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Influence of Correlated Visual Cues on Auditory Signal Detection[1]

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Abstract

Two experiments investigated the effects on auditory signal detection of introducing visual cues that were partially correlated with the signal events. The results were analyzed in terms of a detection model that assumes that such cue-signal correlations will not affect sensitivity, but will instead cause the subject to develop separate response biases for each cue. The model specifies a functional relationship between the asymptotic values of these cue-contingent biases. The overall results of the experiments supported the detection assumptions of the model and the general bias learning assumption, but indicated a more complex learning process than that specified by the model.

Several current models for signal detection represent performance as jointly determined by psychophysical variables (e.g., signal parameters) and such "background" variables as relative frequency of various signal events on previous trials (Atkinson, Carterette, & Kinchla, 1962; Luce, 1963; Swets, Tanner & Birdsall, 1961). Typically these background variables determine the response bias parameters of a hypothetical decision process relating signal-produced sensory states to overt responses. To the extent that the subject's choice is controlled by these biases, rather than by discriminative information provided by the signal presentation, there is a formal similarity between detection experiments and probability learning experiments (Atkinson, Bower, & Crothers, 1965, Ch. 5). The present study deals with a detection situation analogous to probabilistic discrimination learning. In a probabilistic discrimination learning experiment each trial is initiated by one of a set of cues, each of which corresponds to a particular probability distribution over the set of possible trial outcomes. The comparable detection situation is called a cued detection task. Here each detection trial is initiated by one of a set of cues, and each cue corresponds to a distinct probability distribution over the possible signal events. (That is, whenever a trial is initiated by cue C_i the probability of signal event S_j is given by γ_{ij}.) If these distributions are different the cues may be said to be correlated with the signal events. The results of probabilistic discrimination learning experiments (Popper & Atkinson, 1958; Atkinson, Bogartz, & Turner, 1959) suggest that correlated cues should come to control behavior in a cued detection task; i.e., a subject will come to hold several response biases simultaneously, with the effective bias on a given trial being determined by the cue on that trial.

The possibility of multiple-response biases was investigated in the context of an auditory two-interval forced-choice detection task involving three visual cues. The results were analyzed in terms of an extension of a detection model developed by Atkinson & Kinchla (1965) and Luce (1963). For present purposes this model can be outlined as follows. Each trial of the experiment is initiated by one of three cues: C_1, C_2, or C_3. The experimenter then presents the signal in interval 1 or interval 2. It is assumed that with probability σ the occurrence of a signal in interval i gives rise to an "unambiguous" sensory state s_i, whereas with probability $1 - \sigma$ an ambiguous sensory state occurs. The ambiguous sensory state is denoted by b_h when the cue is C_h. If the stimulus presentation elicits s_i the subject makes response A_i indicating that he thought the signal was in interval i. If the ambiguous sensory state b_h occurs the subject makes response A_1 with probability $p_{h,n}$, where n is the trial index. The $p_{h,n}$ can be thought of as momentary response bias parameters associated with the sensory states b_h, whereas σ is a measure of the subject's sensitivity to the signal.

The following notation is used to refer to the various events that occur on trial n:

$C_{h,n}$: the occurrence of cue C_h ($h = 1, 2, 3$);

$S_{i,h}$: presentation of the signal in interval i ($i = 1, 2$);

$A_{j,n}$: the occurrence of response A_j ($j = 1, 2$);

$E_{k,n}$: presentation of information feedback indicating that the correct response was A_k ($k = 1, 2$).

In our experiments correct information feedback was given to the subject

on every trial, i. e., E_1 always occurred on an S_1 trial, and E_2 on an S_2 trial. The relationship between the cues and the signal events is summarized by the conditional probabilities:

$$\gamma_h = \Pr(S_{1,n} | C_{h,n}) \ , \qquad (h = 1, 2, 3).$$

If $\gamma_1 = \gamma_2 = \gamma_3$ the cues are uncorrelated with the signal events, otherwise the schedule is said to be cue dependent or correlated. The probability of cue C_h on any trial is denoted by λ_h $(h = 1, 2, 3)$.

From the assumptions of the model it follows that

$$\Pr(A_{1,n} | S_{1,n} C_{h,n}) = \sigma + (1 - \sigma) E(p_{h,n})$$

$$\Pr(A_{1,n} | S_{2,n} C_{h,n}) = (1 - \sigma) E(p_{h,n}) \ ,$$

where $E(p_{h,n})$ denotes the expectation of $p_{h,n}$. These equations in turn imply

$$\Pr(A_{1,n} | S_{1,n} C_{h,n}) = \Pr(A_{1,n} | S_{2,n} C_{h,n}) + \sigma \qquad [1]$$

$$E(p_{h,n}) = \frac{\Pr(A_{1,n} | S_{2,n} C_{h,n})}{1 - \sigma} \ . \qquad [2]$$

For the two-interval forced-choice situation the receiver-operating-characteristic (ROC) curve is a plot of the observed proportion of "hits" $\hat{\Pr}(A_1 | S_1)$ against the observed proportion of "false alarms" $\hat{\Pr}(A_1 | S_2)$. The present model implies that for each value of the bias parameter the point $[\Pr(A_1 | S_2), \Pr(A_1 | S_1)]$ will fall on a line that has slope one and $\Pr(A_1 | S_1)$ intercept σ. If a block of C_h trials is used to determine a point on the ROC curve the model implies that

$$E[\hat{\Pr}(A_1 | S_1 C_h)] = \sigma + E[\hat{\Pr}(A_1 | S_2 C_h)]$$

where $\hat{\Pr}(A_1 | S_i C_h)$ is the observed proportion of A_1 responses over those

C_h trials on which the signal event was S_i. Thus if the ROC curve is formed by plotting the points $[\hat{Pr}(A_1|S_2C_h), \hat{Pr}(A_1|S_1C_h)]$ for each C_h, the model predicts that the "expected" ROC curve will be a straight line with slope one and intercept σ. Moreover it can be shown that under very general assumptions on the $p_{h,n}$ process the difference $\hat{Pr}(A_1|S_1C_h) - \hat{Pr}(A_1|S_2C_h)$ converges in probability to σ as the block size increases. Consequently to estimate σ we use the consistent estimator

$$\hat{\sigma} = \hat{Pr}(A_1|S_1C_h) - \hat{Pr}(A_1|S_2C_h) . \qquad [3]$$

Note that this estimator can be used to obtain separate estimates of σ for each cue. To estimate the response bias on C_h trials, we use the estimator suggested by Eq. 2:

$$\hat{p}_h = \frac{\hat{Pr}(A_1|S_2C_h)}{1 - \hat{\sigma}} . \qquad [4]$$

For purposes of analysis a linear learning model for the response biases will be considered; namely

$$p_{h,n+1} = \begin{cases} (1-\theta)p_{h,n} + \theta , & \text{if } C_{h,n}, b_{h,n}, S_{1,n} \\ (1-\theta')p_{h,n} , & \text{if } C_{h,n}, b_{h,n}, S_{2,n} \\ p_{h,n} , & \text{otherwise} \end{cases} \qquad [5]$$

where $b_{h,n}$ denotes the occurrence of the ambiguous sensory event b_h on trial n. This model predicts that

$$p_h = \lim_{n\to\infty} E(p_{h,n}) = \frac{\gamma_h}{\gamma_h + (1-\gamma_h)\varphi} \qquad [6]$$

where $\varphi = \theta'/\theta$. If $\varphi = 1$, the limiting response bias on C_h trials matches the conditional probability of an S_1 signal event given cue C_h.

Experiment I investigated the effects of introducing a cue-signal correlation after subjects had had considerable practice on an uncorrelated schedule.

Experiment I

Method

The task employed was the two-interval, forced-choice detection of a 100 msec. 1000 cps signal in a background of band-limited Gaussian noise. The noise was produced by a Grayson-Stadler Model 455-B noise generator, and was presented binaurally to the subject over Permaflux PDR-10 earphones. Each subject sat facing a display on which there were two arrays of lights: a vertical array of three cue lights, and a horizontal array of three interval lights. One of the cue lights came on at the beginning of each trial. One second later the three-interval lights blinked on, one after the other, starting from the left. Each interval light was on for 100 msec. and there was a 500 msec. off period between the offset of one light and the onset of the next light. The first interval light was an alert signal, while the next two indicated the test intervals.[2] On every trial the signal tone was added to the background noise during one of the test intervals. The subject's task was to decide which interval contained the signal. He was given 1.7 sec. following the second test interval to indicate his choice by pressing a pushbutton located directly under the appropriate interval light. At the conclusion of the response period information feedback was provided by a 1-sec. illumination of the pushbutton corresponding to the correct response. The total time for each trial was 4 sec.; the inter-trial delay was 2 sec.

The correspondence between these experimental events and the notation introduced earlier is as follows: the occurrence of a cue light corresponds to C_1, C_2, or C_3 respectively, beginning with the uppermost cue light. The occurrence of the signal in the first or second test interval corresponds to S_1 and S_2 respectively. Similarly, A_1 denotes a response indicating that the subject believed the signal occurred in the first test interval and A_2 denotes a response indicating that the signal occurred in the second test interval. The illumination of the A_2 response button corresponds to the information feedback event E_1, and illumination of the A_2 button corresponds to E_2.

The programming of events during each experimental session, as well as the recording of the data, was fully automated. Program information was automatically read from computer-produced punched paper cards. The trial number, cue light, the interval in which the signal appeared, the subject's response, and his response latency were automatically recorded on similar cards for eventual computer analysis.

A particular noise level was selected for each subject during three days of preliminary testing. During these sessions the three cue lights occurred equally often and were uncorrelated with the signal events. The subjects ran through 360 trials each day with a fixed signal amplitude. The noise amplitude was varied until the experimenter was satisfied that a level had been reached at which the subject would obtain approximately 75 per cent correct responses. The noise was then kept at this level for that particular subject throughout the remainder of the experiment. The signal-to-noise ratios (E/N_0) selected in this manner were approximately 9.1.

The experimental subjects were Stanford University students who had been screened for normal hearing. They were paid at the rate of $2.50 an hour. In addition they were told that a certain minimum level of performance would be required in order for them to continue in the experiment. Each daily run of 360 trials took approximately 45 minutes including a 10-minute rest period half way through the run.

In the main experiment, which began after the three-day calibration period, only two of the cue lights were used; these two appeared equally often, so that $\lambda_1 = \lambda_2 = 1/2$, $\lambda_3 = 0$. Twelve subjects were each run through 360 trials a day for 24 days. During the first 9 days there was no cue-signal correlation, i.e., $\gamma_1 = \gamma_2 = 1/2$. At the start of day 10, unannounced to the subjects, a partial cue-signal correlation ($\gamma_1 = 3/4$, $\gamma_2 = 1/4$) was introduced and maintained for the next ten days. Finally at the start of day 21 the subjects were returned unannounced to the original uncorrelated schedule. All randomizations in this experiment (and in Experiment II) were effected by randomly permuting a fixed number of events for each daily session; e.g., for each day in the first phase of Experiment I exactly 180 trials were C_1 and 90 of these were S_1. Thus the signal events S_1 and S_2 occurred equally often within each of the 24 daily sessions. However, during days 10 through 20 the S_1 signal occurred 75 per cent of the time when C_1 was presented and only 25 per cent of the time when C_2 was presented.

Results

The overall results of Experiment I are summarized in Table 1, which shows daily estimates of the relevant probabilities. These estimates are averages of the corresponding statistics for individual subjects. The

Table 1

Daily estimates of response probabilities from Experiment I

Day	$\hat{Pr}(A_1 \mid S_1C_1)$	$\hat{Pr}(A_1 \mid S_2C_1)$	$\hat{Pr}(A_1 \mid S_1C_2)$	$\hat{Pr}(A_1 \mid S_2C_2)$	$\hat{Pr}(A_1 \mid C_1)$	$\hat{Pr}(A_1 \mid C_2)$	$\hat{Pr}$(Correct)	$\hat{Pr}(A_1)$
1	0.837	0.287	0.849	0.321	0.560	0.587	0.770	0.574
2	0.746	0.331	0.758	0.579	0.541	0.567	0.698	0.555
3	0.764	0.412	0.765	0.411	0.587	0.587	0.676	0.587
4	0.679	0.328	0.720	0.379	0.503	0.550	0.673	0.527
5	0.713	0.293	0.735	0.315	0.503	0.525	0.710	0.514
6	0.676	0.285	0.683	0.282	0.479	0.483	0.698	0.481
7	0.737	0.328	0.758	0.325	0.532	0.542	0.710	0.537
8	0.743	0.316	0.692	0.321	0.528	0.507	0.699	0.518
9	0.781	0.231	0.782	0.315	0.506	0.548	0.754	0.527
10	0.720	0.252	0.721	0.249	0.604	0.367	0.736	0.485
11	0.756	0.278	0.733	0.279	0.636	0.393	0.736	0.515
12	0.793	0.335	0.736	0.247	0.676	0.368	0.756	0.523
13	0.805	0.290	0.704	0.255	0.676	0.366	0.758	0.523
14	0.753	0.274	0.673	0.234	0.631	0.345	0.743	0.486
15	0.795	0.249	0.647	0.236	0.661	0.336	0.760	0.499
16	0.806	0.244	0.736	0.199	0.666	0.332	0.789	0.499
17	0.815	0.300	0.756	0.195	0.687	0.336	0.789	0.511
18	0.825	0.263	0.732	0.168	0.680	0.310	0.804	0.495
19	0.791	0.348	0.690	0.211	0.666	0.346	0.758	0.507
20	0.769	0.282	0.725	0.221	0.540	0.460	0.753	0.500
21	0.780	0.248	0.716	0.220	0.514	0.470	0.757	0.492
22	0.735	0.258	0.742	0.217	0.494	0.480	0.751	0.487
23	0.742	0.238	0.764	0.244	0.491	0.503	0.756	0.497
24	0.771	0.218	0.757	0.290	0.498	0.476	0.780	0.487

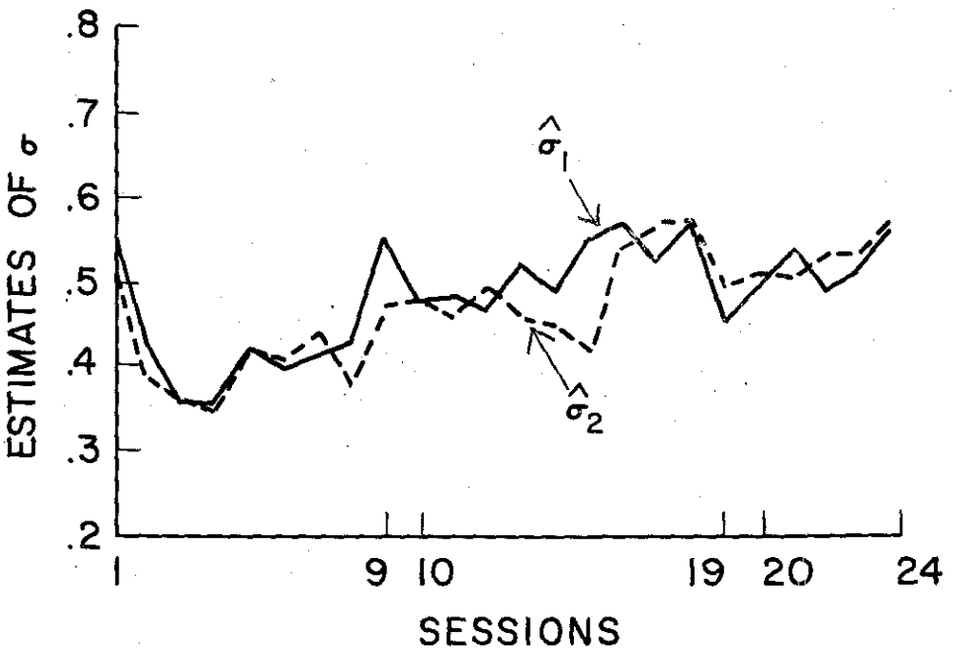

Figure 1. Daily sensitivity estimates, $\hat{\sigma}_1$ and $\hat{\sigma}_2$, based on the data in Table 1.

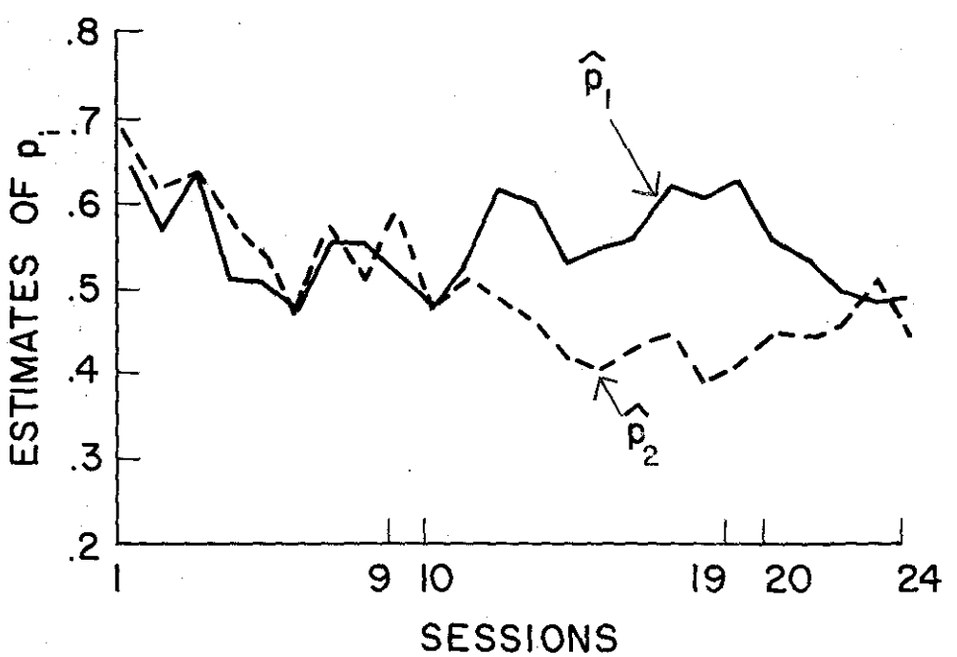

Figure 2. Daily response bias estimates, $\hat{p}_1$ and $\hat{p}_2$, based on the data in Table 1.

most pertinent feature of these data is the separation of the conditional probabilities of a correct response $Pr(A_i|S_iC_h)$ effected by the introduction of a cue-signal correlation on day 10. Beginning with day 11 the estimates of $Pr(A_1|S_1C_1)$ are consistently larger than those of $Pr(A_1|S_1C_2)$ for each day of the cue dependent phase, while $\hat{Pr}(A_2|S_2C_1)$ is consistently smaller than $\hat{Pr}(S_2|S_2C_2)$. These bias effects appear to persist for at least two days after the return to an uncorrelated schedule. Taken as a whole these results indicate a significant conditional response bias effect controlled by the trial initiating cues. This interpretation is supported by an analysis of individual subject's performance over the last three days of the initial uncorrelated schedule, the correlated schedule, and the terminal uncorrelated schedule. The only statistically significant cue effects occurred in the correlated phase; here performances to either signal as a function of the cue event were significantly different ($p < .05$ using a Mann Whitney U Test).

Figure 1 presents daily estimates of the sensitivity parameter computed separately for C_1 and C_2 trials using the data in Table 1 and Eq. 3; these estimates are denoted $\hat{\sigma}_1$ and $\hat{\sigma}_2$ respectively. There does not appear to be any consistent difference in sensitivity on C_1 and C_2 trials. Figure 1 does suggest an initial decrease in sensitivity over days 1 through 4, followed by a gradual, roughly monotonic, increase beginning on day 5. These changes do not appear to be related to the cue-signal correlation.

Figure 2 shows daily estimates of the average values of the response bias parameters p_1 and p_2. These estimates were computed from the data

in Table 1 using Eq. 4. Inspection of the figure indicates that a noncontingent bias in favor of response A_1 existed at the beginning of the experiment. This asymmetry was eliminated by the initial uncorrelated schedule, and with the introduction of a cue-signal correlation on day 10 the cue-contingent biases separate as predicted by the model. By day 19 $\hat{p}_1 = .62$, while $\hat{p}_2 = .40$. Since the estimates of p_1 and p_2 in this phase are roughly symmetrical around .5, φ (in Eq. 6) should be around 1.0. In this case the asymptotes predicted for p_1 and p_2 are .75 and .25, respectively. It is not clear from the graph whether the biases would have continued to increase toward these asymptotes if the correlated schedule had been continued beyond day 19. This question led to the design of Experiment II. In this second experiment subjects were given ample time to achieve an asymptotic response bias on each cue. (Latency data from Experiment I are reported in conjunction with the results of Experiment II.)

Experiment II

Method

The apparatus and the method of presenting the stimuli and recording responses were identical to those of Experiment I. However in Experiment II all three cues were employed with $\lambda_1 = \lambda_2 = \lambda_3 = 1/3$, and the same cue signal correlations obtained throughout the experiment: $\gamma_1 = 3/4$, $\gamma_2 = 1/2$, $\gamma_3 = 1/4$. Thus cues C_1 and C_3 were correlated with the signal events, whereas cue C_2 was uncorrelated. As in Experiment I three preliminary sessions were spent in establishing a noise level for each subject such that he averaged close to 75 per cent correct responding. (During these preliminary sessions C_2 was the only cue employed.) Following the preliminary sessions ten subjects were each run for 360 trials a day for 20 consecutive days.

Results

The analysis of Experiment II focused on individual subject data. Table 2 presents estimates of the relevant conditional probabilities for each of the ten subjects. Each estimate is the corresponding mean proportion for a single subject over the last ten days of the experiment. Thus, for example, each estimate of $Pr(A_1)$ is based on 3600 trials. For each subject these data indicate the predicted response bias effects as a function of the cues: in every case $\hat{Pr}(A_1|S_1C_1) > \hat{Pr}(A_1|S_1C_2) > \hat{Pr}(A_1|S_1C_3)$ and $\hat{Pr}(A_1|S_2C_1) < \hat{Pr}(A_1|S_2C_2) < \hat{Pr}(A_1|S_2C_3)$. Table 2 also indicates that there was no apparent overall tendency to favor one response or the other independent of the cue and signal condition: the group mean of $Pr(A_1)$ is .499 and individual subject values are all quite close to .5.

Figure 3 shows ROC plots for each of the subjects together with the best fitting (by least squares) linear ROC curve having slope one. Inspection of the figure indicates that by and large the predicted ROC curves provide quite a good fit. These results support the assumption that sensitivity is independent of presentation schedules and cue conditions; deviations from such independence would produce either nonlinearity or linearity with a slope not equal to one.

Figure 3 reveals considerable individual differences in the spacing of points along the ROC curve. According to the model these differences must reflect differences in the conditional response biases of individual subjects. Table 3 shows group and individual subject estimates of the response biases p_1, p_2, and p_3. The estimates were computed using Eq. 3 and the data in Table 2. As would be expected from Fig. 3 the predicted ordering $\hat{p}_1 > \hat{p}_2 > \hat{p}_3$ is found in every case, and the group averages of $\hat{p}_1$, $\hat{p}_2$,

Table 2

Estimates of individual and average response probabilities

based on the last ten days of Experiment II

Subject	$\hat{Pr}(A_1 \mid S_1C_1)$	$\hat{Pr}(A_1 \mid S_1C_2)$	$\hat{Pr}(A_1 \mid S_1C_3)$	$\hat{Pr}(A_1 \mid S_2C_1)$	$\hat{Pr}(A_1 \mid S_2C_2)$	$\hat{Pr}(A_1 \mid S_2C_3)$	$\hat{Pr}$(Correct)	$\hat{Pr}(A_1)$
1	0.768	0.708	0.677	0.327	0.263	0.237	0.736	0.497
2	0.808	0.717	0.490	0.423	0.362	0.225	0.710	0.514
3	0.891	0.624	0.450	0.520	0.163	0.092	0.771	0.458
4	0.740	0.537	0.407	0.587	0.411	0.262	0.626	0.491
5	0.890	0.615	0.371	0.712	0.346	0.130	0.707	0.506
6	0.855	0.479	0.333	0.613	0.253	0.134	0.695	0.448
7	0.881	0.587	0.307	0.730	0.432	0.141	0.676	0.512
8	0.815	0.667	0.472	0.581	0.355	0.231	0.689	0.519
9	0.860	0.429	0.389	0.773	0.311	0.253	0.639	0.498
10	0.865	0.575	0.493	0.663	0.349	0.309	0.663	0.544
Average	0.837	0.594	0.439	0.593	0.324	0.202	0.691	0.499

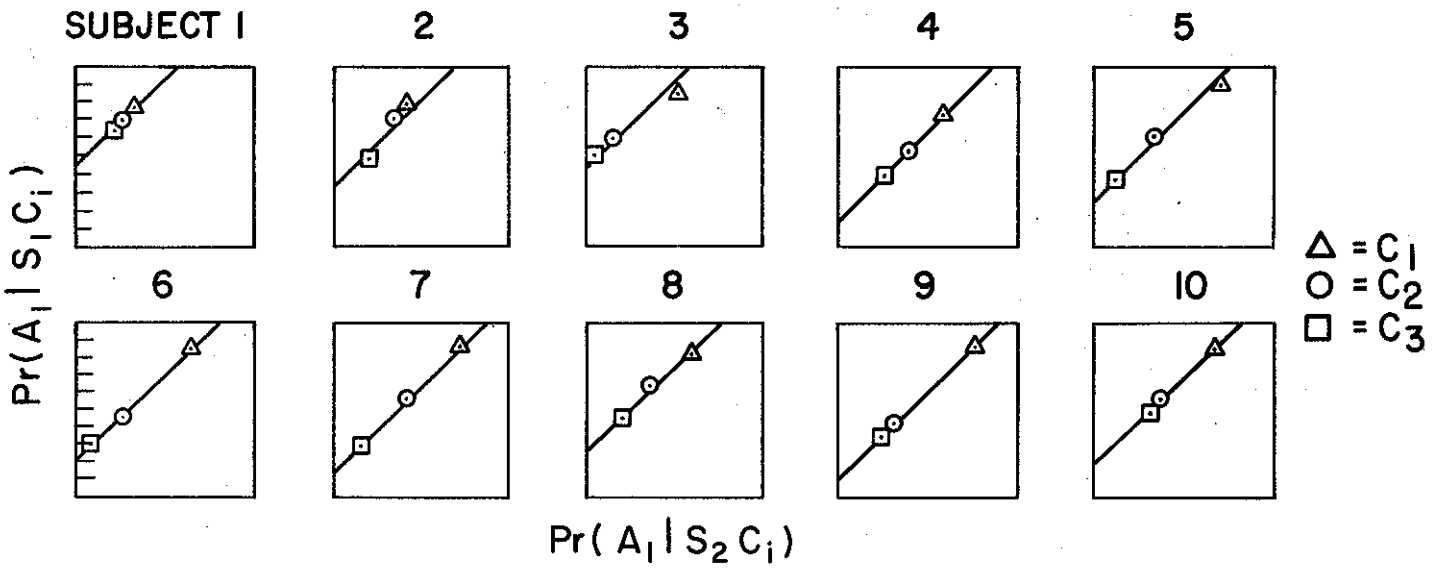

Figure 3. Receiver operating characteristics for individual subjects in Experiment II.

and $\hat{p}_3$ are quite close to the predicted probability-matching values of .75, .50, and .25. However the estimates for individual subjects reveal considerable variability; the p_1 estimates, for example, range from .866 to .584. Although the predicted asymptotes in Eq. 6 depend on the parameter φ, and thus allow for individual deviations from probability matching, it is not possible for the model of Eq. 5 to predict the patterns of deviation revealed by Table 3. The p_h estimates for subject 7, for example, indicate biases which deviate from matching in the direction of optimal performance (i.e., in the direction of $p = 1$ given $\gamma > 1/2$, and $p = 0$ given $\gamma < 1/2$) for both $\gamma = .75$ and $\gamma = .25$, whereas Eq. 6 requires that if p_1 is greater than γ_1, p_3 must also be greater than γ_3 (cf. subject 10). Altogether four subjects (2, 5, 6, and 7) show uniform deviations in the optimal direction, and three (1, 2, and 4) show uniform deviations in direction of non-discriminative performance (i.e., in the direction of $p = .5$ for all cues). It is noteworthy, however, that in spite of the very large number of trials involved here no subject adopted a maximizing strategy.

Table 3 also shows group and individual subject estimates of σ computed separately for each cue condition. These estimates were computed from the data in Table 2 using Eq. 4. Although the average sensitivity estimates in Table 3 show $\hat{\sigma}_2$ to be slightly greater than $\hat{\sigma}_1$ and $\hat{\sigma}_3$, there was no consistent ordinal relationship between sensitivity and cue condition for the individual subjects. A nonparametric test for such a relationship (Kruskal and Wallis, 1952) was not significant.

Table 3

Three cue study: Estimates of σ and p_h

Subject	$\hat{\sigma}_h = \hat{Pr}(A_1 \mid S_1C_h) - \hat{Pr}(A_1 \mid S_2C_h)$			$\hat{p}_h = \hat{Pr}(A_1 \mid S_2C_h)/1 - \hat{\sigma}_h$		
	C_1	C_2	C_3	C_1	C_2	C_3
1	0.441	0.445	0.440	0.584	0.474	0.423
2	0.384	0.355	0.265	0.687	0.561	0.306
3	0.371	0.462	0.358	0.827	0.302	0.144
4	0.153	0.127	0.144	0.693	0.470	0.306
5	0.177	0.270	0.241	0.866	0.473	0.171
6	0.242	0.226	0.200	0.809	0.327	0.167
7	0.151	0.155	0.166	0.860	0.511	0.169
8	0.233	0.312	0.241	0.758	0.516	0.304
9	0.087	0.118	0.135	0.847	0.353	0.293
10	0.204	0.226	0.184	0.834	0.451	0.379
Average	0.244	0.270	0.237	0.776	0.444	0.266

Latency Results

The large number of trials employed in Experiments I and II provided a unique opportunity to obtain good estimates of the latency distributions of individual subjects. In addition it was expected that the effects of the cue-signal correlations might be reflected in conditional response time distributions. This expectation was not confirmed. Analysis of the latency data from both experiments in terms of cue conditions failed to reveal any significant effects. The data did reveal a consistent 50 msec. difference in mean response times on correct and incorrect trials. Figure 4 shows this result for Experiment I. Analysis of individual subject latencies in Experiment II revealed a similar difference for each subject. These results are consistent with the detection model considered here if we assume that response times following an unambiguous sensory state (s_1 or s_2) are realizations of a random variable T_u, while response times following any ambiguous sensory state (b_1, b_2, or b_3) are realizations of another random variable T_a. It is easily shown that these assumptions imply a constant difference between mean response times on correct and incorrect trials independent of cue condition (i.e., independent of response bias).

Examination of the individual subject latency distributions revealed rather consistent individual differences in the forms of these distributions. Figure 5 presents the individual subject distributions computed over successive four-day blocks. The right-hand column represents a pooling of responses over all subjects for each four-day block. Each of the histograms in the other columns represents 1440 responses by a single subject--all of his responses over the four sessions. The idiosyncratic nature of these distributions is quite striking; each subject's distribution

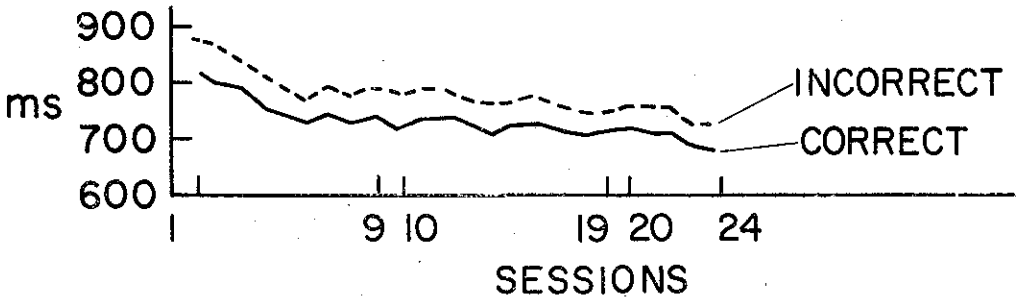

Figure 4. Average response latencies for correct and incorrect responses during Experiment I.

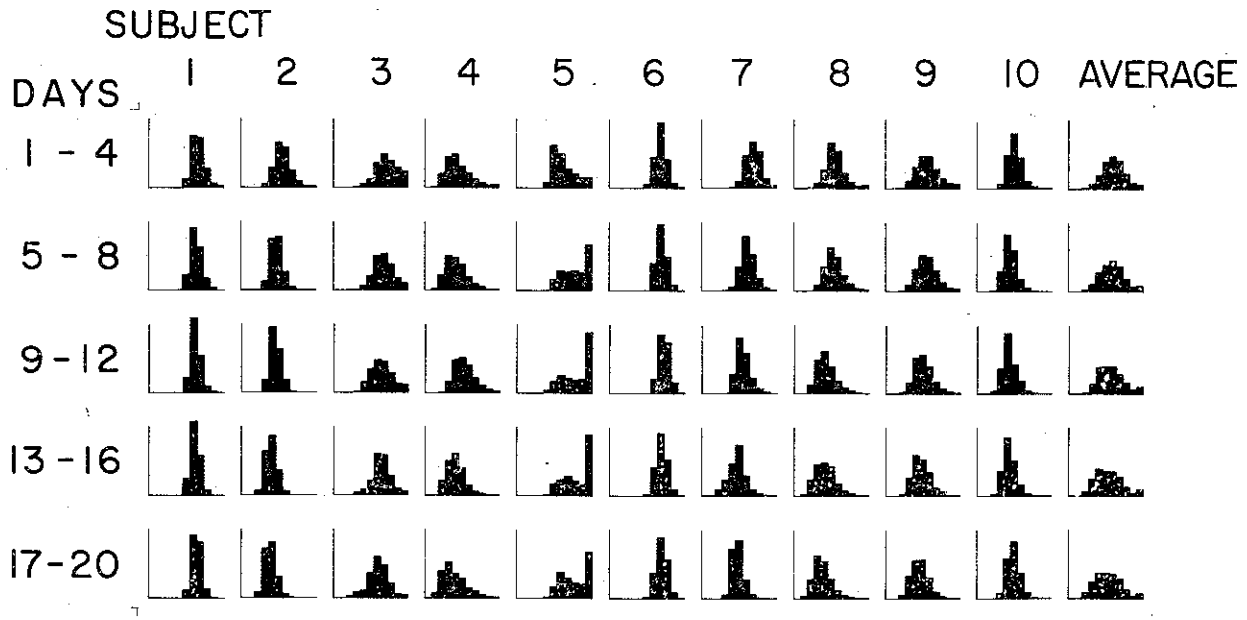

Figure 5. Response latency histograms for individual subjects over successive blocks of four days during Experiment II. The horizontal axis is broken into 11 intervals. The 11th (right-hand) interval represents all times greater than 1 sec.; the others represent latencies less than 1 sec. in .1 sec. increments.

maintains a consistent and unique form over at least the last four blocks of trials. Not surprisingly, in view of the considerable individual differences in the distributions, the group latency curve provides a very deceptive representation of the "typical" subject: compare the distributions for subject 6, for example, to the average distribution.

Discussion

The results of Experiments I and II indicate that subjects in a signal detection task are able to discriminate several concurrent probability distributions over the signal events and to employ different response biases on a trial-by-trial basis as a function of the cues corresponding to these distributions. One implication of this finding is that a cued detection task can be used to simultaneously generate a number of points in the ROC space. An ROC curve generated in this fashion has the advantage of not being affected by session-to-session changes in sensitivity (cf. Fig. 1), since each sensitivity level is equally represented at each point of the curve.

The detection model considered here appears to give an adequate account of those aspects of the data that do not depend on the details of the response bias learning process. In addition, when a large number of trials were run on the correlated schedule the simple linear learning model accurately predicted average subject statistics, such as the mean response bias for each cue, and correctly ordered individual subject performances on each cue. However the model did not provide an adequate account of the details of individual performances. This is not surprising in view of the complex and quite idiosyncratic nature of the individual subject's performance in this task. In addition to the variance in overall response

biases observed in this experiment, a further analysis revealed a large amount of variability in the session-to-session performance of individual subjects. In view of these findings the success of the model in predicting average subject results should probably be attributed to its reflecting the gross features of a rather complex learning process. It is clear that in order to explain the bias learning process in detail a more complex learning model (which takes explicit account of the discrimination aspects of the situation) will be required.

References

Atkinson, R. C., Bogartz, W. H., & Turner, R. N. Supplementary report: Discrimination learning with probabilistic reinforcement schedules. Journal of Experimental Psychology, 1959, 57, 349-350.

Atkinson, R. C., Bower, G. H., & Crothers, E. J. An introduction to mathematical learning theory. New York: Wiley, 1965.

Atkinson, R. C., Carterette, E. C., & Kinchla, R. A. Sequential phenomena in psychophysical judgments: a theoretical analysis. Institute of Radio Engineers Transactions on Information Theory, 1962, IT8, S155-162.

Atkinson, R. C., & Kinchla, R. A. A learning model for forced-choice detection experiments. British Journal of Mathematical and Statistical Psychology, 1965, 18, 87-123.

Kruskal, W. H., & Wallis, W. A. Use of ranks in one-criterion variance analysis. Journal of The American Statistical Association, 1952, 47, 583-621.

Luce, R. D. A threshold model for simple detection experiments. Psychological Review, 1963, 70, 61-79.

Popper, Juliet, & Atkinson, R. C. Discrimination learning in a verbal conditioning situation. Journal of Experimental Psychology, 1958, 56, 21-25.

Swets, J. A., Tanner, W. P., Jr., & Birdsall, T. G. Decision processes in perception. Psychological Review, 1961, 68, 301-340.

Footnotes

[1]Support for this research was provided by the National Aeronautics and Space Administration, Grant No. NGR-05-020-036.

[2]The purpose of the alert signal was to eliminate a time-order error (favoring the second interval) that had been observed in earlier experiments.