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Feature sensitivity, bias, and interdependencies as a function of energy and payoffs

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In our previous research on human perception of simple patterns (Townsend, Hu, & Evans, 1984), positive dependencies in the sampling of features were interpreted in terms of underlying sensory and decisional processes. Those findings suggested a model, called Blobloc here, which is further tested in the present study under various conditions of stimulus duration in Experiment 1 and feature-specific payoff × stimulus duration in Experiment 2. Signal detection microanalyses generally supported Blobloc by discovering estimated d' greater on a given feature when another feature was a "hit" or a "correct rejection." The bias, as estimated by β, was less consistent in the microanalyses. The macroanalyses found that d' and β on individual features behaved as predicted as functions of the experimental conditions. However, in contrast to previous results, the variation in number of features in a pattern was apparently too small to yield consistent d' and β changes. In addition, increasing stimulus duration produced tendencies toward linear increases in β (significant in Experiment 2), a finding consistent with Blobloc. A plausible alternative model (Correlated Noise model) is rejected by the results of the present and previous studies.

Recent studies have begun to clarify how psychological and contextual variables influence the way we perceive simple patterns made up of elementary sets of lines and curves (e.g., Keren & Baggen, 1981; Loomis, 1982; Lupker, 1979; Townsend, Hu, & Ashby, 1980, 1981; Townsend, Hu, & Evans, 1984; Wandmacher, 1976). Undoubtedly in higher forms of visual cognition, or where their presence is directly sought, complex and even illusory mechanisms may be discovered (e.g., Prinzmetal, 1981; Treisman & Gelade, 1980). Nevertheless, there is growing evidence that, although the very simplest of past template and feature models of pattern perception were wrong, there is significant regularity and predictability afforded by fairly straightforward extensions of these models (for a taxonomy of elementary pattern recognition models, see Townsend & Landon, 1983). They also permit an investigation of interesting between- and within-pattern dynamics that have surfaced recently.[1]

The *feature-complete factorial* paradigm has been found useful in explicating such dynamics. In it, stimulus patterns, made up of all possible combinations of features, are shown to the observer, usually in a random order and including the blank pattern. Also, for every stimulus pattern there is assigned exactly one unique response, either a simple listing of component features or a "name" (Townsend et al., 1981; Townsend et al., 1984).[2]

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The Townsend et al. (1984) study employed such a design with 16 stimulus patterns generated by four atomic features. In addition to confirming a number of previous findings, they discovered the following characteristics: (1) The sensitivity (signal detection's d'; Green & Swets, 1966) of individual features fell as the number of features in a pattern increased, and the bias toward reporting individual features (the β criterion of signal detection theory) also decreased. Thus, feature detection was of limited capacity even within a single set of stimuli, although observers were more prone to accept the presence of features for a given observation, when there were more features in a stimulus. The signal detection analyses uncovering the above effects were called *macroanalyses* because they are computed without regard to the detection events of the other features. (2) The reports on individual features were not statistically independent of one another, and the dependencies were overwhelmingly positive. The following *microanalyses* discovered the underlying sensory and decisional reasons for this dependence. (3) When the signal detection analysis of a given feature was conditioned on the correct report of another feature in the stimulus pattern, then the subject averaged d' on the given feature was higher than on the average or than if it was conditioned on the failure to report another feature in the stimulus pattern. The subject averaged decision criterion for a given feature was more stringent (higher) when conditioned on the correct versus the incorrect, or average, report of another feature present in the stimulus. The above results were statistically significant and occurred for all individual features. In addition, the estimates of d' conditioned on the correct report of another present feature were higher than those conditioned on the failure to report the feature for each individual ob-

server. The corresponding βs were also greater for 2 of the 4 observers.[3] In the 1984 study, then, the positive sensitivity dependence overshadowed the mild conditional negative response bias effect, resulting in the positive response dependencies stated in (2).

In contrast to the results in the preceding paragraph, the earlier Townsend et al. (1980, 1981) study, which was feature-complete factorials but used only two constituent features (a subset of the later study), found no difference in sensitivity in one- versus two-feature patterns. Furthermore, the two features were reported in a statistically independent manner.

A tentative model, called Blobloc here and presented below, was developed by Townsend et al. (1984) to explain the results obtained with the 16 stimulus patterns. Because of the independence and other invariances found in the earlier (1980, 1981) work, certain dynamics of Blobloc, or whatever the "true" model is, must have a lower limit where their influence fades out.

The present study was conducted with a feature-complete factorial subset of the stimuli employed by Townsend et al. (1984), and included manipulations of stimulus energy (through stimulus presentation duration) and asymmetric payoffs on individual features. The size of the feature set was three, intermediate between the two features of the 1980, 1981 studies and the four features of the 1984 study, thus generating a total of eight stimulus patterns (see Figure 1). Our goals in the present study were (1) to learn if this size alphabet (8 patterns) would act like the 4 patterns of Townsend et al. (1980, 1981) or more like the 16 patterns of Townsend et al. (1984) and thus fall within the range of Blobloc-predicted dependencies; (2) to test a new prediction of Blobloc—that β would increase with stimulus energy—as well as to test the expected result that featural d' would properly increase with stimulus energy; and (3) to learn if payoffs could bias responses at the level of the individual features, as assessed through β, and to test if featural d' would remain properly invariant under payoff manipulations. (4) In the 1984 study, microanalyses were performed only conditional on the correct report of other present features (hits) and the incorrect reports of other present features (misses). A comparable analysis was conducted here with respect to correct rejections and false alarms on other features. Although another interesting model, which we call the *Correlated Noise* model, can also account for the positive dependencies found in the data, the signal detection macro- and microanalyses help to discriminate it from Blobloc and, in fact, support the Blobloc model. A description of Blobloc, including a comparison of predictions made by it and the Correlated Noise model, follows.

THE BLOBLOC MODEL

Blobloc was devised in order to account for the results of Townsend et al. (1984); it was motivated by the hypothesis that within the time course of a single trial, sensation proceeds from a (global) blurred, defocused type of image to a somewhat sharper (local) representation. That brief visual displays might correspond to a blurred or lowpass-filtered signal has been suggested by Loomis (1982, p. 51). Lupker (1979) proposed an account depicting brief display recognition as a global-to-local process. Eriksen and Schultz (1979), Hoffman (1975), Kinchla, Solis-Macias, and Hoffman (1983), Navon (1977), and others have propagated compatible notions in other contexts.

As in Lupker's global-to-local scheme, perception in Blobloc is viewed analogously to a focusing process. Blobloc states that the perceptual data available at an early point during perceptual processing resembles a blurred image of the stimulus containing low-frequency information, such as its general shape, or envelope. Over time, if the stimulus energy is sufficiently high, the image becomes more well-defined, until, with sufficient processing time, the local features become clear. Figures 2 and 3 illustrate the sensory aspects of Blobloc.

In a high-energy, or long-stimulus-duration, condition, the quality (e.g., the sharpness) of the image increases with time and the image becomes almost "perfect" before stimulus offset (Figure 2a).[4] Essentially the same quality × time curve will occur on each trial due to the high stimulus energy.

In the low-energy, or short-stimulus, condition, however, the quality of the image can only increase until the stimulus is turned off, at which point it starts decaying (Figure 2b). Since the stimulus terminated before the image could become clear, the quality of the image remains low. It is hypothesized that images will achieve different levels of quality, depending on the complexity of the stimulus pattern: More complex patterns presented for a short duration will tend to produce images of lower quality (top graph in Figure 2b) than will simple patterns (bottom of Figure 2b). This seems to be a reasonable as-

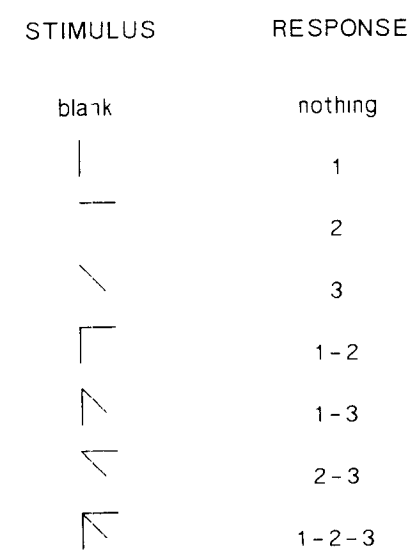

Figure 1. Stimulus-response paradigm.

sumption, since both simple and complex patterns will occupy about the same area of (e.g., retinal) space, thus resulting in lower resolution for the more complex patterns.

In addition, in the low-energy condition, the exact quality × time curve will be expected to vary from trial to trial. This variability for low-energy patterns is shown in Figure 3, which illustrates hypothetical frequency distributions (probability densities) for a complex and a simple pattern, at a fixed time point in processing, as a function of image quality. After processing for a fixed (short) amount of time, more of the complex many-featured patterns are likely to appear as blobs than as clear images (Figure 3a). In contrast, relatively more of the simple few-featured patterns than of the complex patterns, will reach the high-quality status after processing for the same amount of time (Figure 3b).

Blobloc further supposes that as the blob forms, the observer may perceive both the quality of the image and whether there is much or little information in the display (based, for example, on the size of the blob). On the basis of this early perceptual information, it is hypothesized that the observer may be able to reset feature decision criteria at the output level of the feature channels. Alternatively, the observer may be capable of presetting different criteria for patterns of different sizes or complexity. Note that if such a mechanism exists, it need not operate at a conscious level. Low criteria for reporting features would tend to be used in the case of big, low-resolution, lower quality blobs that may occur mainly following the presentation of more complex patterns with many features. High criteria would be employed for images of high quality (see Figure 4). Similarly, higher criteria would be used as stimulus duration increases, since longer stimulus durations would lead to images of higher quality. In addition, it is hypothesized that the quality factor is stronger than the complexity (or the size of the blob) factor: On trials in which a complex pattern nevertheless leads to a high-quality image, the featural criteria are expected to be high.

Thus, Blobloc suggests a two-phase sensory process followed by a decision process. The sensory phase is characterized by continuous growth of the image quality, but the exact growth curve and the maximum achieved will vary from trial to trial, with more variation and a lower maximum in the case of low-energy stimuli or more complex stimuli. In the sensory system, the global information is acquired and processed relatively early, followed by the acquisition and processing of finer grained featural information when stimulus conditions permit. In the decision system, the observers may be able to reset (or preset) their decision criteria at the output level of the fea-

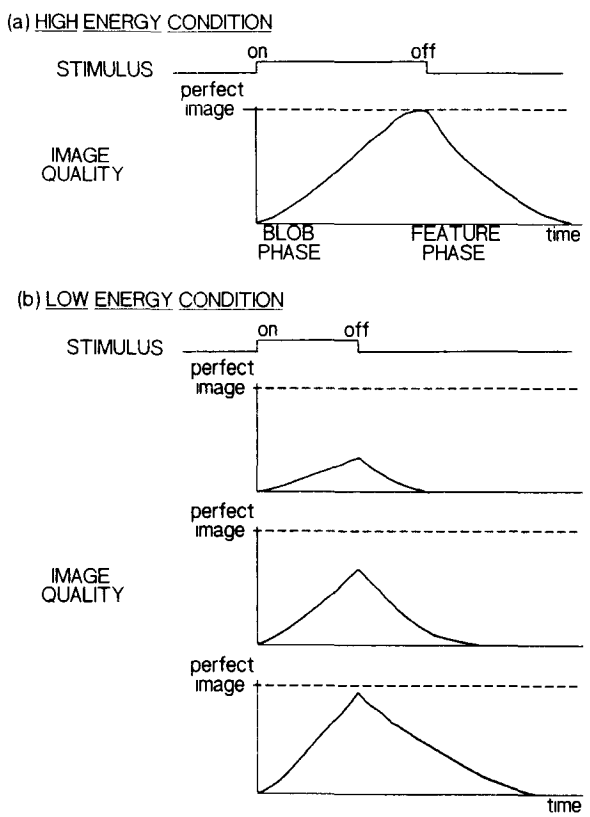

Figure 2. Deterministic time course of an image in a high-energy (long stimulus exposure) condition (a) and three hypothetical examples in a low-energy (short stimulus exposure) condition (b). From top to bottom of (b), we see the result of high, intermediate, and low stimulus complexity.

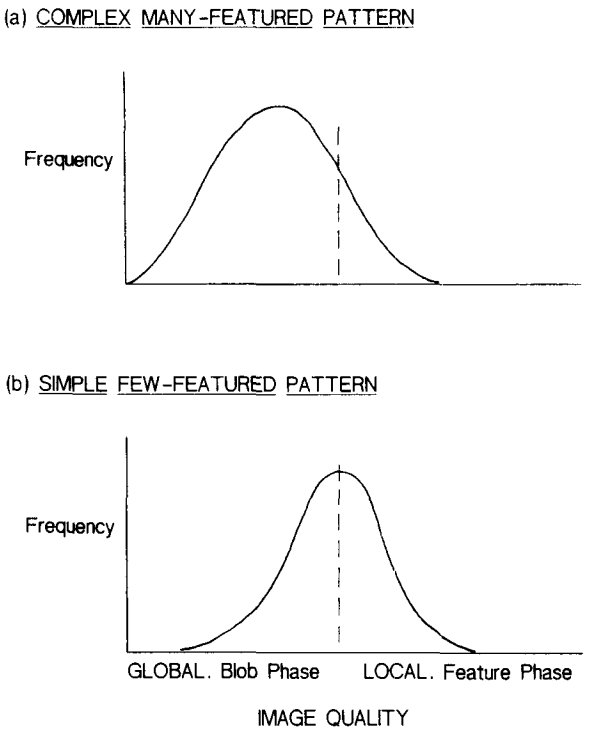

Figure 3. Hypothetical relative frequency distribution of an image at time $T=50$ msec (low-energy condition) for a complex, many-featured pattern (a) and a simple, few-featured pattern (b). See text for further explanation.

ture channels upon the acquisition of perceptual information produced in the sensory system. It is evident that Blobloc predicts the macroanalysis findings of Townsend et al. (1984) listed earlier. In particular, limited capacity is predicted in the sense that the d's and βs yielded by more complex patterns should be smaller than those yielded by simpler patterns.

With regard to the microanalyses of feature interdependencies, Blobloc makes the following predictions. Conditioning on the correct detection of a feature essentially puts the observer in that set of trials on which image quality was high. This increases the probability that another feature present in the pattern would be correctly detected. Thus, conditional d'(micro) would be expected to be higher on such trials. Conversely, a situation in which a feature is not sampled (not reported) but was actually present in the pattern would tend to occur on trials with low-quality images available to the observer. Thus, the conditional d' would tend to be lower.

Interestingly, Blobloc further predicts that if the investigator conditions on a correct rejection, then d' on another feature should be greater than if he/she conditions on a false alarm on another feature. This follows from Blobloc, since, when performance is conditioned on a correct rejection, the observer has perceived an image of high quality, whereas if performance is conditioned on a false alarm, the observer has perceived a low-quality image. This prediction was not tested in Townsend et al. (1984).

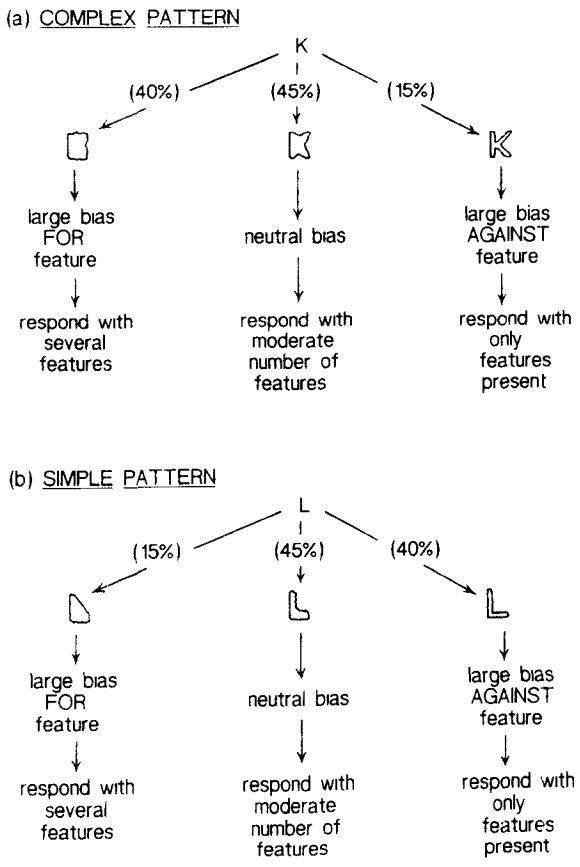

Figure 4. Sequence of events showing the interaction between sensory aspects and decision aspects of Blobloc for (a) complex pattern and (b) simple pattern. (The percent numbers in parentheses indicate the hypothetical percentages of trials on which each resulting blob would be perceived.)

Two further predictions are consistent with Blobloc. The first is that the conditional βs will be larger with a hit or correct rejection on another feature than with a miss or false alarm on another feature. The second is that if high-quality images tend to promote more stringent response criteria, as Blobloc stipulates should happen within trials, then it may be that, across conditions, the overall marginal βs should increase with higher stimulus energy, along with the expected d' increment. This would amount to a move toward minimizing false alarms. However, the latter should not be considered as a strong prediction from the model, since it does not really follow from its fundamental structure.

Finally, with respect to the payoff manipulation, we expect that βs for individual features should be affected by feature-specific payoffs according to the tenets of signal detection theory. This is also consistent with Blobloc, since Blobloc implicitly assumes that the visual system allows for decisional influences at the featural level. This prediction has never been experimentally tested.

We view Blobloc as a theoretical tool that captures certain strong and consistent (across observers) effects found in Townsend et al. (1980, 1981, 1984). It seems reasonable as a start, and helps us to conceptualize our ideas, although there are obvious gaps that will need to be filled. We currently view the criterial (β) aspects of the model as less rigid, simply because these may be more open to vagaries of conscious control and environmental influences. Furthermore, we do not yet know at which alphabet size the Blobloc-predicted sensory effects cease to be observed. For instance, if the macroscopic featural d' fails to decrease as the number of features in a pattern increases, it may be simply that the generating set of features is insufficiently large to cause the predicted loss of sensitivity.

Blobloc attempts to explain the interfeatural dependencies by appealing to across-trial variations in quality, in addition to continuous growth of quality within trials and the overlapping activities of the sensory and decision phases. The critical across-trial variations in quality could be psychologically interesting, but may also be more artifactual in nature. The more interesting effects would include actual sensory variations (e.g., as in signal detection theory), which might occur directly because of shared sensory effects or because of slower alterations in sensory sensitivity. Still of interest, but more cognitive in nature, would be fluctuations in attention over trials. Perhaps of least psychological interest would be effects like oscillations in lens accommodation or inadvertent eye movements or eye blinks. For Blobloc to be an interesting perceptual model, then, the across-trial variations in quality should be of the sensory or attentional type.

There are two basic alternative models that predict a positive statistical dependency among features (the

microanalysis) and do it by way of a within-trial interchannel facilitation rather than an across-trial dynamic. The first is a form of the general recognition model (Ashby & Townsend, 1986) involving a single sensory stage. It assumes that the feature channels simply possess positively correlated d's, or sensitivities, on each trial. This model cannot be presently discriminated from Blobloc, although it does not by itself explain other general effects suggestive of two sensory stages and the underlying mechanism is not intuitively clear.

The second is the Correlated Noise model, which assumes that there is a positive correlation among the separate feature channels, due, for example, to shared noise sources (see, e.g., Graham, Kramer, & Haber, 1985). In this model, if a neighboring channel is active, whether due to noise *or* a signal, then the level of activity in the given channel is increased. Specifically, it makes the following predictions. For a given feature, conditioning on misses or correct rejections of adjacent features (which implies no activity on the adjacent channels and thus no facilitation for the given feature) will be associated with a decrease in both the probability of a hit and the probability of a false alarm on the given feature channel. Analogously, a hit or a false alarm on an adjacent channel will facilitate the given channel, and thereby will increase the probability of a hit and the probability of a false alarm on the given channel. This model, then, predicts a decrease in the estimated value of β when conditioning on hits or false alarms on a neighboring feature but an increase in β when conditioning on misses or correct rejections. Estimated d' should evidence no regular changes in this model. Hence, although the Correlated Noise model is rather natural, if d' is found to be greater when another feature is correctly detected than when it is missed, it will be falsified.

METHOD

Experiment 1: Stimulus Energy Manipulation

Observers. Two observers (denoted Observers 1 and 2) participated in Experiment 1 as part of an upper-division experimental psychology course. Both had normal 20/20 vision.

Apparatus. A Gerbrands two-field tachistoscope (Model T-2b) was used to present the stimuli. A stimulus set was formed by using all combinations of three equal-length lines (30′ visual angle) as features. The three line segments were denoted as left vertical line (designated 1), top horizontal line (designated 2), and major diagonal oblique line (designated 3). Thus, the stimulus set consisted of seven nonblank stimuli plus one blank stimulus (see Figure 1). Each feature was presented an equal number of times overall.

A prestimulus fixation field was represented by a set of four dots arranged as the corners of a square with the stimulus placed in the center. The four dots were on the screen at all times during the brief intervals of stimulus presentation. The fixation field on any side subtended a visual angle of about 2° at the observer's eyes. The stimulus was drawn in dark ink on a white card. The luminance of the prestimulus field was approximately 5.31 cd m^{-2}; the luminance of the stimulus field was about 4.8 cd m^{-2}. The experimental room illuminance was kept at 1.25 fc.

Procedure. Observers 1 and 2 were given 1 h of practice for 5 days to familiarize them with the procedure and the stimulus-response pairs. They were instructed to say "nothing," "1," "2," "3," "1-2," "1-3," "2-3," or "1-2-3" for each corresponding stimulus exhibited at high energy levels, as shown in Figure 1. In each experimental session, there were three experimental conditions: S (short-exposure condition), I (intermediate-exposure condition), and L (long-exposure condition). These three experimental conditions were counterbalanced across sessions. Before the experiment began, the observers were informed of the condition to be presented. The stimulus exposure durations were set for each observer individually so that their averaged probabilities of being correct were approximately 50% in the S condition, 70% in the I condition, and 85% in the L condition.

Each stimulus was presented 20 times in each experimental condition, for a total of 160 trials in each experimental condition, or 480 trials per session. Each session began with 20 warm-up trials and lasted about 2 h for each observer. Each observer participated in 20 sessions; thus, 400 presentations of each stimulus were obtained for both observers in every experimental condition.

Experiment 2: Stimulus Energy and Payoffs

Observers and Apparatus. The two observers (denoted Observers 3 and 4) were paid Purdue undergraduate students. Both had normal 20/20 vision. The apparatus was identical to that used in Experiment 1.

Procedure. As in Experiment 1, each observer practiced for 1 h each day for 5 days to become familiar with the procedure. The three stimulus exposure durations of Experiment 1 were included and, in addition, a payoff variable was manipulated at three levels, designated neutral (N), horizontal (H), and oblique (O). In the N condition, the observers would earn 1 penny for every feature reported in a correct response and lose ½ penny for every feature missed or gained in an incorrect response. In the H condition, the observers would earn 1 extra penny if they correctly reported the horizontal feature but would not experience any extra loss for an incorrect response. In the O condition, the observers would earn 1 extra penny if they correctly reported the oblique feature but would not incur any extra loss for an incorrect response.

Before the experiment began, stimulus exposure durations were set for each observer individually, so that the average overall probabilities of being correct were approximately 50% in the S conditions, 75% in the I conditions, and 95% in the L condition. The stimulus exposure duration (energy) conditions were combined with the payoff conditions into a partial factorial design such that five experimental conditions were created: S-H (short duration and horizontal payoff), S-O (short duration and oblique payoff), I-H (intermediate duration and horizontal payoff), I-O (intermediate duration and oblique payoff), and L-N (long duration and neutral payoff). In each experimental session, the observers received the five conditions in counterbalanced order across sessions. Prior to each experimental condition, the observer was informed of the condition to be presented. Each stimulus was presented 12 times in each condition, for totals of 96 trials per condition and 480 trials (about 2 h duration) per session per observer. Twenty-five practice trials preceded each experimental session. There were 68 sessions, so each observer was presented each stimulus on 810 trials in every experimental condition.

RESULTS AND DISCUSSION

For the general pattern of confusions and for the use of other experimenters, Table 1 shows the individual confusion matrices of the present study. First, we observe that, as in past studies, strong evidence was found for (1) ghost or false-alarm features (i.e., features that were reported but not presented in the stimulus pattern), and (2) unequal detectability of the various features and the

same feature placed in different patterns. (On both points, cf. Geyer & DeWald, 1973; Rumelhart, 1971; Townsend & Ashby, 1982; Townsend et al., 1984.) These and similar results are now so well founded that we will not occupy further space in reporting their analyses, but they can be obtained on request.

We will briefly review the major findings and then provide more detail in the same order as below (given by numbers 1 to 4).

1. Overwhelming evidence of dependencies in feature reports, primarily of a positive nature, was again found across all conditions and observers. These could not be explained on the basis of an independent-feature-extraction process followed by a biased-decision phase, as assessed by many model fits. Microanalyses of d' supported Blobloc's predictions against the alternative Correlated Noise model. The predictions for β were fulfilled for false alarms versus correct rejections, supporting Blobloc, but not for hits versus misses.

2. Duration of stimulus presentation affected overall d's of individual features, as expected. The response bias, as given by β, tended to increase with duration in both experiments but the change was significant only in Experiment 2.

3. Selective payoffs affected the response biases of the various features in the predicted manner, and d' remained unchanged.

4. As the number of features in a stimulus pattern increased, β decreased, as expected, in Experiment 1, but failed to do so in Experiment 2. The sensitivity parameter d' for individual features was invariant over the number of features in a pattern, in contrast to Townsend et al. (1984) but in agreement with the results obtained with the very simple stimuli of Townsend et al. (1981).

1. Positive Feature Report Dependencies and Microanalyses

The most critical prediction of Blobloc is that correct detection of a feature is associated with an increased probability of detecting another feature. It also predicts a higher response criterion β conditional on a correct response to the presence or absence of another feature.

Table 1
$P(R_j S_i)$, the Estimated Probability of Reporting R_j Given Stimulus S_i in a Confusion Matrix for Observers 1, 2, 3, and 4 in Each Experimental Condition

			R_j							
	Observer	$P(R_j \mid S_i)$	ϕ	|	—	\	⌐	⌃	⌄	⌅
			Condition S: Short Stimulus-Exposure Duration							
	1	ϕ	0.91	0.02	0.04	0.02	0 00	0.00	0.00	0.00
		|	0.41	0 55	0 02	0.00	0 00	0.02	0.00	0.00
		—	0.49	0.02	0.45	0.01	0 00	0.00	0.02	0.00
		\	0.56	0.03	0.05	0.36	0.00	0.00	0.00	0.00
		⌐	0.21	0.21	0.24	0.02	0 29	0.01	0.01	0.01
		⌃	0.25	0.24	0.05	0 20	0 00	0 26	0.00	0 00
		⌄	0.33	0.03	0.33	0.16	0.00	0.00	0.14	0.01
		⌅	0.10	0.12	0.14	0.08	0.16	0 10	0.08	0.22
			Condition I: Intermediate Stimulus-Exposure Duration							
	1	ϕ	1.00	0.00	0.00	0.00	0.00	0 00	0.00	0.00
		|	0.16	0.82	0.00	0.00	0.01	0.01	0.00	0.00
		—	0.27	0.00	0.72	0.00	0.00	0.00	0.00	0.00
S_i		\	0.30	0.00	0.01	0.68	0.00	0.00	0.00	0.00
		⌐	0.08	0.14	0.14	0.00	0.62	0.00	0.00	0.01
		⌃	0.11	0.17	0.00	0.12	0.01	0.56	0.00	0 02
		⌄	0.14	0.00	0.34	0.11	0 00	0.00	0.40	0 00
		⌅	0.02	0.04	0.04	0.02	0 15	0.07	0.05	0.62
			Condition L: Long Stimulus-Exposure Duration							
	1	ϕ	1.00	0.00	0.00	0 00	0.00	0.00	0.00	0 00
		|	0.04	0 94	0.00	0.00	0.00	0.01	0.00	0.00
		—	0.11	0.00	0.89	0.00	0 00	0.00	0.00	0 00
		\	0.14	0.00	0.00	0 86	0 00	0 00	0.00	0.00
		⌐	0.01	0 06	0.08	0.00	0 84	0.00	0.00	0.00
		⌃	0.04	0.06	0.00	0 10	0 00	0.79	0.00	0.00
		⌄	0.04	0.00	0.26	0.08	0 00	0.00	0.61	0 01
		⌅	0.00	0.01	0 01	0.00	0 10	0 04	0.04	0 80

Table 1 (Continued)

	Observer	$P(R_j \mid S_i)$	R_j: ϕ							
			Condition S: Short Stimulus-Exposure Duration							
	2	ϕ	0.90	0.03	0.05	0.01	0 00	0.00	0.00	0 00
			0.22	0.58	0.02	0.02	0.08	0.06	0.01	0.01
			0 44	0.04	0.44	0.02	0.03	0.00	0.04	0 00
			0.17	0.00	0.01	0 74	0.00	0.03	0.05	0.00
			0.13	0.20	0 08	0.00	0.46	0.05	0.02	0.04
			0.08	0.04	0.01	0 14	0.00	0 58	0.02	0.11
			0 12	0.00	0 06	0.28	0.00	0.02	0.48	0.02
			0.02	0.04	0.01	0.05	0 03	0 20	0.08	0.58
			Condition I: Intermediate Stimulus-Exposure Duration							
	2	ϕ	0.91	0.04	0 03	0.02	0.00	0.00	0.00	0.00
			0.10	0.68	0.01	0.00	0.09	0.09	0.01	0.01
			0.40	0 01	0.52	0.03	0.02	0.00	0.02	0.00
			0.08	0.00	0.00	0.84	0.00	0.02	0.04	0.00
			0.08	0.13	0.06	0.00	0.61	0.04	0.01	0.06
			0 06	0.03	0.00	0 10	0.00	0.69	0.02	0.10
			0.04	0.01	0.05	0.24	0 00	0.00	0.64	0.02
			0.01	0 02	0.02	0.01	0.04	0.15	0.08	0.70
			Condition L: Long Stimulus-Exposure Duration							
	2	ϕ	0.94	0.02	0.02	0.01	0.00	0.00	0.00	0.00
S_i			0.07	0.74	0.00	0.00	0.10	0.08	0.00	0.01
			0.30	0.01	0.64	0.01	0.02	0.00	0.03	0.00
			0.07	0.01	0.00	0.88	0.00	0.01	0.03	0.00
			0.03	0.09	0.05	0.00	0.75	0.04	0.00	0.04
			0.02	0.01	0.00	0.08	0.00	0.79	0.02	0.08
			0.03	0.00	0.04	0.17	0.00	0.00	0.74	0.02
			0.01	0.00	0.00	0.02	0.02	0.10	0.04	0.82
			Condition S-H: Short Duration and Horizontal Payoff							
	3	ϕ	0.66	0.07	0.14	0.08	0.01	0.00	0.03	0.00
			0.20	0.59	0.05	0.04	0.05	0.06	0.02	0.00
			0.23	0.04	0.60	0.05	0.02	0.00	0.06	0.00
			0.23	0.04	0.08	0.55	0.00	0.02	0.07	0.00
			0.10	0.25	0.13	0.01	0.43	0.03	0.03	0.02
			0.10	0.18	0.04	0.17	0.04	0.38	0.03	0.06
			0.10	0.03	0.14	0.26	0.02	0.01	0.40	0.03
			0.05	0.08	0.07	0.05	0.18	0.12	0.10	0.37
			Condition S-O: Short Duration and Oblique Payoff							
	3	ϕ	0.66	0.07	0.11	0.10	0.02	0.01	0.03	0.00
			0.18	0.60	0.03	0.06	0.05	0.06	0.01	0.01
			0.22	0.03	0.58	0 06	0.03	0.00	0.07	0.00
			0.21	0.04	0.06	0.59	0 00	0.02	0.08	0.00
			0.10	0.25	0.11	0.03	0.44	0.03	0.03	0.01
			0.09	0.16	0.03	0.19	0.04	0.41	0.04	0.04
			0.13	0.03	0.14	0.25	0.03	0.02	0.38	0.02
			0.06	0 09	0 05	0.07	0.16	0.13	0.09	0.35

Table 1 (Continued)

	Observer	$P(R_j \mid S_i)$	R_j: ϕ	$\vert$	$-$	$\diagdown$	$\ulcorner$	$\nwarrow$	$\swarrow$	$\nearrow$
			Condition I-H: Intermediate Duration and Horizontal Payoff							
	3	ϕ	0.84	0.02	0.08	0.03	0.00	0.00	0.01	0.00
		$\vert$	0.11	0.80	0.00	0.01	0.03	0.02	0.00	0.00
		$-$	0.11	0.00	0.83	0.01	0.01	0.00	0.03	0.00
		$\diagdown$	0.14	0.01	0.02	0.75	0.00	0.02	0.05	0.00
		$\ulcorner$	0.04	0.13	0.06	0.00	0.73	0.00	0.00	0.03
		$\nwarrow$	0.04	0.11	0.00	0.10	0.01	0.69	0.01	0.05
		$\swarrow$	0.04	0.01	0.08	0.19	0.01	0.00	0.68	0.01
		$\nearrow$	0.02	0.04	0.02	0.01	0.11	0.09	0.04	0.67
			Condition I-O: Intermediate Duration and Oblique Payoff							
	3	ϕ	0.87	0.02	0.05	0.04	0.00	0.00	0.01	0.00
		$\vert$	0.08	0.84	0.01	0.01	0.03	0.03	0.00	0.00
		$-$	0.14	0.00	0.79	0.02	0.01	0.00	0.03	0.00
		$\diagdown$	0.13	0.00	0.02	0.79	0.00	0.01	0.05	0.00
		$\ulcorner$	0.02	0.12	0.04	0.00	0.76	0.01	0.01	0.03
		$\nwarrow$	0.03	0.09	0 00	0.10	0.01	0.71	0.01	0.05
		$\swarrow$	0.03	0.00	0.07	0.19	0.00	0.01	0.68	0.02
		$\nearrow$	0.01	0.04	0.02	0.02	0.12	0.10	0.05	0.64
			Condition L-N: Long Duration and Neutral Payoff							
	3	ϕ	0.95	0.01	0.02	0.02	0.00	0.00	0.00	0.00
		$\vert$	0.02	0.95	0.00	0.00	0.02	0.00	0.00	0.00
		$-$	0.03	0.00	0.95	0.00	0.00	0.00	0.01	0.00
S_i		$\diagdown$	0.05	0.00	0.00	0.92	0.00	0.00	0.02	0.00
		$\ulcorner$	0.00	0.04	0.01	0.00	0.92	0.00	0.00	0.02
		$\nwarrow$	0.01	0.04	0.00	0.03	0.00	0.89	0.00	0.02
		$\swarrow$	0.01	0.00	0.03	0.07	0.00	0.00	0.88	0.01
		$\nearrow$	0.00	0.01	0.00	0.00	0.04	0.05	0.02	0.87
			Condition S-H: Short Duration and Horizontal Payoff							
	4	ϕ	0.57	0.02	0.22	0.09	0.02	0.01	0.07	0.00
		$\vert$	0.20	0.38	0.08	0.08	0.05	0.11	0.07	0.02
		$-$	0.15	0.01	0.66	0.05	0.01	0.00	0.11	0.00
		$\diagdown$	0.23	0.01	0.12	0.47	0.01	0.02	0.13	0.00
		$\ulcorner$	0.07	0.13	0.23	0.03	0.32	0.06	0.10	0.06
		$\nwarrow$	0.09	0.14	0.10	0.20	0.06	0.25	0.12	0.06
		$\swarrow$	0.08	0.01	0.28	0.19	0.01	0.01	0.40	0.00
		$\nearrow$	0.04	0.06	0.12	0.05	0.16	0.09	0.21	0.26
			Condition S-O: Short Duration and Oblique Payoff							
	4	ϕ	0.60	0.02	0.14	0.12	0.01	0.02	0.09	0.01
		$\vert$	0.20	0.34	0.07	0.10	0.05	0.13	0.09	0.02
		$-$	0.17	0.01	0.63	0.06	0.02	0.00	0.11	0.00
		$\diagdown$	0.25	0.01	0.11	0.47	0.01	0.01	0.13	0.01
		$\ulcorner$	0.06	0.14	0.20	0.04	0.32	0.08	0.10	0.07
		$\nwarrow$	0.11	0.11	0.07	0.25	0.04	0.23	0.12	0.06
		$\swarrow$	0.09	0.01	0.26	0.22	0.02	0.01	0.38	0.02
		$\nearrow$	0.04	0.05	0.14	0.08	0.16	0.10	0.20	0.23

Table 1 (Continued)

Observer	$P(R_j \mid S_i)$	R_j: ϕ	|	—	\	⌐	⌐	¬	¬
		Condition I-H: Intermediate Duration and Horizontal Payoff							
4	ϕ	0.80	0 01	0 11	0.04	0.00	0 00	0.03	0.00
	|	0.13	0 66	0.03	0.02	0.03	0 10	0 02	0.01
	—	0.11	0 00	0.82	0 02	0 00	0 00	0.04	0.00
	\	0.16	0 01	0.04	0.69	0.00	0.01	0.08	0 00
	⌐	0 02	0.10	0 11	0.00	0.62	0 04	0.04	0 07
	⌐	0 05	0 10	0.03	0.21	0.02	0 41	0.06	0 12
	¬	0.04	0.00	0.18	0 16	0.00	0.01	0 61	0 01
	¬	0.02	0.03	0.07	0.03	0 19	0.08	0 12	0.46
		Condition I-O: Intermediate Duration and Oblique Payoff							
4	ϕ	0.82	0 01	0.07	0.06	0.00	0.01	0.02	0.00
	|	0.14	0 66	0 01	0 02	0 03	0.11	0.02	0.01
S_i	—	0.12	0.00	0.81	0.01	0.01	0 00	0.05	0.00
	\	0.16	0.00	0.02	0.74	0.00	0.01	0.06	0.00
	⌐	0.02	0.11	0.09	0.01	0 63	0.04	0.02	0.08
	⌐	0.04	0.11	0 01	0 20	0.01	0.45	0.06	0.12
	¬	0 04	0.00	0.16	0.16	0.00	0.00	0 62	0.00
	¬	0 00	0.02	0 06	0 03	0.16	0.08	0.14	0.50
		Condition L-N: Long Duration and Neutral Payoff							
4	ϕ	0.93	0 01	0.03	0.02	0.00	0.00	0.01	0.00
	|	0 05	0 84	0.00	0.01	0.02	0.06	0.00	0.01
	—	0 05	0.00	0.92	0 01	0.00	0.00	0.02	0.00
	\	0 07	0.00	0.00	0.88	0.00	0.00	0.04	0.00
	⌐	0.00	0 06	0.05	0.00	0 81	0.01	0.01	0.06
	⌐	0.01	0.06	0.01	0.12	0.01	0.65	0.01	0.13
	¬	0.01	0.00	0.08	0 10	0.00	0.00	0.81	0.00
	¬	0 00	0 01	0 02	0.00	0.11	0 04	0.05	0.76

As will be seen, the first prediction was strongly upheld whereas results on the second were mixed.

A positive report dependence between two features, k_1 and k_2, is observed when the chance of one feature being sampled is more likely if the other feature has been sampled than if the feature is sampled alone.[5] In conditional probability terminology, this is $Pr(k_1 \mid k_2) > Pr(k_1)$, or $Pr(k_1 \,\&\, k_2) > Pr(k_1) \times Pr(k_2)$. The reverse inequality reveals a negative dependence of two features, k_1 and k_2, whereas an equality indicates feature sampling independence.

Table 2 shows the joint probabilities versus the product of the marginal probabilities for all possible feature combinations contained in the stimulus pattern. Within each experimental condition, the joint probability (left column) is greater than or equal to (within statistical uncertainty) the product of the marginal probabilities (right column), thus positive dependence is overwhelmingly supported for Observers 1, 2, and 3. This finding is verified by sign tests ($p < .0001$) for each of these 3 observers.

Table 2 suggests that, in contrast to the other observers, Observer 4 shows a negative correlation in her featural sampling probabilities in the short-stimulus-duration conditions. This is verified by a sign test ($p < .01$). [In the longer stimulus duration conditions, the sign test indicates a positive dependence ($p < .01$), as was found with the other 3 observers.] This apparent deviation from the other 3 observers in the short-stimulus-exposure conditions is due to her large probabilities of reporting ghost features (features not in the stimulus pattern), which are not taken into account when we view the data from this gross perspective. However, when we examine the data from our detection microanalyses where the probabilities of false alarms are assessed, this apparent deviation from the other observers disappears.

As in the Townsend et al. (1984) microanalyses, the parameters d' and β were computed for each feature conditioned on (1) the correct sampling of another feature in a particular stimulus (i.e., a hit) versus (2) the failure to sample another feature (a miss). Table 3 shows the positive and negative (conditional) d' and β values averaged over conditions, features, and stimuli for each observer. The d' statistic in the case of the correct sampling of another feature (i.e., conditional on a hit) is greater than

the d' conditioned on the failure to sample another feature in the stimulus (conditional on a miss) for each observer (paired t tests showed that $p < .01$ for each observer). Table 3 also includes results for each of the observers from Townsend et al. (1984) for comparison.

Thus, the most critical prediction of Blobloc was confirmed: Measured featural sensitivity is enhanced when it is known that another feature has been correctly sampled. On the other hand, β shows no consistent trend, unlike Townsend et al. (1984), where the measured β averaged over all observers increased when another feature was correctly sampled (see also Footnote 3). We shall see below that β acts more as predicted when conditioned on correct rejections versus false alarms.

Conditioning on the presence (a hit) or the absence (a miss) of another feature in the stimulus pattern provides useful insights into the processing of stimuli. In a similar manner, we may also compare results of the signal detection parameters conditioned on a correct rejection and a false alarm of another feature in the stimulus pattern. These types of microanalysis can then help us to distinguish between certain types of models of perception. Consider the parallel Correlated Noise model, which assumes that if a feature channel is active due to a signal or noise, then surrounding channels tend to be activated. In some ways, this model is the polar opposite of the interchannel inhibition model of Estes (1972), which seems most compatible with negative dependencies.

As mentioned in the introduction, such a model would make the following predictions for microanalyses conditional on hits and misses of other features. In a two-feature stimulus, for example, $\sqcap$, conditioning on a hit of $\overline{}$ would mean that the $\overline{}$ channel is active and is facilitating the | channel; therefore the probability of a hit and the probability of a false alarm of | (to a stimulus $\overline{}$), conditional on the hit of $\overline{}$ would be expected to increase, implying a decrease in measured β. Similarly, conditioning on a miss of $\overline{}$ would imply that the $\overline{}$ channel is inactive, thereby providing no facilitation to the | channel. This implies that the probability that the feature | is hit or the probability of a false alarm of |, conditioned on $\overline{}$ missed (and | not in the stimulus in the latter case), would both decrease. In this case, the conditional β would tend to increase. (Note that β is not necessarily a parameter of the Correlated Noise model; it results from the way that the various probabilities are predicted to vary in the different conditions.) Recall that the Blobloc model makes the opposite prediction for these conditional βs, since when conditioning on a hit, the resolution of the image is probably high, which would increase β, whereas conditioning on a miss would imply a low resolution image, which would lower β. In addition, and in marked contrast to Blobloc, the Correlated Noise model predicts that d' conditional on hits and misses will not vary systematically.

For the parameters conditioned on false alarms or correct rejections of other features, the Blobloc model makes the following predictions. Conditioning on a false alarm would imply that the observer has perceived a big fuzzy image, thus the β of feature | conditioned on the false alarm of feature $\overline{}$ would be expected to decrease. In the parallel Correlated Noise model, conditioning on a false alarm means that the $\overline{}$ channel is active (albeit due to noise), which in turn facilitates the | channel, and β of feature | conditioned on the false alarm of feature $\overline{}$ would also be expected to decrease.

By the same reasoning, the Blobloc model predicts that β conditioned on the correct rejection of feature $\overline{}$ would increase, since the subject would have a clear, small image of the stimulus available. The Correlated Noise model makes the same prediction in this case again: correct rejection implies that the $\overline{}$ channel was not activated; it therefore does not increase activity in the | channel and β of feature | conditioned on the correct rejection of feature $\overline{}$ would increase. Again, the Correlated Noise model predicts unsystematic variation in d's conditional on false alarms or correct rejections, whereas Blobloc predicts that d' conditional on a correct rejection should be greater than the d' conditional on the false alarm of another feature.

Estimates of the d' and β values, conditional on correct rejections and false alarms, from the data of the present experiments, averaged over all features, stimuli, and conditions, are presented in Table 4. (The calculations for the d' and β of one feature, conditional on the correct rejection and false alarm of another, are analogous to the calculations of d's and βs conditional on the hits and misses, which were presented in the Appendix of Townsend et al., 1984.) For every observer in each experimental condition in which both probability of a hit and probability of a false alarm were estimable, the d' conditioned on the correct rejection was greater than the d' conditioned on false alarm (except for one case: Observer 1's d' of feature $\diagdown$ in stimulus $\sqcap\!\diagdown$, conditioned on the correct rejection of feature $\overline{}$, was smaller than the corresponding d' conditioned on the false alarm). The average values of d' and β conditional on the correct rejection were significantly greater than the values conditional on the false alarms at the $\alpha = .05$ level, or less, for each observer. [For example, the t test for d' values of Observer 3 was $t(73) = 7.01, p < .001$.] Table 4 also shows that some of the d' and β values were not estimable, primarily when conditioning on false alarms. This was due to the small number of confusions, particularly in the longer stimulus exposure conditions, which led to marginal probabilities of zero.

The same results were obtained for the Townsend et al. (1984) data, as shown at the bottom of Table 4. The d'

Table 2
The Joint Probabilities of Sampling Two of Three Features Versus the Product of Marginal Probabilities of Sampling Features for the Corresponding Stimuli

Observer	Joint Probability	Product of Marginals	Stimulus	Duration Conditions: Short		Intermediate		Long	
1	p(⌐)	p(|)p(¯)	⌐	297	283	.627	.593	840	835
			⌖	372	351	767	.748	900	895
	p(⌖)	p(|)p(\ )	⌖	257	227	580	532	792	765
			⌖	313	281	692	.667	.840	832
	p(⌙)	p(¯)p(\ )	⌙	145	148	407	.388	.617	614
			⌖	.290	279	.667	648	837	.834
	p(⌖)	p(|)p(¯)p(\ )	⌖	215	.166	620	.569	.802	788
	p(⌖)	p(|)p(⌙)	⌐	.215	173	620	.585	.802	791
	p(⌖)	p(¯)p(⌖)	⌖	.215	185	620	.590	802	796
	p(⌖)	p(\ )p(⌐)	⌙	215	176	.620	583	.802	792
2	p(⌐)	p(|)p(¯)	⌐	505	466	.667	.619	790	775
			⌖	607	587	.732	.736	.832	812
	p(⌖)	p(|)p(\ )	⌖	.690	635	785	.742	865	.847
			⌖	.780	765	.845	.830	912	902
	p(⌙)	p(¯)p(\ )	⌙	497	.453	.652	.628	.757	.741
			⌖	.655	.629	.772	.763	860	.851
	p(⌖)	p(|)p(¯)p(\ )	⌖	577	.531	.697	683	817	789
	p(⌖)	p(|)p(⌙)	⌐	577	544	.697	691	.817	797
	p(⌖)	p(¯)p(⌖)	⌖	.577	.542	.697	695	.817	.798
	p(⌖)	p(\ )p(⌐)	⌙	577	549	.697	679	.817	.809

				Experimental Conditions: S-H		S-O		I-H		I-O	
3	p(⌐)	p(|)p(¯)	⌐	456	.449	456	.437	.754	732	.787	774
			⌖	.544	524	514	.480	.784	.771	765	.751
	p(⌖)	p(|)p(\ )	⌖	.436	.418	.450	.442	.734	.713	.756	741
			⌖	.486	.467	.480	.467	.762	.745	.744	.731
	p(⌙)	p(¯)p(\ )	⌙	434	.424	.402	.384	.686	.671	.693	.683
			⌖	464	.446	.438	.417	.713	.687	.692	.669
	p(⌖)	p(|)p(¯)p(\ )	⌖	.368	330	350	.306	.671	.628	.645	.606
	p(⌖)	p(|)p(⌙)	⌐	.368	344	350	322	.671	652	.645	.617
	p(⌖)	p(¯)p(⌖)	⌖	368	.344	.350	.314	.671	.642	645	.617
	p(⌖)	p(\ )p(⌐)	⌙	.368	.343	.350	.327	.671	.639	.645	.617
4	p(⌐)	p(|)p(¯)	⌐	.378	403	.394	.420	.689	696	716	.713
			⌖	.421	438	.398	402	644	.638	664	.662
	p(⌖)	p(|)p(\ )	⌖	.302	308	.294	.296	.536	.527	.564	562
			⌖	.356	.358	.335	.334	.537	524	.576	.567
	p(⌙)	p(¯)p(\ )	⌙	409	428	.394	.415	.621	.628	628	.628
			⌖	.476	.467	430	445	.583	.581	.640	.650
	p(⌖)	p(|)p(¯)p(\ )	⌖	.264	.270	235	244	.457	.441	498	.494
	p(⌖)	p(|)p(⌙)	⌐	.264	.276	235	.236	.457	.442	.498	.486
	p(⌖)	p(¯)p(⌖)	⌖	264	269	.235	.245	.457	.452	.498	.502
	p(⌖)	p(\ )p(⌐)	⌙	264	.260	235	242	.457	445	.498	.495

Note—S = short duration, H = horizontal payoff, I = intermediate duration, O = oblique payoff.

Table 3
Values of d' and β Conditional on Hits and Misses for Each Observer Averaged Across Features, Stimuli, and Experimental Conditions

	d'		β	
Observer	Hits	Misses	Hits	Misses
		Experiment 1		
1	3.19	2.48	19 29	16.47
2	2 76	1.86	1 76	2 66
		Experiment 2		
3	2 75	1.84	2 69	2.66
4	2 20	1 79	5 21	2.56
		Townsend et al. (1984) study		
1	2.28	1.66	2.78	1 66
2	1 97	1 55	2 00	1.85
3	2 06	1 28	1 76	1.86
4	2.24	1 41	4 45	2 48

and β values of one feature conditioned on the correct rejection of another feature were significantly greater than the corresponding d' and β values conditioned on false alarms. This was supported by t test for each observer at the $\alpha = .01$ or less. More of the d' and β values were estimable in this data set. The Townsend et al. (1984) study used stimulus durations such that the observers were correct on approximately 50% of the trials (comparable to Condition S in the present experiments). This seemed to produce a sufficient number of confusions to compute most of these estimates.

We conducted sequential analyses to test whether a regular waxing and waning of observer sensitivity or attention across trials could have accounted for the positive conditional effects (see also Atkinson, 1963, and Norman, 1964, for general discussions of variable sensitivity). It is possible that the positive within-trial correlation is associated with a between-trial correlation. If, for example, the observer's attention level was high for some consecutive trials and then lower for the next few trials, we might expect the sequences of these trials to be clustered, with comparable levels of sensitivity in each sequence. Conversely, if attention varied widely from trial to trial, a scattered sequence of responses for the session would result. Several techniques were applied to try to locate evidence for such effects.

First, the sequence of trials was transformed into a binary code in which a correct response was coded as 1 and an incorrect response was coded as 0. An autocorrelation analysis on each of these sequences showed that more than 95% of the autocorrelation coefficients were less than 0.20 in absolute value, suggesting no systematic attentional variations. The transformation to a binary code, however, results in much loss of information, since each of the eight stimuli has eight alternative responses, but a correct response is designated as 1 and an incorrect response is coded as 0 regardless of whether it was made to a complex stimulus or a simple one. The following technique was therefore designed to derive a more sensitive measure for finding systematic attentional variations.

Two matched categories of scattered and clustered sequences were formed, and conditional d's were calculated to test the hypothesis that clustered sequences yield high positive conditional d's (due to increased sensitivity resulting from a higher attentional level), while scattered sequences result in low conditional d's. To form the matched categories, the obtained response sequences were dichotomized into scattered or clustered categories on the basis of the following two criteria. First, the sequences were matched on the basis of their overall probability of correct responses. Since some sequences lacked matches, these were dropped during this dichotomizing procedure. Second, the sequences were categorized as scattered or clustered as follows: A clustered sequence was defined as one containing at least 10 trials, with four correct responses on both the first 5 and last 5 trials, and more than 65% of the trials being correct. If the sequence failed to meet these criteria, it was categorized as scattered.

A sign test on the conditional d's for the clustered versus scattered sequences showed that there was no significant difference in the conditional d's for the two categories. The results of both analyses thus argue against a strong association between the increased conditional d's within trials and a periodic fluctuation of sensitivity or attention across trials. Consequently, a form of Blobloc in which

Table 4
Values of d' and β Conditional on Correct Rejections (CR) and False Alarms (FA) for Each Observer Averaged Across Features, Stimuli, and Experimental Conditions

	d'		β	
Observer	CR	FA	CR	FA
		Experiment 1		
1	2 18 (N=16)	– (N=0)	7.65	–
2	2.68 (N=36)	1 47 (N=4)	3 79	1 37
		Experiment 2		
3	2.53 (N=57)	1 10 (N=18)	2.53	1 72
4	2.26 (N=57)	0 97 (n=32)	2 99	1.39
		Townsend et al. (1984) Study		
1	2.47 (N=48)	1 18 (N=38)	3.01	1 36
2	2.15 (N=48)	1.45 (N=46)	2.34	1 70
3	2 06 (N=48)	1.18 (N=46)	2.52	1 52
4	2 19 (N=48)	1.10 (N=43)	5.04	1.75

Note—The maximum number of conditional d' and β estimates was 36 in Experiment 1, 60 in Experiment 2, and 48 in Townsend et al. (1984) The numbers (N) in parentheses indicate the actual number of estimable values.

trial-to-trial fluctuations in stimulus quality are relatively independent of one another is tentatively supported.

2. Stimulus Energy Effects

As noted above, the dependency results were discovered across all the energy (via stimulus-duration manipulation) and payoff manipulations, but it is of interest to learn how the selective payoffs affected the marginal (average) sensitivity and bias measurements for individual features. It was expected that as the stimulus energy increased, d', which can be interpreted as the signal-to-noise ratio, would increase. This expected result was strongly confirmed, and the tendency for response bias β also to increase as stimulus energy increased was intriguing.

Both results are shown in the left half of Figure 5. (The right half will be discussed in the next section.) Because of the very large variance in the β estimates, the incline did not reach statistical significance in Experiment 1 [ANOVA for the main effect was not significant, $F(2,69) = 2.95$], but did in Experiment 2 [for linear trend, $F(1,117) = 5.46$, $p < .05$]. This finding suggests that observers may become more conservative with stronger signals. Although it is not directly derived from Blobloc's assumptions, this result is compatible with Blobloc, since Blobloc associates looser decision criteria with weaker signals and stricter criteria with stronger signals within trials.

3. The Influence of Feature-Selective Payoffs

The right half of Figure 5 shows the estimates of marginal β and d' under the two payoff conditions—enhanced earnings for reporting a horizontal feature versus enhanced earnings for reporting an oblique feature. (As in Section 2, marginal values are used here, since we are not conditioning on other features in the stimuli.) These values were averaged over all observers, stimulus durations, and features in Experiment 2, and the fact that the values do not differ serves as a control result for differential feature effects.

The estimates of β as a function of the individual features, as seen in Figure 6, indicate the expected crossover; when the horizontal (oblique) feature was rewarded in Conditions H-S and H-I (O-S and O-I), the criterion for the horizontal (oblique) feature was lowered relative to that found when the oblique (horizontal) feature was rewarded. The crossover supports the idea that individual parts of patterns may be separately influenced by environmental variables such as the payoff situation. Notice also that the β is much larger for the vertical feature than for the other two; the vertical feature was not selectively rewarded in any of the conditions, and its criteria remained higher.

Since the neutral condition is confounded with the long stimulus exposure condition, an analysis of variance was

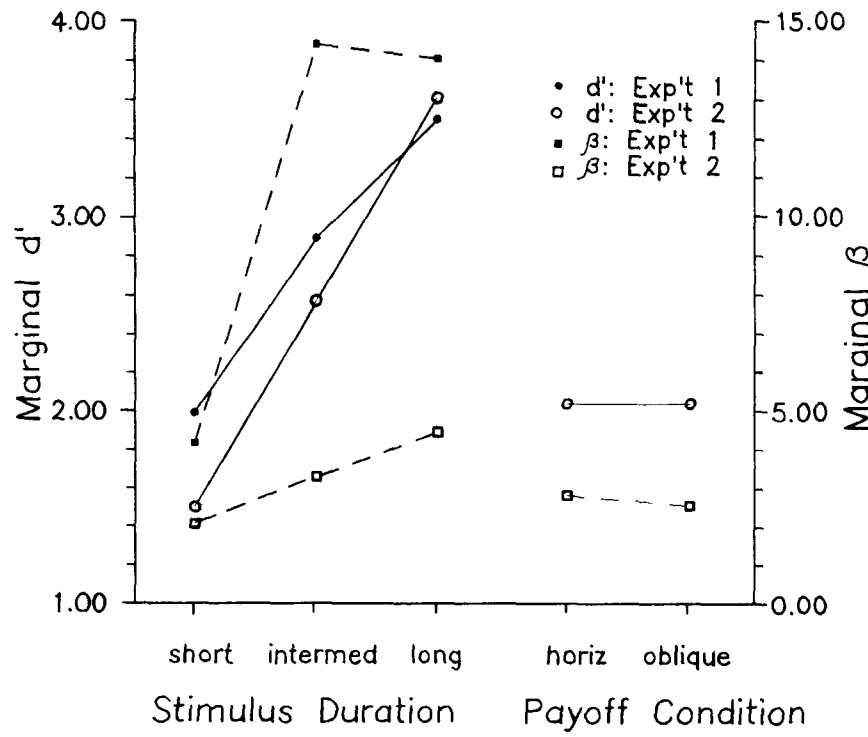

Figure 5. Marginal d' (circles) and β (squares) averaged over observers, features, and stimuli, showing the effects of stimulus exposure duration in Experiment 1 (solid symbols) and in Experiment 2 (open symbols), and the averaged payoff effects in Experiment 2.

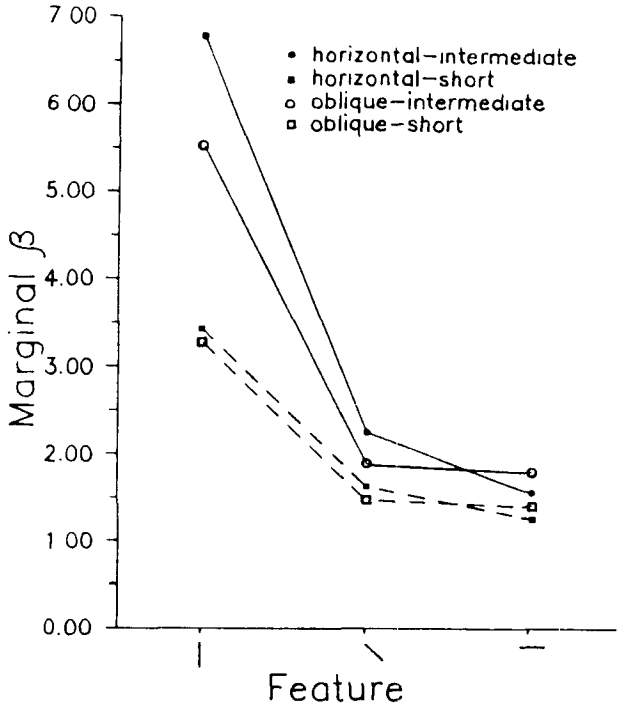

Figure 6. Marginal β values obtained in Experiment 2, averaged across observers, for each individual feature. (Circles denote intermediate stimulus duration, squares denote short stimulus duration; solid symbols denote horizontal feature payoff, open symbols denote oblique feature payoff.)

done only on the S-H, S-O, I-H, and I-O conditions, looking at each feature individually. The interaction between the stimulus duration and feature shown in Figure 6 was significant [$F(2,84) = 4.79$, $p < .05$], as were the two main effects for feature and stimulus duration [$F(2,84) = 32.67$, $p < .01$, and $F(1,84) = 11.51$, $p < .01$, respectively]. Thus, the response criteria were lowered for the two features with higher payoffs, as expected. All other effects in this analysis were nonsignificant.

Since most of the variance was due to the vertical feature, which was not selectively rewarded, we conducted an analysis of variance only on the two rewarded features in each condition, to see if there would be a selective payoff effect for the two features of most interest. This would bolster the qualitative crossover visible in Figure 6. This analysis again revealed a significant main effect for stimulus exposure duration, and a marginally significant interaction between features and the payoff conditions [$F(1,56) = 3.28$, $p = .08$]. In both exposure-duration conditions, the horizontal payoff lowered the β of the horizontal feature, relative to the oblique feature, while oblique payoff resulted in a lower β for the oblique features. It seems probable that bigger payoff asymmetries would produce more sizable β effects.

The d' values remained relatively invariant with payoff, as they should. An analysis of variance showed significant main effects only for stimulus-exposure duration [$F(1,84) = 323.48$, $p < .01$] and feature [$F(2,84) = 56.08$, $p < .01$]. Larger d' values were obtained in the intermediate-stimulus-exposure condition than in the short-stimulus-exposure condition, and, interestingly, higher d' values were obtained for the vertical feature than for the horizontal and oblique features, which did not differ from each other. This is consistent with previous findings (Townsend et al., 1981). All interactions for the d's were nonsignificant.

4. Reaction of d' and β to the Number of Features in the Stimulus Patterns

With regard to a sensory phase, although various theoretical positions predict that features might be more easily lost than artificially gained under degraded presentations, others predict the opposite (e.g., Garner & Haun, 1978; Geyer & DeWald, 1973; Lupker, 1979; Rumelhart, 1971; Townsend & Ashby, 1982). Although most investigators have placed the main focus of any asymmetry in the sensory phase, the decision phase is also important. If an observer believes that features are more likely to be lost than gained, he or she will tend to report patterns that possess a greater or equal number of features in them. Conversely, if an observer believes features are more likely to be gained, the tendency will be to report patterns with a smaller number of features. In experiments in which observers must report entire symbols, there is evidence that more features are lost than gained and that observers tend to act as if they almost never acquired ghost features (Townsend & Ashby, 1982; other whole-symbol-report studies have not provided for an analysis of this nature).

When all feature combinations are possible, it becomes feasible to separately analyze d' and β at the level of the individual feature within the context of a model that posits direct report of the detected features (see, e.g., Townsend & Ashby, 1982; Townsend et al., 1984). At this level, a lost feature is simply a "miss" and a ghost feature is simply a "false alarm." The pertinent thing to look for from this more delicate perspective is how (marginal) β and d' change as the number of features in a stimulus pattern increases.

Table 1 suggests that observers have a tendency to report fewer features than the presented patterns actually contain. Our macroanalyses, summarized in Figure 7 (i.e., signal detection analyses on the marginal d's and βs), reveal that, due to β values that are greater than 1, misses are much more frequent than false alarms. In Experiment 1, these response criteria decreased linearly as the number of features in a stimulus pattern increased [$F(1,69) = 6.58$, $p < .01$, for a linear trend analysis], which is the same pattern discovered in Townsend et al. (1984). However, in Experiment 2, the main effect of the number of features was not significant [$F(2,117) = 2.03$], even with extreme β values removed [$F(1,97) = 0.14$]. Nevertheless, as was the case in the earlier study, the lowered criteria still remained above a value of 1, leaving the predominance of lost over ghost features.

Unlike Townsend et al. (1984), there was no decrease in featural d' with increased complexity (see Figure 7).

Analysis of variance yielded a nonsignificant main effect for pattern complexity in both experiments [$F(2,69) = 0.77$ in Experiment 1 and $F(2,117) = 0.33$ in Experiment 2]. The failure to find a decrease in featural d' here was probably due to the fact that the feature set contained only three features, generating 8 patterns, whereas in the 1984 investigation, four features generated 16 patterns. Apparently, the range of complexity was not sufficiently great to cause sensitivity loss in the present experiments. In the 1980 and 1981 reports, where two straight lines at right angles generated 4 stimulus patterns, the sensitivity also did not change systematically from one to two features (see also Graham et al., 1985). Thus, it seems that an alphabet size of up to 8 patterns is insufficiently large to produce the sensory capacity limitations foreseen by Blobloc.

SUMMARY AND CONCLUSION

Blobloc has proven helpful in organizing our thoughts about a rather complex welter of relationships. Whether it will succeed in its substantive explanations is harder to foresee. Currently, its strongest support has come from the significant and consistent interfeatural dependencies, particularly the elevated featural d' conditional on correct responses on other features (also found in Townsend et al., 1984). The overall regularity of our results in recent studies seems to encourage the use of feature-detection macro- and microanalyses in other experimental contexts, such as in multisymbol interactions (e.g., Bjork & Murray, 1977; Egeth, Jonides, & Wall, 1972; Egeth & Santee, 1981; Estes, 1972, 1982; Santee & Egeth, 1980, 1982; Shapiro & Krueger, 1983).

The limitations of Blobloc have been pointed out throughout this report. While Blobloc postulates that interfeatural dependencies result from across-trial variations of image quality, a within-trial type of dependency cannot be conclusively dismissed at this time, although our analyses help to constrain the nature that this dependency could assume. In addition, Blobloc does not currently possess structure capable of depicting the fade-out of the featural capacity limitations as the stimulus patterns become simpler (invariance of d' with number of features in a stimulus pattern), found here and in Townsend et al. (1981), or the analogous disappearance of interfeatural dependencies found in the earlier (1981) study.

The results on β, the featural decision criterion, were mixed. There were some indications of a tendency for β to act as predicted as the number of pattern features was varied, but in one of the present experiments this effect

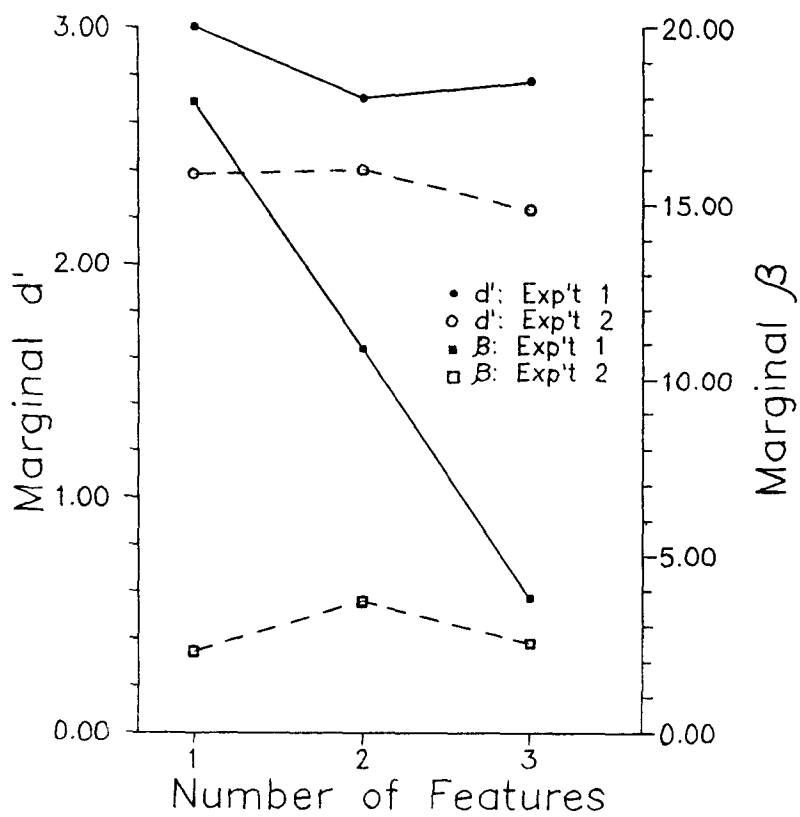

Figure 7. Marginal d' (circles) and β (squares) averaged across observers, experimental conditions, features, and stimuli for Experiment 1 (solid symbols) and Experiment 2 (open symbols).

was nonsignificant. Furthermore, although the conditional βs acted as predicted on correct rejections versus false alarms, they failed to vary systematically on hits versus misses. The response bias β consistently increased with stimulus energy, a result that can be derived from Blobloc if one supposes that certain within-trial phenomena (elevation of β with higher quality percepts) may be manifested across experimental conditions as stimulus energy is manipulated.

Finally, with respect to our energy and payoff manipulations, the tenets of signal detection theory regarding d' and β as functions of signal energy and payoffs were found to operate at the featural level. This is true in the strongest sense for β, which varied appropriately with selective interfeature payoffs. Although featural d' varied with stimulus pattern energy, we have not yet manipulated energy at the individual feature level.

In contrast to Blobloc, the general recognition model of Ashby and Townsend (1986) views recognition as involving a single sensory phase rather than two. A paper in progress (Townsend & Kadlec, 1988) relates our d' and β measures to the Ashby and Townsend propositions and treats our present and other feature data from this latter point of view.

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NOTES

1. Put another way, we feel there would seem to be merit in building a psychophysics of elementary pattern recognition with as much reduction of top-down and other complex influences as possible. This is analogous to the psychophysics of scaling or signal detection, where one attempts to experiment in an environment relatively devoid of higher order phenomena and to move to more complex models only when the simpler are falsified.

2 We have elsewhere referred to such experiments as "complete identification" paradigms (e.g., Ashby & Townsend, 1986, which provides other good reasons for using this paradigm). However, this term traditionally necessitates only the second stipulation, that there is exactly one response for each and every stimulus (i e., it is a noncategorizing experiment; Luce, 1963; Townsend, 1971). We therefore suggest the above term. The feature-complete factorial paradigm is akin to Graham, Kramer, and Haber's (1985) "concurrent experiment" with a one-to-one stimulus response assignment.

3. Observers 2 and 3 of the Townsend et al. (1984) study showed no statistical differences in their two β estimates. For Observers 1 and 4, however, the difference between the mean βs was highly significant. See Table 3 of this report for the d' and β values averaged over conditions for each individual observer.

4. Even though an individual feature can have its own "quality" or sharpness, Blobloc does not address the issue of how the qualities of individual features relate to the overall pattern quality. If the qualities of the individual features are low, then the pattern image may also have a low quality, or its quality may be increased by relational properties of the features in the pattern Similarly, if the individual features have high quality, it does not necessarily follow that the pattern quality will be high, since other aspects could degrade the image. Thus, what we mean by image quality is the sharpness, or clarity, of the image of the entire stimulus pattern

5 We refer to both the estimated and theoretical probabilities simply as probabilities to simplify our terminology, since it should be clear from the context which are implied. This remark also applies to the estimated and theoretical d' and β values of signal detection theory

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