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Conjunctive Search for One and Two Identical Targets

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The assumptions of feature integration theory as a blind, serial, self-terminating search (SSTS) mechanism are extended to displays containing 2 identical targets.The SSTS predicts no differences in negative-response displays, which require an exhaustive search of the display. Quantitative predictions are confirmed for the positive responses, but not for the negatives, suggesting that the SSTS model is incorrect. Two possible explanations for the results in the negative conditions, differential search rates and early quitting in the negatives, are rejected. It is suggested that using any self-terminating search mechanism will lead to difficulty in interpreting the results, including accounts for which the search is parallel over small groups of items. A resource-limited parallel model, which is based on the diffusion model of Ratcliff (1978), appears to fit the data well.

The feature integration theory has been successful in predicting and explaining the results of numerous experiments (for example, see Treisman & Gelade, 1980). A central tenet of the feature integration theory is that attention must be focused on a single location in order to conjoin the separable feature dimensions present at that location. The empirical distinction between conjunctive and feature search is generally assumed to show that although information concerning the presence of visual features is available preattentively, the relations among features can only be recovered with focal attention (Treisman & Gelade). The conclusion that search for a conjunctive target is a serial, self-terminating search (SSTS) process is based on the approximation to 2:1 slope ratios found between the negative and positive conditions of a typical conjunctive search experiment. A blind, serial search of the display implies that there is no information available to distinguish conjunctive targets from their distractors without sequentially focusing attention on single items.

However, in some respects, the claim that search for a conjunctive target is serial and self-terminating has been tested only within a limited methodology. Typically, subjects in a conjunctive search task are asked to search for a single target (e.g., Treisman & Gelade, 1980; Treisman, Sykes, & Gelade, 1977; Egeth, Virzi, & Garbart, 1984). Thus, whether search for conjunctive targets could occur in parallel is difficult to determine. In this article, we develop and test predictions based upon feature integration theory for searches involving one and two identical targets. Our predictions explicitly test the assumption that search for a conjunctive target is a blind, self-terminating search. In developing our predictions, we will first map the blind search mechanism of feature integration onto a simple urn model. Then we will use this model to generate predictions for searches involving one and two redundant targets.

A blind search, such as conjunctive search as understood in the feature integration theory, can be conceptualized as a classical urn problem. Imagine that we fill an urn with a number of balls, N. There are d black balls in the urn, equivalent to the number of distractors in the display. There are $N - d$, or t, white balls in the urn, representing the number of targets in the display. Drawing randomly from the urn is equivalent to choosing a location to attend to in the conjunctive search display. The task is to sample randomly from the urn without replacement until it is determined whether the urn contains at least a requisite number, g, of target balls. The variable g is then the minimum number of targets the subject must find to distinguish between the positive and negative displays. It can be seen that the standard visual search task, in which there is a single target in the positive conditions and no targets in the negative conditions, corresponds to an urn model in which $g = 1$ and $t = 1$ in the positive conditions and $t = 0$ in the negative conditions. We will use the term *display composition* to refer to the values of t and g for a given search task. A particular display composition will be notated by giving the number of targets in the positive and negative conditions. For example, a display composition with 2 targets in the positive conditions and 0 targets in the negative conditions would be notated as 2/0. Note that in order to force subjects to attempt to locate g targets, g must always be 1 greater than the number of targets in the negative conditions; the 2/0 notation thereby fully satisfies the requirements of a display composition. The experiments reported here use three display compositions: 1/0, which is a replication of the standard conjunctive search task; 2/0, in which subjects must find 1 of the 2 targets present in the positive conditions; and 2/1, in which subjects must find both of the targets in the positive conditions.

Having mapped the visual search task onto an urn model, we can now develop predictions for an SSTS model in the various display compositions. This is simple for the negative conditions, in which the number of targets is less than the number of goals, that is, $t < g$. In order to completely ensure that an urn does not contain g targets, the subject must make

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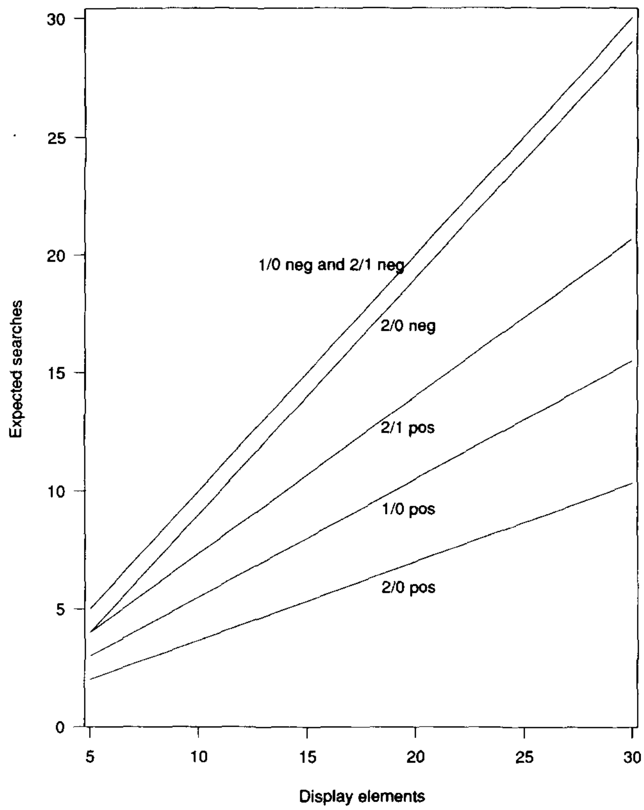

Figure 1. Expected number of searches for a serial, self-terminating search model for all display compositions as a function of t, g, and N.

an exhaustive search so that the number of balls left unsearched is less than g.

In the positive conditions, where $t \geq g$, the situation is more complex. We want to know, on the average, how many draws will be necessary to select g target balls. The number of expected searches can be calculated using the negative hypergeometric distribution. The expected number of searches required to find g targets by sampling without replacement from a group of N total elements and t targets is simply $(g * N + 1) / (t + 1)$ (e.g., Johnson & Kotz, 1977). Figure 1 plots the expected number of searches for the three display compositions for different values of N. It can be seen that for given values of t and g, the expected number of searches increases linearly with the total number of display elements, N. The slopes of the lines representing the predicted increase in searches with display elements vary in the positives but are the same in the negatives for all display compositions. The predicted ratio of negative to positive slopes is 2:1, 3:1, and 3:2 for the 1/0, 2/0, and 2/1 display compositions, respectively. We evaluate the SSTS model with respect to these predictions.

Method

Subjects. All 25 subjects were Carnegie Mellon undergraduates participating for class credit.

Design. Subjects were asked to determine if a specific number of targets, either one or two, were present in the display. A four-factor design was used. The first factor was whether the display contained the requisite number of targets—positive displays had the required number, negative did not. The second factor was level of display size, which refers to the total number of elements in the display including targets: 5, 10, 20, or 30 elements. These two factors were always varied within subjects. The third factor was display composition, which was varied between subjects. There were three levels of this factor, and within each level the number of targets present in both the positive and negative conditions was varied. In the notation described earlier, the three levels of display composition were 1/0, 2/0, and 2/1. The fourth factor was subject group. Subjects participated in two of the three display compositions. The first group of 13 subjects participated in the 1/0 and 2/1 display compositions; the second group of 12 subjects participated in the 1/0 and 2/0 display compositions.

Stimuli. Stimulus materials were presented on an IBM PC. In all cases, the target letter was a magenta N. Distractors were green Ns and magenta Os. The numbers of green N and magenta O distractors within a display were made as nearly equal as possible. In these displays, neither form nor color is sufficient in itself to identify the target, making this a conjunctive search task (Treisman & Gelade, 1980). Target elements, if any, were placed randomly on the display, and distractors were added so that the numbers of display elements in each quadrant of the screen were as nearly equal as possible. Each letter subtended about 0.8 × 0.8°, and the displays were presented in an area subtending about 12 × 12°.

Procedure. Trials were organized into 16 blocks of 64 trials each. The level of display composition alternated every 4 blocks. Each subject therefore ran 512 trials in each of two display composition conditions. The order of alternation was counterbalanced between subjects. Within a block, the subject received 8 trials of each display size in both the positive and negative condition. Subjects were instructed to determine as quickly as possible if the display contained the required number of targets. It was made clear to the subjects how many targets they would need to find in order to make a positive response (i.e., 1 target in the 1/0 and 2/0 sets and 2 targets in the 2/1 set). The presentation of a trial was as follows: A fixation cross appeared in the center of the screen for 1 s. The fixation cross was followed by the stimulus display. The display remained on the screen until the subject responded. Subjects responded by pressing a key on the keyboard, using their dominant hand to make a positive response. Subjects were informed if their response was in error. If the subject's error rate rose to more than 10%, the subject was instructed to slow down and proceed more carefully. Following subject errors, a random trial was presented for which the results were not recorded. After the subject had made a response, the fixation cross would appear again, and the cycle of trials would be repeated for the rest of the block. The entire task took about 45 min.

Results

The mean reaction times (RT) for correct trials are shown for each condition in Figure 2a. Reaction times that were more than 3 standard deviations from the condition mean were not included in the analysis. Data from all blocks are included in the analyses here, as the relative slopes of the different conditions did not appear to change significantly with practice. The factors used in the ANOVA to make this determination were subject group, number of targets in the positive displays, display size, positive or negative display, and block number. The five-way interaction was not signifi-

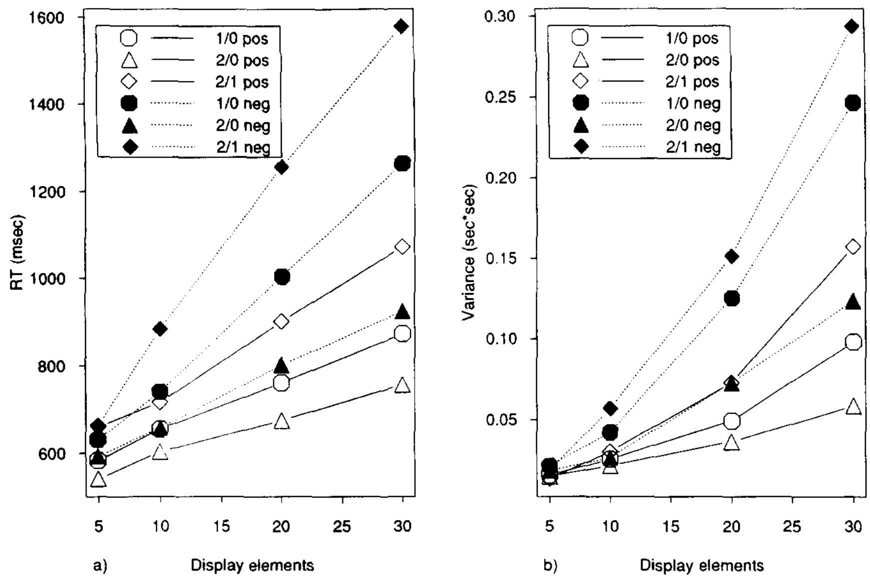

Figure 2. a. Mean reaction times as a function of display size. b. Variances as a function of display size.

cant, $F(21, 483) = 0.617$, indicating that the relative slopes for combinations of the display composition and positive/negative factors did not change significantly with block number. Means for the 1/0 display composition include scores from both subject groups. There was no significant difference in reaction time between the two groups, $F(1, 23) = 0.016$, and subject group did not interact with any other factor in the experiment.

Results from the ANOVA on the RT data in Figure 2 only confirm what seems apparent from the figure. The 2/0 conditions were the fastest, followed by the 1/0 and then the 2/1 conditions. The significance of these differences are indicated by the interaction of group and target number, $F(1, 23) = 53.1$, $p < .001$. There were significant main effects of display size, $F(3, 69) = 160.5$, $p < .001$, and positive versus negative displays, $F(1, 23) = 99.0$, $p < .001$. There was also a significant interaction of display size and positive versus negative displays, $F(3, 69) = 75.0$, $p < .001$, so that the difference between positive and negative displays became greater with increasing display size. The four-way interaction of all of these factors was significant, $F(3, 69) = 13.5$, $p < .001$, so that there was less interaction of the positive versus negative and display size factors in the display compositions producing the lower RTs.

In all conditions, search time increased roughly linearly with display size. Table 1 summarizes the linear regression data, and shows that the least squares fit to the average RTs accounts for over 99% of the variance in all conditions. Table 1 also shows the error rates for the positive and negative conditions. The overall error rate was less than 4%. False-positive rates were low and showed no systematic variance with increasing display size. However, in all display compositions, the false-negative rate increased with display size, as is typical in studies of this type (Egeth, et al., 1984; Pashler, 1987; Treisman & Gormican, 1988).

The 1/0 display composition in this experiment is intended as a replication of the standard conjunctive search task described in Experiment 1 of Treisman and Gelade (1980). As found by Treisman and Gelade, linear fits to the data in the 1/0 condition account for over 99% of the variance. In addition, the ratio of negative to positive slopes in the 1/0 set is 2.25:1, which is roughly in line with a similar ratio of 2.34:1 found by Treisman and Gelade.

The variances illustrated in Figure 2b are not consistent with those found by Treisman and Gelade (1980); they report that the positive variances increase faster than the negative variances with display size. Not only in the 1/0 display composition but also in all three display compositions, the negative variances grow at a greater rate than the positive variances. The rank ordering of RTs across conditions correlates almost perfectly with the rank ordering of variances. It is not likely that the discrepancy is due to the blocking of display compositions in this study. The greater increase in the negative variances over the positive variances is observed in all blocks, including the first four blocks, through which subjects have seen only one type of display composition.

Finally we examine the fit of the SSTS model to our RT data. Table 2 compares the observed RT slopes with those predicted by the SSTS model. The significance of the differences indicated by this comparison was assessed by first equating the different conditions for the number of searches predicted by the SSTS model. Figure 3 plots the mean RT for each condition against the expected number of searches predicted by the SSTS model. If we assume that the time to execute a single search is constant across display compositions, then the SSTS model predicts data from all conditions will fall along a single line, the slope of which would represent the time required per search. Figure 3 shows that these estimated search times coincide quite closely for the 1/0 negatives

Table 1
Summary of Regression Analysis: Mean Reaction Times and Percentages of Errors by Condition

Display size	Positive conditions Mean RT (ms)	Positive conditions % error	Negative conditions Mean RT (ms)	Negative conditions % error
1/0 display composition				
5	583	2.0	631	2.3
10	655	3.7	740	1.5
20	760	6.7	1,004	1.6
30	873	12.6	1,265	1.4
Intercept (ms)	532		494	
Slope (ms/item)	11.4		25.6	
R^2	.998		.999	
2/0 display composition				
5	541	1.9	593	3.5
10	603	3.0	658	1.8
20	674	4.2	801	1.8
30	756	8.1	925	3.3
Intercept (ms)	508		526	
Slope (ms/item)	8.33		13.42	
R^2	.992		.999	
2/1 display composition				
5	661	2.4	662	3.0
10	716	3.0	884	3.6
20	901	6.1	1,257	3.0
30	1,073	12.0	1,578	3.4
Intercept (ms)	564		503	
Slope (ms/item)	16.9		36.4	
R^2	.996		.996	

Note. RT = reaction time; R^2 = coefficient of determination.

and all the positive conditions. However, it is apparent from Figure 3 that the 2/0 and 2/1 negatives differ from the predictions of the SSTS model. In pairwise comparison of the slopes shown in Figure 3, the slopes for 2/0 negative and 2/1 negative conditions were significantly different from all other conditions, $p < .05$, with one exception (2/1 negative and 2/1 positive, $p < .06$). Linear regression provides one means of assessing the fit of the SSTS model. A regression of RTs on the number of searches predicted by the SSTS model produces a coefficient of determination (r^2) of .79. If the 2/0 and 2/1 negative conditions are excluded from the regression, the r^2 is .985.

Discussion

The SSTS model has two major failings in accounting for our data: (a) It does not explain the variances we observe, and (b) the RTs in the 2/1 and 2/0 negative conditions are not as predicted. We will examine both of these problems in detail and then propose a model that seems consistent with our results.

The SSTS model fails to predict both the relative variances between the positive and negative conditions and the rate of increase in variance in the negative conditions. In the SSTS model, search is terminated upon finding the target in the positive conditions, and search proceeds exhaustively through all display elements in the negative conditions (or through all but one element in the 2/0 displays). Thus the variability in the number of searches performed would be greatest in the positive conditions. This does not seem consistent with our finding that variance in the negative conditions is greater and increases faster than variance in the positive conditions. A second potential source of variance in RTs in the SSTS model is the variance in the time required to search a single display element. Because the SSTS model predicts more searches in the negative conditions than in the positive conditions, it is theoretically possible for variance in the negative conditions to exceed variance in the positive conditions when single-item search times are highly variable. The SSTS model could therefore be consistent with a wide range of variance results. However, variance in single-item search times can most likely be ruled out as an account of the present variance data. A linear regression comparing the standard deviation of RTs observed in the 1/0 positives with the standard deviation in the number of searches expected by the SSTS model in the 1/0 positives resulted in an r^2 of .992. Thus, according to the SSTS model, the expected variance in the number of searches would account for virtually all of the variance in RTs observed in the 1/0 positive condition. If variance in single-item search times is so small a factor in the 1/0 positive condition, then it is difficult to see how this source of variance could produce such large effects in the 1/0 negatives. It therefore seems unlikely that the greater variance observed in the negative conditions over the positive conditions is the result of variance in single-item search times. Interestingly, however, the time to conduct a single search as estimated by the slope of the above regression equation was 25.5 ms per search, a figure in good agreement with the time per search as estimated by the slope of RTs in the 1/0 negative condition (25.6 ms per search) shown in Table 1.

The increase of variances in our data appears to violate another prediction of the SSTS model. The increase in variance in both positive and negative conditions appears to be faster than linear with display size. Schneider and Shiffrin (1977) have shown that if the negative displays are being searched serially and exhaustively, then variance should increase only linearly with display size. Theoretically, RTs in the negative conditions reflect the summation of a number of comparison processes, one comparison for each display element. The variance in the sum of comparison processes should then be equal to the sum of the variances for each comparison process. Variance should therefore increase linearly with the number of comparison processes in the negatives. The fact that they do not suggests that, under an SSTS

Table 2
Comparison of Predicted and Observed Slopes in Milliseconds per Item

Display composition	Positive conditions Predicted	Positive conditions Observed	Negative conditions Predicted	Negative conditions Observed
1/0	1.5	1.37	3	3.07
2/0	1	1	3	1.61
2/1	2	2.02	3	4.37

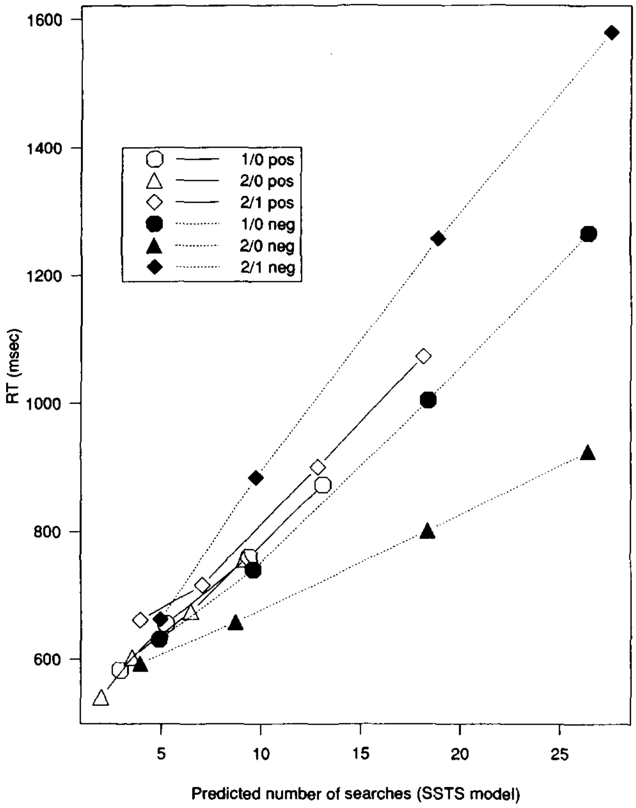

Figure 3. Mean reaction time as a function of expected number of searches computed by the serial, self-terminating search model.

model, there would be sources of variance in the negatives other than variance in the comparison process.

As noted earlier, the variances we report here do not agree with previous reports by Treisman and Gelade (1980). In their conjunctive search task, positive variances increased faster than negative variances. The significance of this failure to replicate the form of variances found by Treisman and Gelade is not clear. The normative form of variance to be expected in conjunctive search is not established at this time because, unfortunately, variance in RTs has generally not been reported in conjunctive search tasks. In unpublished results, A. Treisman (personal communication, August 9, 1988) reports cases of conjunctive search tasks where variance increases faster in the negatives than in the positives. Presently, it seems that the characteristics of positive and negative variance in conjunctive search require further examination.

The second major problem with the SSTS model is that it fails to predict our mean RT results in the 2/1 and 2/0 negatives. Although the SSTS model can explain effects of display composition on RT in the positive conditions, it is basically insensitive to display composition in the negative conditions, predicting exhaustive search in all display compositions. In contrast, it appears that subjects are sensitive to display composition in both positive and negative conditions and adjust their search accordingly. The problem in reconciling the SSTS model to the data is in making the SSTS model similarly sensitive to display composition in the negative conditions without disrupting sensitivity in the positive conditions.

Some minor variants of the SSTS model can be quickly discounted. The rate of search within each different display composition could be adjusted to fit the negative conditions; but from Figure 3, it seems that the time to execute a single search is constant for all three display compositions in the positive conditions. Proposed differences in processing speed between display compositions must explain why this difference in speed would be apparent only in the negative conditions. Another variant of the SSTS model assumes that subjects are not searching every location in the display but are quitting early after searching some large portion. Search will therefore be terminated before finding the target in a small number of positive displays, providing a reasonable amount of the false negatives. Because subjects would presumably find the target before reaching the cutoff in most of the positive displays, early quitting would reduce search times in the negative more than in the positive conditions, thereby lowering the ratio of negative-to-positive slopes. Early quitting might therefore explain why ratios of negative to positive slopes would be lower than predicted, as in the 2/0 composition, but would not explain why these ratios would be greater than predicted, as in the 2/1 composition.

Cluster models. Recently, Pashler (1987) and Treisman and Gormican (1988) have both suggested models in which search for a conjunctive target can occur in parallel within small clusters of display elements and continue in a process that is serial and self-terminating between clusters. The predictions generated for the relative slopes in the standard SSTS model may be largely applicable to these models. However, there are complications in considering how RTs in the cluster model might be affected by display composition. Since the cluster model predicts exhaustive search over clusters in the negatives, it faces one of the central difficulties of the SSTS model: unless it is assumed that some variable of the cluster model varies with display composition, such as cluster size or the search time within a cluster, the cluster model will be unable to account for the differences between display composition in the negative conditions. Unfortunately, including these types of variables considerably complicates analysis of the cluster model, making predictions about performance between display compositions difficult. Nevertheless, we can still make some useful characterizations about the cluster model by examining the predictions of the model on the ratios of negative-to-positive slopes within the three display compositions. As noted by Pashler (1987), the cluster model predicts differences in positive and negative slopes only when cluster size is less than the number of elements in the display. Accordingly, we will limit our discussion to cases in which cluster size is smaller than total display size.

The 1/0 composition is simplest. When only one or zero targets appear in a cluster, the cluster model can be mapped directly to the SSTS model already developed. Rather than operating over single elements representing targets and distractors, the SSTS process operates over larger units that can be determined to represent the presence or absence of a target.

The cluster model should therefore predict a negative-to-positive slope ratio of 2:1 in the 1/0 compositions, just as in the standard SSTS model.

In the 2/0 positive conditions, it is possible that a cluster will contain both targets. This situation is analogous to the 1/0 composition, because in this case there is only a single cluster in the display that can terminate the search process. The likelihood of both targets appearing in the same cluster decreases as we decrease the proportion of the total display contained within each cluster. Thus, in the 2/0 compositions, we would expect the ratio of negative to positive slopes in the cluster model to have a conservative lower bound of 2:1 and we would expect this ratio to increase toward the standard SSTS prediction of 3:1, as the probability of both targets appearing in a single cluster decreases. This would be the case if we held the cluster size constant as we increased the total number of elements in the display.

The predictions for the 2/1 compositions depend on specific assumptions about the nature of the parallel within-cluster search process and in particular on whether it is assumed that the parallel search can distinguish between one and two targets in a cluster. Unless the ability to make this distinction is assumed, the nature of the task in the 2/1 compositions requires that cluster size be small to reduce the possibility of two targets within a cluster. With only one target per cluster, the cluster model will produce the same predictions for negative to positive slope ratios as the standard SSTS model. If the parallel search process is presumed to be capable of detecting the presence of two targets within a cluster, the situation changes. As mentioned earlier, when there is only one cluster in the display that can terminate search, the situation is analogous to the 1/0 composition. We would then expect a negative to positive slope ratio with an upper bound of 2:1 and would expect this ratio to approach the SSTS prediction of 3:2, with increasing numbers of clusters in the display.

In summary, although the cluster model does improve somewhat upon the predictions of the standard SSTS model in predicting our data, it still seems to share many of the difficulties of the SSTS model in predicting the RT data we observe. First, unless it is assumed that the parallel search process is capable of counting the number of targets in a cluster, the cluster model will not differ at all from the SSTS model in the 2/1 compositions. Second, as the number of clusters per display increases, the predictions of the cluster model tend to look like the standard SSTS model. Only when cluster sizes are so large that both targets are likely to occur in the same cluster do the 2/0 and 2/1 compositions approach the 2:1 ratios of negative to positive slopes that approximate our findings. However, if both targets tend to always appear in the same cluster, the 2/0 and 2/1 compositions will look identical to the cluster model in the positive conditions. In both compositions, there would be a single cluster in the positive conditions, containing both targets, that would terminate the search when found. In this case, the cluster model would not predict the relative speed of the 2/0 composition over the 2/1 composition unless it is further assumed that search rate within a cluster varies between display compositions. Finally, the cluster model is exhaustive over the negative conditions, and self-terminating over the positive conditions; as such, it makes the same qualitative predictions for variance as the standard SSTS model.

The diffusion model. An alternative model that may be able to account for both our RT means and variance trends is based on the Ratcliff (1978) diffusion model. Similar models have been used to reproduce the 2:1 negative-to-positive slope ratio characteristic of a serial, self-terminating search (Broadbent, 1987). In the diffusion model, one views processing as an evidence-accumulation process, much like a random walk, that proceeds simultaneously over all display locations. The important assumptions of the diffusion model, as we have adapted it for the present task, are as follows: (a) For each item in the display, there is a corresponding detector that accumulates evidence for and against the hypothesis that the item is a target, so that search occurs in parallel over the display. One such detector is illustrated in Figure 4. (b) For all detectors, there is a resting activation level (z), a positive threshold (a), and a negative threshold (fixed at 0.0). Search terminates with a positive decision when enough (i.e., g) detectors have crossed their positive threshold. (c) Search terminates with a negative decision when all but ($g - 1$) detectors have crossed their negative threshold. (d) Although this was not assumed in the original Ratcliff model, we assume that search for a conjunctive target is subject to limitations on attentional resources. This assumption is operationalized by making the rate at which evidence accumulates for and against target presence inversely proportional to the square root of N, the number of elements in the display. In the diffusion model, each detector is assigned a base evidence-accumulation rate, with a mean of u for targets and v for nontargets and with a variance of η^2. The rate of evidence accumulation for a particular detector on a particular trial is then a normally distributed random variable with a mean of $u/\sqrt{N}$ for targets ($v/\sqrt{N}$ for distractors) and variance of η^2.

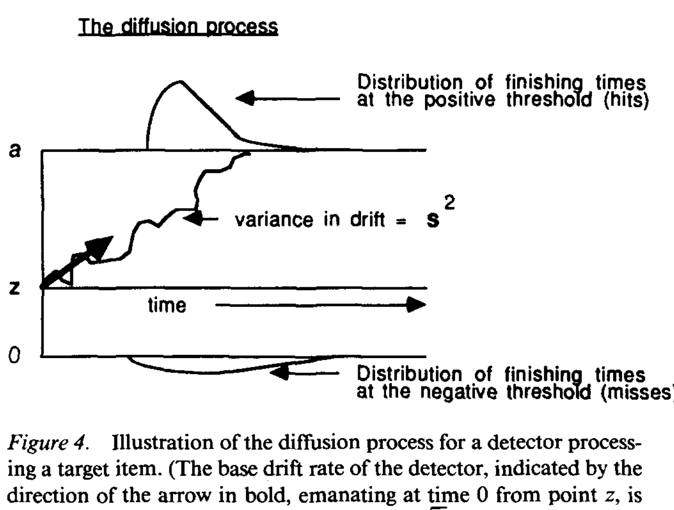

Figure 4. Illustration of the diffusion process for a detector processing a target item. (The base drift rate of the detector, indicated by the direction of the arrow in bold, emanating at time 0 from point z, is sampled from a distribution with mean $u/\sqrt{N}$ and variance η^2. At each time step, the actual direction of movement varies normally around this base drift rate with variance s^2.)

The mean rate of movement, or drift, toward the thresholds will be equal to a detector's base rate. At each time step, the actual direction of drift varies normally around this base drift rate with a variance of s^2, the sixth and final parameter of the model.

First let us examine the qualitative performance of the model when we hold all parameters constant across display composition. The effects of display composition in the positive conditions follow in a straightforward manner. In the 2/0 display compositions, search time is determined by the first of the two detectors in target locations to cross the positive threshold, and in the 1/0 display compositions, search time is determined by the time for the single detector in the target position to cross the positive threshold. On average, the faster of two random processes will be faster than a single random process, and we would therefore expect the 2/0 display compositions to be faster than the 1/0 display compositions. False negatives should also be less likely in the 2/0 than in the 1/0 composition, because there are two target detectors that must cross the negative threshold in the 2/0 composition, as opposed to the single target detector in the 1/0 composition. Similarly, in the 2/1 display compositions, where search time is determined by the last of the two target detectors to cross the threshold, the 2/1 display compositions should be slower than the 1/0 display compositions, because the slower of two random processes will be slower on average than a single random process. The false-negative rate will be highest in the 2/1 composition, because false negatives are possible whenever either of the two target detectors crosses the negative threshold.

The effects of display composition in the negative conditions are also straightforward. As in the positive, display composition determines not only search time, but also error rates. In both the 2/1 and 1/0 compositions, search time in the negatives is determined by the time for all distractors to cross the negative threshold. Because there is one less distractor in the 2/1 negatives than in the 1/0 negatives, the 2/1 composition is slightly faster than and will produce fewer errors than the 1/0 composition, when all parameters are fixed. The 2/0 composition is faster and less errorful than the other compositions, because in this case, search time is determined by the time for all but one of the distractors to cross the negative threshold.

Thus, with all parameters fixed across display compositions, the model captures most of the qualitative trends in RTs but fails to capture the differences we observe between the 2/1 and 1/0 negatives and fails to account for the relatively constant rate of false negatives across display compositions. Both of these difficulties may be addressed by supposing that subjects may vary their thresholds in response to task variables. A reasonable strategy would be to adopt an acceptable rate of false negatives and adjust the resting activation level and thresholds in response to display composition to maintain this false-negative rate. For example, as we increase the distance between the resting level and the negative threshold, the rate of false negatives decreases, and latency in the negatives, as well as the rate of false positives, will increase.

In order to maintain roughly equivalent error rates in a more difficult task, thresholds in the 2/1 composition must be more widely separated than in the 1/0 composition. Conversely, the separation of positive and negative thresholds should be smallest in the 2/0 composition. In the simulation illustrated in Figure 5, thresholds were varied in each display composition so that the simulation produced error rates approximating the actual error rates we observed. A comparison of the error rates given in Table 3, those generated by the simulation, with the error rates given in Table 1 shows that the simulation captures the increase in false negatives with display size, as well as the relatively low and stable false-positive error rates. There is a tendency for the model to make more false-positive errors on larger display sizes, but this tendency is minimized by the ceiling effect of the almost perfect performance in the negatives. Varying thresholds with display composition not only produces roughly correct error rates, but also brings search times between display compositions closer to our observed RTs. In particular, the 1/0 negatives become faster than the 2/1 negatives. A linear regression of mean RTs onto the search times generated by the simulation produces an r^2 of .966 when an additional intercept parameter is added to negative RTs.

The predictions of the diffusion model for variance results are complex. In the current simulation, the model generates the variance functions shown in Figure 5b, which look similar to those in our data. In particular, the variances in the negative conditions increase faster than in the positive conditions, although this difference is minimal in the 2/0 composition. For both positive and negative conditions, the increase in variance is faster than linear. However, the diffusion model does not necessarily produce variance functions of this sort. In predicting how variance changes with display size in the diffusion model, there are two important factors to consider. The first factor is the distribution of times expected for a single detector to reach threshold. In the model, this factor is a function of the rate of evidence accumulation. As the rate of evidence accumulation decreases, the right tail of the distribution is extended, but the left tail remains relatively stable, resulting in increased mean RT and a greater variance in the distribution. Because the rate of evidence accumulation is assumed to be a function of the number of elements in the display, this would tend to produce the largest variances in the conditions with the slowest RTs, as observed in our results. The second factor to be considered in estimating the variance is the number of detectors that must finish before the response can be selected. The variance of the last of n finishing times generally decreases with n. So, as display size increases in the negative conditions, there will be less variability in the time for the last detector to cross negative threshold. In these conditions, then, the change in variance with display size predicted by the model will result from the interaction of two variables: (a) how quickly variance in single-detector crossing times increases with display size, and (b) how quickly variance in the final detector's finishing time decreases with display size. Within a particular display composition, the number of detectors required to cross threshold in the positive conditions does not change with display size. The change in variance with display size for the positive conditions will only be a function of the increased variability of single-detector crossing times.

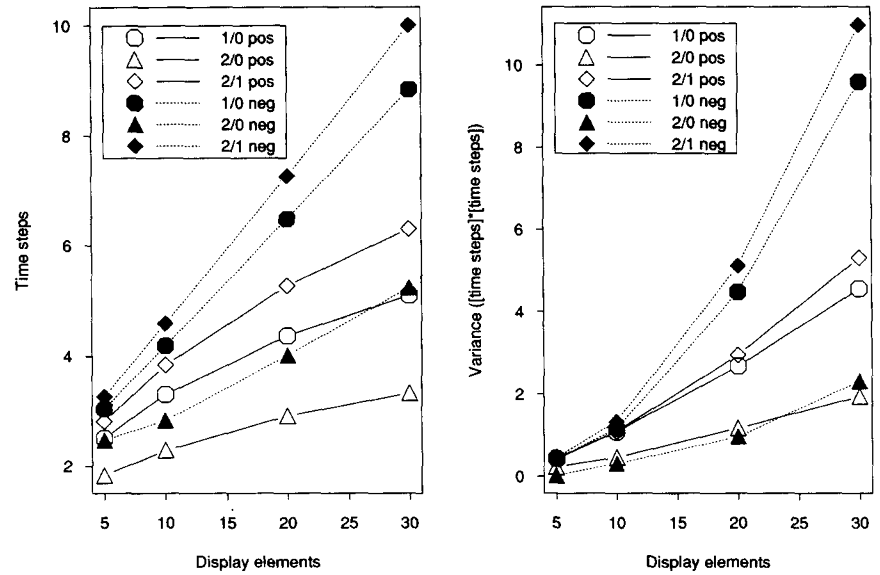

Figure 5. Results from the diffusion simulation. (Parameters for the simulation were as follows: For all display compositions: $u = 6.025$, $v = -4.656$, $\eta = .07$, $s = 1.15$. Thresholds varied between display compositions: 1/0: $a = 6.65$, $z = 1.23$; 2/0: $a = 5.0$, $z = .74$; 2/1: $a = 7.0$, $z = 1.65$.) a. Search times for all display compositions predicted by simulation of the diffusion model. (This figure includes an additional intercept parameter of 1.45 time steps in all negative conditions.) b. Variance in search times for the diffusion model simulation. (No intercept parameter has been included.)

The loosely constrained nature of variance predictions in the diffusion model suggests a possible resolution of the discrepancy between the variances we report and those of Treisman and Gelade (1980). If we lower the rate of evidence accumulation for targets, we predict greater positive variances. A simulation of the Treisman and Gelade data was performed by taking the parameters used in the simulation of our own data and lowering the rate of evidence accumulation for targets, u. In order to fit the error rates reported by Treisman and Gelade, the positive and negative thresholds were separated to compensate for the lower value of u, resulting in greater search latencies. The resulting ratio of negative to positive slopes for search time was 2.0:1, and the ratio of negative to positive slopes for variance was 0.87:1, a result at least qualitatively consistent with Treisman and Gelade. The suggestion that targets in the Treisman and Gelade study were less easily identified than in our study is consistent with the fact that the materials used by Treisman and Gelade were drawn with colored marker pens on white tachistoscopic cards and probably provided considerably less contrast than our CRT displays. Furthermore, the slopes of RT functions in the Treisman and Gelade data are steeper than in our data. As noted by Treisman and Gelade, increased RT slopes are indicative of more difficult discriminations between targets and nontargets. The diffusion model thereby offers a means of explaining different variance results by providing a theoretical link between target identifiability and the relative variance between positive and negative conditions.

Table 3
Error Rates (Percentage Error) Generated by the Diffusion Model Simulation

	Display size			
Condition	5	10	20	30
1/0				
Positive	0.7	2.9	8.1	12.6
Negative	0.2	0.4	1.0	3.6
2/0				
Positive	0.2	1.4	4.8	7.8
Negative	0.0	0.0	0.0	0.4
2/1				
Positive	0.3	1.8	7.0	12.3
Negative	0.1	0.3	1.1	3.8

Conclusion

Besides providing a good fit to mean RTs, the diffusion model also accounts for error rate trends and some aspects of RT variance trends and may even provide a means for explaining differences between experiments. Although it may be possible to fashion some variant of a serial model that can account for all of this data, this has not been done; the evidence presented here suggests a parallel, rather than serial, search. Given this, one may return to the fundamental issue raised by Treisman and Gelade (1980): Is information concerning the conjunction of features available before attention is focused on a single location? In other words, do conjunctive targets require serial search? Our present findings, as well as recent arguments by Pashler (1987) and Treisman and Gormican (1988), suggest that at least some form of information regarding the conjunction of features is available preattentively, although exactly what information may be represented is still an open question.

In any case, one thing should be very clear. It is perilous at best to rely on linearly increasing RT functions and approximately 2:1 slope ratios between positive and negative RTs in the 1/0 display composition as evidence of an SSTS process. Models such as Ratcliff's (1978) diffusion model have proven capable of accounting for apparently serial findings, as well as aspects of the data that do not conform well to a serial account, both in this research and in other contexts. Such models therefore deserve our consideration as we try to understand the process of visual search.

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