50R		25.000000	24.000000	29.000000	44.000000	55.000000
F.50R		23.000000	33.000000	40.000000	43.000000	42.000000
F.50RB		17.000000	25.000000	35.000000	27.000000	17.000000
0.25R	S 5	18.000000	22.000000	24.000000	30.000000	35.000000
F.25R		28.000000	23.000000	33.000000	27.000000	33.000000
0.75D		38.000000	32.000000	44.000000	43.000000	32.000000
0.50DB		47.000000	45.000000	56*000000	53.000000	41.000000
F.75D		28.000000	30.000000	15.000000	30.000000	25.000000
0.50D		29.000000	27.000000	22.000000	23"000000	32.000000
F.50D		29.000000	37.000000	51.000000	50.000000	55.000000
F.50DB		34.000000	34.000000	39.000000	40.000000	41.000000
0.25D		43.000000	28.000000	40.000000	39.000000	51.000000
F.25D		25.000000	23.000000	15.000000	26.000000	15.000000M

TOTAL RI's

COND	BLOCK	1	2	3	4	5
0.75R		105.00000	114.00000	91.000000	87.000000	86.000000
0.50RB		71.000000	63.000000	89.000000	87.000000	67.000000
F.75R		97.000000	110.00000	87.000000	107.00000	101.00000
0.50R		79.000000	87.000000	96.000000	79.000000	92.000000
F.50R		85.000000	81.000000	90.000000	82.000000	88.000000
F.50RB		86.000000	100.00000	97.000000	102.00000	93.000000
0.25R		23.000000	29.000000	46.000000	61.000000	45.000000
F.25R		33.000000	51.000000	43.000000	29.000000	33.000000
0.75D		102.00000	92.000000	117.00000	103.00000	92.000000
0.50DB	S 1	70.000000	51.000000	53.000000	52.000000	62.000000
F.75D		98.000000	114.00000	103.00000	105.00000	116.00000
0.50D		54.000000	63.000000	56.000000	40.000000	82.000000
F.50D		55.000000	90.000000	84.000000	93.000000	88.000000
F.50DB		72.000000	60.000000	57.000000	43.000000	68.000000
0.25D		48.000000	25.000000	30.000000	38.000000	31.000000
F.25D		40.000000	54.000000	58.000000	44.000000	23.000000
0.75R		82.000000	89.000000	92.000000	79.000000	84.000000
0.50RB		62.000000	80.000000	67.000000	77.000000	60.000000
F.75R		102.00000	104.00000	113.00000	103.00000	113.00000
0.50R		52.000000	55.000000	57.000000	72.000000	57.000000
F.50R		64.000000	76.000000	67.000000	65.000000	76.000000
F.50RB		70.000000	74.000000	61.000000	69.000000	62.000000
0.25R		53.000000	36.000000	45.000000	31.000000	37.000000
F.25R	S 2	50.000000	46.000000	40.000000	33.000000	50.000000
0.75D		96.000000	88.000000	85.000000	93.000000	94.000000
0.50DB		64.000000	62.000000	69.000000	75.000000	57.000000
F.75D		102.00000	92.000000	95.000000	104.00000	107.00000
0.50D		69.000000	70.000000	66.000000	77.000000	73.000000
F.50D		68.000000	76.000000	64.000000	66.000000	64.000000
F.50DB		74.000000	72.000000	71.000000	54.000000	60.000000
0.25D		51.000000	44.000000	47.000000	44.000000	45.000000
F.25D		37.000000	47.000000	41.000000	46.000000	45.000000
0.75R		106.00000	105.00000	105.00000	101.00000	94.000000
0.50RB		63.000000	80.000000	60.000000	68.000000	85.000000
F.75R		111.00000	120.00000	131.00000	131.00000	109.00000
0.50R		76.000000	88.000000	89.000000	91.000000	99.000000
F.50R		83.000000	70.000000	75.000000	69.000000	60.000000
F.50RB		76.000000	95.000000	72.000000	80.000000	79.000000
0.25R	S 3	55.000000	56.000000	53.000000	42.000000	47.000000
F.25R		48.000000	40.000000	44.000000	53.000000	27.000000
0.75D		102.00000	108.00000	105.00000	113.00000	105.00000
0.50DB		68.000000	75.000000	75.000000	73.000000	81.000000
F.75D		103.00000	98.000000	89.000000	88.000000	98.000000
0.50D		72.000000	74.000000	71.000000	72.000000	70.000000
F.50D		63.000000	75.000000	69.000000	88.000000	100.00000
F.50DB		67.000000	71.000000	73.000000	58.000000	70.000000
0.25D		62.000000	49.000000	64.000000	56.000000	47.000000
F.25D		44.000000	20.000000	40.000000	34.000000	30.000000

COND

0.75R		83.000000	87.000000	80.000000	83.000000	93.000000
0.50RB		66.000000	76.000000	72.000000	88.000000	79.000000
F.75R		101.00000	114.00000	98.000000	103.00000	104.00000
0.50R		69.000000	63.000000	75.000000	81.000000	73.000000
F.50R		81.000000	72.000000	66.000000	90.000000	74.000000
F.50RB		68.000000	76.000000	81.000000	65.000000	78.000000
0.25R		52.000000	59.000000	45.000000	36.000000	49.000000
F.25R	S 4	53.000000	49.000000	26.000000	35.000000	46.000000
0.75D		79.000000	101.00000	94.000000	96.000000	98.000000
0.50DB		71.000000	68.000000	72.000000	63.000000	76.000000
F.75D		97.000000	104.00000	106.00000	102.00000	111.00000
0.50D		75.000000	89.000000	84.000000	82.000000	79.000000
F.50D		74.000000	80.000000	71.000000	66.000000	78.000000
F.50DB		43.000000	73.000000	82.000000	77.000000	77.000000
0.25D		60.000000	52.000000	57.000000	60.000000	56.000000
F.25D		46.000000	52.000000	49.000000	40.000000	38.000000

0.75R		80.000000	96.000000	105.00000	108.00000	93.000000
0.50RB		71.000000	86.000000	79.000000	92.000000	94.000000
F.75R		106.00000	110.00000	105.00000	105.00000	116.00000
0.50R		80.000000	82.000000	92.000000	104.00000	97.000000
F.50R		71.000000	89.000000	86.000000	95.000000	98.000000
F.50RB		84.000000	74.000000	78.000000	66.000000	79.000000
0.25R		43.000000	47.000000	59.000000	63.000000	68.000000
F.25R		46.000000	45.000000	37.000000	37.000000	32.000000
0.75D	S 5	98.000000	89.000000	93.000000	87.000000	96.000000
0.50DB		76.000000	72.000000	68.000000	80.000000	85.000000
F.75D		102.00000	101.00000	105.00000	107.00000	103.00000
0.50D		94.000000	88.000000	78.000000	72.000000	70.000000
F.50D		77.000000	79.000000	73.000000	72.000000	65.000000
F.50DB		74.000000	78.000000	82.000000	81.000000	83.000000
0.25D		58.000000	50.000000	53.000000	50.000000	63.000000
F.25D		47.000000	42.000000	36.000000	32.000000	42.000000

TOTAL LATENCIES (MS) (ignore - sign)

COND	BLOCK	1	2	3	4	5
0.75R		-98278.000	-113261.00	-249842.00	-125051.00	-93119.000
0.50RB		-201911.00	-102756.00	-130496.00	-109288.00	-127308.00
F.75R		-88724.000	-112939.00	-380077.00	-91218.000	-68992.000
0.50R		-498073.00	-531032.00	-103138.00	-124062.00	-142543.00
F.50R		-151163.00	-157247.00	-127526.00	-134933.00	-140465.00
F.50RB	S 1	-101622.00	-103138.00	-145623.00	-81404.000	-80484.000
0.25R		-83778.000	-57045.000	-74090.000	-59540.000	-70318.000
F.25R		-124158.00	-91593.000	-81614.000	-83646.000	-80066.000
0.75D		-171375.00	-261591.00	-301250.00	-135120.00	-116940.00
0.50DB		-134490.00	-160748.00	-168401.00	-168263.00	-158787.00
F.75D		-189120.00	-161131.00	-123277.00	-100627.00	-92589.000
0.50D		-176006.00	-195846.00	-270852.00	-286218.00	-143356.00
F.50D		-379106.00	-137444.00	-188162.00	-326990.00	-111375.00
F.50DB		-123541.00	-139115.00	-164297.00	-339861.00	-106453.00
0.25D		-149159.00	-170787.00	-162161.00	-306344.00	-406673.00
F.25D		-185829.00	-182217.00	-165718.00	-120702.00	-174111.00
0.75R		-181306.00	-77764.000	-88387.000	-68960.000	-56380.000
0.50RB		-1[illegible]7233.00	-69018.000	-63053.000	-67883.000	-64571.000
F.75R		-77053.000	-66283.000	-65071.000	-64885.000	-63499.000
0.50R		-152089.00	-134841.00	-157714.00	-125099.00	-173273.00
F.50R		-79214.000	-81126.000	-71934.000	-75519.000	-75067.000
F.50RB		-83739.000	-66116.000	-72722.000	-68609.000	-64233.000
0.25R		-144761.00	-80864.000	-87103.000	-71204.000	-73872.000
F.25R		-76071.000	-65579.000	-69200.000	-63300.000	-64381.000
0.75D	S 2	-103040.00	-74185.000	-67710.000	-70910.000	-81125.000
0.50DB		-129852.00	-97766.000	-79041.000	-80055.000	-90846.000
F.75D		-117168.00	-75946.000	-69397.000	-66133.000	-65254.000
0.50D		-85079.000	-88714.000	-87372.000	-69001.000	-82013.000
F.50D		-257056.00	-105427.00	-103515.00	-98260.000	-109034.00
F.50DB		-140189.00	-82531.000	-104077.00	-114296.00	-133777.00
0.25D		-140310.00	-73082.000	-71951.000	-79006.000	-76065.000
F.25D		-84632.000	-80474.000	-87495.000	-76735.000	-81328.000
0.75R		-94102.000	-126113.00	-77327.000	-105966.00	-86957.000
0.50RB		-142982.00	-116058.00	-109297.00	-113088.00	-120[illegible]67.00
F.75R		-115307.00	-316769.00	-254860.00	-320605.00	-96125.000
0.50R		-134246.00	-193426.00	-183687.00	-206467.00	-201648.00
F.50R		-88105.000	-91337.000	-88981.000	-79324.000	-100332.00
F.50RB		-108962.00	-98790.000	-144624.00	-103141.00	-103000.00
0.25R		-111489.00	-83752.000	-111084.00	-100142.00	-76063.000
F.25R	S 3	-110533.00	-93208.000	-104899.00	-171758.00	-329289.00
0.75D		-568974.00	-117908.00	-163354.00	-89721.000	-90707.000
0.50DB		-150103.00	-116425.00	-101329.00	-114716.00	-186350.00
F.75D		-123717.00	-83074.000	-252012.00	-99387.000	-95238.000
0.50D		-133350.00	-133245.00	-105472.00	-86398.000	-88256.000
F.50D		-175577.00	-162002.00	-141837.00	-255018.00	-554455.00
F.50DB		-113619.00	-91775.000	-95169.000	-78482.000	-84947.000
0.25D		-127328.00	-168251.00	-125635.00	-113478.00	-143126.00
F.25D		-168986.00	-476507.00	-121731.00	-133306.00	-165482.00

COND

0.75R		-114015.00	-109650.00	-116161.00	-107897.00	-007299.00
0.5ØRB		-78570.000	-78238.000	-83421.000	-80469.000	-76927.000
F.75R		-93449.000	-74881.000	-86290.000	-85864.000	-94169.000
0.5ØR		-127288.00	-139180.00	-126429.00	-121730.00	-132910.00
F.5ØR		-87031.000	-77307.000	-88624.000	-83579.000	-88568.000
F.5ØRB		-81012.000	-80836.000	-99851.000	-88283.000	-85160.000
0.25R		-97334.000	-106488.00	-101019.00	-95970.000	-96327.000
F.25R		-99300.000	-99406.000	-99428.000	-121472.00	-103144.00
0.75D		-102136.00	-97497.000	-105847.00	-107725.00	-102687.00
0.5ØDB		-103716.00	-94163.000	-110738.00	-95208.000	-96484.000
F.75D		-189037.00	-131488.00	-138206.00	-128973.00	-111767.00
0.5ØD	S 4	-116528.00	-95264.000	-113272.00	-109716.00	-101005.00
F.5ØD		-99990.000	-81145.000	-81508.000	-85054.000	-87923.000
F.5ØDB		-113982.00	-102708.00	-109008.00	-111338.00	-102047.00
0.25D		-227011.00	-123669.00	-124210.00	-145607.00	-142487.00
F.25D		-106090.00	-124426.00	-122583.00	-132821.00	-125196.00

0.75R		-112937.00	-71291.000	-89773.000	-111257.00	-101031.00
0.5ØRB		-79797.000	-67668.000	-57713.000	-50805.000	-89416.000
F.75R		-104685.00	-107286.00	-96097.000	-109081.00	-112682.00
0.5ØR		-131379.00	-102255.00	-95807.000	-122727.00	-173578.00
F.5ØR		-115516.00	-106136.00	-146190.00	-145389.00	-132924.00
F.5ØRB		-100509.00	-130104.00	-359154.00	-147475.00	-86244.000
0.25R		-67968.000	-67184.000	-78026.000	-101539.00	-70757.000
F.25R		-99254.000	-117674.00	-141702.00	-133532.00	-135149.00
0.75D		-119496.00	-123348.00	-118157.00	-150596.00	-114127.00
0.5ØDB		-107046.00	-161073.00	-175081.00	-102229.00	-95614.000
F.75D	S 5	-139521.00	-112183.00	-98238.000	-116737.00	-105288.00
0.5ØD		-107734.00	-102778.00	-97097.000	-115237.00	-117466.00
F.5ØD		-104408.00	-84280.000	-120043.00	-121571.00	-158441.00
F.5ØDB		-114506.00	-86787.000	-85294.000	-78703.000	-82997.000
0.25D		-95970.000	-76845.000	-66328.000	-66548.000	-71398.000
F.25D		-129636.00	-112278.00	-98930.000	-98197.000	-108356.00

TOTAL ERRORS

COND	BLOCK	1	2	3	4	5
SOE		1.0000000	2.0000000	.00000000	.00000000	.00000000
LOE		1.0000000	1.0000000	1.0000000	.00000000	.00000000
SVE		.00000000	.00000000	1.0000000	.00000000	1.0000000
LVE		1.0000000	.00000000	.00000000	1.0000000	.00000000
SFE		3.0000000	.00000000	.00000000	.00000000	1.0000000
LFE		1.0000000	.00000000	.00000000	1.0000000	2.0000000
SOM		25.000000	34.000000	17.000000	24.000000	24.000000
LOM		31.000000	29.000000	18.000000	17.000000	14.000000
SVM		48.000000	36.000000	27.000000	24.000000	35.000000
LVM		34.000000	24.000000	15.000000	28.000000	33.000000
SFM	S 1	19.000000	24.000000	16.000000	25.000000	23.000000
LFM		43.000000	42.000000	36.000000	40.000000	42.000000
SOD		56.000000	55.000000	63.000000	68.000000	86.000000
LOD		37.000000	27.000000	24.000000	40.000000	33.000000
SVD		16.000000	23.000000	15.000000	24.000000	20.000000
LVD		39.000000	29.000000	30.000000	43.000000	40.000000
SFD		28.000000	33.000000	28.000000	33.000000	31.000000
LFD		25.000000	32.000000	36.000000	27.000000	27.000000
SOE		6.0000000	4.0000000	3.0000000	8.0000000	1.0000000
LOE		2.0000000	3.0000000	1.0000000	4.0000000	4.0000000
SVE		1.0000000	.00000000	1.0000000	.00000000	3.0000000
LVE		2.0000000	4.0000000	3.0000000	5.0000000	3.0000000
SFE		4.0000000	1.0000000	2.0000000	8.0000000	5.0000000
LFE		6.0000000	7.0000000	9.0000000	7.0000000	7.0000000
SOM		30.000000	21.000000	17.000000	28.000000	29.000000
LOM		37.000000	39.000000	37.000000	42.000000	48.000000
SVM		28.000000	25.000000	21.000000	23.000000	26.000000
LVM	S 2	33.000000	28.000000	27.000000	24.000000	23.000000
SFM		25.000000	21.000000	26.000000	25.000000	17.000000
LFM		37.000000	37.000000	36.000000	38.000000	29.000000
SOD		50.000000	49.000000	42.000000	41.000000	41.000000
LOD		44.000000	42.000000	25.000000	26.000000	18.000000
SVD		29.000000	32.000000	26.000000	24.000000	22.000000
LVD		46.000000	50.000000	54.000000	55.000000	53.000000
SFD		24.000000	34.000000	27.000000	38.000000	40.000000
LFD		75.000000	55.000000	39.000000	51.000000	67.000000
SOE		5.0000000	7.0000000	7.0000000	8.0000000	5.0000000
LOE		6.0000000	2.0000000	6.0000000	7.0000000	6.0000000
SVE		3.0000000	1.0000000	4.0000000	6.0000000	4.0000000
LVE		10.000000	5.0000000	4.0000000	7.0000000	5.0000000
SFE		1.0000000	1.0000000	2.0000000	4.0000000	.00000000
LFE		9.0000000	2.0000000	9.0000000	7.0000000	6.0000000
SOM		21.000000	26.000000	19.000000	10.000000	22.000000
LOM	S 3	19.000000	19.000000	20.000000	28.000000	30.000000
SVM		60.000000	63.000000	52.000000	15.000000	15.000000
LVM		22.000000	20.000000	21.000000	14.000000	25.000000
SFM		21.000000	17.000000	17.000000	16.000000	14.000000
LFM		13.000000	12.000000	13.000000	19.000000	14.000000
SOD		46.000000	51.000000	45.000000	48.000000	42.000000
LOD		42.000000	50.000000	44.000000	44.000000	63.000000
SVD		52.000000	58.000000	46.000000	53.000000	63.000000
LVD		58.000000	53.000000	39.000000	41.000000	45.000000
SFD		55.000000	63.000000	66.000000	56.000000	41.000000
LFD		58.000000	55.000000	56.000000	40.000000	53.000000

COND

SOE		1.0000000	13.000000	8.0000000	3.0000000	6.0000000
LOE		5.0000000	3.0000000	1.0000000	4.0000000	10.000000
SVE		2.0000000	4.0000000	6.0000000	6.0000000	6.0000000
LVE		1.0000000	1.0000000	1.0000000	2.0000000	1.0000000
SFE		3.0000000	6.0000000	6.0000000	2.0000000	5.0000000
LFE		.00000000	2.0000000	.00000000	1.0000000	.00000000
SOM		21.000000	29.000000	21.000000	18.000000	26.000000
LOM	S 4	10.000000	18.000000	17.000000	12.000000	15.000000
SVM		36.000000	34.000000	33.000000	28.000000	32.000000
LVM		3.0000000	8.0000000	12.000000	14.000000	10.000000
SFM		23.000000	27.000000	19.000000	16.000000	21.000000
LFM		9.0000000	7.0000000	10.000000	19.000000	26.000000
SOD		44.000000	34.000000	38.000000	40.000000	39.000000
LOD		33.000000	58.000000	55.000000	44.000000	64.000000
SVD		28.000000	33.000000	36.000000	38.000000	48.000000
LVD		38.000000	53.000000	48.000000	39.000000	50.000000
SFD		53.000000	51.000000	68.000000	71.000000	72.000000
LFD		28.000000	16.000000	26.000000	28.000000	33.000000

SOE		2.0000000	3.0000000	.00000000	.00000000	2.0000000
LOE		3.0000000	4.0000000	1.0000000	1.0000000	2.0000000
SVE		2.0000000	1.0000000	.00000000	1.0000000	3.0000000
LVE		4.0000000	13.000000	3.0000000	1.0000000	1.0000000
SFE		2.0000000	1.0000000	.00000000	1.0000000	1.0000000
LFE		1.0000000	.00000000	.00000000	.00000000	.00000000
SOM		16.000000	23.000000	17.000000	39.000000	19.000000
LOM		10.000000	30.000000	34.000000	24.000000	25.000000
SVM	S 5	10.000000	10.000000	19.000000	18.000000	10.000000
LVM		21.000000	25.000000	18.000000	16.000000	22.000000
SFM		15.000000	9.0000000	11.000000	19.000000	8.0000000
LFM		20.000000	13.000000	22.000000	7.0000000	22.000000
SOD		41.000000	45.000000	37.000000	38.000000	30.000000
LOD		56.000000	54.000000	50.000000	32.000000	38.000000
SVD		39.000000	33.000000	48.000000	55.000000	50.000000
LVD		37.000000	28.000000	21.000000	48.000000	40.000000
SFD		46.000000	27.000000	47.000000	56.000000	53.000000
LFD		45.000000	56.000000	63.000000	63.000000	58.000000

TOTAL RESPONSES

COND	Block	1	2	3	4	5
SOE		79.000000	53.000000	76.000000	84.000000	65.000000
LOE		76.000000	68.000000	72.000000	66.000000	71.000000
SVE		69.000000	81.000000	78.000000	60.000000	74.000000
LVE		80.000000	80.000000	67.000000	64.000000	79.000000
SFE		71.000000	67.000000	59.000000	79.000000	68.000000
LFE		72.000000	68.000000	68.000000	71.000000	61.000000
SOM		68.000000	68.000000	71.000000	53.000000	78.000000
LOM		54.000000	53.000000	53.000000	56.000000	57.000000
SVM		48.000000	62.000000	65.000000	69.000000	60.000000
LVM		73.000000	63.000000	62.000000	43.000000	45.000000
SFM	S1	73.000000	57.000000	72.000000	58.000000	67.000000
LFM		64.000000	61.000000	54.000000	48.000000	50.000000
SOD		56.000000	51.000000	54.000000	43.000000	49.000000
LOD		65.000000	53.000000	47.000000	51.000000	40.000000
SVD		71.000000	56.000000	56.000000	51.000000	57.000000
LVD		48.000000	40.000000	38.000000	47.000000	55.000000
SFD		56.000000	59.000000	62.000000	52.000000	65.000000
LFD		67.000000	63.000000	70.000000	71.000000	50.000000
SOE		70.000000	72.000000	64.000000	67.000000	72.000000
LOE		62.000000	85.000000	68.000000	61.000000	70.000000
SVE		60.000000	69.000000	76.000000	67.000000	63.000000
LVE		69.000000	61.000000	77.000000	67.000000	79.000000
SFE		62.000000	73.000000	68.000000	57.000000	68.000000
LFE		61.000000	62.000000	67.000000	66.000000	72.000000
SOM		70.000000	86.000000	68.000000	76.000000	52.000000
LOM		70.000000	72.000000	78.000000	69.000000	70.000000
SVM		70.000000	62.000000	62.000000	61.000000	63.000000
LVM		100.00000	72.000000	56.000000	64.000000	69.000000
SFM		77.000000	63.000000	81.000000	54.000000	77.000000
LFM		73.000000	75.000000	78.000000	76.000000	80.000000
SOD	S2	66.000000	68.000000	76.000000	84.000000	75.000000
LOD		44.000000	81.000000	67.000000	65.000000	59.000000
SVD		66.000000	64.000000	64.000000	65.000000	74.000000
LVD		77.000000	79.000000	83.000000	90.000000	86.000000
SFD		73.000000	69.000000	80.000000	80.000000	70.000000
LFD		60.000000	64.000000	64.000000	59.000000	72.000000
SOE		62.000000	79.000000	72.000000	85.000000	61.000000
[illegible]		66.000000	77.000000	64.000000	65.000000	65.000000
SVE		70.000000	64.000000	62.000000	67.000000	70.000000
LVE		79.000000	80.000000	65.000000	70.000000	74.000000
SFE		67.000000	78.000000	70.000000	75.000000	67.000000
LFE		63.000000	66.000000	79.000000	75.000000	78.000000
SOM		73.000000	74.000000	76.000000	70.000000	77.000000
LOM		88.000000	78.000000	77.000000	87.000000	89.000000
SVM		85.000000	77.000000	72.000000	89.000000	78.000000
LVM		77.000000	72.000000	72.000000	69.000000	70.000000
SFM	S3	84.000000	77.000000	67.000000	67.000000	83.000000
LFM		75.000000	75.000000	75.000000	73.000000	74.000000
SOD		65.000000	89.000000	88.000000	83.000000	71.000000
LOD		75.000000	83.000000	72.000000	94.000000	71.000000
SVD		77.000000	72.000000	85.000000	76.000000	69.000000
LVD		73.000000	74.000000	67.000000	79.000000	82.000000
SFD		60.000000	63.000000	74.000000	73.000000	67.000000
LFD		82.000000	73.000000	71.000000	88.000000	84.000000

(CONT)

SOE		64.000000	73.000000	66.000000	73.000000	78.000000
LOE		69.000000	68.000000	62.000000	77.000000	77.000000
SVE		71.000000	64.000000	70.000000	81.000000	72.000000
LVE		59.000000	77.000000	71.000000	65.000000	67.000000
SFE		63.000000	57.000000	66.000000	63.000000	60.000000
LFE		73.000000	63.000000	81.000000	76.000000	77.000000
SOM		53.000000	60.000000	66.000000	56.000000	60.000000
LOM	S 4	68.000000	62.000000	71.000000	71.000000	65.000000
SVM		90.000000	89.000000	89.000000	88.000000	85.000000
LVM		83.000000	76.000000	70.000000	79.000000	70.000000
SFM		68.000000	65.000000	73.000000	72.000000	63.000000
LFM		64.000000	71.000000	74.000000	78.000000	69.000000
SOD		86.000000	77.000000	78.000000	85.000000	84.000000
LOD		73.000000	46.000000	66.000000	75.000000	64.000000
SVD		72.000000	82.000000	70.000000	80.000000	81.000000
LVD		91.000000	87.000000	95.000000	98.000000	86.000000
SFD		90.000000	72.000000	67.000000	88.000000	84.000000
LFD		53.000000	81.000000	74.000000	60.000000	70.000000

SOE		63.000000	63.000000	62.000000	70.000000	72.000000
LOE		74.000000	78.000000	69.000000	77.000000	65.000000
SVE		63.000000	66.000000	60.000000	72.000000	72.000000
LVE		65.000000	64.000000	61.000000	73.000000	70.000000
SFE		71.000000	73.000000	65.000000	63.000000	69.000000
LFE		56.000000	59.000000	74.000000	58.000000	70.000000
SOM		73.000000	83.000000	85.000000	82.000000	79.000000
LOM		75.000000	90.000000	91.000000	92.000000	80.000000
SVM	S 5	71.000000	72.000000	68.000000	58.000000	69.000000
LVM		80.000000	87.000000	74.000000	78.000000	80.000000
SFM		83.000000	74.000000	80.000000	76.000000	78.000000
LFM		76.000000	69.000000	78.000000	79.000000	79.000000
SOD		73.000000	63.000000	67.000000	79.000000	85.000000
LOD		77.000000	82.000000	84.000000	74.000000	65.000000
SVD		53.000000	60.000000	48.000000	57.000000	52.000000
LVD		68.000000	70.000000	64.000000	65.000000	53.000000
SFD		72.000000	56.000000	63.000000	63.000000	46.000000
LFD		62.000000	56.000000	51.000000	52.000000	63.000000

TOTAL LATENCIES (MS) Ignore - sign

COND	BLOCK	1	2	3	4	5
SOE		-97765.000	-63760.000	-72856.000	-71988.000	-82121.000
LOE		-95214.000	-71697.000	-74961.000	-72749.000	-80784.000
SVE		-71528.000	-71295.000	-76897.000	-73985.000	-67864.000
LVE		-79738.000	-72359.000	-81633.000	-93852.000	-104146.00
SFE		-100390.00	-63756.000	-57906.000	-57852.000	-57823.000
LFE		-98037.000	-76358.000	-74975.000	-87459.000	-79324.000
SOM		-120302.00	-104827.00	-86955.000	-116693.00	-101367.00
LOM		-125374.00	-107904.00	-106921.00	-103767.00	-103929.00
SVM		-176610.00	-148052.00	-171938.00	-156477.00	-160977.00
LVM		-146575.00	-131911.00	-147050.00	-130632.00	-159845.00
SFM	S 1	-107732.00	-89123.000	-78750.000	-91675.000	-92165.000
LFM		-172486.00	-183349.00	-160138.00	-157399.00	-176954.00
SOD		-151894.00	-151112.00	-142175.00	-157637.00	-138648.00
LOD		-210175.00	-130601.00	-117354.00	-124215.00	-122804.00
SVD		-107657.00	-108712.00	-97044.000	-106928.00	-106897.00
LVD		-163483.00	-146602.00	-162520.00	-160483.00	-163916.00
SFD		-115296.00	-100335.00	-96062.000	-122993.00	-102437.00
LFD		-148245.00	-136085.00	-145426.00	-148029.00	-148386.00
SOE		-71560.000	-50499.000	-53455.000	-54009.000	-54026.000
LOE		-79033.000	-77637.000	-63759.000	-80008.000	-79197.000
SVE		-111038.00	-96874.000	-111901.00	-150346.00	-128125.00
LVE		-56400.000	-57333.000	-57003.000	-61931.000	-61370.000
SFE		-88857.000	-63703.000	-64711.000	-56153.000	-55923.000
LFE		-56038.000	-59764.000	-57679.000	-57229.000	-67413.000
SOM		-172634.00	-125674.00	-122728.00	-104328.00	-123774.00
LOM		-156268.00	-144995.00	-149452.00	-151959.00	-148974.00
SVM		-92470.000	-89585.000	-85615.000	-88770.000	-92147.000
LVM		-117990.00	-132142.00	-136311.00	-119807.00	-115412.00
SFM	S 2	-162010.00	-144567.00	-123774.00	-128210.00	-120129.00
LFM		-199146.00	-253276.00	-112331.00	-115937.00	-100171.00
SOD		-157330.00	-121043.00	-115082.00	-120630.00	-122541.00
LOD		-145066.00	-303490.00	-112740.00	-123649.00	-138888.00
SVD		-174414.00	-116966.00	-123119.00	-111888.00	-108188.00
LVD		-193593.00	-232938.00	-206399.00	-149647.00	-156682.00
SFD		-107175.00	-126045.00	-97864.000	-100852.00	-96075.000
LFD		-221784.00	-178043.00	-145959.00	-157704.00	-148695.00
SOE		-120930.00	-60895.000	-62317.000	-63160.000	-63003.000
LOE		-110706.00	-118702.00	-152021.00	-176968.00	-172956.00
SVE		-221213.00	-83906.000	-86347.000	-77528.000	-73858.000
LVE		-122962.00	-78188.000	-68678.000	-67608.000	-65030.000
SFE		-140166.00	-149636.00	-171145.00	-153347.00	-130194.00
LFE		-121345.00	-93083.000	-127288.00	-130435.00	-123345.00
SOM	S 3	-116062.00	-122752.00	-124383.00	-96318.000	-120096.00
LOM		-160659.00	-92045.000	-84228.000	-80618.000	-80811.000
SVM		-210547.00	-165820.00	-148170.00	-132236.00	-110224.00
LVM		-161257.00	-110816.00	-110031.00	-121870.00	-162492.00
SFM		-100844.00	-113244.00	-105286.00	-115849.00	-103827.00
LFM		-128916.00	-100888.00	-100375.00	-108064.00	-105048.00
SOD		-152077.00	-109756.00	-161409.00	-150567.00	-105866.00
LOD		-184815.00	-205090.00	-165902.00	-98022.000	-98659.000
SVD		-303512.00	-153036.00	-127273.00	-109851.00	-114118.00
LVD		-180010.00	-136061.00	-173763.00	-164723.00	-152633.00
SFD		-220444.00	-123467.00	-102299.00	-167814.00	-164745.00
LFD		-265500.00	-246681.00	-209932.00	-169598.00	-149162.00

COND

SOE		-97611.000	-112995.00	-88646.000	-88021.000	-87433.000
LOE		-102759.00	-102797.00	-90290.000	-96111.000	-107576.00
SVE		-71902.000	-78273.000	-74356.000	-93287.000	-84090.000
LVE		-98179.000	-80047.000	-111602.00	-80346.000	-130850.00
SFE		-70232.000	-90338.000	-65552.000	-72338.000	-76838.000
LFE		-90668.000	-101314.00	-83504.000	-94937.000	-37860.000
SOM		-96295.000	-112600.00	-91995.000	-86550.000	-99190.000
LOM		-94066.000	-98493.000	-108044.00	-97622.000	-92516.000
SVM		-118818.00	-99291.000	-95951.000	-96514.000	-95738.000
LVM		-118374.00	-107896.00	-113296.00	-112285.00	-121592.00
SFM		-97471.000	-77327.000	-84229.000	-88509.000	-85398.000
LFM	S 4	-101364.00	-97586.000	-98486.000	-107444.00	-99704.000
SOD		-126435.00	-108317.00	-118942.00	-135335.00	-110963.00
LOD		-119578.00	-107398.00	-94315.000	-123025.00	-124388.00
SVD		-123990.00	-102127.00	-96040.000	-90257.000	-110692.00
LVD		-117415.00	-106221.00	-102903.00	-99756.000	-97956.000
SFD		-98961.000	-77677.000	-71102.000	-71148.000	-62172.000
LFD		-101027.00	-95476.000	-99441.000	-99158.000	-117103.00

SOE		-85012.000	-79075.000	-122655.00	-114954.00	-86476.000
LOE		-154330.00	-101702.00	-88895.000	-106962.00	-122950.00
SVE		-96718.000	-84704.000	-123395.00	-76916.000	-102361.00
LVE		-152395.00	-321993.00	-82191.000	-130532.00	-138748.00
SFE		-86286.000	-107315.00	-83872.000	-95318.000	-104254.00
LFE		-101165.00	-108267.00	-107020.00	-107002.00	-125876.00
SOM		-91595.000	-85430.000	-106131.00	-139453.00	-81984.000
LOM		-144236.00	-224095.00	-394139.00	-189712.00	-83608.000
SVM	S 5	-72409.000	-73943.000	-85802.000	-85732.000	-85667.000
LVM		-111995.00	-124073.00	-143626.00	-134401.00	-134837.00
SFM		-79936.000	-73702.000	-96301.000	-96159.000	-88919.000
LFM		-150059.00	-124997.00	-111673.00	-100556.00	-110811.00
SOD		-117762.00	-122854.00	-109469.00	-104365.00	-100767.00
LOD		-178622.00	-144654.00	-153357.00	-143996.00	-125588.00
SVD		-124663.00	-111344.00	-109874.00	-115697.00	-108303.00
LVD		-117678.00	-140868.00	-142578.00	-160873.00	-125112.00
SFD		-97151.000	-109307.00	-120365.00	-121964.00	-114321.00
LFD		-150357.00	-172521.00	-199014.00	-178201.00	-153182.00

Block Condition

1	2	3	4	5		
1368772.0	-1450807.0	-1290136.0	-1471539.0	-1009330.0	)	
805062.00	-623421.00	-601614.00	-646627.00	-451882.00	)	
3437852.0	-3377807.0	-3698642.0	-5182675.0	-6643910.0	)	O
2077364.0	-1934252.0	-2133309.0	-1721276.0	-1661423.0	)	
1573583.0	-1711146.0	-1970543.0	-1916446.0	-1854466.0	)	
1812072.0	-2013615.0	-1870059.0	-1964511.0	-1970286.0	)	
1361763.0	-657397.00	-673600.00	-640536.00	-580259.00	)	
3252719.0	-2539552.0	-2771315.0	-3598527.0	-4682011.0	)	V
2637874.0	-3594951.0	-2988585.0	-3094632.0	-2783956.0	)	
1738151.0	-1922599.0	-1605813.0	-1034050.0	-1233149.0	)	
1782667.0	-1902990.0	-1813807.0	-1717160.0	-1186124.0	)	
1619073.0	-1463081.0	-1317180.0	-1410743.0	-1243965.0	)	
2513372.0	-2058405.0	-2456688.0	-2342159.0	-2408930.0	)	
2272289.0	-2512130.0	-2463854.0	-2467095.0	-2451462.0	)	F
2592463.0	-2811962.0	-2929331.0	-1827022.0	-2125939.0	)	

Total latencies in S
(ignore – sign)

18.000000	15.000000	18.000000	17.000000	14.000000	)	
70.000000	61.000000	61.000000	73.000000	77.000000	)	
33.000000	60.000000	45.000000	43.000000	60.000000	)	O
78.000000	76.000000	68.000000	90.000000	85.000000	)	
36.000000	42.000000	39.000000	46.000000	45.000000	)	
31.000000	34.000000	39.000000	36.000000	25.000000	)	
66.000000	66.000000	71.000000	74.000000	67.000000	)	
42.000000	29.000000	30.000000	35.000000	59.000000	)	V
79.000000	80.000000	84.000000	61.000000	76.000000	)	
38.000000	43.000000	30.000000	27.000000	32.000000	)	
66.000000	82.000000	63.000000	68.000000	61.000000	)	
64.000000	65.000000	60.000000	47.000000	44.000000	)	
69.000000	66.000000	61.000000	67.000000	70.000000	)	F
56.000000	63.000000	61.000000	39.000000	56.000000	)	
62.000000	57.000000	65.000000	43.000000	38.000000	)	

Total errors

70.000000	66.000000	58.000000	62.000000	67.000000	)	
63.000000	62.000000	78.000000	66.000000	79.000000	)	O
79.000000	63.000000	65.000000	62.000000	62.000000	)	
84.000000	85.000000	72.000000	53.000000	73.000000	)	
77.000000	88.000000	96.000000	78.000000	82.000000	)	
63.000000	58.000000	71.000000	57.000000	86.000000	)	
73.000000	72.000000	82.000000	92.000000	84.000000	)	
98.000000	79.000000	86.000000	76.000000	87.000000	)	V
82.000000	98.000000	102.00000	117.00000	110.00000	)	
79.000000	73.000000	73.000000	63.000000	75.000000	)	
94.000000	81.000000	90.000000	91.000000	111.00000	)	
89.000000	99.000000	88.000000	100.00000	106.00000	)	
111.00000	96.000000	104.00000	99.000000	112.00000	)	F
71.000000	63.000000	82.000000	70.000000	77.000000	)	
41.000000	55.000000	49.000000	67.000000	73.000000	)	

Total responses

A P P E N D I X B

This contains examples of the analysis of variance, performed on the output of program overall for each of the four experiments. This is followed by the raw data for the analyses performed on experiments 2 - 4 not given in the text.

Analyses of Variance in Average Information contained in a response

EXPERIMENT 1

a) Analysis of Recognition data only:

Source	df	SS	MS	F
Stim. Prob.	2	.037	.019	1.3
Within Treatment	12	.171	.014	
Total	14	.208		

b) Analysis of all experimental conditions:

Source	df	SS	MS	F
Treatments	3	.049	.016	1.6
Within Treatment	21	.215	.010	
Total	24	.264		

EXPERIMENT 2

a) Not including burst data:

Source	df	SS	MS	F
Task (T)	1	.004	.004	3.0
Stim Prob (P)	2	.176	.088	40.0
Feedback (F)	1	.032	.032	26.7
S	4	.021	.005	1.5
T x P	2	.002	.001	.3
T x F	1	.002	.002	3.1
P x F	2	.027	.014	5.0
T x S	4	.006	.001	
P x S	8	.020	.002	
F x S	4	.005	.001	
T x P x F	2	.009	.005	1.3
T x P x S	8	.023	.003	
T x F x S	4	.003	.001	
F x P x S	8	.021	.003	
T x P x F x S	8	.029	.004	

b) Not including unequal stimulus probability data:

Source	df	SS	MS	F
Task (T)	1	.0016	.0016	4.3
Burst (B)	1	.0000	.0000	.0
Feedback (F)	1	.0009	.0009	4.5
S	4	.0048	.0012	5.4
T X B	1	.0000	.0000	.1
T X F	1	.0008	.0008	1.2
F X B	1	.0003	.0003	1.8
T x S	4	.0015	.0004	
B X S	4	.0012	.0003	
F x S	4	.0008	.0002	
T x B x F	1	.0002	.0002	.8
T x B x S	4	.0009	.0002	
T x F x S	4	.0027	.0007	
B x F x S	4	.0007	.0002	
T x B x F x S	4	.0009	.0002	

EXPERIMENT 3

Source	df	SS	MS	F
Time (T)	1	.0003	.0003	1.38
Feedback (F)	2	.0008	.0004	2.18
Difficult (D)	2	.0042	.0021	6.34
Subjects (S)	4	.0029	.0007	3.32
T x F	2	.0001	.0000	.36
T x D	2	.0002	.0001	.86
F x D	4	.0008	.0002	1.25
T x S	4	.0010	.0002	
F x S	8	.0015	.0002	
D x S	8	.0025	.0003	
T x F x D	4	.0013	.0003	1.53
T x F x S	8	.0010	.0001	
T x D x S	8	.0011	.0001	
F x D x S	16	.0027	.0002	
T x F x D x S	16	.0034	.0002	

In all the above designs each main effect is tested against the interaction between itself and subjects, i.e. $F_A = {}^{MSA}/_{MSAS}$. The subjects effect was tested against the highest order interaction, i.e. $F_S = {}^{MSS}/_{MSABCS}$. In the analysis reported in pp 150 all effects were first tested against the highest order interaction.

EXPERIMENT 4

Source	df	SS	MS	F
Treatments	2	.0119	.0060	1.89
Within Treatments	12	.0379	.0032	
Total	14	.0498		

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	.7937	.8418	.7728	.8438	.8438
F.75R	.8239	.8155	.7532	.8091	.8587
0.50R	.9998	.9952	.9990	.9961	1.000
F.50R	.9991	.9976	.9981	1.000	.9998
0.25R	.8026	.8438	.7914	.8340	.8457
F.25R	.8026	.8605	.7845	.8004	.8476
0.75D	.8218	.8239	.7868	.8218	.8259
F.75D	.8091	.8280	.8457	.7914	.8587
0.50D	.9995	.9996	.9995	.9981	.9999
F.50D	.9999	.9986	.9992	.9995	.9991
0.25D	.8004	.8113	.8320	.8418	.8155
F.25D	.8113	.7655	.8399	.8259	.8340

Average information in S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	.8925	.9651	.8360	.9651	.8846
F.75R	.8457	.7868	.5927	.8197	.7704
0.50R	.9529	.9796	.9509	.9974	.9341
F.50R	.9017	.9986	.9816	.9985	.9924
0.25R	.8694	.8641	.9399	.9316	.9643
F.25R	.8495	.8925	.8862	.8729	.8495
0.75D	.8569	.9376	.8070	.9160	.9187
F.75D	.7704	.8605	.9076	.8155	.8320
0.50D	.9862	.9935	.9988	.9796	.9873
F.50D	.9809	.9967	.9999	.9911	.9862
0.25D	.7822	.9118	.9651	.9733	.9717
F.25D	.9017	.8925	.8026	.9032	.8476

Average information in R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	.0055	.0060	.0074	.0190	.0573
F.75R	.0030	.0573	.0391	.0355	.0228
0.50R	.0104	.0081	.0359	.0167	.0155
F.50R	.0031	.0123	.0675	.0095	.0079
0.25R	.0031	.0074	.0098	.0040	.0166
F.25R	.0040	.0195	.0009	.0135	.0088
0.75D	.0016	.0058	.0151	.0282	.0175
F.75D	.0077	.0098	.0215	.0335	.0462
0.50D	.0052	.0053	.0049	.0259	.0115
F.50D	.0052	.0038	.0164	.0166	.0011
0.25D	.0093	.0061	.0023	.0384	.0059
F.25D	.0068	.0115	.0112	.0197	.0400

Average information in T and S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	.0599	.0373	.0246	.0042	.1535
F.75R	.0422	.0838	.0357	.0658	.0836
0.50R	.0191	.0110	.0125	.0033	.0200
F.50R	.0017	.0111	.1134	.0068	.0106
0.25R	.0117	.0181	.0041	.0018	.1046
F.25R	.0048	.0567	.0012	.0271	.0453
0.75D	.0720	.0096	.0258	.0137	.0615
F.75D	.1565	.0278	.0576	.0649	.1057
0.50D	.0247	.0052	.0041	.0143	.0148
F.50D	.0049	.0110	.0164	.0358	.0100
0.25D	.0526	.0757	.0146	.0686	.0476
F.25D	.0018	.0341	.0117	.0511	.1144

Average information in T and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	.0017	.0746	.3819	.3409	.2044
F.75R	.0008	.3709	.2361	.3727	.1356
0.50R	.0046	.0420	.2061	.3384	.1805
F.50R	.0032	.3637	.4043	.5461	.3387
0.25R	.0001	.3614	.2428	.4438	.2894
F.25R	.0023	.4390	.1870	.2439	.1620
0.75D	.0071	.1824	.2529	.3882	.0894
F.75D	.0725	.1469	.3000	.3644	.2072
0.50.	.1454	.0419	.2888	.4785	.3078
F.50D	.0263	.0943	.3480	.4593	.1580
0.25D	.0139	.0477	.1845	.2913	.0904
F.25D	.0083	.1550	.1563	.2600	.2748

Average information in S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	-.0009	-.0159	-.0103	-.0183	.0465
F.75R	-.0018	.0437	-.0028	.0296	.0047
0.50R	.0002	-.0146	-.0320	-.0734	-.0279
F.50R	-.0063	-.0098	.0549	-.0092	-.0232
0.25R	-.0051	-.0027	-.0014	-.0114	-.0217
F.25R	-.0067	.0047	-.0087	-.0003	-.0046
0.75D	-.0037	.0011	-.0125	-.0154	-.0223
F.75D	.0026	.0043	.0106	.0112	.0024
0.50D	-.0201	.0000	-.0066	-.0174	-.0264
F.50D	.0004	-.0030	-.0019	-.0549	-.0030
0.25D	.0039	.0049	-.0119	.0026	-.0017
F.25D	-.0013	-.0041	-.0205	.0155	.0213

Average information in T S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	5.607	6.394	7.208	18.98	57.18
F.75R	3.070	58.76	35.66	35.30	23.33
0.50R	10.60	8.227	36.42	16.93	15.85
F.50R	3.134	12.52	66.66	9.730	8.089
0.25R	3.064	7.616	10.59	4.053	16.64
F.25R	4.118	19.92	.9279	13.33	8.927
0.75D	1.615	5.949	15.42	30.28	18.12
F.75D	8.159	10.17	21.71	31.55	45.20
0.50D	5.323	5.430	4.977	26.29	11.79
F.50D	5.292	3.878	16.64	16.92	1.099
0.25D	9.221	6.306	2.305	35.03	5.918
F.25D	6.710	11.19	11.46	19.64	39.03

χ^2 df_3 measuring dep T and S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	59.41	36.85	24.09	4.287	135.3
F.75R	46.00	83.10	31.05	63.52	80.45
0.50R	19.09	11.26	12.63	3.342	19.64
F.50R	1.765	11.37	104.0	6.906	10.79
0.25R	11.98	18.03	4.193	1.878	96.09
F.25R	5.035	55.47	1.245	28.29	42.12
0.75D	68.43	9.572	25.58	14.03	60.54
F.75D	147.6	28.43	58.06	60.76	100.3
0.50D	25.10	5.346	4.218	14.50	15.25
F.50D	5.041	11.14	16.63	36.57	10.11
0.25D	52.42	72.58	14.87	64.31	46.45
F.25D	1.815	34.47	11.31	47.18	104.3

χ^2 df_3 measuring dep T and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	1.814	77.52	412.4	325.5	218.4
F.75R	.8406	406.1	292.4	403.6	150.7
0.50R	4.687	42.40	195.7	315.7	173.7
F.50R	3.229	339.6	373.0	484.0	318.4
0.25R	.0708	378.4	247.1	425.8	282.9
F.25R	2.405	440.7	202.7	263.3	176.4
0.75D	7.464	189.5	284.6	387.6	95.37
F.75D	81.88	160.5	309.9	398.9	225.0
0.50D	144.0	42.57	275.3	413.1	289.9
F.50D	26.81	94.68	327.2	416.9	156.1
0.25D	15.11	51.10	186.5	280.0	93.22
F.25D	8.782	168.5	173.7	272.7	296.6

χ^2 df_1 measuring dep S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	1.243	17.44	13.42	29.71	43.66
F.75R	1.802	68.25	88.11	31.58	19.99
0.50R	1.048	14.67	33.47	48.60	30.11
F.50R	6.250	9.534	7.688	4.965	17.50
0.25R	4.499	12.34	6.370	10.12	24.34
F.25R	8.266	32.58	9.046	9.777	13.73
0.75D	8.866	4.772	18.63	43.59	13.53
F.75D	32.58	3.476	5.030	19.77	5.859
0.50D	25.13	.1311	5.741	16.13	19.84
F.50D	.9399	4.204	7.021	36.13	2.353
0.25D	1.859	4.344	5.643	17.81	6.873
F.25D	1.122	5.796	12.02	10.63	20.22

χ^2 df_3 testing 3-way dependence T S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	2.268	2.973	5.613	.2643	.7285
F.75R	5.917	1.347	14.90	2.689	.4942
0.50R	19.59	.4228	4.086	2.017	3.104
F.50R	30.58	1.938	4.639	8.817	33.30
0.25R	5.865	1.098	2.948	1.688	30.99
F.25R	5.470	.8779	23.91	4.297	2.710
0.75D	17.30	1.291	.8879	.7060	2.914
F.75D	4.475	2.051	1.741	1.330	8.611
0.50D	9.755	10.50	7.263	2.554	4.538
F.50D	4.496	.7453	13.86	.6543	5.316
0.25D	7.015	1.856	3.937	.9597	3.595
F.25D	.8821	1.633	34.07	2.647	2.198

Fdf4, 735 testing stationarity latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	2.881	1.956	14.46	.7963	1.098
F.75R	8.148	1.921	10.32	4.885	.8549
0.50R	37.72	.8554	8.457	1.129	29.53
F.50R	21.39	4.671	6.275	5.738	33.55
0.25R	8.476	1.870	17.24	4.834	26.45
F.25R	10.21	13.59	23.22	4.783	1.612
0.75D	15.75	1.995	13.07	2.041	11.25
F.75D	37.16	6.227	1.269	10.32	2.348
0.50D	32.54	17.40	10.20	6.307	6.016
F.50D	7.741	1.818	17.69	1.896	2.613
0.25D	5.049	-.7188	5.990	2.385	7.266
F.25D	14.81	1.562	13.43	1.139	1.347

Fdf4, 635 testing stationarity latencies ignoring first 100 words

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	2.442	2.134	15.21	1.112	1.054
F.75R	4.114	3.255	23.07	7.994	1.214
0.50R	9.273	.6572	6.337	.7585	24.91
F.50R	24.48	2.599	9.282	5.612	29.28
0.25R	6.916	3.864	12.06	2.173	14.26
F.25R	4.314	9.411	17.33	4.493	.6848
0.75D	30.31	2.597	7.146	1.466	4.667
F.75D	24.13	2.622	.7581	7.547	3.975
0.50D	31.13	22.91	18.11	4.607	10.41
F.50D	6.287	2.201	7.530	1.974	1.146
0.25D	7.642	.9165	4.501	3.333	3.634
F.25D	13.27	4.927	32.73	.6041	4.969

F df4, 535 testing stationarity latencies ignoring the first 200 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	1.149	.7089	1.748	1.730	1.650
F.75R	.9832	3.330	4.078	1.118	1.647
0.50R	.9316	2.359	2.036	1.169	5.458
F.50R	2.016	1.083	2.754	.3540	2.781
0.25R	1.879	1.061	3.870	.7624	1.434
F.25R	.9471	1.400	.4108	2.946	.6011
0.75D	2.315	.1599	.9128	2.307	1.140
F.75D	.9567	1.494	.7101	3.774	2.206
0.50D	4.688	1.711	.3516	.6919	.9195
F.50D	1.222	2.615	1.874	1.647	.3366
0.25D	.4876	2.237	.1405	.6179	2.212
F.25D	.6584	.6583	3.023	2.418	1.757

Ffd4, 65 testing stationarity errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	3.232	.5032	.5922	.7785	4.717
F.75R	1.122	1.148	4.893	1.204	.7557
0.50R	.8204	1.337	2.087	.8170	2.193
F.50R	.7240	.8775	1.397	1.167	.7879
0.25R	2.321	2.451	.9843	2.130	1.500
F.25R	2.488	1.834	1.305	4.071	.7173
0.75D	1.593	.7195	.3528	2.048	.5869
F.75D	1.211	1.376	1.545	.8943	.1935
0.50D	4.353	.5288	.0458	.7970	2.836
F.50D	1.498	2.526	.7024	.3679	.4851
0.25D	1.275	.2881	1.360	.3124	.5972
F.25D	2.554	.4627	2.651	.9351	.9152

Fdf4, 65 testing stationarity responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	255.8	121.2	172.1	16.83	91.52
F.75R	152.1	47.20	184.6	9.280	65.04
0.50R	367.9	130.4	68.62	21.03	96.34
F.50R	228.8	24.67	53.97	41.86	174.6
0.25R	565.6	37.07	80.97	18.24	136.5
F.25R	223.4	70.65	73.30	27.81	75.05
0.75D	319.6	28.68	119.7	6.204	167.6
F.75D	286.1	55.74	27.21	36.86	101.9
0.50D	112.5	40.36	72.44	44.02	75.77
F.50D	170.7	47.00	33.81	11.97	68.56
0.25D	196.7	48.69	64.59	13.58	104.6
F.25D	178.8	15.56	44.05	42.01	148.6

X^2df9 testing first order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	85.03	63.18	75.97	44.42	60.87
F.75R	74.85	54.36	43.57	48.58	55.02
0.50R	161.0	38.78	55.39	33.85	56.44
F.50R	77.14	40.46	44.81	40.76	124.1
0.25R	196.9	44.14	47.04	42.61	59.42
F.25R	58.33	54.28	59.83	55.43	37.35
0.75D	76.00	48.49	72.67	40.78	143.9
F.75D	156.3	40.81	45.73	43.83	105.7
0.50D	38.85	52.92	36.58	54.61	41.00
F.50D	88.90	50.22	56.58	22.79	44.88
0.25D	89.15	56.50	31.39	50.92	107.3
F.25D	121.0	68.67	36.35	38.12	79.33

X^2df36 testing second order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	65.31	8.462	8.407	.3118	5.133
F.75R	133.7	3.362	1.408	.1803	.2439
0.50R	20.48	.5503	3.025	2.594	2.210
F.50R	36.46	.4810	4.716	1.628	4.119
0.25R	222.7	4.430	16.77	2.067	26.13
F.25R	25.82	.0616	60.31	7.550	3.317
0.75D	57.40	1.503	12.88	2.574	.7898
F.75D	25.66	.3343	1.994	.9115	.3254
0.50D	19.52	.0634	8.429	.6085	1.575
F.50D	29.24	2.111	2.162	2.370	.1995
0.25D	85.55	.6019	.6560	5.031	6.680
F.25D	158.3	.1115	.1753	.0270	.2091

X^2df1 testing first order dependence R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	2.597	12.82	1.567	.3711	1.473
F.75R	.1188	.3270	8.664	2.623	5.393
0.50R	39.75	24.28	1.924	.9923	2.988
F.50R	5.333	.6566	15.06	.0213	7.385
0.25R	22.11	3.042	.9748	.0227	11.36
F.25R	2.363	1.922	18.20	1.488	6.188
0.75D	25.61	5.304	.7575	2.025	1.060
F.75D	8.267	1.999	1.471	.6470	.2773
0.50D	12.79	.0787	3.786	2.386	.8899
F.50D	25.37	4.556	2.918	1.228	1.501
0.25D	4.721	1.822	.6423	1.818	4.861
F.25D	9.163	4.235	1.724	4.107	5.916

X^2df_2 testing second order dependence R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	7.375	12.57	9.212	.2090	.0808
F.75R	9.136	1.800	.4772	.1035	.2519
0.50R	.0316	16.71	19.51	4.863	13.34
F.50R	.0569	.0488	.0562	.1237	1.519
0.25R	18.00	7.014	17.45	1.373	17.05
F.25R	14.65	.0239	34.17	.2984	.8618
0.75D	5.321	4.314	.1151	.0316	.0820
F.75D	2.633	.6262	.5109	2.436	.3804
0.50D	2.268	.1871	5.132	2.603	2.084
F.50D	3.154	1.917	1.621	.1832	.2721
0.25D	8.190	.5317	.7367	1.354	1.043
F.25D	9.068	.5187	.2410	.3345	3.888

X^2df_1 testing first order dependence errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	2.060	4.513	1.976	1.812	6.225
F.75R	4.835	.4117	.7763	.0460	5.527
0.50R	1.467	1.707	11.39	.5211	2.201
F.50R	2.177	2.236	3.109	.5935	.0549
0.25R	5.732	3.754	6.041	3.576	1.672
F.25R	10.64	2.783	7.014	4.151	13.04
0.75D	3.544	5.115	.3744	2.605	2.113
F.75D	6.127	4.206	1.337	.4785	2.125
0.50D	7.357	.4504	6.162	.1155	4.528
F.50D	1.012	12.02	.8698	2.209	2.612
0.25D	7.003	4.342	6.200	1.242	4.640
F.25D	7.561	.9548	8.118	1.912	3.175

X^2df_2 testing second order dependence errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	76.99	24.94	28.03	8.979	19.12
F.75R	242.7	25.84	7.215	5.399	7.386
0.50R	27.59	26.43	40.84	34.10	25.25
F.50R	160.8	18.87	24.32	5.963	11.42
0.25R	230.4	19.32	39.90	7.346	65.00
F.25R	280.2	12.96	109.9	16.75	16.22
0.75D	68.60	29.75	22.18	4.029	11.92
F.75D	59.80	9.772	11.98	10.94	9.611
0.50D	63.52	6.285	24.27	5.425	7.795
F.50D	41.26	13.65	9.727	13.20	22.02
0.25D	120.2	9.114	13.11	14.15	11.06
F.25D	206.7	7.373	8.844	14.61	10.19

$X^2 df_9$ testing first order dependence
SR sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	48.49	47.61	41.06	20.06	34.47
F.75R	26.97	44.91	34.30	31.87	58.43
0.50R	73.78	67.38	56.63	39.99	39.26
F.50R	34.03	30.68	51.04	38.77	52.81
0.25R	66.75	61.19	30.38	26.16	35.13
F.25R	40.21	25.21	51.12	38.92	66.50
0.75D	68.44	38.87	23.04	26.20	24.79
F.75D	44.09	42.56	42.23	34.22	23.59
0.50D	50.82	35.77	46.70	25.17	30.58
F.50D	50.47	53.34	33.15	23.48	35.32
0.25D	39.69	40.66	66.23	26.90	49.70
F.25D	45.56	40.11	50.34	36.39	41.12

$X^2 df_{36}$ testing second order dependence
SR sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	-919.3	-590.1	-644.9	-734.8	-624.7
F.75R	-1003	-443.9	-1485	-578.5	-704.9
0.50R	-1897	-925.9	-1236	-879.7	-815.5
F.50R	-694.9	-472.9	-741.4	-591.4	-1118
0.25R	-467.5	-535.2	-630.0	-672.9	-521.3
F.25R	-604.9	-443.8	-1087	-702.4	-849.5
0.75D	-1319	-504.0	-741.1	-691.5	-834.5
F.75D	-847.9	-490.1	-844.4	-875.0	-768.3
0.50D	-1450	-561.2	-727.0	-714.9	-734.8
F.50D	-1185	-719.8	-625.8	-715.6	-593.3
0.25D	-1618	-596.3	-907.1	-904.5	-494.4
F.25D	-1041	-557.9	-1439	-823.1	-720.6

Total latencies (   ) ignoring
sign

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	3.407	2.236	2.379	2.086	1.979
F.75R	3.050	2.379	3.871	1.336	2.393
0.50R	1.879	7.236	7.621	2.129	13.16
F.50R	4.036	1.143	3.093	.3357	4.086
0.25R	8.443	1.550	7.736	.6929	3.229
F.25R	2.657	1.321	1.286	3.736	1.300
0.75D	5.907	.3571	1.121	2.586	2.371
F.75D	1.979	2.300	.9786	4.193	2.907
0.50D	12.20	5.021	.8786	.9429	1.236
F.50D	3.236	7.550	2.664	1.764	.8071
0.25D	1.407	3.479	.3357	.8786	4.907
F.25D	2.193	1.129	5.371	3.414	2.086

Var total errors in each 140 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
0.75R	10.88	1.979	1.764	1.800	8.486
F.75R	5.843	2.179	7.914	2.607	1.593
0.50R	4.164	4.307	4.879	1.943	7.771
F.50R	2.879	2.193	5.450	3.307	3.229
0.25R	16.23	5.343	2.521	5.193	8.071
F.25R	5.800	3.800	6.950	8.764	2.521
0.75D	7.550	1.479	1.236	5.236	1.521
F.75D	4.121	2.821	2.979	1.893	.4143
0.50D	16.79	1.250	.1571	1.979	7.629
F.50D	9.036	5.443	2.479	1.200	.9500
0.25D	5.664	.6214	4.093	.7857	2.264
F.25D	13.44	1.229	6.200	2.400	2.443

Var total responses in each 140 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	1.000	.9977	1.000	1.000	.9999
NØR	.9998	.9952	.9990	.9961	1.000
BFR	.9981	.9983	.9997	1.000	1.000
NFR	.9991	.9996	.9981	1.000	.9998
BØD	.9997	.9996	.9986	1.000	1.000
NØD	.9995	.9996	.9995	.9981	.9999
BFD	1.000	.9999	.9959	.9955	.9993
NFD	.9999	.9986	.9992	.9995	.9991

Average information S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.9979	.9998	.9996	.9939	.9651
NØR	.9529	.9796	.9509	.9974	.9341
BFR	.9762	1.000	.9997	.9935	.9477
NFR	.9017	.9986	.9816	.9985	.9924
BØD	.9776	.9967	.9952	.9999	.9911
NØD	.9862	.9985	.9988	.9796	.9873
BFD	.9783	.9991	.9846	.9979	.9952
NFD	.9809	.9967	.9999	.9911	.9862

Average information R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BOR	.0046	.0021	.0529	.0140	.0064
NOR	.0104	.0081	.0359	.0167	.0155
BFR	.0020	.0027	.0162	.0084	.0169
NFR	.0031	.0123	.0675	.0095	.0079
BØD	.0006	.0036	.0058	.0392	.0071
NØD	.0052	.0053	.0049	.0259	.0115
BFD	.0089	.0048	.0031	.0293	.0177
NFD	.0052	.0038	.0164	.0166	.0011

Average information T and S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.ØØ14	.ØØ32	.Ø551	.Ø153	.Ø132
NØR	.Ø191	.Ø11Ø	.Ø125	.ØØ33	.Ø2ØØ
BFR	.Ø215	.ØØ46	.Ø139	.ØØ8Ø	.Ø343
NFR	.ØØ17	.Ø111	.1134	.ØØ68	.Ø1Ø6
BØD	.ØØ4Ø	.ØØØ5	.ØØ45	.Ø3Ø8	.Ø425
NØD	.Ø247	.ØØ52	.ØØ41	.Ø143	.Ø148
BFD	.ØØ96	.ØØ45	.Ø1Ø2	.Ø188	.Ø199
NFD	.ØØ49	.Ø11Ø	.Ø164	.Ø358	.Ø1ØØ

Average information T and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.ØØØØ	.3Ø61	.3118	.6Ø56	.Ø341
NØR	.ØØ46	.Ø42Ø	.2Ø61	.3384	.18Ø5
BFR	.ØØØ1	.26Ø3	.4141	.4Ø76	.1862
NFR	.ØØ32	.3637	.4Ø43	.5461	.3387
BØD	.Ø56Ø	.ØØØØ	.353Ø	.5443	.Ø7Ø7
NØD	.1454	.Ø419	.2888	.4785	.3Ø78
BFD	.ØØ26	.Ø696	.2581	.4916	.Ø861
NFD	.Ø263	.Ø943	.348Ø	.4593	.158Ø

Average information S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
ØR	-.ØØ38	-.Ø169	.Ø332	.ØØ23	-.Ø213
ØR	.ØØØ2	-.Ø146	-.Ø32Ø	-.Ø734	-.Ø279
FR	-.ØØØ4	-.Ø157	.ØØ35	-.ØØ4Ø	-.ØØ38
FR	-.ØØ63	-.ØØ98	.Ø549	-.ØØ92	-.Ø232
ØD	-.Ø273	-.ØØ19	-.Ø2Ø3	-.ØØ14	-.ØØ43
ØD	-.Ø2Ø1	.ØØØØ	-.ØØ66	-.Ø174	-.Ø264
FD	-.Ø145	-.ØØ47	-.Ø734	.ØØ53	-.ØØ44
FD	.ØØØ4	-.ØØ3Ø	-.ØØ19	-.Ø549	-.ØØ3Ø

Average information T S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	4.692	2.142	53.06	14.33	6.509
NØR	10.60	8.227	36.42	16.93	15.85
BFR	2.097	2.731	16.41	8.622	17.14
NFR	3.134	12.52	66.66	9.730	8.089
BØD	.5786	3.651	5.914	39.40	7.238
NØD	5.323	5.430	4.977	26.29	11.79
BFD	9.097	4.946	3.153	29.56	18.06
NFD	5.292	3.878	16.64	16.92	1.099

$X^2 df_3$ measuring dependence T and S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	1.410	3.287	54.92	15.57	13.23
NØR	19.09	11.26	12.63	3.342	19.64
BFR	22.01	4.730	14.16	8.176	34.11
NFR	1.765	11.37	104.0	6.906	10.79
BØD	4.077	.5376	4.658	31.15	42.57
NØD	25.10	5.346	4.218	14.50	15.25
BFD	9.759	4.606	10.43	19.02	20.15
NFD	5.041	11.14	16.63	36.57	10.11

$X^2 df_3$ measuring dependence T and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.0000	290.3	296.0	520.8	34.66
NØR	4.687	42.40	195.7	315.7	173.7
BFR	.1165	250.3	382.4	374.7	179.8
NFR	3.229	339.6	373.0	484.0	318.4
BØD	56.66	.0105	331.8	483.3	71.26
NØD	144.6	42.57	275.3	413.1	289.9
BFD	2.669	70.21	249.5	444.4	86.61
NFD	26.81	94.68	327.2	416.9	156.1

$X^2 df_1$ measuring dependence S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	3.471	7.382	1.482	1.922	25.03
NØR	1.048	14.67	33.47	48.60	30.11
BFR	.5819	12.03	3.726	5.422	19.75
NFR	6.250	9.534	7.688	4.965	17.50
BØD	26.24	1.941	14.15	11.41	8.778
NØD	25.13	.1311	5.741	16.13	19.84
BFD	16.18	2.493	56.01	6.209	13.90
NFD	.9399	4.204	7.021	36.13	2.353

$X^2 df_3$ testing 3-way dependence T S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.8379	1.355	.2498	1.251	2.533
NØR	19.59	.4228	4.086	2.017	3.104
BFR	4.553	.7185	2.918	1.288	1.982
NFR	30.58	1.938	4.639	8.817	33.30
BØD	2.723	1.381	4.656	.6782	12.49
NØD	9.755	10.50	7.263	2.554	4.538
BFD	4.594	1.654	6.117	.7845	5.496
NFD	4.496	.7453	13.86	.6543	5.316

$F df_{4,735}$ testing stationarity latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	10.84	2.610	.9650	1.277	3.414
NØR	37.72	.8554	8.457	1.129	29.53
BFR	11.55	.7543	5.610	4.971	5.994
NFR	21.39	4.671	6.275	5.738	33.55
BØD	4.741	1.141	11.33	1.556	13.50
NØD	32.54	17.40	10.20	6.307	6.016
BFD	5.956	1.439	6.041	1.798	9.657
NFD	7.741	1.818	17.69	1.896	2.613

$F df_{4,635}$ testing stationarity latencies ignoring first 100 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
B0R	12.34	.7851	.1170	.5197	3.629
N0R	9.273	.6572	6.337	.7585	24.91
BFR	5.178	.9078	1.697	5.097	2.748
NFR	24.48	2.599	9.282	5.612	29.28
B0D	.6436	1.451	9.250	1.550	15.02
N0D	31.13	22.91	18.11	4.607	10.41
BFD	18.53	1.440	4.097	1.640	6.131
NFD	6.287	2.201	7.530	1.974	1.146

Fdf4,535 testing stationarity ignoring first 200 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
B0R	.0852	2.174	.5393	3.028	.7860
N0R	.9316	2.359	2.036	1.169	5.458
BFR	1.895	.4178	.3683	1.203	2.327
NFR	2.016	1.083	2.754	.3540	2.781
B0D	3.601	.6230	.7282	.0225	.8952
N0D	4.688	1.711	.3516	.6919	.9195
BFD	2.450	2.676	2.568	.9493	4.160
NFD	1.222	2.615	1.874	1.647	.3366

Fdf4,65 testing stationarity errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
B0R	1.068	2.662	3.506	1.405	2.464
N0R	.8204	1.337	2.087	.8170	2.193
BFR	.2311	.8040	1.505	1.632	2.292
NFR	.7240	.8775	1.397	1.167	.7879
B0D	2.203	1.221	.4711	.4759	1.162
N0D	4.353	.5288	.0458	.7970	2.836
BFD	6.276	1.119	6.026	.6498	.6581
NFD	1.498	2.526	.7024	.3679	.4851

Fdf4,65 testing stationarity responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	212.3	14.06	69.27	6.011	153.9
NØR	367.9	130.4	68.62	21.03	96.34
BFR	97.57	5.947	56.60	13.74	44.22
NFR	228.8	24.67	53.97	41.86	174.6
BØD	49.31	63.82	49.92	15.65	84.44
NØD	112.5	40.36	72.44	44.02	75.77
BFD	277.8	62.57	76.46	11.80	81.51
NFD	170.7	47.00	33.81	11.97	68.56

$X^2 df_9$ measuring first order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	70.22	45.72	39.01	54.23	142.6
NØR	161.0	38.78	55.39	33.85	56.44
BFR	98.92	30.83	38.39	30.71	58.33
NFR	77.14	40.46	44.81	40.76	124.1
BØD	27.00	34.80	29.06	31.16	44.68
NØD	38.85	52.92	36.58	54.61	41.00
BFD	179.4	47.89	54.09	57.34	81.45
NFD	88.90	50.22	56.58	22.79	44.88

$X^2 df_{36}$ measuring second order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	108.2	21.47	1.361	.0105	.1367
NØR	20.48	.5503	3.025	2.594	2.210
BFR	8.365	12.49	5.508	.9052	4.165
NFR	36.46	.4810	4.716	1.628	4.119
BØD	24.87	.0075	1.189	3.120	.1098
NØD	19.52	.0634	8.429	.6085	1.575
BFD	2.008	.2295	2.806	.0000	.4025
NFD	29.24	2.111	2.162	2.370	.1995

$X^2 df_1$ measuring first order dependence responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	80.90	.3370	2.458	6.644	3.980
NØR	39.75	24.28	1.924	.9923	2.988
BFR	42.02	.0800	1.634	1.135	.6723
NFR	5.333	.6566	15.06	.0213	7.385
BØD	5.724	1.024	10.75	2.621	1.820
NØD	12.79	.0787	3.786	2.386	.8899
BFD	12.34	5.030	4.163	.7556	2.734
NFD	25.37	4.556	2.918	1.228	1.501

$X^2 df_2$ measuring second order dependence R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.0921	2.250	14.21	.9036	.2519
NØR	.0316	16.71	19.51	4.863	13.34
BFR	.0055	.0971	.6473	.0033	.3400
NFR	.0569	.0488	.0562	.1237	1.519
BØD	.1117	.5493	.4612	1.436	.3377
NØD	2.268	.1871	5.132	2.603	2.084
BFD	.0292	.0888	6.995	3.118	1.357
NFD	3.154	1.917	1.621	.1832	.2721

$X^2 df_1$ measuring first order dependence responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	5.726	.4475	6.192	16.37	2.846
NØR	1.487	1.707	11.39	.5211	2.201
BFR	.5429	.0748	.0381	3.370	2.730
NFR	2.177	2.236	3.109	.5935	.0549
BØD	.8649	3.697	1.024	1.199	1.968
NØD	7.357	.4504	6.162	.1155	4.528
BFD	1.051	.2402	3.935	4.781	1.196
NFD	1.012	12.02	.8698	2.209	2.612

$X^2 df_2$ measuring second order dependence responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	114.2	36.18	32.77	9.891	8.822
NØR	27.59	26.43	40.84	34.10	25.25
BFR	14.03	21.39	33.07	9.315	5.679
NFR	160.8	18.87	24.32	5.963	11.42
BØD	36.10	9.620	9.597	6.151	8.868
NØD	63.52	6.285	24.27	5.425	7.795
BFD	53.17	9.442	12.34	15.89	9.078
NFD	41.26	13.65	9.727	13.20	22.02

$X^2 df_1$ measuring first order dependence SR sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	137.4	44.69	43.45	32.57	53.96
NØR	73.78	67.38	56.63	39.99	39.26
BFR	80.07	54.94	26.24	37.21	47.26
NFR	34.03	30.68	51.04	38.77	52.81
BØD	34.09	40.50	44.69	29.08	56.59
NØD	50.82	35.77	46.70	25.17	30.58
BFD	53.80	34.72	57.92	26.96	37.61
NFD	50.47	53.34	33.15	23.48	35.32

$X^2 df_2$ measuring second order dependence SR sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	-785.0	-457.3	-744.4	-540.7	-467.4
NØR	-1897	-925.9	-1236	-879.7	-815.5
BFR	-965.3	-511.2	-604.4	-568.3	-849.6
NFR	-694.9	-472.9	-741.4	-591.4	-1118
BØD	-1072	-619.9	-896.7	-657.2	-852.8
NØD	-1450	-561.2	-727.0	-714.9	-734.8
BFD	-1547	-763.5	-1679	-566.6	-773.7
NFD	-1185	-719.8	-625.8	-715.6	-593.3

Total latencies ( ) ignoring -ve signs

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	.1648	3.986	1.086	2.771	1.879
NØR	1.879	7.236	7.621	2.129	13.16
BFR	4.593	.5500	.5500	1.714	4.979
NFR	4.036	1.143	3.093	.3357	4.086
BØD	7.907	1.464	.8714	.0214	2.629
NØD	12.20	5.021	.8786	.9429	1.236
BFD	6.521	7.193	6.093	1.121	8.557
NFD	3.236	7.550	2.664	1.764	.8071

Var total errors in each 140 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
BØR	10.06	5.693	8.407	4.800	6.450
NØR	4.164	4.307	4.879	1.943	7.771
BFR	1.050	2.521	5.093	6.057	7.907
NFR	2.879	2.193	5.450	3.307	3.229
BØD	4.807	3.379	1.557	1.679	3.157
NØD	16.79	1.250	.1571	1.979	7.629
BFD	17.04	1.771	15.96	2.229	2.086
NFD	9.036	5.443	2.479	1.200	.9500

Var total responses in each 140 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.9995	1.000	.9988	.9999	.9967
LØE	.9993	1.000	.9985	.9990	.9996
SVE	.9995	.9986	.9952	1.000	.9979
LVE	.9985	.9997	.9995	.9996	.9985
SFE	.9999	.9993	1.000	.9942	.9999
LFE	.9998	.9974	.9997	.9949	.9961
SØM	1.000	.9996	.9993	.9990	.9946
LØM	.9995	.9999	1.000	.9992	1.000
SVM	.9999	1.000	.9983	1.000	1.000
LVM	1.000	.9999	.9999	.9996	1.000
SFM	.9999	.9996	.9995	1.000	.9979
LFM	.9992	1.000	.9990	.9990	.9998
SØD	.9999	.9998	.9991	1.000	.9995
LØD	1.000	.9992	.9959	.9999	.9974
SVD	.9993	1.000	.9999	.9999	.9999
LVD	.9920	.9972	.9999	1.000	1.000
SFD	1.000	.9998	1.000	.9983	1.000
LFD	.9979	.9990	.9995	.9985	1.000

Average information in S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.9993	.9999	.9990	.9999	.9969
LØE	.9999	.9999	.9983	1.000	.9993
SVE	.9995	.9986	.9985	.9999	.9985
LVE	.9981	.9998	.9981	.9995	.9985
SFE	.9998	.9985	.9998	.9915	1.000
LFE	.9996	.9959	.9986	.9961	.9959
SØM	.9983	.9998	.9974	.9822	.9834
LØM	.9709	.9990	.9693	.9991	.9717
SVM	.9883	.9946	.9857	.9498	.9992
LVM	.9685	.9990	.9996	.9935	.9846
SFM	.9967	1.000	.9952	.9999	.9883
LFM	.9685	.9924	.9972	.9993	.9964
SØD	.9433	.9974	.9888	.9783	.9983
LØD	.9433	.9928	.9857	.9961	.9924
SVD	.9796	.9986	.9952	.9911	.9668
LVD	.9047	.9783	.9974	.9304	.9946
SFD	.9851	.9961	.9998	.9846	.9851
LFD	.9949	.9946	.9868	.9999	.9755

Average information in R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.2656	.0033	.0007	.0024	.1096
LØE	.2350	.0073	.0060	.0197	.0501
SVE	.0810	.0060	.0005	.0011	.0602
LVE	.0293	.0059	.0009	.0012	.0214
SFE	.3667	.0234	.0030	.0067	.1541
LFE	.0584	.0384	.0001	.0097	.0323
SØM	.0254	.0541	.0013	.0252	.0145
LØM	.0198	.0075	.0002	.0053	.0003
SVM	.0467	.0026	.0010	.0319	.0513
LVM	.0196	.0271	.0031	.0143	.0133
SFM	.0243	.0054	.0039	.0016	.0269
LFM	.0054	.0163	.0035	.0017	.0134
SØD	.0017	.0204	.0047	.0233	.0018
LØD	.0233	.0012	.0016	.0002	.0014
SVD	.0310	.0087	.0042	.0042	.0141
LVD	.0107	.0031	.0071	.0190	.0246
SFD	.0070	.0273	.0059	.0021	.0095
LFD	.0109	.0007	.0100	.0072	.0104

Average information in T and S

Average information T x R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.1633	.0037	.0011	.0015	.1151
LØE	.2328	.0114	.0020	.0137	.0482
SVE	.0837	.0055	.0006	.0028	.0548
LVE	.0292	.0041	.0004	.0013	.0326
SFE	.3573	.0263	.0025	.0066	.1554
LFE	.0566	.0438	.0001	.0085	.0323
SØM	.0278	.1219	.0031	.0121	.0046
LØM	.0283	.0070	.0017	.0030	.0105
SVM	.0050	.0038	.0008	.0350	.0449
LVM	.0025	.0278	.0020	.0126	.0369
SFM	.0207	.0131	.0045	.0009	.0256
LFM	.0052	.0108	.0141	.0049	.0185
SØD	.0447	.0269	.0042	.0335	.0075
LØD	.0070	.0033	.0014	.0059	.0037
SVD	.0029	.0253	.0046	.0055	.0158
LVD	.0535	.0037	.0315	.0308	.0236
SFD	.0079	.0213	.0111	.0052	.0210
LFD	.0205	.0006	.0094	.0038	.0119

Average information S x R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.9617	.7937	.7360	.7429	.9198
LØE	.9524	.8575	.7665	.8013	.8888
SVE	.9725	.9307	.8340	.7888	.9223
LVE	.9740	.8420	.7382	.9225	.8055
SFE	.9416	.8214	.9079	.7954	.9417
LFE	.9523	.7056	.7149	.9525	.9825
SØM	.3307	.3323	.4181	.3755	.4097
LØM	.3914	.1417	.3776	.5346	.3599
SVM	.2187	.3451	.1415	.2360	.5498
LVM	.2966	.3031	.3300	.6112	.4321
SFM	.3815	.3738	.4712	.3836	.5748
LFM	.1326	.1782	.5326	.5334	.4584
SØD	.0320	.0948	.0620	.1594	.1599
LØD	.2501	.2470	.0639	.0619	.0902
SVD	.4567	.3099	.0304	.1694	.1002
LVD	.1667	.0590	.0714	.1154	.1932
SFD	.2546	.2279	.0245	.0060	.0917
LFD	.2747	.0211	.0507	.2935	.0294

Average information T x S x R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.2588	-.0240	-.0003	-.0120	.0994
LØE	.2254	-.0015	-.0061	-.0115	.0412
SVE	.0766	-.0003	-.0021	-.0133	.0469
LVE	.0264	-.0008	-.0013	-.0031	.0022
SFE	.3517	.0183	-.0032	.0035	.1406
LFE	.0465	.0286	-.0023	.0025	.0298
SØM	-.0389	.0144	-.0111	-.0073	-.0363
LØM	-.0712	-.0127	-.0073	-.0202	-.0499
SVM	-.0737	-.0140	-.0008	.0058	.0066
LVM	-.0735	-.0078	-.0015	-.0210	-.0381
SFM	-.0019	-.0347	-.0030	-.0083	-.0080
LFM	-.0319	-.0154	.0064	-.0245	-.0260
SØD	-.0020	-.0005	-.0079	.0036	-.0305
LØD	-.1054	-.0317	-.0013	-.0066	-.0117
SVD	-.0679	-.0288	-.0083	-.0030	-.0025
LVD	-.0651	-.0128	-.0049	.0071	-.0155
SFD	-.0340	-.0052	-.0039	-.0061	-.0072
LFD	-.0522	-.0074	-.0480	-.0031	-.0089

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	241.1	3.346	.7526	2.444	104.7
LØE	217.0	7.438	6.170	19.96	50.42
SVE	80.15	6.174	.4788	1.168	59.18
LVE	29.79	6.072	.9088	1.228	21.68
SFE	314.7	23.65	3.087	6.360	144.2
LFE	58.18	38.23	.0595	9.858	32.71
SØM	25.71	54.36	1.358	25.68	14.75
LØM	20.17	7.714	.1892	5.433	.2757
SVM	46.90	2.638	.9970	32.35	51.22
LVM	19.91	27.57	3.130	14.55	13.56
SFM	24.63	5.559	3.981	1.622	27.43
LFM	5.563	16.62	8.704	1.776	13.63
SØD	1.790	20.31	4.865	23.65	1.861
LØD	23.65	1.277	1.631	.1946	1.432
SVD	31.22	8.924	4.341	4.341	14.33
LVD	10.82	3.229	7.238	19.31	25.00
SFD	7.151	27.77	5.989	2.124	9.708
LFD	11.12	.7362	10.21	7.383	10.65

$X^2 df_3$ testing independence T and S

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	243.8	3.779	1.169	1.579	109.6
LØE	215.1	11.65	2.095	13.95	48.58
SVE	82.70	5.654	.6663	2.828	54.23
LVE	29.67	4.196	.4065	1.342	32.78
SFE	309.5	26.54	2.552	6.716	145.6
LFE	56.35	48.30	.0650	8.668	32.21
SØM	28.30	118.2	3.168	12.28	4.669
LØM	29.14	7.145	1.738	8.156	10.86
SVM	5.071	3.899	.7720	34.33	44.70
LVM	2.548	28.02	2.007	12.93	37.95
SFM	20.91	13.38	4.571	.9245	26.30
LFM	5.351	11.01	14.39	4.994	18.90
SØD	46.99	27.30	4.348	34.08	7.629
LØD	7.002	3.423	1.478	6.059	3.846
SVD	2.981	25.71	4.745	5.664	16.15
LVD	56.48	3.856	31.81	29.43	24.07
SFD	8.008	21.67	11.38	5.346	21.12
LFD	20.92	.6318	9.690	3.871	11.93

$X^2 df_3$ testing independence T and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	728.0	647.1	613.7	617.5	712.1
LØE	724.1	681.3	632.1	648.0	696.7
SVE	732.0	716.2	666.5	643.6	712.2
LVE	732.0	673.5	614.1	712.3	654.4
SFE	720.1	662.2	704.6	650.3	720.1
LFE	724.1	595.3	599.6	724.1	736.0
SØM	312.1	313.8	383.2	341.9	362.0
LØM	357.8	140.5	343.7	476.5	329.9
SVM	212.1	323.8	140.6	224.1	487.0
LVM	277.9	288.4	354.2	528.4	390.8
SFM	355.0	348.9	423.3	357.1	504.1
LFM	131.5	174.8	469.3	472.8	415.2
SØD	2.029	95.05	62.49	156.6	157.6
LØD	235.4	236.9	64.77	62.57	90.19
SVD	402.3	294.1	30.94	166.3	100.1
LVD	164.7	59.32	71.97	113.7	188.8
SFD	243.7	220.6	25.00	6.166	91.84
LFD	261.1	21.50	51.47	279.6	29.96

$X^2 df_1$ testing independence S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.5978	2.772	.1161	1.879	2.49Ø
LØE	.465Ø	.Ø879	.1291	3.648	.Ø668
SVE	.17Ø7	.Ø921	.1175	.6295	1.ØØ2
LVE	.291Ø	.26Ø9	.2132	.Ø748	1.273
SFE	.5[illegible]88	.5229	.1226	1.Ø46	.3422
LFE	.2Ø19	2.982	.4593	.5424	.66Ø4
SØM	3[illegible].11	15.12	4.155	9.527	21.23
LØM	49.83	12.63	2.175	9.819	3Ø.97
SVM	48.88	9.772	1.Ø37	5.795	11.Ø8
LVM	47.27	17.Ø7	.5Ø24	8.967	26.8Ø
SFM	9.522	22.Ø7	3.881	4.278	11.37
LFM	29.9Ø	17.Ø8	.9Ø5Ø	7.616	15.68
SØD	2.Ø3Ø	9.455	7.548	5.318	25.82
LØD	7Ø.53	2Ø.93	.5671	5.737	9.434
SVD	33.76	25.29	9.527	3.Ø56	6.6Ø3
LVD	79.27	12.Ø3	9.181	4.39Ø	22.27
SFD	22.89	13.24	2.92Ø	5.458	1Ø.14
LFD	45.Ø9	6.969	51.25	3.286	12.15

$X^2 df_3$ testing 3-way dependence T S and R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.5566	1.Ø92	1.Ø97	11.97	1.562
LØE	.4841	1.95Ø	6.145	7.473	8.615
SVE	.7166	4.Ø28	.997Ø	8.531	11.Ø7
LVE	23.57	4.524	1.117	1.693	4.142
SFE	1.8Ø3	.8618	.5794	12.2Ø	1.584
LFE	1.266	2.542	.92Ø1	5.847	1.Ø43
SØM	2.769	4.843	.5Ø56	12.67	6.429
LØM	.8832	.1296	1.645	5.567	17.7Ø
SVM	1.768	.967Ø	5.278	1.949	7.151
LVM	2.496	1.572	2.416	.2Ø49	2.323
SFM	1.854	6.92Ø	1.585	.9Ø1Ø	4.448
LFM	1.ØØ1	21.75	1.968	.4164	6.838
SØD	2.847	6.674	1.338	1.277	2.366
LØD	1.Ø85	7.917	1.7Ø4	6.334	3.558
SVD	.5578	1Ø.62	47.34	2.919	.6899
LVD	.3815	14.79	.5987	8.183	5.896
SFD	4.172	1Ø.89	1.655	1Ø.85	2.132
LFD	.1566	2.812	8.258	8.454	1.438

Fdf4,735 testing stationarity latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	12.49	2.743	1.818	9.31Ø	5.56Ø
LØE	4.41Ø	7.514	9.581	7.731	4.721
SVE	5.Ø3Ø	6.314	.9344	8.695	5.197
LVE	23.67	4.492	4.113	1.347	2.849
SFE	5.538	11.62	4.195	5.294	1.352
LFE	1Ø.Ø5	2.ØØ9	11.13	2.759	3.215
SØM	4.517	3.Ø13	2.7Ø8	5.222	9.665
LØM	.34Ø6	1.952	4.8ØØ	4.25Ø	13.15
SVM	.195Ø	2.962	32.ØØ	3.689	4.549
LVM	2.9Ø5	3.289	7.196	1Ø.58	.7286
SFM	3.Ø19	4.467	1.Ø76	11.36	3.28Ø
LFM	3.992	42.5Ø	.3567	4.4Ø8	5.715
SØD	1.624	.7265	9.55Ø	6.336	5.141
LØD	6.365	3.669	13.13	8.447	5.Ø36
SVD	1.ØØ3	5.124	41.29	5.488	.8772
LVD	2.386	21.35	4.49Ø	6.832	4.286
SFD	2.669	9.8Ø9	12.45	2Ø.Ø8	1.156
LFD	2.283	1Ø.Ø7	17.11	5.Ø27	.6983

Fdf4,635 testing stationarity latencies ignoring first 100 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	8.305	1.359	1.475	12.70	2.402
LØE	.6460	10.63	4.180	11.07	6.357
SVE	4.900	2.200	1.213	4.663	6.865
LVE	20.99	5.378	6.433	1.671	4.249
SFE	3.530	10.05	3.735	7.737	.9120
LFE	7.251	.6818	6.979	13.22	2.676
SØM	3.253	4.840	1.224	5.203	9.722
LØM	1.992	.7351	6.306	4.732	17.92
SVM	.8303	2.395	34.61	1.065	2.365
LVM	1.443	5.755	10.04	1.917	.9790
SFM	6.185	5.992	1.223	3.076	5.105
LFM	7.168	9.405	.5612	.8925	1.605
SØD	.7107	2.116	8.739	4.407	1.639
LØD	1.521	7.411	10.99	5.208	2.585
SVD	1.844	1.575	11.46	4.737	2.133
LVD	2.756	27.83	2.019	2.587	2.415
SFD	4.511	4.341	15.67	1.122	.9072
LFD	.5462	2.470	14.75	6.349	1.074

Fdf4,535 testing stationarity latencies ignoring first 200 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	1.405	1.614	.2896	2.718	1.444
LØE	.5000	.6208	.8206	2.362	.7318
SVE	.7500	1.653	1.062	.4262	1.018
LVE	.7500	.3233	.8928	.1711	4.429
SFE	2.402	1.573	1.661	.8445	.5159
LFE	.9100	.1789	1.670	.8000	1.000
SØM	1.815	1.341	2.613	.9191	3.606
LØM	3.079	1.351	1.173	.6050	2.975
SVM	3.028	.4532	30.90	.3074	1.225
LVM	2.340	.7327	.7825	.5909	.6810
SFM	.9304	.6088	.4443	.6623	1.751
LFM	.2967	.4126	.6081	4.032	1.866
SØD	5.109	.4602	1.512	.4132	.9312
LØD	1.573	5.660	1.988	6.125	3.431
SVD	.6406	.5566	1.302	2.214	2.287
LVD	1.339	.4028	2.136	1.279	3.783
SFD	.2422	2.714	3.877	2.828	5.967
LFD	1.019	6.715	1.289	1.560	1.597

Fdf4,65 testing stationarity error sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	5.418	.2589	3.787	1.201	.6476
LØE	.4956	1.945	.7809	1.441	1.083
SVE	1.977	.9615	.3471	1.269	1.073
LVE	2.327	1.264	1.381	1.562	.6210
SFE	1.473	1.058	.6290	.3165	.4139
LFE	.4845	.5687	2.142	1.293	2.048
SØM	1.390	2.645	.2047	.5716	.5914
LØM	.0605	.3259	.8923	.5719	1.799
SVM	1.087	.3033	1.507	.0896	.6459
LVM	5.063	9.655	.2373	.6830	.5779
SFM	1.323	3.290	1.824	.5153	.2581
LFM	1.831	.2051	.0217	1.008	.6123
SØD	.4145	.8107	3.866	.5581	1.616
LØD	2.151	4.450	2.562	2.561	1.601
SVD	1.470	.4221	1.515	1.069	.5532
LVD	1.432	.9473	.9571	1.131	1.594
SFD	.6285	.6603	1.019	2.951	3.692
LFD	2.133	.8231	1.510	2.955	.9079

Fdf4,65 testing stationarity response sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	59.23	34.00	141.4	80.12	100.4
LØE	47.35	99.70	44.43	76.98	28.07
SVE	63.98	100.2	24.81	93.80	23.18
LVE	65.30	30.21	51.34	123.3	77.23
SFE	43.40	34.39	68.39	92.20	36.39
LFE	25.13	31.91	92.83	91.13	65.80
SØM	41.24	132.8	31.29	61.54	67.52
LØM	22.74	49.62	149.7	27.82	187.5
SVM	35.94	34.55	26.60	34.75	39.79
LVM	13.42	53.68	7.793	97.96	13.97
SFM	43.81	57.00	36.56	75.64	60.18
LFM	16.88	108.3	111.6	68.75	78.92
SØD	46.54	49.23	100.5	52.73	63.92
LØD	36.96	102.0	239.8	105.6	28.19
SVD	37.02	93.73	239.8	86.01	58.78
LVD	18.28	80.34	26.24	48.69	35.31
SFD	45.18	17.55	115.5	204.2	63.61
LFD	17.58	16.05	61.83	45.59	19.21

$X^2 df_9$ testing first order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	54.04	57.28	75.52	56.72	115.7
LØE	76.40	80.67	51.98	89.21	46.60
SVE	36.97	100.7	58.48	51.61	70.15
LVE	74.08	41.43	59.45	84.37	61.25
SFE	39.31	48.75	71.06	66.51	51.91
LFE	68.46	[illegible]7.93	66.90	86.95	78.30
SØM	25.18	68.08	41.20	50.15	39.76
LØM	53.93	52.34	118.9	40.81	69.76
SVM	59.49	59.33	43.04	35.26	34.95
LVM	58.03	79.90	23.75	64.51	49.90
SFM	40.91	82.46	43.53	58.39	33.09
LFM	48.52	97.49	77.03	52.12	71.56
SØD	40.06	50.24	104.0	52.95	42.11
LØD	57.66	60.56	85.76	57.07	75.98
SVD	48.51	71.22	85.76	41.37	46.87
LVD	46.58	68.27	43.68	55.06	42.49
SFD	44.41	58.76	84.98	70.92	65.77
LFD	41.40	33.99	64.01	59.76	34.65

$X^2 df_{36}$ testing second order dependence latencies

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	1.519	.0914	.7251	3.400	.6255
LØE	.0480	3.655	.7330	.1357	.2249
SVE.	.2207	.5779	2.950	.3596	2.130
LVE	.0101	.0254	1.979	.1057	1.547
SFE	.3454	.5210	.0289	.0702	.0054
LFE	.6307	3.174	9.415	1.094	.3607
SØM	6.738	18.80	.1015	.0859	.2571
LØM	6.720	3.540	1.116	2.754	.6073
SVM	9.017	11.22	3.479	.0536	.0020
LVM	.9909	3.808	.0420	1.132	2.022
SFM	1.135	7.030	.5161	.0062	.1975
LFM	1.492	.2646	.0076	.1541	.0549
SØD	33.68	37.28	1.368	.2242	2.446
LØD	3.523	2.507	.2965	1.229	.0470
SVD	.0670	7.563	12.27	4.501	11.48
LVD	.4154	.0149	4.337	6.335	7.042
SFD	4.792	1.790	.3624	7.899	16.14
LFD	.0720	2.884	.1414	.4434	5.774

$X^2 df_1$ testing first order dependence R

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	2.439	1.579	2.206	3.623	3.722
LØE	.6390	.1547	.6181	1.856	1.030
SVE	.8474	.8143	.2456	3.946	2.835
LVE	.6676	.7450	.5787	.0363	1.070
SFE	8.373	5.112	.8197	1.408	4.727
LFE	2.273	4.067	.7011	1.504	.2525
SØM	9.063	11.93	.6375	2.349	.5814
LØM	7.186	1.499	1.574	.4542	10.41
SVM	1.402	.9574	1.995	.5706	5.240
LVM	15.67	.1623	1.495	.2476	6.422
SFM	3.594	.7454	1.484	1.689	3.023
LFM	.8759	3.950	5.256	1.487	8.282
SØD	3.775	.6120	5.146	.9613	2.409
LØD	10.62	12.61	.4257	6.409	6.565
SVD	1.644	1.133	3.484	.9456	3.258
LVD	1.933	.3453	3.433	1.377	1.234
SFD	1.564	.2189	.9331	17.71	3.067
LFD	1.856	.8438	.3359	5.776	2.181

$X^2 df_2$ testing second order dependence responses

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.3402	.1300	15.54	.2954	.1939
LØE	.2637	1.651	1.104	2.036	4.393
SVE	.0054	.0496	.5166	5.865	.0677
LVE	.0054	.9903	9.224	.0677	8.902
SFE	.0343	.4089	.2014	.7637	.0343
LFE	.2637	.0011	1.975	.0219	1.001
SØM	.0133	2.710	.0689	2.827	15.34
LØM	.3338	7.425	2.738	2.436	2.521
SVM	.8315	2.867	7.820	.4712	19.73
LVM	.6617	.4610	.1366	5.299	1.134
SFM	.0295	.6704	2.648	2.616	.0159
LFM	.1777	.0738	3.327	4.702	13.34
SØD	.2623	3.805	1.727	.0191	3.528
LØD	.0175	1.254	.7023	.1020	2.785
SVD	2.010	.0191	.1062	.1349	.5880
LVD	6.648	3.169	1.824	.3399	.0224
SFD	1.444	.9915	.1912	.1120	2.841
LFD	2.136	.0548	6.506	9.019	.0883

$X^2 df_1$ testing first order dependence errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.0082	.8048	2.824	12.02	.0583
LØE	.0165	.3584	1.149	.9200	.2514
SVE	.0055	.0500	.4997	.6267	.0683
LVE	.0055	.4373	2.258	.0683	21.33
SFE	.0346	.5859	.1008	2.291	.0346
LFE	.0165	.1305	.4717	44.38	.0000
SØM	.9145	2.081	.6494	1.248	.2012
LØM	2.871	7.167	.7444	5.253	13.26
SVM	.6244	1.075	8.024	5.930	.3327
LVM	.1276	.6878	1.270	.4097	5.263
SFM	1.525	.7754	.4577	1.237	.5953
LFM	1.416	1.112	2.449	.0778	.2650
SØD	9.942	1.572	2.233	1.245	4.584
LØD	.1601	.4683	.7328	.1589	.8187
SVD	.2377	5.302	.7994	.4828	2.111
LVD	1.274	.1643	1.167	4.485	3.522
SFD	.7890	1.753	1.405	3.621	.8835
LFD	3.548	.2525	3.275	1.237	11.70

$X^2 df_2$ testing second order dependence errors

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	4.678	7.157	33.14	21.36	5.376
LØE	5.488	19.99	3.535	9.265	14.35
SVE	4.245	4.423	10.07	23.24	8.360
LVE	.0238	12.64	29.39	5.880	54.70
SFE	8.128	10.15	2.965	5.731	5.479
LFE	6.226	15.87	24.43	1.129	2.478
SØM	27.04	44.48	7.710	11.09	32.11
LØM	22.92	22.38	6.127	16.45	24.59
SVM	32.26	38.89	17.80	20.07	35.57
LVM	30.98	16.12	3.055	20.04	16.07
SFM	5.956	15.42	9.831	13.42	16.53
LFM	15.97	20.75	6.987	16.07	19.68
SØD	41.41	64.51	9.752	12.52	21.54
LØD	44.30	19.56	9.797	12.72	7.022
SVD	24.18	28.17	37.94	18.99	22.05
LVD	22.44	13.79	13.86	13.72	25.14
SFD	16.09	10.50	5.181	47.99	31.31
LFD	10.08	6.794	13.89	30.03	41.08

$X^2 df_9$ testing first order dependence SR sequences

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	8.693	20.32	16.79	39.05	10.46
LØE	3.354	12.05	17.41	17.94	22.41
SVE	4.518	9.790	16.05	21.12	12.43
LVE	6.608	21.07	16.35	14.47	57.14
SFE	14.92	15.80	13.61	32.46	11.80
LFE	6.462	19.13	19.51	108.7	1.041
SØM	41.41	47.82	31.90	29.50	26.48
LØM	44.47	39.58	33.29	37.43	73.65
SVM	49.35	40.36	45.95	28.69	42.72
LVM	41.07	31.87	21.81	20.54	42.50
SFM	41.08	42.94	26.82	44.13	36.66
LFM	31.26	41.12	62.22	45.12	50.82
SØD	47.60	50.58	41.63	49.41	62.24
LØD	44.49	40.70	21.49	40.17	50.28
SVD	17.76	34.56	37.81	43.26	47.06
LVD	36.21	30.83	23.67	30.99	35.73
SFD	34.66	37.29	34.01	76.05	43.30
LFD	35.47	41.54	41.62	43.66	44.06

$X^2 df_{36}$ testing second order dependence SR

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	-477.4	-361.0	-428.0	-642.0	-630.9
LØE	-499.2	-503.8	-968.1	-679.7	-782.3
SVE	-481.7	-797.6	-545.8	-541.8	-657.1
LVE	-584.7	-399.7	-477.8	-681.1	-1117
SFE	-417.6	-403.5	-960.2	-505.0	-650.0
LFE	-541.8	-405.4	-764.4	-617.7	-727.1
SØM	-702.1	-853.0	-752.5	-662.5	-682.4
LØM	-717.5	-1002	-598.2	-666.5	-1405
SVM	-1101	-604.9	-993.0	-667.4	-548.8
LVM	-961.4	-825.9	-862.2	-744.3	-882.0
SFM	-603.4	-908.4	-729.9	-566.2	-591.7
LFM	-1132	-1040	-718.4	-669.6	-812.1
SØD	-1003	-853.1	-858.9	-788.7	-754.2
LØD	-846.1	-1118	-913.8	-773.9	-997.1
SVD	-701.0	-842.3	-1069	-689.0	-772.6
LVD	-1071	-1258	-1033	-710.1	-935.2
SFD	-721.0	-715.8	-955.7	-506.7	-762.7
LFD	-952.5	-1105	-1368	-695.3	-1158

Total latencies in each 1/5th of the experiments ignoring negative signs

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	.0571	.5214	.1286	1.550	.1286
LØE	.0214	.1214	.2714	.8071	.1214
SVE	.0214	.1071	.2357	.2286	.0929
LVE	.0214	.0929	.4071	.0143	1.771
SFE	.1214	.5357	.1643	.2357	.0357
LFE	.0500	.0857	.5929	.0571	.0143
SØM	2.621	2.321	2.521	1.393	6.371
LØM	4.193	3.193	2.050	.8071	5.914
SVM	6.250	.5214	41.39	.6286	1.557
LVM	4.264	1.107	1.164	.4857	.8786
SFM	1.021	1.014	.4643	1.229	1.486
LFM	.5571	.9500	.5500	4.621	3.121
SØD	11.31	1.450	3.379	.9286	2.193
LØD	3.193	9.286	5.271	10.84	7.857
SVD	1.164	1.129	2.950	3.914	5.607
LVD	2.336	.9500	4.657	3.236	7.907
SFD	.4500	3.414	6.693	7.393	9.121
LFD	1.450	14.06	3.664	2.800	4.071

Var in T errors in each 1/5th of 700 trials

COND	SUB1	SUB2	SUB3	SUB4	SUB5
SØE	11.02	.8571	7.836	2.336	1.536
LØE	1.057	6.621	2.093	2.950	2.164
SVE	4.379	2.679	.9143	2.664	2.057
LVE	4.393	3.914	2.807	3.229	1.664
SFE	3.729	2.736	1.736	.8357	1.229
LFE	1.321	1.379	3.764	3.286	4.629
SØM	5.950	11.06	.5357	1.714	1.557
LØM	.2357	.9429	2.407	1.093	4.164
SVM	4.479	.9500	3.264	.2643	2.236
LVM	11.73	19.87	.6786	2.307	1.586
SFM	4.093	9.343	4.914	1.336	.8714
LFM	3.414	.5214	.0571	1.979	1.264
SØD	1.807	3.657	8.157	1.250	5.629
LØD	6.014	12.87	6.607	9.407	4.021
SVD	4.050	1.271	2.621	2.214	1.536
LVD	3.307	1.964	2.393	1.879	3.107
SFD	1.336	2.021	2.664	7.371	6.679
LFD	5.193	1.871	3.807	6.629	2.193

Var in T responses in each 1/5th of 700 trials

O	.99719636	.99985377	.99846220	.99955866	.99922662
V	.99979580	.99979580	.99998023	.99985377	.99895251
F	.99909484	.99964825	.99879963	.99909484	.99955866

Av info S

O	.99668981	.99990119	.99766059	.99879963	.96684664
V	.99955866	.97897028	.96337608	.83989689	.99863619
F	.91601381	.89717465	.82386609	.99808252	.97897028

Av info R

O	.00217389	.00119668	.02175355	.00547782	.04686390
V	.12800275	.00671928	.02161836	.00183006	.03959634
F	.00043776	.00365187	.00429168	.02863556	.01264220

Av info TS

O	.00429689	.00094918	.01646663	.05041537	.04109854
V	.11362584	.00201495	.01761288	.00868399	.03159570
F	.00202144	.00613799	.00605622	.10418668	.03287588

Av info TR

O	.49463620	.00004574	.05926008	.01412375	.11541312
V	.23915328	.00019399	.18209540	.01096062	.21233161
F	.00054962	.03483557	.00441587	.02971320	.04409537

Av info TSR

O	-.03370793	-.00233788	-.02291673	-.00076070	-.02086019
V	.04269531	-.00542154	-.02639722	-.00261084	-.00868895
F	.00386246	-.00804321	-.00096055	.00451743	-.01444092

$X^2 df_3$ measuring dependence TS

O	2.2302396	1.2272511	22.116960	5.5979067	47.119834
V	123.49193	6.8774842	21.940701	1.8760183	40.014045
F	.44920318	3.7422900	4.3910005	28.895130	12.910341

$X^2 df_3$ measuring dependence TR

O	4.4038892	.97308670	16.805487	50.737443	41.838599
V	119.39217	2.0652820	17.730038	8.9837357	31.994965
F	2.0685220	6.1281564	6.3443291	102.55693	33.016678

$X^2 df_1$ measuring dependence SR

0	438.29718	.04692539	59.873578	14.444094	115.02711
V	231.48753	.19901530	176.76102	11.171301	207.05631
F	.56399163	35.350325	4.5091589	30.253489	44.650184

X^2df_3 testing dependence T and R

0	14.928381	2.5001131	28.906146	2.6271919	24.933732
V	36.019509	6.0377360	21.099074	4.3205972	18.827643
F	4.0297767	7.5211090	2.3934383	9.7320161	15.540460

X^2df_1 testing dependencies S and R

0	1.3430956	3.0476678	19.348094	2.0537007	.30707706
V	.35944356	3.3509057	3.1985054	1.6851329	6.7245784
F	8.1543939	3.0790667	1.6407971	.52394347	10.460307

X^2df_3 testing 3-way dependence T S and R

0	.88160769	5.5109123	33.730023	7.0221305	.47070921
V	1.8522731	17.336201	2.5180633	5.7771100	35.586053
F	6.4081225	8.2521011	2.7930472	1.7479091	9.0361907

$F4,735$ testing stationarity latencies

0	.91890483	4.2453916	23.492746	5.3234861	2.1321398
[illegible]	.28164342	9.1682947	1.7118125	4.7437016	18.069035
F	5.7181939	5.1645821	3.2711045	1.0742134	20.128975

$F4,635$ testing stationarity latencies ignoring first 100 trials

0	.22204969	2.0332126	4.1290721	1.4689959	.55394089
V	.53611370	.59224082	2.7841786	1.5521188	1.8654910
F	1.9044055	2.1916492	.37238007	2.2948718	4.2287356

$F4,535$ testing stationarity latencies ignoring first 200 trials

0	1.0085409	1.5511880	1.0884970	3.1468705	1.2277558
V	4.7323694	1.5565611	2.2102432	6.4162465	1.1018022
F	1.8928831	3.0542789	1.4327344	1.3516899	8.0480699

$F4,65$ testing stationarity errors

0	235.44580	484.49695	127.61680	56.445837	40.091083
V	14.272906	282.71872	59.597813	18.797354	103.54776
F	132.99706	40.886953	19.140375	16.756756	20.481939

$F4,65$ testing stationarity responses

O	135.33033	115.93720	79.545137	45.000679	53.789766
V	31.869328	96.211959	47.860019	59.147642	83.612856
F	49.970023	30.343085	80.095029	33.689302	61.299814

$X^2 df_9$ measuring first order dependence latencies

O	4.1772320	.00542642	25.080909	26.220174	13.325375
V	.00807036	2.6426431	2.1148551	2.1821697	.16112710
F	19.590089	24.414986	2.8956623	.05689602	44.284664

$X^2 df_{36}$ measuring second order dependence latencies

O	9.7305921	8.6939040	.71040882	4.5134417	1.3242191
V	1.3128312	15.790512	2.9816506	3.2322843	.17842451
F	19.930521	9.0472741	1.5810288	3.7701138	1.9516505

$X^2 df_1$ measuring first order dependence R sequences

O	.24482317	.09285270	.20695085	5.3539329	.58557260
V	5.0305320	.77172546	2.3112237	2.9999832	1.5147417
F	.00675021	.25186213	1.0488895	1.0535466	.14507730

$X^2 df_2$ measuring second order dependence R sequences

O	2.8099455	.40[illegible]42763	2.3832645	5.8539690	.09342585
V	1.7565202	.33012878	3.3509804	.09149084	1.0826522
F	3.5513808	4.3823194	3.3735361	6.4274667	.07851741

$X^2 df_1$ measuring first order dependence error sequences

O	10.938956	2.0216432	30.147861	45.511305	30.361971
V	11.633567	150.45549	17.477517	48.817198	18.472689
F	31.195248	55.048784	18.623846	13.510509	81.959563

$X^2 df_2$ measuring second order dependence error sequences

O	41.287364	42.216974	35.927023	52.223436	33.298678
V	38.256538	86.856925	38.295645	39.346312	26.972411
F	73.507622	42.064542	43.046853	37.127259	36.421320

$X^2 df_9$ measuring first order dependence SR sequences

O	-9500.3234	-4592.0622	-32400.348	-13970.039	-13147.524
V	-14013.590	-5821.3248	-24623.575	-22302.360	-10992.811
F	-12165.995	-10368.622	-17226.287	-17716.161	-17643.968

$X^2 df_{36}$ measuring second order dependence SR sequences

.23571429	3.7000000	9.1928571	5.1285714	1.2357143	Var total errors in each 140 trials
1.2642857	2.0214286	5.5500000	5.5142857	2.9642857	
4.8928571	6.8928571	.37357143	6.3928571	10.107143	

1.5571429	4.8735714	3.7642857	11.878571	4.4428571	Var total responses in each 140 trials
10.250000	4.9142857	5.1928571	12.585714	2.4857143	
8.5928571	4.2357143	3.5928571	3.7357143	12.142857	

APPENDIX C

Estimate of Signal detection parameters for the models fitted in experiments 2, 3 and 4 (for an explanation, see p 137-143).

Session codes for Experiments 2 and 3

EXP 2

	Session	Cond.		
	1	0.75	R	
	2	0.5	RB	
	3	F.75	R	
	4	0.5	R	
	5	F.5	R	
Subj 1	6	F.5	RB	Subj 1
	7	0.25	R	
	8	F.25	R	
	9	0.75	D	
	10	0.5	DB	
	11	F.75	D	
	12	0.5	D	
	13	F.5	D	
	14	F.5	DB	
	15	0.25	D	
	16	F.25	D	

EXP 3

Session	Cond.
1	SOE
2	LOE
3	SVE
4	LVE
5	SFE
6	LFE
7	SOM
8	LOM
9	SVM
10	LVM
11	SFM
12	LFM
13	SOD
14	LOD
15	SVD
16	LVD
17	SFD
18	LFD

Later sessions are reflections of the above for subjects 2 to 4.

O - indicates not enough data to make estimate

EXPERIMENT NO 2
ESTIMATION 1LUCES CHOICE MODEL

STATE ON LAST TRIAL SESSION	Z OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	.883	.884	.938	.775	.962	2.10	4.29	.969	1.72	.808
2	1.01	1.20	.928	.893	.975	1.11	2.87	.456	2.18	.513
3	.917	1.07	.799	.734	1.35	2.56	18.8	.866	.937	.369
4	.844	.810	.866	.887	.910	1.67	2.31	.866	2.06	1.35
5	1.03	1.15	1.06	.945	.912	1.43	1.52	.996	1.98	1.24
6	.866	.489	1.09	.922	.816	2.19	10.6	5.00	1.60	.439
7	.981	1.04	.883	1.03	.854	.410	1.74	.221	2.23	.144
8	.863	1.13	.740	.897	.690	.410	4.54	2.84	.345	.104
9	.785	.664	.813	.752	.851	2.29	3.28	.941	3.99	1.03
10	.561	.511	.620	.552	.522	.689	.330	1.00	.576	.938
11	.441	.396	.377	.560	.175	2.62	4.46	1.66	1.51	.408
12	.382	.360	.295	.407	.331	.723	.955	.226	2.69	.585
13	.884	.754	.984	.827	1.05	1.47	3.26	1.78	.844	.999
14	.679	.626	.703	.914	.567	.713	1.18	.606	1.06	.411
15	.692	.594	.541	.829	.567	.358	.693	.135	1.54	.242
16	.768	.000	.921	.721	.833	.529	.000	.533	1.30	.156
17	.471	.416	.653	.509	.400	1.13	1.48	.861	.702	.938
18	.226	.167	.289	.280	.225	.849	1.70	.533	.715	.539
19	.127	.104	.151	.147	.132	2.28	3.04	1.66	3.39	.981
20	.605	.576	.886	.828	.387	.672	.755	.599	.695	.632
21	.264	.229	.264	.242	.278	.929	1.32	.843	1.45	.598
22	.189	.151	.194	.193	.220	.810	.981	1.55	.608	.644
23	.149	.151	.122	.361	.125	.657	.820	.980	1.08	.546
24	.113	.096	.158	.073	.114	.802	1.22	1.58	1.02	.663
25	.285	.235	.388	.229	.318	1.08	.878	.737	1.19	2.54
26	1.01	1.07	1.03	.826	1.06	.869	.931	.723	.807	1.04
27	.330	.320	.318	.324	.339	1.74	1.80	2.36	.881	1.86
28	.612	.552	.507	.778	.651	1.09	1.02	1.12	1.25	1.05
29	.525	.491	.432	.566	.579	.937	.956	1.45	.776	.813
30	.469	.462	.375	.424	.546	.895	.661	1.05	.982	.990
31	.538	.506	.435	.464	.597	.641	.469	.531	.928	.622
32	.303	.308	.356	.285	.292	.784	.677	.978	.968	.776
33	.117	.090	.176	.343	.158	1.22	1.32	.474	5.83	1.15
34	.224	.150	.490	.320	.211	1.07	1.52	.752	1.44	.871
35	.150	.141	.000	.111	.179	5.26	6.04	.000	6.00	3.05
36	.285	.132	.921	.420	.302	2.25	3.72	1.69	3.03	1.57
37	.162	.067	.214	.176	.238	1.03	2.17	.813	1.23	.763
38	.160	.105	.101	.147	.216	1.67	2.67	2.21	2.72	1.04
39	.210	.189	.280	.174	.188	1.21	1.60	1.12	4.01	.836
40	.270	.142	.246	.550	.215	.768	2.06	.246	2.42	.463
41	.200	.223	.000	.264	.134	1.85	2.22	.000	4.74	.997
42	.194	.211	.224	.118	.173	1.19	1.48	1.34	1.26	.860
43	.190	.172	.120	.387	.221	1.18	1.13	.980	.775	1.51
44	.241	.199	.380	.313	.204	1.20	1.80	.657	1.66	.854
45	.263	.219	.385	.382	.249	1.37	1.47	1.43	1.81	1.07
46	.202	.240	.098	.157	.188	1.04	1.20	.328	1.06	1.04
47	.285	.253	.312	.275	.299	1.14	.886	.935	1.79	1.08
48	.308	.186	.322	.363	.333	.436	.465	.322	.472	.448
49	.144	.137	.156	.000	.149	.602	.592	.443	.000	.641
50	.074	.072	.000	.000	.076	2.01	1.73	.000	.000	1.97
51	.131	.121	.163	.109	.162	1.74	1.79	1.36	2.62	1.61
52	.200	.141	.321	.239	.225	1.46	1.49	.374	3.35	1.40
53	.162	.116	.108	.198	.214	1.49	1.69	1.73	1.31	1.38
54	.104	.101	.077	.000	.110	1.28	1.51	1.08	.000	.986
55	.090	.119	.000	.112	.077	1.67	1.75	.000	2.24	1.52
56	.219	.198	.183	.255	.207	.742	1.38	.913	.729	.613
57	.118	.126	.105	.000	.106	.783	.900	.501	.000	.630
58	.106	.104	.065	.057	.118	1.08	1.26	.907	1.25	.918
59	.132	.112	.143	.195	.167	1.63	1.68	.775	1.02	2.00
60	.095	.086	.000	.108	.100	3.23	3.29	.000	3.89	2.87
61	.126	.106	.302	.089	.123	.967	.929	1.36	1.02	.857
62	.136	.110	.302	.072	.167	1.53	1.60	1.66	2.43	1.32
63	.177	.217	.000	.000	.197	1.59	1.43	.000	.000	1.36
64	.214	.109	.136	.127	.265	.839	1.00	.544	1.90	.762
65	.268	.321	.144	.302	.144	1.51	1.90	.577	1.51	.894
66	.639	.666	.570	.659	.588	1.59	1.45	2.60	1.69	1.32
67	.331	.322	.374	.392	.286	2.75	2.76	4.02	2.89	2.06
68	.305	.264	.274	.579	.232	2.37	2.29	1.30	3.04	2.25
69	.308	.311	.388	.306	.297	2.11	2.22	1.84	2.53	1.74
70	.204	.214	.258	.236	.167	1.38	1.55	.816	2.30	1.14
71	.187	.162	.171	.000	.155	1.38	2.37	.343	.000	.838
72	.311	.333	.375	.261	.288	.532	.704	.667	1.04	.412
73	.433	.403	.374	.422	.600	1.43	1.35	.963	1.90	1.96
74	.526	.496	.551	.574	.504	1.28	1.31	.813	1.34	1.53
75	.260	.287	.199	.231	.173	2.08	2.28	1.79	2.17	1.25
76	.219	.236	.215	.302	.176	1.60	1.56	1.22	2.17	1.52
77	.491	.465	.564	.545	.453	1.18	1.01	1.20	1.61	1.15
78	.368	.453	.355	.356	.261	1.37	1.22	2.37	2.23	1.02
79	.425	.319	.591	.466	.434	1.01	1.59	.709	1.09	.868
80	.201	.217	.175	.398	.175	.586	.564	.760	.730	.542

FOR FIRST PARAMETER OVERALL FRIEDMAN 7.49
STIM FRIEDMAN 1.17RESP FRIEDMAN 3.26COR WR FRIEDMAN 7.67

EXPERIMENT NO. 2

ESTIMATION 2TANNER SWETS GREEN MODEL

STATE ON LAST TRIAL SESSION	DPRIME OVERALL	DPRIME S1R1	DPRIME S1R2	DPRIME S2R1	DPRIME S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	.156	.154	.080	.320	.048	.106	.125	.039	.202	.022
2	-.007	-.231	.093	.142	.032	-.004	-.171	.029	.097	.011
3	.109	-.079	.280	.387	-.379	.079	-.075	.130	.187	-.103
4	.212	.264	.180	.150	.118	.133	.184	.084	.101	.068
5	-.032	-.180	-.069	.071	.115	-.019	-.109	-.034	.047	.064
6	.180	.873	-.104	.101	.255	.123	.791	-.086	.062	.078
7	.023	-.053	.156	-.043	.197	.007	-.033	.028	-.029	.025
8	.184	-.157	.376	.136	.462	.054	-.129	.277	.035	.045
9	.304	.510	.259	.356	.202	.211	.389	.126	.284	.102
10	.721	.830	.596	.739	.808	.296	.214	.299	.274	.392
11	1.01	1.13	1.20	.722	2.06	.717	.900	.735	.432	.696
12	1.19	1.26	1.46	1.10	1.35	.507	.616	.314	.785	.521
13	.154	.353	.020	.237	-.063	.092	.269	.013	.109	-.031
14	.484	.585	.441	.112	.705	.202	.316	.167	.058	.210
15	.459	.649	.757	.236	.702	.122	.268	.096	.143	.142
16	.330	.000	.104	.410	.228	.114	.000	.036	.231	.031
17	.934	1.08	.532	.840	1.13	.493	.639	.247	.350	.550
18	1.80	2.12	1.51	1.55	1.80	.840	1.27	.558	.667	.681
19	2.40	2.58	2.23	2.21	2.39	1.53	1.73	1.31	1.56	1.19
20	.627	.688	.152	.237	1.17	.254	.298	.057	.097	.465
21	1.62	1.78	1.62	1.72	1.55	.785	.989	.754	.988	.612
22	2.00	2.24	1.96	1.96	1.82	.920	1.11	1.14	.798	.754
23	2.25	2.24	2.46	1.25	2.43	.959	1.04	1.22	.649	.971
24	2.54	2.71	2.18	2.98	2.53	1.18	1.44	1.27	1.50	1.10
25	1.53	1.75	1.17	1.78	1.39	.792	.831	.504	.953	.964
26	-.017	-.090	-.038	.240	-.076	-.008	-.043	-.016	.107	-.039
27	1.36	1.39	1.39	1.38	1.32	.840	.869	.947	.652	.839
28	.613	.741	.845	.315	.537	.319	.373	.444	.175	.275
29	.802	.884	1.04	.709	.681	.389	.433	.607	.311	.307
30	.941	.957	1.21	1.06	.754	.446	.387	.619	.526	.375
31	.771	.846	1.03	.953	.643	.305	.277	.368	.460	.249
32	1.46	1.44	1.27	1.53	1.50	.654	.600	.630	.756	.670
33	2.51	2.77	2.06	1.29	2.19	1.33	1.50	.750	1.07	1.15
34	1.81	2.24	.885	1.39	1.88	.930	1.29	.383	.807	.888
35	2.17	2.21	.000	2.44	2.02	1.67	1.75	.000	1.89	1.41
36	1.52	2.32	.103	1.06	1.46	1.01	1.66	.065	.784	.871
37	2.16	3.03	1.86	2.07	1.74	1.10	1.84	.854	1.12	.775
38	2.17	2.58	2.64	2.23	1.85	1.28	1.68	1.64	1.50	.940
39	1.88	1.99	1.55	2.03	2.00	1.01	1.17	.814	1.51	.934
40	1.59	2.28	1.66	.741	1.84	.710	1.43	.395	.519	.647
41	1.92	1.80	.000	1.58	2.37	1.19	1.17	.000	1.25	1.18
42	1.97	1.87	1.81	2.50	2.09	1.05	1.08	1.01	1.34	.988
43	1.99	2.10	2.48	1.17	1.82	1.06	1.10	1.23	.518	1.05
44	1.72	1.93	1.19	1.42	1.91	.927	1.18	.484	.861	.897
45	1.63	1.83	1.18	1.18	1.69	.917	1.05	.683	.747	.865
46	1.93	1.73	2.63	2.20	2.01	.976	.928	.869	1.12	1.02
47	1.53	1.67	1.43	1.57	1.48	.808	.793	.693	.971	.763
48	1.43	2.00	1.37	1.24	1.34	.469	.716	.370	.419	.443
49	2.28	2.33	2.18	.000	2.25	.940	.959	.780	.000	.950
50	2.94	2.97	.000	.000	2.92	1.76	1.71	.000	.000	1.74
51	2.38	2.46	2.15	2.54	2.16	1.41	1.47	1.20	1.66	1.26
52	1.93	2.31	1.38	1.70	1.80	1.11	1.31	.410	1.24	1.02
53	2.16	2.51	2.58	1.94	1.85	1.23	1.47	1.51	1.07	1.04
54	2.63	2.66	2.93	.000	2.58	1.41	1.50	1.50	.000	1.28
55	2.76	2.48	.000	2.53	2.93	1.59	1.46	.000	1.59	1.64
56	1.83	1.94	2.04	1.66	1.89	.809	1.09	.983	.722	.768
57	2.50	2.43	2.60	.000	2.60	1.15	1.17	1.02	.000	1.11
58	2.61	2.63	3.09	3.21	2.50	1.34	1.41	1.51	1.70	1.22
59	2.38	2.54	2.29	1.96	2.12	1.38	1.48	1.05	.990	1.32
60	2.66	2.76	.000	2.51	2.62	1.80	1.86	.000	1.79	1.73
61	2.43	2.61	1.46	2.79	2.45	1.20	1.27	.827	1.40	1.16
62	2.34	2.56	1.46	2.96	2.13	1.34	1.47	.887	1.85	1.17
63	2.06	1.84	.000	.000	1.95	1.21	1.05	.000	.000	1.09
64	1.86	2.59	2.34	2.41	1.61	.866	1.30	.928	1.46	.717
65	1.60	1.39	2.28	1.46	2.29	.935	.882	.923	.859	1.10
66	.558	.507	.699	.521	.662	.341	.300	.500	.326	.375
67	1.34	1.37	1.20	1.15	1.52	.953	.974	.933	.831	.985
68	1.44	1.61	1.58	.679	1.75	.977	1.07	.874	.507	1.15
69	1.43	1.42	1.17	1.43	1.48	.941	.947	.740	.990	.911
70	1.91	1.86	1.65	1.73	2.13	1.07	1.09	.755	1.15	1.12
71	2.01	2.14	2.07	.000	2.21	1.12	1.40	.641	.000	1.04
72	1.42	1.35	1.21	1.63	1.51	.522	.571	.495	.831	.482
73	1.04	1.12	1.21	1.07	.636	.603	.638	.596	.685	.418
74	.800	.871	.743	.691	.851	.447	.491	.335	.394	.510
75	1.63	1.51	1.93	1.76	2.09	1.05	1.01	1.18	1.15	1.13
76	1.83	1.75	1.85	1.45	2.07	1.08	1.03	.997	.960	1.19
77	.883	.950	.714	.755	.981	.475	.477	.388	.462	.522
78	1.23	.980	1.26	1.26	1.63	.701	.535	.864	.847	.825
79	1.06	1.40	.655	.948	1.03	.533	.839	.274	.492	.483

EXPERIMENT NO 2
ESTIMATION 3CLASSICAL THRESHOLD MODEL

STATE ON LAST TRIAL SESSION	THRESHOLD OVERALL	THRESHOLD S1R1	THRESHOLD S1R2	THRESHOLD S2R1	THRESHOLD S2R2	P(C) OVERALL	P(C) S1R1	P(C) S1R2	P(C) S2R1	P(C) S2R2
1	.155	.181	.061	.276	.034	.237	.372	.024	-.252	-.032
2	-.006	-.314	.046	.144	.017	-.003	-.031	.017	.005	.011
3	.118	-.128	.188	.259	-.179	.245	.424	.083	.134	-.333
4	.191	.255	.125	.149	.102	.083	.120	.079	.075	.040
5	-.031	-.189	-.057	.073	.097	-.022	-.069	-.027	-.013	.045
6	.179	.727	-.148	.095	.117	.048	.027	.050	.040	.121
7	.011	-.055	.044	-.048	.039	.223	-.208	.323	-.200	.417
8	.082	-.229	.359	.054	.069	.274	-.345	-.131	.288	.481
9	.286	.464	.182	.366	.151	.288	.397	.086	.295	.088
10	.378	.290	.380	.355	.467	.277	.236	.235	.295	.316
11	.690	.775	.699	.501	.679	.516	.558	.500	.367	.482
12	.559	.632	.396	.724	.569	.442	.472	.387	.317	.468
13	.136	.350	.021	.159	-.051	.059	.108	.022	.096	-.025
14	.276	.398	.234	.088	.285	.185	.236	.154	.042	.244
15	.177	.348	.141	.204	.203	.380	.344	.492	-.045	.455
16	.167	.000	.056	.309	.048	.271	.000	.174	.100	.442
17	.548	.646	.326	.430	.589	.382	.479	.182	.246	.415
18	.749	.885	.595	.663	.670	.626	.701	.537	.536	.589
19	.932	.956	.896	.937	.867	.807	.831	.793	.667	.766
20	.334	.380	.087	.144	.527	.223	.257	.005	.102	.411
21	.724	.808	.709	.807	.630	.580	.623	.581	.623	.530
22	.782	.847	.856	.730	.709	.678	.738	.690	.625	.624
23	.797	.825	.876	.652	.801	.770	.755	.784	.458	.808
24	.865	.918	.886	.928	.842	.810	.804	.692	.864	.814
25	.727	.745	.557	.795	.799	.569	.598	.368	.644	.603
26	-.012	-.071	-.026	.157	-.064	-.008	-.034	-.034	.089	-.031
27	.749	.762	.792	.654	.749	.574	.590	.563	.486	.574
28	.400	.451	.511	.244	.356	.241	.289	.324	.125	.213
29	.465	.502	.626	.393	.388	.312	.342	.374	.268	.264
30	.512	.463	.634	.573	.452	.363	.368	.455	.404	.294
31	.386	.358	.446	.523	.328	.388	.440	.500	.380	.354
32	.655	.622	.641	.710	.664	.577	.580	.478	.564	.594
33	.900	.929	.707	.833	.858	.807	.854	.560	.714	.741
34	.786	.890	.460	.734	.769	.634	.720	.313	.493	.649
35	.951	.958	.000	.970	.914	.765	.762	.000	.800	.775
36	.816	.949	.098	.724	.763	.487	.614	.000	.315	.519
37	.842	.966	.755	.848	.719	.721	.846	.647	.692	.606
38	.889	.952	.947	.928	.790	.707	.751	.824	.676	.645
39	.815	.863	.738	.929	.788	.621	.600	.538	.333	.705
40	.686	.917	.470	.568	.651	.615	.625	.689	.072	.718
41	.866	.864	.000	.882	.866	.723	.709	.000	.702	.764
42	.828	.836	.814	.902	.807	.675	.639	.630	.788	.699
43	.831	.842	.878	.567	.829	.699	.719	.784	.405	.685
44	.785	.865	.542	.758	.773	.607	.627	.433	.506	.659
45	.781	.829	.671	.706	.760	.582	.640	.437	.422	.602
46	.803	.786	.762	.849	.817	.664	.611	.759	.727	.684
47	.735	.728	.677	.801	.713	.534	.615	.538	.474	.527
48	.530	.690	.448	.491	.510	.605	.741	.634	.500	.580
49	.790	.797	.722	.000	.794	.675	.687	.596	.000	.674
50	.959	.955	.000	.000	.957	.834	.847	.000	.000	.833
51	.914	.923	.869	.949	.884	.802	.814	.744	.824	.772
52	.845	.895	.483	.880	.817	.645	.733	.561	.489	.616
53	.878	.924	.930	.834	.825	.707	.776	.778	.667	.632
54	.915	.928	.928	.000	.889	.807	.808	.857	.000	.802
55	.941	.923	.000	.940	.946	.780	.710	.000	.690	.822
56	.735	.841	.806	.693	.716	.678	.612	.707	.615	.708
57	.857	.864	.818	.000	.846	.762	.765	.722	.000	.757
58	.900	.914	.929	.953	.874	.808	.809	.879	.895	.789
59	.909	.926	.826	.808	.897	.802	.831	.714	.677	.750
60	.963	.968	.000	.962	.957	.726	.741	.000	.626	.744
61	.870	.887	.743	.913	.861	.775	.807	.522	.838	.776
62	.901	.925	.769	.966	.863	.748	.793	.484	.839	.705
63	.872	.827	.000	.000	.840	.626	.589	.000	.000	.619
64	.760	.892	.785	.922	.690	.669	.804	.795	.663	.616
65	.788	.767	.783	.758	.843	.623	.583	.679	.586	.734
66	.422	.381	.554	.407	.452	.211	.203	.196	.185	.260
67	.795	.802	.787	.745	.806	.576	.577	.649	.495	.633
68	.804	.834	.764	.559	.858	.465	.521	.571	.187	.563
69	.790	.793	.702	.808	.779	.479	.486	.404	.462	.498
70	.836	.839	.709	.857	.848	.653	.632	.583	.575	.711
71	.850	.912	.647	.000	.824	.637	.559	.750	.000	.747
72	.569	.603	.550	.745	.540	.591	.563	.493	.579	.617
73	.624	.645	.620	.673	.489	.457	.481	.449	.507	.339
74	.513	.547	.415	.469	.561	.306	.326	.290	.275	.321
75	.828	.816	.864	.856	.852	.641	.609	.695	.671	.733
76	.837	.821	.811	.797	.869	.618	.600	.636	.485	.682
77	.535	.537	.464	.525	.570	.341	.366	.268	.298	.374
78	.681	.579	.760	.753	.743	.458	.375	.457	.412	.586
79	.577	.749	.355	.548	.541	.401	.420	.345	.349	.425
80	.715	.688	.788	.545	.733	.710	.699	.720	.474	.744

FOR FIRST PARAMETER OVERALL FRIEDMAN 14.7
STIM FRIEDMAN .014RESP FRIEDMAN 9.06COR WR FRIEDMAN 1.75

EXPERIMENT NO 2

ESTIMATION 4NONPARAMETRIC ANALYSIS

STATE ON LAST TRIAL SESSION	APRIME OVERALL	S1R1	S1R2	S2R1	S2R2	BIAS OVERALL	S1R1	S1R2	S2R1	S2R2
1	.558	.557	.531	.612	.519	-8.45	-14.2	.201	-12.6	.812
2	.497	.418	.536	.553	.513	-.059	-16.3	5.41	-8.04	1.64
3	.541	.470	.600	.633	.373	-7.36	-10.7	3.15	1.98	24.2
4	.578	.594	.567	.556	.545	-8.18	-15.3	2.04	-7.96	-2.76
5	.487	.433	.473	.527	.544	-.917	-5.76	.021	-3.65	-1.97
6	.566	.712	.461	.539	.591	-10.1	-68.8	-10.4	-3.67	14.6
7	.509	.479	.557	.483	.570	1.55	-2.24	14.7	-2.56	21.0
8	.568	.442	.626	.551	.639	11.5	-14.8	-24.9	10.0	45.1
9	.606	.660	.593	.619	.575	-17.2	-35.0	1.26	-28.9	-.448
10	.718	.730	.690	.721	.739	18.8	48.2	-.153	26.7	3.94
11	.766	.770	.807	.718	.896	-50.4	-67.6	-36.2	-20.6	70.4
12	.807	.820	.813	.781	.829	25.0	4.21	76.1	-54.2	41.2
13	.555	.619	.508	.586	.476	-4.56	-25.8	-.905	3.14	.006
14	.660	.687	.647	.543	.709	12.1	-7.40	15.7	-.525	37.1
15	.649	.702	.700	.585	.700	29.2	16.9	60.3	-7.65	49.3
16	.615	.000	.540	.639	.580	14.9	.000	4.92	-8.06	23.4
17	.764	.789	.673	.744	.800	-8.18	-27.5	6.06	20.4	5.36
18	.886	.911	.847	.858	.879	18.7	-52.8	49.3	31.3	53.6
19	.924	.927	.919	.897	.934	-71.4	-82.5	-52.3	-82.0	2.87
20	.696	.711	.557	.586	.803	17.6	13.9	5.90	6.54	33.0
21	.868	.884	.868	.876	.855	8.26	-29.6	18.0	-36.2	43.5
22	.905	.925	.899	.898	.886	24.9	2.75	-44.4	48.6	42.7
23	.922	.924	.939	.819	.931	46.1	25.4	3.14	-7.25	60.6
24	.942	.951	.917	.964	.940	29.6	-27.8	-48.3	-3.09	47.8
25	.857	.882	.804	.885	.824	-8.39	14.8	23.5	-19.7	-60.1
26	.493	.465	.485	.587	.471	.187	.510	.965	3.99	-.233
27	.829	.833	.827	.837	.823	-42.2	-44.7	-57.3	12.2	-45.1
28	.694	.724	.746	.611	.675	-4.02	-.876	-6.88	-5.40	-2.05
29	.738	.755	.781	.716	.710	3.94	3.02	-25.4	13.1	10.4
30	.766	.767	.812	.788	.727	7.75	26.0	-4.71	1.43	.561
31	.729	.740	.776	.768	.699	23.2	37.9	38.4	5.33	21.0
32	.847	.843	.822	.853	.852	22.9	33.6	2.09	3.60	24.2
33	.941	.954	.900	.782	.921	-26.8	-37.0	64.0	-76.4	-18.7
34	.888	.922	.754	.637	.894	-8.51	-45.9	17.7	-31.2	16.5
35	.874	.872	.000	.891	.885	-89.1	-91.0	.000	-92.6	-77.0
36	.844	.902	.539	.772	.845	-58.1	-85.0	-4.12	-56.6	-38.1
37	.919	.959	.892	.911	.880	-4.69	-73.7	23.5	-25.4	28.3
38	.914	.931	.939	.907	.892	-52.0	-78.7	-72.0	-76.2	-5.33
39	.894	.901	.860	.875	.905	-22.1	-47.2	-11.8	-83.5	21.7
40	.863	.919	.839	.717	.880	26.1	-65.6	78.4	-38.4	61.9
41	.892	.875	.000	.824	.933	-55.4	-62.5	.000	-79.8	.463
42	.902	.891	.886	.940	.913	-21.0	-39.7	-31.0	-30.3	19.1
43	.905	.914	.940	.805	.886	-20.5	-15.9	3.09	20.1	-40.5
44	.879	.893	.806	.838	.897	-20.3	-54.0	31.1	-40.5	18.8
45	.867	.887	.805	.803	.875	-30.4	-38.7	-27.0	-40.6	-7.49
46	.899	.879	.930	.921	.906	-4.58	-19.8	82.9	-8.22	-4.68
47	.857	.873	.844	.855	.851	-13.5	13.4	6.76	-47.7	-7.75
48	.332	.695	.815	.838	.821	56.9	64.1	66.0	49.2	53.9
49	.923	.926	.909	.000	.922	52.8	54.5	68.7	.000	48.1
50	.956	.960	.000	.000	.955	-69.7	-60.9	.000	.000	-68.6
51	.928	.933	.916	.929	.914	-56.8	-59.6	-35.7	-77.8	-49.3
52	.897	.926	.821	.851	.885	-39.7	-45.1	61.5	-74.8	-34.3
53	.916	.937	.941	.899	.891	-43.4	-56.2	-58.4	-30.1	-33.7
54	.947	.947	.961	.000	.945	-32.5	-48.8	-12.4	.000	2.17
55	.951	.935	.000	.933	.959	-57.5	-58.2	.000	-71.7	-51.0
56	.889	.899	.909	.870	.891	31.6	-35.2	11.8	31.1	47.1
57	.940	.937	.939	.000	.943	32.0	15.1	66.8	.000	52.5
58	.947	.947	.967	.971	.941	-11.4	-31.4	15.7	-33.2	12.7
59	.929	.939	.927	.902	.907	-52.6	-56.1	31.7	-3.23	-62.1
60	.930	.936	.000	.914	.932	-84.5	-85.6	.000	-87.4	-81.3
61	.937	.947	.847	.956	.938	5.12	11.3	-28.0	-3.65	21.4
62	.928	.941	.844	.953	.915	-47.2	-52.9	-41.4	-78.0	-32.9
63	.907	.889	.000	.000	.900	-47.4	-36.5	.000	.000	-33.8
64	.892	.946	.925	.929	.866	20.4	-.593	59.9	-62.5	26.9
65	.862	.831	.922	.846	.928	-37.6	-47.5	55.6	-35.4	15.4
66	.679	.666	.707	.669	.705	-18.2	-13.8	-38.7	-19.0	-13.3
67	.815	.819	.783	.785	.846	-61.5	-62.4	-67.6	-57.8	-54.1
68	.833	.853	.861	.700	.870	-58.5	-60.4	-25.9	-41.8	-62.4
69	.835	.832	.799	.830	.845	-53.6	-55.4	-40.9	-60.8	-44.7
70	.896	.889	.870	.867	.916	-34.8	-43.0	21.2	-63.0	-17.5
71	.904	.904	.891	.000	.922	-35.4	-70.2	76.4	.000	22.7
72	.836	.831	.809	.869	.840	47.7	29.4	30.6	-4.97	60.8
73	.782	.797	.813	.782	.696	-24.5	-22.6	3.36	-39.8	-27.7
74	.736	.751	.724	.712	.746	-14.3	-16.7	11.3	-14.5	-24.2
75	.858	.843	.893	.672	.912	-56.6	-58.6	-53.6	-60.9	-27.2
76	.885	.878	.891	.637	.908	-44.7	-42.0	-22.7	-55.1	-44.2
77	.754	.768	.718	.725	.773	-10.4	-.773	-9.57	-24.0	-9.81
78	.814	.773	.809	.810	.870	-24.9	-13.9	-54.3	-51.8	-2.57
79	.788	.836	.703	.767	.783	-.965	-37.8	16.0	-5.90	10.6
80	.893	.684	.911	.799	.905	50.5	51.6	31.9	23.6	57.1

FOR FIRST PARAMETER OVERALL FRIEDMAN 9.77

STIM FRIEDMAN .362RESP FRIEDMAN 2.45COR WR FRIEDMAN 9.06

EXPERIMENT NO 2
ESTIMATION 5ATKINSONS MODEL

STATE ON LAST TRIAL SESSION	SIGMA OVERALL	SIGMA S1R1	SIGMA S1R2	SIGMA S2R1	SIGMA S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	.054	.038	.032	.118	.019	1.44	.683	3.28	1.73	3.94
2	-.003	-.071	.032	.049	.011	.897	.386	2.25	.446	1.97
3	.035	-.006	.111	.153	-.119	1.07	.161	3.44	2.96	6.74
4	.079	.089	.071	.053	.046	.594	.407	1.24	.481	.763
5	-.013	-.069	-.028	.025	.045	.632	.615	.905	.450	.715
6	.062	.118	-.023	.038	.086	.404	.055	.199	.568	2.33
7	.008	-.019	.037	-.015	.035	.794	.186	1.57	.147	2.52
8	.061	-.037	.116	.041	.064	.836	.077	.099	.985	4.19
9	.102	.146	.103	.091	.081	1.15	.708	3.03	.640	2.76
10	.273	.248	.234	.269	.313	1.54	3.84	.886	2.08	1.11
11	.320	.280	.430	.271	.633	.816	.391	1.88	1.78	6.90
12	.438	.471	.371	.346	.477	1.51	1.15	8.74	.257	1.82
13	.059	.101	.007	.094	-.025	.668	.265	.562	1.22	1.01
14	.186	.229	.164	.045	.231	1.53	.794	1.81	.978	3.25
15	.142	.247	.132	.090	.178	1.06	.528	3.67	.205	1.80
16	.119	.000	.038	.160	.043	.681	.000	.636	.243	2.46
17	.358	.399	.209	.317	.428	2.30	1.49	3.40	4.37	2.83
18	.629	.689	.515	.552	.598	1.46	.373	4.69	1.52	3.16
19	.723	.727	.717	.625	.768	.690	.343	.289	1.99	2.60
20	.237	.265	.057	.091	.424	1.93	1.71	1.99	1.80	2.32
21	.581	.620	.580	.598	.540	1.25	.747	1.80	.335	2.45
22	.679	.738	.658	.653	.621	1.48	1.31	.097	1.12	2.53
23	.726	.734	.782	.469	.750	.771	.496	.578	.264	1.23
24	.793	.822	.709	.864	.783	.591	.910	-.010	.061	.697
25	.556	.618	.433	.624	.442	2.53	3.48	4.14	3.06	.716
26	-.007	-.036	-.015	.094	-.030	1.20	1.11	1.44	1.31	1.00
27	.476	.484	.453	.509	.459	1.24	1.13	1.04	3.40	1.10
28	.240	.289	.326	.123	.211	.944	1.02	.985	.819	.968
29	.311	.342	.385	.273	.264	1.07	1.05	.629	1.30	1.26
30	.361	.355	.454	.404	.294	1.06	1.66	.771	.761	.974
31	.287	.290	.362	.366	.240	.592	.861	.822	.347	.611
32	.529	.515	.475	.557	.542	.418	.425	.205	.341	.467
33	.787	.830	.653	.278	.726	2.38	1.63	17.7	.157	3.96
34	.634	.725	.336	.502	.650	.901	.692	1.23	.684	1.11
35	.532	.518	.000	.582	.592	.229	.201	.000	.159	.407
36	.498	.636	.038	.318	.517	.268	.139	.546	.193	.414
37	.721	.843	.644	.696	.609	.981	.209	1.97	1.13	1.54
38	.701	.743	.775	.663	.645	.459	.206	-.272	.195	1.18
39	.649	.663	.562	.547	.681	.228	.123	.334	.045	.406
40	.568	.709	.443	.243	.592	.464	.078	2.99	.092	1.19
41	.632	.578	.000	.392	.764	1.17	.826	.000	.200	4.96
42	.673	.637	.626	.785	.702	.818	.656	.701	.651	1.18
43	.679	.705	.786	.436	.622	2.00	2.27	2.14	4.95	1.07
44	.608	.637	.433	.499	.658	.706	.417	1.68	.385	1.17
45	.575	.627	.433	.417	.601	.711	.543	.748	.542	1.13
46	.664	.610	.738	.728	.684	.879	.608	39.2	.964	.939
47	.555	.594	.524	.537	.540	.293	.532	.518	.091	.329
48	.467	.635	.406	.419	.444	1.28	1.78	2.58	.788	1.19
49	.727	.737	.675	.000	.725	6.50	7.26	16.2	.000	4.56
50	.835	.849	.000	.000	.833	.271	.420	.000	.000	.247
51	.744	.759	.711	.738	.701	1.15	1.33	2.53	.756	.674
52	.653	.740	.431	.489	.622	.456	.419	10.1	.089	.474
53	.708	.773	.783	.663	.637	.500	.255	.561	.487	.707
54	.807	.806	.856	.000	.802	.651	.390	.369	.000	1.20
55	.818	.764	.000	.752	.848	.141	.164	.000	.040	.168
56	.632	.660	.690	.584	.635	.526	.210	1.00	.297	.750
57	.784	.776	.777	.000	.794	4.50	3.10	16.6	.000	10.3
58	.808	.808	.876	.890	.788	.868	.527	6.22	-.316	1.64
59	.748	.779	.744	.673	.673	1.35	1.12	5.09	2.14	1.51
60	.737	.755	.000	.677	.743	.110	.138	.000	.262	.049
61	.776	.807	.527	.837	.779	1.24	1.69	.965	-.202	1.30
62	.746	.786	.513	.823	.707	.500	.265	.740	-.080	.897
63	.681	.632	.000	.000	.662	.169	.174	.000	.000	.274
64	.645	.804	.731	.743	.574	.470	.307	1.08	.275	.517
65	.561	.476	.723	.521	.747	1.40	1.02	15.0	1.45	2.34
66	.209	.194	.224	.193	.255	.582	.639	.328	.558	.708
67	.416	.425	.315	.349	.508	.576	.593	.208	.660	.688
68	.467	.520	.563	.202	.564	.271	.266	.501	.255	.273
69	.479	.469	.409	.455	.513	.324	.262	.437	.237	.519
70	.652	.630	.586	.556	.712	.600	.504	1.31	.212	.903
71	.676	.659	.611	.000	.730	.218	.094	3.10	.000	.439
72	.488	.489	.440	.586	.483	.987	.815	.562	.379	1.42
73	.386	.417	.456	.374	.225	1.74	1.78	3.12	1.13	1.34
74	.307	.332	.287	.265	.317	.718	.726	1.33	.648	.552
75	.538	.493	.637	.571	.700	.808	.773	1.35	.768	.767
76	.620	.600	.642	.482	.685	.454	.454	.927	.283	.506
77	.339	.365	.277	.280	.375	.855	.977	.936	.550	.916
78	.454	.373	.412	.419	.586	.681	.822	.246	.376	1.03
79	.404	.496	.250	.364	.393	.331	.150	.558	.268	.431
80	.640	.613	.695	.422	.669	.877	1.07	.348	.514	1.06

FOR FIRST PARAMETER OVERALL FRIEDMAN 10.5
STIM FRIEDMAN .130RESP FRIEDMAN .710COR WR FRIEDMAN 7.67

FOR SECOND PARAMETER OVERALL FRIEDMAN 44.9
STIM FRIEDMAN 1.75RESP FRIEDMAN 32.0COR WR FRIEDMAN .362

EXPERIMENT NO 3
ESTIMATION 1LUCES CHOICE MODEL

STATE ON LAST TRIAL SESSION	Z OVERALL	Z S1R1	Z S1R2	Z S2R1	Z S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	.004	.000	.000	.000	.006	1.45	.000	.000	.000	.978
2	.005	.000	.000	.000	.000	.584	.000	.000	.000	.000
3	.003	.000	.000	.000	.000	1.03	.000	.000	.000	.000
4	.000	.000	.000	.000	.000	H	.000	.000	.000	.000
5	.007	.000	.000	.000	.008	.807	.000	.000	.000	1.35
6	.005	.000	.000	.000	.000	.565	.000	.000	.000	.000
7	.210	.211	.185	.151	.194	.852	1.13	.285	2.34	.665
8	.154	.145	.213	.000	.135	.459	.550	.376	.000	.344
9	.296	.259	.300	.211	.306	.711	.967	.257	1.69	.660
10	.217	.327	.291	.109	.095	.496	.601	.405	1.96	.269
11	.180	.186	.241	.081	.172	.801	.867	.860	1.86	.667
12	.397	.399	.502	.316	.353	.619	.413	.781	.949	.655
13	.893	.855	.916	1.06	.794	.567	.855	.364	1.17	.420
14	.241	.341	.191	.000	.145	.419	.523	.225	.000	.271
15	.115	.125	.000	.000	.104	.381	.346	.000	.000	.492
16	.327	.346	.485	.288	.259	.427	.378	.350	.360	.518
17	.262	.271	.341	.277	.200	.641	.751	.539	1.52	.465
18	.247	.317	.192	.000	.219	.696	.736	.635	.000	.707
19	.033	.025	.000	.000	.037	.915	.724	.000	.000	1.05
20	.020	.014	.000	.000	.021	.809	1.29	.000	.000	.502
21	.008	.000	.000	.000	.009	.957	.000	.000	.000	.539
22	.024	.014	.000	.000	.032	.960	1.25	.000	.000	.932
23	.027	.013	.000	.000	.035	.706	.418	.000	.000	.778
24	.054	.066	.000	.174	.042	.796	.597	.000	1.91	1.05
25	.212	.244	.326	.128	.137	1.00	1.37	.396	4.35	.643
26	.389	.396	.541	.521	.273	1.10	1.21	.892	1.72	.881
27	.200	.265	.135	.094	.120	.742	1.21	.655	1.70	.320
28	.232	.277	.336	.215	.166	1.10	1.32	.864	1.25	.845
29	.186	.181	.216	.224	.151	.942	1.35	.993	1.34	.578
30	.341	.424	.542	.250	.234	1.30	1.47	1.48	.767	1.35
31	.473	.360	.561	.411	.446	1.16	1.76	.503	3.11	.731
32	.271	.239	.331	.259	.258	.702	.628	.514	2.42	.682
33	.226	.196	.238	.218	.208	.858	1.40	1.35	.873	.483
34	.549	.565	.797	.618	.379	1.52	1.50	1.05	1.45	2.10
35	.290	.290	.471	.263	.261	1.26	1.21	1.65	1.05	1.36
36	.712	.793	.780	.618	.657	.843	.744	.997	.751	.917
37	.047	.032	.000	.293	.043	1.01	1.52	.000	.488	.893
38	.039	.039	.000	.000	.039	1.03	1.17	.000	.000	.859
39	.019	.000	.000	.000	.019	2.17	.000	.000	.000	1.03
40	.045	.048	.000	.161	.026	1.38	1.05	.000	.886	2.38
41	.010	.011	.000	.000	.000	1.89	1.01	.000	.000	.000
42	.051	.084	.000	.000	.016	1.32	1.00	.000	.000	3.06
43	.157	.168	.129	.094	.147	1.41	1.32	.516	3.02	1.48
44	.158	.143	.316	.213	.145	2.28	2.39	1.26	2.50	2.25
45	.391	.347	.659	.468	.314	1.35	1.72	1.22	1.26	1.01
46	.181	.169	.125	.205	.199	1.07	1.06	1.00	.903	1.11
47	.127	.090	.225	.181	.146	1.63	2.00	2.47	1.44	1.40
48	.102	.103	.167	.128	.089	1.71	1.58	1.50	2.81	1.69
49	.548	.504	.652	.587	.525	1.34	1.19	1.19	1.45	1.52
50	.542	.581	.613	.557	.437	1.29	1.14	1.19	1.49	1.50
51	.659	.858	.585	.628	.516	1.19	1.11	2.66	.746	1.16
52	.528	.496	.652	.558	.455	1.14	.816	1.59	1.31	1.29
53	.689	.751	.696	.742	.603	.968	.895	1.09	.981	.918
54	.583	.569	.810	.708	.414	1.33	1.15	1.58	1.58	1.23
55	.045	.020	.000	.000	.039	1.01	.282	.000	.000	2.28
56	.027	.034	.000	.000	.017	1.91	1.36	.000	.000	2.99
57	.034	.022	.000	.000	.037	1.34	1.29	.000	.000	1.61
58	.009	.011	.000	.000	.000	.841	.486	.000	.000	.000
59	.031	.039	.000	.000	.022	.657	.878	.000	.000	.427
60	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
61	.164	.145	.273	.126	.152	.481	.401	.416	.567	.568
62	.110	.132	.165	.189	.078	.950	.907	.826	.707	1.02
63	.260	.244	.000	.168	.348	2.21	1.92	.000	5.04	1.97
64	.076	.062	.149	.000	.080	1.73	1.50	.745	.000	1.68
65	.181	.170	.283	.223	.167	.949	.974	.441	.780	1.13
66	.107	.110	.000	.258	.083	1.41	1.27	.000	2.07	1.60
67	.359	.422	.250	.335	.309	1.54	1.41	1.33	2.35	1.47
68	.547	.452	.601	.545	.621	.847	.704	.832	.917	.971
69	.353	.312	.520	.298	.356	1.35	1.01	.997	1.33	2.06
70	.410	.400	.354	.428	.393	2.15	1.55	2.30	2.50	3.21
71	.831	.727	.479	1.30	.958	1.33	2.27	1.26	1.03	.874
72	.236	.187	.402	.331	.196	.885	.637	.581	1.07	1.42
73	.010	.008	.000	.000	.007	1.08	1.29	.000	.000	.679
74	.015	.011	.000	.000	.016	1.36	1.01	.000	.000	1.48
75	.009	.000	.000	.000	.012	1.50	.000	.000	.000	2.24
76	.031	.019	.000	.000	.033	.954	1.42	.000	.000	.997
77	.007	.006	.000	.000	.008	1.22	.986	.000	.000	1.40
78	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
79	.132	.072	.385	.306	.129	2.66	3.34	.577	2.63	2.92
80	.169	.123	.274	.128	.202	2.22	2.66	2.19	6.63	1.54
81	.103	.097	.360	.172	.072	.826	.944	.520	1.55	.716
82	.141	.128	.196	.113	.140	1.94	1.41	.784	4.42	2.52
83	.088	.093	.000	.100	.063	1.71	1.21	.000	1.60	3.13
84	.137	.122	.495	.240	.108	1.47	1.35	.866	1.56	1.73
85	.368	.333	.389	.480	.321	1.17	1.11	.572	1.56	1.34
86	.477	.556	.281	.457	.493	1.33	1.28	1.61	1.37	1.26
87	.453	.509	.538	.329	.389	.611	.452	.567	.329	.913
88	.327	.227	.236	.455	.398	.786	.493	.660	.865	1.07
89	.473	.519	.339	.504	.470	.723	.431	.774	.644	1.09
90	.663	.689	.665	.705	.590	.677	.389	.447	.881	1.15

FOR FIRST PARAMETER OVERALL FRIEDMAN 31.3
STIM FRIEDMAN 19.7RESP FRIEDMAN 1.92COR WR FRIEDMAN 11.1

FOR SECOND PARAMETER OVERALL FRIEDMAN 14.2
STIM FRIEDMAN 11.1RESP FRIEDMAN .077COR WR FRIEDMAN 2.77
FP OFLO

EXPERIMENT NO 3

ESTIMATION 2TANNER SWETS GREEN MODEL

STATE ON LAST TRIAL SESSION	DPRIME OVERALL	DPRIME S1R1	DPRIME S1R2	DPRIME S2R1	DPRIME S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	5.33	.000	.000	.000	5.07	2.79	.000	.000	.000	2.53
2	5.18	.000	.000	.000	.000	2.41	.000	.000	.000	.000
3	5.56	.000	.000	.000	.000	2.79	.000	.000	.000	.000
4	38.2	.000	.000	.000	.000	35.7	.000	.000	.000	.000
5	4.95	.000	.000	.000	4.85	2.40	.000	.000	.000	2.53
6	5.18	.000	.000	.000	.000	2.40	.000	.000	.000	.000
7	1.88	1.88	1.98	2.22	1.96	.881	.983	.544	1.43	.831
8	2.20	2.27	1.84	.000	2.32	.801	.900	.581	.000	.747
9	1.48	1.64	1.45	1.87	1.45	.633	.811	.340	1.12	.596
10	1.83	1.37	1.49	2.56	2.65	.668	.534	.472	1.55	.804
11	2.05	2.01	1.73	2.86	2.09	.940	.952	.810	1.69	.893
12	1.14	1.13	.856	1.41	1.28	.447	.348	.378	.689	.521
13	.142	.196	.110	-.068	.289	.052	.090	.029	-.036	.086
14	1.71	1.32	1.93	.000	2.23	.563	.475	.457	.000	.626
15	2.49	2.40	.000	.000	2.61	.861	.783	.000	.000	1.02
16	1.36	1.29	.894	1.50	1.63	.438	.383	.241	.443	.600
17	1.63	1.59	1.32	1.56	1.92	.665	.700	.483	.918	.683
18	1.70	1.41	1.97	.000	1.83	.724	.610	.818	.000	.791
19	3.69	3.95	.000	.000	3.60	1.81	1.85	.000	.000	1.82
20	4.11	4.41	.000	.000	4.06	1.97	2.30	.000	.000	1.76
21	4.81	.000	.000	.000	4.71	2.39	.000	.000	.000	2.13
22	3.99	4.43	.000	.000	3.73	1.98	2.30	.000	.000	1.84
23	3.88	4.42	.000	.000	3.65	1.80	1.88	.000	.000	1.72
24	3.27	3.07	.000	2.07	3.50	1.54	1.32	.000	1.28	1.77
25	1.87	1.71	1.36	2.34	2.34	.937	.962	.419	1.72	.992
26	1.17	1.14	.765	.811	1.58	.607	.622	.362	.508	.749
27	1.93	1.62	2.35	2.72	2.43	.855	.872	1.01	1.58	.769
28	1.77	1.56	1.34	1.85	2.14	.919	.873	.627	1.01	1.00
29	2.01	2.04	1.85	1.81	2.23	.985	1.14	.922	1.01	.900
30	1.32	1.06	.763	1.68	1.76	.737	.623	.452	.751	.985
31	.929	1.26	.719	1.09	1.00	.497	.783	.245	.806	.428
32	1.59	1.73	1.35	1.63	1.64	.679	.703	.483	1.10	.693
33	1.80	1.95	1.74	1.84	1.87	.843	1.10	.972	.869	.678
34	.746	.711	.284	.601	1.19	.447	.424	.145	.354	.787
35	1.51	1.51	.932	1.63	1.63	.830	.816	.573	.830	.920
36	.426	.291	.311	.600	.525	.195	.124	.155	.258	.251
37	3.40	3.72	.000	1.49	3.48	1.70	2.03	.000	.524	1.69
38	3.55	3.56	.000	.000	3.56	1.79	1.84	.000	.000	1.72
39	4.12	.000	.000	.000	4.18	2.36	.000	.000	.000	2.10
40	3.43	3.36	.000	2.17	3.87	1.84	1.70	.000	1.04	2.28
41	4.62	4.59	.000	.000	.000	2.54	2.30	.000	.000	.000
42	3.31	2.84	.000	.000	4.24	1.77	1.42	.000	.000	2.55
43	2.19	2.13	2.39	2.67	2.26	1.23	1.17	.931	1.78	1.29
44	2.17	2.27	1.41	1.84	2.26	1.40	1.48	.776	1.24	1.44
45	1.16	1.30	.520	.941	1.42	.657	.802	.286	.521	.711
46	2.05	2.12	2.44	1.91	1.94	1.05	1.08	1.22	.915	1.01
47	2.41	2.76	1.78	2.04	2.27	1.40	1.66	1.20	1.16	1.27
48	2.64	2.63	2.13	2.37	2.77	1.54	1.50	1.22	1.59	1.60
49	.750	.852	.535	.663	.801	.428	.460	.290	.391	.480
50	.762	.677	.612	.728	1.02	.427	.360	.332	.432	.606
51	.522	.191	.667	.580	.824	.283	.101	.480	.249	.442
52	.814	.872	.534	.727	.977	.432	.394	.327	.410	.545
53	.466	.359	.453	.374	.630	.229	.169	.237	.185	.302
54	.674	.703	.264	.432	1.09	.382	.375	.161	.264	.596
55	3.43	4.04	.000	.000	3.52	1.72	1.53	.000	.000	2.10
56	3.85	3.69	.000	.000	4.20	2.18	1.97	.000	.000	2.52
57	3.68	4.04	.000	.000	3.59	1.96	2.12	.000	.000	1.99
58	4.70	4.54	.000	.000	.000	2.29	2.00	.000	.000	.000
59	3.76	3.55	.000	.000	4.00	1.71	1.72	.000	.000	1.67
60	38.0	.000	.000	.000	.000	2.33	.000	.000	.000	.000
61	2.14	2.25	1.57	2.42	2.22	.789	.774	.507	.982	.892
62	2.57	2.39	2.14	2.00	2.91	1.27	1.15	.998	.868	1.47
63	1.63	1.70	.000	2.05	1.29	1.07	1.07	.000	1.59	.835
64	2.92	3.12	2.25	.000	2.87	1.69	1.73	1.01	.000	1.65
65	2.05	2.12	1.53	1.81	2.14	1.00	1.05	.508	.817	1.12
66	2.60	2.57	.000	1.63	2.85	1.44	1.38	.000	1.06	1.62
67	1.26	1.07	1.68	1.33	1.43	.749	.616	.939	.906	.836
68	.750	.984	.635	.755	.595	.345	.412	.289	.362	.293
69	1.28	1.43	.813	1.48	1.26	.724	.715	.406	.828	.829
70	1.10	1.13	1.27	1.04	1.14	.734	.676	.861	.731	.850
71	.233	.399	.914	-.327	.054	.133	.276	.507	-.166	.025
72	1.75	2.00	1.12	1.36	1.95	.832	.833	.425	.698	1.11
73	4.70	4.78	.000	.000	4.88	2.38	2.48	.000	.000	2.31
74	4.37	4.60	.000	.000	4.28	2.30	2.30	.000	.000	2.29
75	4.76	.000	.000	.000	4.51	2.53	.000	.000	.000	2.55
76	3.77	4.16	.000	.000	3.70	1.86	2.21	.000	.000	1.85
77	4.95	5.09	.000	.000	4.84	2.54	2.54	.000	.000	2.54
78	38.4	.000	.000	.000	.000	2.76	.000	.000	.000	.000
79	2.34	2.92	1.17	1.43	2.37	1.55	1.95	.444	1.00	1.60
80	2.10	2.42	1.57	2.30	1.92	1.35	1.60	1.03	1.83	1.12
81	2.64	2.70	1.25	2.09	2.99	1.24	1.33	.448	1.21	1.36
82	2.30	2.41	1.95	2.46	2.29	1.41	1.34	.887	1.80	1.50
83	2.78	2.74	.000	2.66	3.06	1.61	1.45	.000	1.52	1.99
84	2.34	2.46	.874	1.72	2.58	1.32	1.35	.407	1.02	1.51
85	1.23	1.35	1.16	.909	1.39	.658	.704	.437	.549	.783
86	.920	.731	1.54	.969	.878	.520	.409	.924	.556	.487
87	.981	.838	.770	1.35	1.17	.380	.268	.283	.368	.559
88	1.37	1.78	1.75	.975	1.14	.614	.644	.728	.455	.586
89	.928	.814	1.33	.850	.936	.394	.252	.590	.338	.486
90	.514	.466	.510	.437	.658	.208	.132	.159	.205	.352

FOR FIRST PARAMETER OVERALL FRIEDMAN 33.0

STIM FRIEDMAN 17.3RESP FRIEDMAN 1.23COR WR FRIEDMAN 9.31

EXPERIMENT NO 3

ESTIMATION 3CLASSICAL THRESHOLD MODEL

STATE ON LAST TRIAL SESSION	THRESHOLD OVERALL	THRESHOLD S1R1	THRESHOLD S1R2	THRESHOLD S2R1	THRESHOLD S2R2	P(C) OVERALL	P(C) S1R1	P(C) S1R2	P(C) S2R1	P(C) S2R2
1	.997	.000	.000	.000	.994	.992	.000	.000	.000	.989
2	.992	.000	.000	.000	.000	.989	.000	.000	.000	.000
3	.997	.000	.000	.000	.000	.995	.000	.000	.000	.000
4	1.00	.000	.000	.000	.000	.995	.000	.000	.000	.000
5	.992	.000	.000	.000	.994	.986	.000	.000	.000	.984
6	.992	.000	.000	.000	.000	.989	.000	.000	.000	.000
7	.767	.805	.585	.918	.745	.651	.649	.589	.714	.655
8	.732	.774	.610	.000	.705	.689	.717	.622	.000	.678
9	.642	.736	.420	.849	.620	.531	.589	.407	.600	.511
10	.663	.578	.533	.936	.733	.599	.492	.482	.778	.707
11	.790	.795	.736	.952	.771	.691	.685	.612	.830	.693
12	.513	.428	.455	.675	.569	.418	.358	.329	.520	.475
13	.079	.134	.046	-.060	.128	.058	.078	.072	-.032	.068
14	.598	.535	.521	.000	.638	.545	.459	.537	.000	.596
15	.758	.723	.000	.000	.817	.721	.692	.000	.000	.773
16	.506	.459	.320	.510	.622	.478	.412	.259	.560	.587
17	.661	.681	.541	.781	.671	.567	.565	.477	.547	.608
18	.694	.628	.740	.000	.727	.586	.500	.647	.000	.630
19	.964	.967	.000	.000	.964	.935	.949	.000	.000	.928
20	.975	.989	.000	.000	.959	.959	.972	.000	.000	.951
21	.991	.000	.000	.000	.983	.984	.000	.000	.000	.979
22	.976	.989	.000	.000	.966	.954	.973	.000	.000	.938
23	.963	.969	.000	.000	.956	.946	.965	.000	.000	.930
24	.934	.897	.000	.889	.960	.897	.871	.000	.750	.920
25	.789	.798	.490	.956	.809	.650	.604	.455	.651	.743
26	.627	.636	.440	.560	.706	.439	.424	.292	.297	.569
27	.756	.763	.814	.939	.716	.659	.578	.744	.792	.690
28	.782	.764	.639	.814	.812	.623	.560	.508	.649	.710
29	.806	.853	.783	.814	.774	.686	.688	.645	.630	.708
30	.700	.637	.517	.707	.806	.485	.388	.299	.593	.614
31	.552	.723	.324	.734	.497	.355	.434	.238	.278	.372
32	.669	.683	.541	.843	.677	.559	.585	.472	.544	.573
33	.751	.844	.802	.762	.668	.629	.658	.610	.633	.605
34	.513	.494	.207	.433	.725	.268	.263	.109	.225	.380
35	.745	.739	.605	.745	.782	.545	.547	.353	.580	.577
36	.268	.180	.220	.339	.331	.171	.115	.123	.250	.208
37	.954	.978	.000	.571	.953	.911	.935	.000	.500	.917
38	.962	.966	.000	.000	.955	.924	.923	.000	.000	.925
39	.991	.000	.000	.000	.982	.948	.000	.000	.000	.963
40	.966	.954	.000	.824	.988	.910	.907	.000	.714	.935
41	.994	.989	.000	.000	.000	.976	.978	.000	.000	.000
42	.960	.916	.000	.000	.995	.900	.845	.000	.000	.953
43	.877	.862	.787	.961	.890	.715	.702	.722	.739	.730
44	.912	.925	.720	.880	.920	.672	.695	.500	.588	.689
45	.657	.732	.367	.569	.687	.436	.473	.195	.355	.522
46	.827	.838	.875	.781	.814	.694	.712	.778	.661	.667
47	.913	.949	.870	.860	.886	.753	.802	.538	.692	.732
48	.934	.929	.875	.941	.942	.791	.796	.700	.649	.817
49	.498	.523	.372	.467	.539	.281	.320	.204	.235	.318
50	.497	.439	.413	.501	.626	.300	.269	.231	.291	.403
51	.364	.148	.539	.329	.509	.203	.077	.185	.244	.324
52	.501	.469	.408	.483	.586	.314	.333	.217	.275	.365
53	.307	.237	.315	.256	.384	.184	.144	.176	.149	.243
54	.459	.453	.227	.345	.619	.263	.273	.103	.179	.416
55	.955	.933	.000	.000	.982	.913	.927	.000	.000	.903
56	.985	.975	.000	.000	.994	.935	.931	.000	.000	.945
57	.974	.983	.000	.000	.976	.932	.955	.000	.000	.921
58	.989	.977	.000	.000	.000	.981	.972	.000	.000	.000
59	.954	.956	.000	.000	.950	.938	.925	.000	.000	.944
60	.990	.000	.000	.000	.000	.989	.000	.000	.000	.000
61	.726	.719	.559	.805	.771	.667	.656	.505	.769	.709
62	.886	.858	.811	.761	.923	.802	.769	.730	.667	.855
63	.834	.835	.000	.940	.747	.530	.572	.000	.478	.451
64	.952	.956	.815	.000	.948	.843	.873	.750	.000	.843
65	.813	.827	.560	.739	.848	.694	.710	.559	.630	.714
66	.919	.909	.000	.830	.944	.797	.794	.000	.560	.832
67	.707	.632	.789	.777	.747	.455	.402	.600	.389	.517
68	.425	.485	.371	.441	.375	.290	.372	.260	.293	.232
69	.693	.689	.479	.744	.744	.469	.524	.316	.533	.421
70	.699	.667	.758	.697	.754	.370	.413	.424	.318	.347
71	.191	.358	.559	-.304	.040	.097	.176	.356	-.130	.018
72	.746	.746	.495	.680	.845	.615	.658	.383	.508	.658
73	.991	.993	.000	.000	.989	.981	.982	.000	.000	.985
74	.989	.989	.000	.000	.989	.970	.979	.000	.000	.966
75	.994	.000	.000	.000	.995	.981	.000	.000	.000	.969
76	.968	.986	.000	.000	.967	.940	.959	.000	.000	.936
77	.995	.994	.000	.000	.994	.986	.989	.000	.000	.984
78	.997	.000	.000	.000	.000	.997	.000	.000	.000	.000
79	.936	.974	.511	.812	.942	.674	.764	.500	.423	.676
80	.903	.942	.822	.965	.848	.655	.696	.615	.545	.651
81	.879	.898	.514	.873	.904	.810	.823	.415	.655	.859
82	.914	.902	.769	.962	.929	.718	.762	.680	.646	.697
83	.944	.921	.000	.932	.976	.824	.832	.000	.783	.816
84	.897	.904	.481	.817	.930	.745	.777	.355	.587	.782
85	.657	.683	.505	.588	.723	.458	.502	.419	.316	.494
86	.569	.482	.784	.593	.544	.341	.273	.543	.351	.331
87	.456	.349	.364	.446	.596	.361	.292	.277	.407	.440
88	.631	.649	.696	.519	.613	.502	.580	.596	.387	.432
89	.469	.332	.616	.418	.543	.350	.247	.493	.340	.360
90	.283	.190	.225	.279	.431	.196	.134	.191	.175	.260

FOR FIRST PARAMETER OVERALL FRIEDMAN 28.8
STIM FRIEDMAN 22.2RESP FRIEDMAN 4.92COR WR FRIEDMAN 13.0

FOR SECOND PARAMETER OVERALL FRIEDMAN 30.9
STIM FRIEDMAN 7.69RESP FRIEDMAN .308COR WR FRIEDMAN 15.1

ESTIMATION ‡NONPARAMETRIC ANALYSIS

STATE ON LAST TRIAL SESSION	APRIME OVERALL	APRIME S1R1	APRIME S1R2	APRIME S2R1	APRIME S2R2	BIAS OVERALL	BIAS S1R1	BIAS S1R2	BIAS S2R1	BIAS S2R2
1	.998	.000	.000	.000	.997	-52.2	.000	.000	.000	4.35
2	.997	.000	.000	.000	.000	65.6	.000	.000	.000	.000
3	.999	.000	.000	.000	.000	-5.26	.000	.000	.000	.000
4	.999	.000	.000	.000	.000	-100	.000	.000	.000	.000
5	.997	.000	.000	.000	.996	34.6	.000	.000	.000	-44.3
6	.997	.000	.000	.000	.000	67.7	.000	.000	.000	.000
7	.894	.894	.876	.910	.900	18.9	-14.7	80.1	-70.5	42.1
8	.911	.920	.874	.000	.911	67.2	58.5	70.3	.000	79.0
9	.849	.871	.816	.888	.844	30.7	3.87	73.3	-49.1	35.4
10	.881	.831	.838	.937	.925	58.5	39.9	61.3	-65.7	87.4
11	.909	.906	.879	.954	.910	26.5	17.8	16.9	-64.8	43.3
12	.797	.787	.748	.842	.820	33.5	51.4	15.0	5.33	32.9
13	.553	.572	.542	.474	.601	6.08	2.40	7.85	-.835	17.1
14	.863	.821	.861	.000	.895	64.1	46.3	84.1	.000	84.0
15	.926	.917	.000	.000	.940	77.4	79.6	.000	.000	67.9
16	.822	.809	.744	.835	.861	56.2	59.0	49.1	65.6	53.8
17	.865	.863	.822	.858	.887	40.3	27.8	44.8	-37.6	63.0
18	.874	.839	.899	.000	.888	35.2	27.1	45.6	.000	35.6
19	.983	.987	.000	.000	.981	15.4	46.0	.000	.000	-8.55
20	.990	.993	.000	.000	.987	33.5	-39.3	.000	.000	73.2
21	.996	.000	.000	.000	.995	8.25	.000	.000	.000	70.3
22	.988	.993	.000	.000	.984	7.50	-34.7	.000	.000	12.4
23	.986	.991	.000	.000	.982	48.3	81.6	.000	.000	37.4
24	.973	.964	.000	.904	.979	33.6	59.3	.000	-59.3	-8.33
25	.894	.876	.820	.897	.928	-.605	-31.4	59.1	-87.9	48.5
26	.805	.802	.729	.736	.863	-7.88	-15.3	6.55	-25.5	13.5
27	.898	.867	.929	.948	.916	32.7	-20.0	47.4	-58.1	82.0
28	.884	.860	.832	.891	.916	-11.3	-27.0	13.5	-25.3	21.4
29	.907	.908	.892	.886	.918	7.83	-34.0	.924	-31.0	55.0
30	.828	.785	.727	.874	.881	-22.8	-26.6	-20.5	27.2	-31.1
31	.763	.814	.715	.775	.775	-10.2	-40.8	31.2	-58.1	21.2
32	.862	.876	.825	.854	.868	33.2	43.1	47.9	-63.1	36.1
33	.886	.900	.879	.890	.884	17.5	-36.5	-30.7	16.0	60.5
34	.723	.716	.602	.690	.800	-21.4	-19.8	-1.01	-15.9	-47.5
35	.854	.654	.761	.868	.867	-22.4	-19.0	-29.8	-5.73	-30.4
36	.644	.603	.610	.690	.671	5.57	6.55	.076	12.6	3.52
37	.977	.983	.000	.843	.978	-1.96	-54.2	.000	53.3	18.7
38	.980	.980	.000	.000	.980	-4.77	-24.9	.000	.000	24.5
39	.988	.000	.000	.000	.991	-77.3	.000	.000	.000	-5.37
40	.976	.976	.000	.919	.982	-44.3	-9.20	.000	16.0	-80.5
41	.994	.995	.000	.000	.000	-71.2	-1.07	.000	.000	.000
42	.974	.958	.000	.000	.987	-39.4	-.400	.000	.000	-88.4
43	.919	.915	.927	.933	.923	-39.1	-32.7	63.4	-83.0	-44.2
44	.907	.914	.841	.876	.914	-68.9	-72.0	-21.6	-68.1	-69.3
45	.803	.821	.670	.765	.843	-22.9	-40.4	-7.96	-15.3	-.654
46	.910	.916	.938	.897	.900	-8.64	-8.48	.000	12.6	-12.8
47	.932	.948	.870	.907	.925	-52.9	-68.1	-66.7	-39.8	-39.2
48	.944	.945	.913	.916	.951	-57.8	-52.3	-43.7	-78.6	-58.0
49	.725	.748	.674	.705	.735	-15.8	-10.6	-7.00	-17.5	-22.8
50	.728	.709	.693	.720	.779	-14.1	-6.68	-8.04	-20.0	-26.8
51	.670	.571	.699	.685	.742	-6.75	-1.52	-37.9	12.4	-9.22
52	.740	.752	.673	.720	.772	-7.90	12.8	-17.6	-14.2	-17.1
53	.656	.625	.652	.629	.698	1.20	3.12	-3.15	.575	4.15
54	.708	.715	.594	.645	.792	-13.7	-7.41	-9.00	-14.2	-15.5
55	.977	.982	.000	.000	.975	-2.05	91.0	.000	.000	-78.0
56	.984	.983	.000	.000	.986	-70.4	-43.7	.000	.000	-87.8
57	.983	.989	.000	.000	.980	-42.3	-38.3	.000	.000	-58.6
58	.995	.993	.000	.000	.000	28.7	75.5	.000	.000	.000
59	.983	.980	.000	.000	.985	54.5	21.4	.000	.000	80.2
60	.998	.000	.000	.000	.000	100	.000	.000	.000	.000
61	.907	.911	.848	.931	.918	64.3	73.3	61.7	58.2	56.1
62	.945	.934	.917	.903	.961	7.90	13.9	24.0	37.5	-3.78
63	.857	.869	.000	.867	.817	-59.4	-54.1	.000	-87.4	-47.2
64	.958	.967	.924	.000	.956	-60.7	-50.9	35.2	.000	-58.4
65	.910	.915	.844	.887	.916	7.00	3.62	58.5	27.0	-16.5
66	.945	.944	.000	.860	.955	-42.3	-32.1	.000	-56.5	-54.5
67	.817	.787	.873	.818	.842	-33.3	-24.0	-29.1	-55.6	-33.3
68	.726	.772	.699	.727	.690	9.21	23.1	8.74	4.97	1.37
69	.822	.844	.740	.849	.812	-24.7	-.849	.195	-26.3	-48.5
70	.785	.796	.810	.773	.782	-46.1	-31.0	-53.3	-50.0	-60.7
71	.585	.634	.760	.385	.521	-5.07	-21.8	-15.1	-.846	.580
72	.882	.902	.794	.834	.899	14.0	45.8	36.5	-6.26	-37.2
73	.995	.996	.000	.000	.996	-13.5	-39.4	.000	.000	53.4
74	.992	.995	.000	.000	.991	-44.8	-2.62	.000	.000	-53.2
75	.995	.000	.000	.000	.992	-55.1	.000	.000	.000	-79.1
76	.985	.990	.000	.000	.983	8.55	-49.0	.000	.000	.514
77	.997	.997	.000	.000	.996	-32.4	2.69	.000	.000	-48.6
78	.999	.000	.000	.000	.000	100	.000	.000	.000	.000
79	.916	.944	.802	.828	.914	-76.6	-86.8	38.0	-62.2	-79.6
80	.902	.921	.850	.875	.895	-66.9	-77.3	-57.9	-92.5	-43.3
81	.948	.951	.812	.910	.963	26.7	9.09	45.0	-45.8	43.9
82	.921	.934	.901	.905	.913	-62.5	-41.2	27.8	-89.0	-74.1
83	.951	.953	.000	.946	.952	-59.2	-26.7	.000	-53.4	-85.9
84	.928	.937	.752	.875	.941	-44.1	-37.3	9.25	-41.7	-58.2
85	.815	.833	.800	.757	.837	-13.4	-9.76	38.3	-26.5	-25.9
86	.761	.721	.855	.770	.753	-18.0	-13.2	-40.9	-20.9	-14.6
87	.770	.738	.727	.813	.806	30.6	39.0	28.3	64.8	7.74
88	.835	.875	.878	.772	.801	21.6	58.1	39.9	10.3	-5.42
89	.762	.732	.829	.745	.765	20.6	39.8	22.2	24.8	-5.80
90	.668	.651	.664	.647	.705	14.5	27.8	26.5	4.26	-7.10

FOR FIRST PARAMETER OVERALL FRIEDMAN 34.8
STI: FRIEDMAN 13.0RESP FRIEDMAN 2.77COR WR FRIEDMAN 17.3

FOR SECOND PARAMETER OVERALL FRIEDMAN 11.5
STI: FRIEDMAN 7.69RESP FRIEDMAN .308COR WR FRIEDMAN .308

EXPERIMENT NO 3
ESTIMATION 5ATKINSONS MODEL

STATE ON LAST TRIAL SESSION	SIGMA OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	.992	.000	.000	.000	.989	.500	.000	.000	.000	-1.72
2	.989	.000	.000	.000	.000	3.00	.000	.000	.000	.000
3	.995	.000	.000	.000	.000	1.00	.000	.000	.000	.000
4	.994	.000	.000	.000	.000	-.000	.000	.000	.000	.000
5	.986	.000	.000	.000	.984	1.50	.000	.000	.000	-2.60
6	.989	.000	.000	.000	.000	3.00	.000	.000	.000	.000
7	.650	.651	.556	.679	.660	1.30	1.00	18.0	.000	1.61
8	.683	.717	.565	.000	.674	3.60	2.30	15.4	.000	5.51
9	.530	.589	.390	.626	.516	1.66	1.04	8.14	.747	1.70
10	.598	.483	.477	.771	.715	3.11	2.35	4.13	.151	6.34
11	.690	.684	.610	.828	.692	1.43	1.26	1.39	.193	1.96
12	.412	.367	.327	.519	.462	1.87	2.98	1.29	1.04	1.94
13	.052	.077	.034	-.027	.096	1.76	1.14	2.79	.830	2.48
14	.543	.454	.500	.000	.614	3.94	2.67	23.7	.000	5.75
15	.727	.693	.000	.000	.777	5.87	8.68	.000	.000	3.52
16	.444	.406	.274	.462	.548	2.86	2.78	2.77	7.33	2.90
17	.566	.566	.457	.550	.614	2.02	1.53	2.99	.546	3.07
18	.592	.509	.659	.000	.629	2.00	1.68	2.00	.000	2.48
19	.935	.950	.000	.000	.928	1.18	.499	.000	.000	1.90
20	.959	.972	.000	.000	.949	1.50	-.363	.000	.000	-6.52
21	.984	.000	.000	.000	.978	1.00	.000	.000	.000	-5.24
22	.954	.973	.000	.000	.938	1.12	.992	.000	.000	1.07
23	.945	.964	.000	.000	.930	1.86	-6.04	.000	.000	.850
24	.896	.863	.000	.667	.920	1.37	28.5	.000	-.210	.336
25	.650	.598	.434	.614	.743	1.05	.586	5.22	.008	2.76
26	.439	.430	.297	.295	.570	.865	.829	1.04	.479	1.17
27	.658	.578	.748	.809	.690	1.62	.712	1.45	2.39	7.12
28	.623	.559	.495	.642	.712	.878	.670	2.13	.492	1.15
29	.686	.686	.645	.626	.712	1.15	.606	1.61	.603	2.47
30	.485	.392	.287	.594	.613	.681	.616	.580	1.53	.599
31	.356	.443	.253	.322	.375	.789	.441	2.20	.229	1.42
32	.562	.593	.462	.519	.576	1.86	2.09	3.37	.221	2.03
33	.629	.662	.607	.640	.607	1.28	.691	.542	.687	3.16
34	.281	.266	.113	.229	.403	.517	.518	.874	.548	.317
35	.546	.546	.340	.583	.577	.680	.676	.454	1.53	.572
36	.167	.113	.123	.231	.207	1.12	1.27	.911	1.40	1.02
37	.911	.933	.000	.500	.917	1.06	.259	.000	3.64	1.51
38	.924	.924	.000	.000	.924	.867	1.82	.000	.000	.404
39	.951	.000	.000	.000	.963	.188	.000	.000	.000	26.2
40	.910	.907	.000	.721	.931	.571	1.94	.000	.408	-.216
41	.976	.978	.000	.000	.000	.286	.777	.000	.000	.000
42	.899	.945	.000	.000	.948	.609	2.82	.000	.000	-.482
43	.718	.706	.737	.747	.730	.522	.688	1.22	.154	.401
44	.671	.689	.514	.574	.693	.247	.190	1.02	.183	.300
45	.430	.458	.203	.358	.522	.719	.471	.923	.876	.986
46	.694	.711	.778	.659	.667	.915	.744	1.10	1.77	.949
47	.756	.805	.560	.682	.736	.400	.268	.273	.250	.634
48	.795	.798	.700	.692	.819	.351	.343	.369	.418	.304
49	.287	.328	.209	.252	.299	.636	.791	.770	.609	.473
50	.292	.264	.239	.274	.379	.830	.975	1.04	.686	.602
51	.204	.076	.211	.224	.318	.793	.869	.299	1.51	.725
52	.315	.334	.200	.279	.370	.833	1.28	.539	.712	.737
53	.184	.142	.179	.148	.247	1.03	1.14	.917	1.03	1.04
54	.259	.274	.100	.163	.411	.744	.918	.643	.610	.762
55	.913	.928	.000	.000	.901	1.00	15.3	.000	.800	.151
56	.936	.932	.000	.000	.946	.263	.643	.000	.000	-.032
57	.932	.956	.000	.000	.921	.563	.780	.000	.000	.368
58	.981	.971	.000	.000	.000	1.33	2.02	.000	.000	.000
59	.935	.924	.000	.000	.941	1.88	2.66	.000	.000	2.26
60	.990	.000	.000	.000	.000	H	.000	.000	.000	.000
61	.673	.679	.502	.752	.710	3.73	3.23	4.82	-61.9	3.44
62	.802	.766	.713	.672	.855	1.03	1.94	41.8	1.15	.256
63	.530	.569	.000	.509	.443	.291	.341	.000	.122	.354
64	.841	.874	.733	.000	.835	.381	1.13	-460	.000	.097
65	.694	.710	.498	.630	.713	1.09	1.05	7.93	1.50	.653
66	.799	.798	.000	.541	.834	.500	.873	.000	.193	.342
67	.454	.397	.592	.435	.513	.534	.600	.495	.391	.535
68	.291	.368	.247	.294	.234	1.26	1.72	1.42	1.13	.980
69	.470	.524	.316	.533	.429	.633	.912	1.05	.624	.359
70	.371	.412	.418	.337	.333	.341	.530	.287	.306	.184
71	.091	.135	.348	-.130	.022	.810	.419	.783	1.05	1.26
72	.617	.667	.402	.502	.661	1.33	2.04	2.21	.651	.861
73	.981	.983	.000	.000	.984	.750	-18.0	.000	.000	-.216
74	.970	.979	.000	.000	.966	.571	2.24	.000	.000	.073
75	.981	.000	.000	.000	.969	.400	.000	.000	.000	-.305
76	.940	.960	.000	.000	.936	1.00	-6.48	.000	.000	.206
77	.986	.989	.000	.000	.984	.667	7.28	.000	.000	1.00
78	.997	.000	.000	.000	.000	H	.000	.000	.000	.000
79	.693	.784	.418	.449	.685	.154	.161	3.22	.193	.080
80	.656	.710	.514	.523	.647	.257	.305	.024	.011	.431
81	.810	.823	.433	.689	.860	1.41	1.32	2.26	2.00	1.18
82	.718	.763	.667	.642	.686	.316	.638	4.00	.062	.130
83	.820	.828	.000	.803	.816	.413	.288	.000	16.4	.315
84	.747	.776	.336	.594	.784	.492	.436	1.56	.524	.372
85	.460	.499	.413	.336	.505	.754	.658	2.10	.566	.711
86	.348	.281	.540	.364	.335	.609	.656	.343	.609	.645
87	.358	.284	.279	.402	.440	1.91	2.79	1.99	4.97	1.12
88	.502	.583	.602	.373	.431	1.45	3.05	1.73	1.64	.882
89	.350	.271	.488	.316	.360	1.55	2.80	1.63	2.04	.882
90	.196	.150	.173	.172	.257	1.61	2.99	2.69	1.19	.814

FOR FIRST PARAMETER OVERALL FRIEDMAN 33.9
STIM FRIEDMAN 11.1RESP FRIEDMAN .692COR WR FRIEDMAN 13.0

FOR SECOND PARAMETER OVERALL FRIEDMAN 12.2
STIM FRIEDMAN 4.92RESP FRIEDMAN 1.92COR WR FRIEDMAN .692

EXPERIMENT NO 4
ESTIMATION 1LUCES CHOICE MODEL

STATE ON LAST TRIAL SESSION	Z OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	.113	.134	.000	.000	.101	.542	.491	.000	.000	.679
2	.990	1.04	.974	.947	.965	1.02	1.07	.915	.968	1.13
3	.555	.522	.703	.464	.540	.860	1.40	.610	1.04	.595
4	1.32	1.11	1.65	1.61	1.14	1.08	1.95	.729	1.43	.648
5	.420	.394	.368	.290	.473	1.63	2.13	.989	2.95	1.01
6	.281	.239	.318	.468	.265	.961	.964	.900	.932	.958
7	.966	1.16	1.11	.990	.774	1.41	4.90	3.02	.603	.547
8	.325	.316	.375	.426	.274	1.84	1.83	1.02	2.85	1.68
9	1.32	1.27	1.90	1.38	.837	2.79	3.62	5.54	2.62	.837
10	.309	.244	.274	.173	.428	1.07	1.31	1.33	.480	.987
11	.943	.603	.900	1.03	1.12	2.01	2.46	1.71	2.83	.962
12	.617	.579	.784	.622	.487	2.25	1.23	2.94	2.87	[illegible].73
13	.831	1.01	1.08	.693	.737	2.93	3.36	4.17	2.96	1.66
14	.666	.568	.722	.742	.687	1.13	.892	.933	1.57	1.23
15	.595	.472	.614	.544	.633	.683	.271	.559	.459	1.63

FOR FIRST PARAMETER OVERALL FRIEDMAN 6.17
STIM FRIEDMAN .000RESP FRIEDMAN 2.57COR WR FRIEDMAN 4.57

FOR SECOND PARAMETER OVERALL FRIEDMAN 2.49
STIM FRIEDMAN .000RESP FRIEDMAN 1.14COR WR FRIEDMAN .286
FP OFLO
.FP OFLO

EXPERIMENT NO 4
ESTIMATION 2TANNER SWETS GREEN MODEL

STATE ON LAST TRIAL SESSION	DPRIME OVERALL	S1R1	S1R2	S2R1	S2R2	B OVERALL	S1R1	S1R2	S2R1	S2R2
1	2.52	2.35	.000	.000	2.65	1.01	.892	.000	.000	1.17
2	.013	-.055	.033	.068	.044	.007	-.028	.016	.034	.023
3	.734	.808	.441	.952	.765	.340	.468	.168	.486	.289
4	-.346	-.127	-.622	-.591	-.166	-.180	-.084	-.264	-.347	-.065
5	1.07	1.15	1.23	1.49	.930	.655	.763	.614	1.07	.467
6	1.55	1.74	1.41	.891	1.62	.761	.855	.671	.431	.793
7	.043	-.186	-.132	.012	.321	.025	-.154	-.099	.005	.114
8	1.37	1.41	1.21	1.05	1.57	.866	.884	.610	.761	.953
9	-.344	-.298	-.788	-.399	.223	-.252	-.233	-.661	-.288	.102
10	1.44	1.71	1.58	2.07	1.05	.739	.948	.882	.761	.523
11	.074	.274	.133	-.042	-.138	.049	.195	.084	-.031	-.068
12	.602	.682	.304	.591	.881	.414	.375	.226	.435	.758
13	.231	-.011	-.097	.458	.382	.172	-.009	-.078	.342	.238
14	.508	.705	.407	.373	.469	.269	.333	.196	.227	.259
15	.647	.925	.609	.755	.570	.265	.208	.220	.243	.352

FOR FIRST PARAMETER OVERALL FRIEDMAN 6.17
STIM FRIEDMAN .286RESP FRIEDMAN 1.14COR WR FRIEDMAN 4.57

FOR SECOND PARAMETER OVERALL FRIEDMAN 7.29
STIM FRIEDMAN 1.14RESP FRIEDMAN .286COR WR FRIEDMAN 2.57

EXPERIMENT NO 4
ESTIMATION 4.NONPARAMETRIC ANALYSIS

	APRIME					BIAS				
STATE ON LAST TRIAL SESSION	OVERALL	S1R1	S1R2	S2R1	S2R2	OVERALL	S1R1	S1R2	S2R1	S2R2
1	.937	.923	.000	.000	.947	61.8	65.7	.000	.000	46.7
2	.505	.479	.513	.527	.517	-.023	-.278	.235	.177	-.430
3	.722	.737	.647	.768	.727	8.28	-18.8	15.6	-3.13	26.1
4	.379	.452	.305	.312	.438	-2.07	-6.30	14.2	-15.2	5.47
5	.786	.793	.816	.832	.764	-32.5	-47.0	.976	-67.2	-.761
6	.859	.881	.841	.756	.867	4.40	4.45	10.4	4.76	4.85
7	.517	.433	.450	.505	.612	-1.16	-17.8	-10.1	.489	13.9
8	.830	.835	.813	.771	.857	-45.6	-46.1	-1.51	-54.4	-44.1
9	.383	.398	.289	.367	.582	-22.7	-23.6	-58.2	-24.7	3.11
10	.845	.876	.861	.902	.786	-6.61	-28.1	-27.6	63.6	1.00
11	.529	.597	.550	.484	.448	-3.87	-16.8	-5.41	-3.17	.430
12	.686	.710	.605	.681	.722	-30.7	-10.5	-21.2	-36.4	-64.8
13	.583	.496	.463	.648	.630	-16.6	-.971	-9.01	-30.4	-13.9
14	.667	.716	.639	.628	.656	-4.78	6.09	2.21	-12.3	-7.46
15	.701	.743	.690	.721	.682	17.4	56.7	23.7	35.5	-19.4

FOR FIRST PARAMETER OVERALL FRIEDMAN 6.17
STIM FRIEDMAN .286RESP FRIEDMAN 1.14COR WR FRIEDMAN 4.57

FOR SECOND PARAMETER OVERALL FRIEDMAN 3.86
STIM FRIEDMAN 1.14RESP FRIEDMAN 1.14COR WR FRIEDMAN .286
FP OFLO

EXPERIMENT NO 4
ESTIMATION 5 ATKINSONS MODEL

STATE ON LAST TRIAL SESSION	SIGMA OVERALL	SIGMA S1R1	SIGMA S1R2	SIGMA S2R1	SIGMA S2R2	B OVERALL	B S1R1	B S1R2	B S2R1	B S2R2
1	.769	.724	.000	.000	.806	3.40	6.87	.000	.000	1.22
2	.005	-.022	.013	.027	.018	1.01	.965	1.12	1.06	.908
3	.285	.306	.165	.366	.261	1.32	.687	2.03	.919	2.14
4	-.137	-.045	-.239	-.225	-.063	.892	.506	1.17	.759	1.41
5	.389	.388	.462	.449	.358	.538	.374	.768	.278	1.01
6	.561	.614	.517	.344	.581	1.03	.940	.835	1.28	1.07
7	.017	-.042	-.040	.005	.117	.724	.232	.360	1.71	2.09
8	.475	.486	.455	.322	.544	.396	.471	1.05	.195	.363
9	-.107	-.081	-.168	-.127	.088	.420	.326	.267	.455	1.22
10	.528	.600	.563	.658	.401	.977	.713	.864	2.55	1.09
11	.026	.090	.049	-.013	-.055	.524	.404	.611	.386	1.12
12	.203	.264	.092	.181	.166	.386	.819	.323	.271	.097
13	.070	-.003	-.024	.138	.142	.286	.274	.229	.250	.518
14	.200	.275	.161	.141	.183	.805	1.08	1.06	.546	.715
15	.246	.251	.221	.258	.212	1.69	6.51	2.22	2.59	.564

FOR FIRST PARAMETER OVERALL FRIEDMAN 5.23
STIM FRIEDMAN 1.14RESP FRIEDMAN 1.14COR WR FRIEDMAN 1.14

FOR SECOND PARAMETER OVERALL FRIEDMAN 2.31
STIM FRIEDMAN 1.14RESP FRIEDMAN 2.57COR WR FRIEDMAN .286
FP OFLO