Tracking visual search over space and time

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Visual perception consists of early preattentive processing and subsequent attention-demanding processing. Most researchers implicitly treat preattentive processing as a domain-dependent, indivisible stage. We show, however, by interrupting preattentive visual processing of color before its completion, that it can be dissected both temporally and spatially. The experiment depends on changing easy (preattentive) selection into difficult (attention-demanding) selection. We show that although the mechanism subserving preattentive selection completes processing as early as 200 msec after stimulus onset, partial selection information is available well before completion. Furthermore, partial selection occurs first at locations near fixation, spreading radially outward as processing proceeds.

Vision affords an enormous amount of information about the world, only a small fraction of which is submitted to detailed analysis. Thus, before anything else, perception must sift the incoming information to identify portions likely to merit further processing. This process must be fast enough that the organism can respond adaptively to dynamic environments. In this paper, we investigate how visual selection occurs, using data from a search task. In visual search tasks, observers determine whether or not a target appears in a complex display; data from search tasks are an effective probe of those visual features to which the early mechanisms that subserve selection are sensitive.

Researchers categorize visual search performance in terms of response time (RT) patterns. In *pop-out* search, RT for correct responses is independent of the number of distractors in the stimulus; in *difficult* search, RTs are much longer and increase roughly linearly with the number of distractors (Treisman & Gelade, 1980). Pop-out search is possible for some target-distractor differences and not for others. The distinction is thought to indicate properties of the neural mechanisms that subserve early vision: preattentive mechanisms performing pop-out search, and performing difficult search attention-demanding processing (Treisman & Gelade, 1980; Wolfe, 1994; Wolfe, Cave, & Franzel, 1989). Although theorists recognize the importance of preattentive processing (Enns & Rensink, 1990; Julesz, 1981; Treisman & Gormican, 1988), most work on attention implicitly considers preattentive processing to be performed by a domain-dependent, all-or-nothing mechanism (Treisman & Gelade, 1980; Wolfe, 1994). Our experiments show, however,

that preattentive processing of color can be dissected both temporally and spatially.

Two recent studies (Bauer, Jolicœur, & Cowan, 1996; D'Zmura, 1991) described a characterization of the target-distractor relationship that affords pop-out search. Whenever a target can be segregated from every distractor by a single straight line in an appropriate (two-dimensional) stimulus space, pop-out search is possible. Such targets are *linearly separable* from the distractors. Targets that are not linearly separable produce difficult search patterns. These studies used color differences to define target-distractor relationships, because color perception can be quantitatively characterized by a three-dimensional feature space (Wyszecki & Stiles, 1982). In this space, two dimensions appear as chromatic hue and saturation, and the third dimension appears as intensity. Each color is a point in this three-dimensional space. At constant stimulus intensity (*equiluminance*), each color is a point in a two-dimensional plane in the space. Two equiluminant distractor colors define a line in that plane, and if the target color falls on the line between those two points, search for the target is difficult; otherwise, the target pops out (Bauer, Jolicœur, & Cowan, 1996, 1998, 1999; D'Zmura, 1991; see also Olds, Cowan, & Jolicœur, 1999). Thus, the conditions for pop-out search are linear computations along standardized psychophysical dimensions, the same dimensions that predict color matches.

This paper analyzes the spatial and temporal characteristics of pop-out search provided by linearly separable stimuli, by interrupting pop-out search before it finishes. Our methodology allows us to examine critical theoretical questions concerning early vision. For example, most early theories consider feature search (pop-out) to occur homogeneously in the entire field of vision (Treisman & Gelade, 1980). However, target eccentricity has recently been shown to affect performance (Carrasco, Evert, Chang, & Katz, 1995). Are eccentricity effects perceptual, attentional, or both (Carrasco & Frieder, 1997; Wolfe, O'Neill, & Bennett, 1998)? Only a more detailed model of spatial performance will answer such questions: In this paper, we

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describe a way to track the development of pop-out search across different locations in the visual field.

Furthermore, theories of pop-out search implicitly consider pop-out to occur in an all-or-nothing fashion (Treisman & Gelade, 1980; Wolfe, 1994), despite suggestions (e.g., Wolfe, 1994, p. 229) that target location information could accrue over time. In what form, if any, is this information available to attentional processes? That is, does information from *partially completed* pop-out search inform and influence other search processes? Again, a quantitative model of temporal performance is needed. The experiments described below provide constraints that must be satisfied by any model of spatial and temporal effects in early vision.

In our experiments, an observer reports the presence or absence of a target, seen among distractors. The target, present on half the trials, is a disk of color T; the distractors are identical but differ in color. The first portion of a trial presents the target and distractors of one color, D1. Pop-out search is possible for such stimuli. Later, a second set of distractors of color D2 is added (in the locations not already occupied by D1 distractors). In the experiment reported here, D2 is chosen so that T is not linearly separable among D1 and D2 (i.e., T is between D1 and D2 in color space) making a display for which pop-out search is not possible. Thus the second set of distractors serves as a mask that prevents further pop-out processing and as a probe by which to examine the influence of incomplete pop-out search on difficult search. Importantly, the D2 distractors mask pop-out processing *without* masking the existing display. (Control experiments have shown that the onset of extra distractors in itself only minimally disrupts efficient search; Olds, Cowan, & Jolicœur, 2000.)

Overall RT is often used as a measure of search difficulty, with a pattern of fast RTs being labeled as pop-out search. However, RT includes motor and other nonperceptual components required in order to make a response. The interruption technique allowed us to measure the duration of pop-out search *independently of overall RT*, thus pinpointing the perceptual components, as follows. If the linearly separable display (the first portion of the trial) is presented for a sufficiently long duration, the target can be detected before the second set of distractors interrupt pop-out processing. In the extreme, imagine the second set of distractors appearing after 5 sec, after the observer has responded. RT will be fast, similar to RT in a control condition in which there is always only one color of distractor. As we decrease the duration of the linearly separable stimulus, we can measure how much time these fast processes require to complete. We measure the smallest duration that still results in the pattern of RTs characteristic of pop-out search. This is our measure of how long the perceptual component of pop-out search takes.

Watson and Humphreys (1997) used a similar technique in which additional items are added to a search display after a delay. In their experiments, some of the distractors were previewed, and then after a delay, more

distractors appeared along with the target. That is, like our displays, the displays of Watson and Humphreys had items added after a delay; however, their technique measured whether previewed distractors could be ignored in subsequent search (a kind of priming), whereas our technique uses delayed-onset distractors as a way to interrupt certain kinds of search processes (a kind of mask).

METHOD

The first portion of the stimulus contains the D1 distractors and, on half of the trials, the target. The second portion of the stimulus contains everything from the first portion plus the D2 distractors. The duration for which the first portion of the stimulus is present, before the onset of the D2 distractors, is the stimulus onset asynchrony (SOA). In the experiment described below, trials with different SOAs were presented blocked, so the observer always knew what SOA to expect. The SOAs were 0, 50, 100, 150, 200, 250, 300, and 1,000 msec, and there was a control condition ($SOA = \infty$) in which the second part of the display never appeared. The $SOA = \infty$ condition was a control condition measuring pop-out search performance. The $SOA = 0$ condition was a control condition as well, measuring pure difficult search, because the stimulus never contained distractors of a single color.

Observer

Because the results appear most clearly as within-subjects comparisons, we present here the results for 1 female, aged 28 (author E.O.), with normal color vision by standard measures. The results are typical of other observers as well.

Equipment

Testing was carried out on a Macintosh PowerMac 6100 computer, using MATLAB software and Brainard's (1997) Psychophysics Toolbox routines. The stimulus colors were set with a Minolta Chroma Meter CS-100.

Stimuli

The experimental stimuli were colored disks measuring 8 mm in diameter (0.75° of visual angle), on a near-gray background with chromaticity coordinates ($x, y = 0.327, 0.332$). The disks and background were equiluminant (25 candelas/m²). The target's chromaticity coordinates were (0.416, 0.364); the distractors' chromaticities were (0.416, 0.351) for D1 and (0.416, 0.377) for D2. *CIE*Luv is a color space in which distance corresponds roughly to perceived color difference; the *CIE*Luv coordinates were (100, 0.206, 0.472) for the background, (100, 0.255, 0.501) for T, and (100, 0.249, 0.507) and (100, 0.261, 0.495) for D1 and D2, respectively.

The stimulus contained 18 distractors of each of two distractor colors (set size—i.e., the number of items in the display—was not varied), when there was no target present. When the target was present, it replaced one of the distractors. The colored disks appeared in a 6×6 grid (7.6° across), so that during the second portion of the stimulus (except in the $SOA = \infty$ control condition), the grid was filled with 36 disks. Each disk location was randomly perturbed up to one-seventh of a disk diameter both horizontally and vertically. The target could appear at any of the possible grid locations, except for the four corners.

Design

Each testing session consisted of nine blocks (one for each SOA) of 64 trials each (32 target positions crossed with present/absent). A pseudo-random ordering of trials prevented runs of more than 3 consecutive trials with the same trial type (present/absent) and runs

of more than 4 consecutive trials with the same target position. The positions of the D1 and D2 distractors were randomized on each trial.

Procedure

On each trial, the observer saw a white fixation stimulus, which was a + for the first trial. On subsequent trials, the fixation was a + after a correct response and a - after an error. The fixation stimulus was present for 400 msec, followed by a blank screen for 400 msec. Next, the stimulus was displayed until the observer responded. Each block of 64 experimental trials was preceded by 15 practice trials. The observer adapted for several minutes in the dimly illuminated experimental room before testing began.

The observer completed six sessions for a total of 3,456 experimental trials.

RESULTS AND DISCUSSION

A recursive outlier screening procedure (described in Van Selst & Joliceur, 1994) eliminated 2.3% of correct trials based on RT (RTs were screened from cells defined by present/absent and SOA). Analyses are reported for the screened data only, but the results differ little from those for the original data. We focus on responses to target-present trials, because target-absent responses are thought to depend on a more varied range of strategies (see, e.g., Chun & Wolfe, 1996).

The effect of SOA on hit (target present, observer responds *present*) RT was significant [$F(8,1429) = 317$, $MS_e = 249,866$, $p < .0001$]. Hit RT decreased with increasing SOA until RT performance was indistinguishable from the pop-out control condition, $SOA = \infty$ (see Figure 1A; Figure 1B will be addressed later in the discussion). Improved detection performance, as compared with the difficult control condition ($SOA = 0$), shows that useful processing occurs on some trials with only 50 msec of exposure to the linearly separable stimulus.

The frequency distributions for hit RTs for the different SOA conditions are shown in Figure 2A. The control conditions yielded RT frequency distributions for pure difficult search ($SOA = 0$) and for pure pop-out ($SOA = \infty$). Note that the two control distributions do not overlap: The maximum RT for the pop-out search control condition was 694 msec, and the minimum RT for the difficult search control condition was 830 msec. Because the distributions of the overt response times do not overlap, we assume that the distributions of the finishing times for the perceptual processing that *mediates* the two types of overt response also do not overlap. To investigate the interactions between the mechanisms responsible for pop-out and difficult search, we compared the control distributions with the distributions for the intermediate conditions.

We tested the hypothesis that the difficult search results are unaffected by the prior existence of conditions affording pop-out search, except that when pop-out search succeeds, difficult search does not occur. The class of models that could be included under this hypothesis includes race models, in which two processes start together, with the first to complete providing the response. It also includes mixture models, in which each trial randomly produces either difficult or pop-out search. We call this the *independ-*

dence hypothesis, because the pop-out and difficult search mechanisms are assumed to function without interacting, except through access to response selection.

We analyze such models starting with a hypothetical model, the convex model. In the convex model, there are two mechanisms, which operate independently of each other. The composite response on any trial is produced by picking one mechanism at random and accepting its response. In the convex model, the RT distribution of the two mechanisms running together is a convex combination of the RT distributions of the two mechanisms. (The convex combination is a weighted sum of the two distributions, with nonnegative weights that add to one.) Results of the convex model are easy to calculate, and often models like race and mixture models have results that are small systematic deviations from the results of the convex model. This is true for the particular component distributions found in our experiment, as we will show, later in the paper, with Monte Carlo simulations (and with algebraic calculations; see Olds et al., 2000).

The mixing parameter, the proportion of trials on which the difficult mechanism finds the target, is defined to be λ . $\lambda = 1$ when $SOA = 0$, because there is no chance for the pop-out search mechanism to operate in a display that is not linearly separable; $\lambda = 0$ in the all pop-out condition ($SOA = \infty$). λ should fall with increasing exposure to the linearly separable display (i.e., with increasing SOA), as the pop-out search mechanism succeeds on an increasing proportion of trials.

Describing distributions by their moments is a well-accepted technique in mathematical statistics (e.g., Brunk, 1975). It recognizes that average quantities of distributions are the best-characterized parameters, particularly when the distribution is estimated from a small sample. We used the first four moments to characterize the distributions, higher moments being increasingly noisy. The j th moment, $\bar{x}^j$, is defined as

$$\bar{x}^j = \frac{\sum_{i=1}^n (x_i^j)}{N}. \quad (1)$$

The first moment $\bar{x}^1$ is the sample mean, whereas the second, third, and fourth moments ($\bar{x}^2$, $\bar{x}^3$, $\bar{x}^4$) are related to variance, skewness, and kurtosis, respectively. Moments of mixtures of distributions are linear combinations of the moments of the original distributions entering into the mixture. If two distributions, x and y , are mixed together in a 3:1 ratio, for example, their moments will be mixed together in the same way: The first moment of the mixture will be $(.75\bar{x}^1 + .25\bar{y}^1)$, the second moment will be $(.75\bar{x}^2 + .25\bar{y}^2)$, and so on. That is, given independence, every moment is the same convex combination of the difficult and the pop-out moments as the distribution is of the difficult and the pop-out distributions. Therefore, we use the moments, rather than the full distributions, to compute the mixing parameter λ . The independence prediction is that each moment (for a given intermediate SOA) will yield the same estimate of λ .

Figure 1. (A) Mean response time (RT) for correct responses as a function of stimulus onset asynchrony (SOA). Mean RT for target-present and target-absent trials, for observer E.O. (normal color vision by standard measures). Error bars show one standard error above and one standard error below the mean (these are quite small because of the large number of trials, and most are hidden by the plot symbols). (B) Hit RT as a function of SOA, plotted separately for targets appearing in each orbit. Targets in the four orbits appeared roughly 0.8°, 1.9°, 2.9°, and 3.4° away from fixation.

To test independence, we calculated λ for the first four moments of each intermediate RT distribution by solving the following equation:

$$\overline{x^j}_{(SOA)} = \lambda_{j(SOA)} * \overline{x^j}_{(SOA=0)} + (1 - \lambda_{j(SOA)}) * \overline{x^j}_{(SOA=\infty)} \quad (2)$$

The results are shown in Figure 2B: There are clear systematic variations of mixing parameter λ with SOA for the

different moments.¹ Therefore, the mechanisms responsible for difficult and pop-out search are not independent; they interact with one another. In particular, the higher the moment used to calculate λ , the faster λ falls as SOA is increased. The higher moments tend to reflect the properties of the tails of the distribution; for positively skewed distributions, such as we have in our results, the higher moments reflect properties of the right tail. Thus, the right tail of the RT distribution shrinks with increasing SOA

faster than the mean of the distribution does, indicating that the slowest trials are being disproportionately sped up as SOA is increased (the distributions in Figure 2A show how quickly the right tail is brought in with increasing SOA). This quantitative effect is possible only if incomplete pop-out search assists difficult search by speeding the longest trials.

Monte Carlo Simulations

The λ s are predicted to coincide for the convex model, where two noninteracting processes begin simultaneously. To demonstrate this prediction, we combined bootstrapping methods with Monte Carlo simulation. The empirically obtained pop-out control RT distribution ($\text{SOA} = \infty$) contained 174 data points, and the difficult search control distribution ($\text{SOA} = 0$) contained 176 data points (after outliers were removed; see Figure 2A). Eighty-five RTs were sampled with replacement from the pop-out distribution, and 85 RTs were sampled from the difficult distribution; these 170 data points were combined for a predicted intermediate distribution. This arbitrarily chosen sampling was meant to simulate roughly a situation in which pop-out detected the target on 50% of the trials. The first four moments for the actual pop-out and difficult search distributions and for the simulated intermediate distribution were calculated. Then λ , the proportion of difficult search, was calculated for each moment. This procedure was repeated 1,000 times. The mean λ s are presented in Figure 3A (the point representing 50% sampling from the pop-out distribution); they clearly coincide, unlike the λ s derived from the empirical data from intermediate SOA conditions (Figure 2B). Therefore, using the data from our control conditions, we have shown that linear combinations of the control distributions tend to produce coinciding λ s, unlike those shown in Figure 2B.

Second, we created a simulation based on another plausible mixture model, one in which difficult search does not begin until pop-out has failed. That is, difficult search is deployed in response to the failure of pop-out search to locate a target during the time that pop-out search is possible. In this model, as in the previously described Monte Carlo simulation, pop-out and difficult search each detect the target on some proportion of the trials (half, in the simulation). However, on the trials for which difficult search detected the target, it was delayed by 100 msec (i.e., the RT was increased by 100 msec).² This delay of 100 msec caused λ s calculated from higher moments to lie above those calculated from lower moments (Figure 3B; the opposite pattern from that shown in Figure 2B), but by a very small amount. (Note that this model is not identical to the convex model described above, because of the constant added to the difficult search RTs.)

To illustrate the pattern expected in the λ s when the delay for difficult search is large, we repeated the above procedure, but with a delay of 600 msec (again for all the difficult search trials). This is not plausible, given that pop-out occurred within about 200 msec. However, it

serves to illustrate the pattern of λ s under a mixture model with a delay for difficult search (Figure 3C) and to highlight that this pattern is in the *opposite* direction to that found in our data (Figure 2B). The mixture model predicts that λ for lower moments will be closer to pop-out levels than will λ for higher moments. All three trends demonstrated in the above simulations have also been demonstrated algebraically by Olds et al. (2000).

The simulations described above are all mixture models and modified mixture models. What about race models? Since our two control RT distributions do not overlap, pop-out will always win a race under normal viewing conditions. Therefore, this race is not interesting. However, in our experiment, pop-out processes are, in a sense, "racing" to finish before the onset of the second set of distractors. Difficult search, rather than pop-out search, will detect the target on trials in which pop-out loses this "race"—that is, when pop-out fails to finish before interruption. Therefore, we performed a final Monte Carlo simulation, where we sampled only from the left half of the pop-out distribution. That is, we sampled from the smaller RT values, which are likely to result from faster perceptual processing and response processing. Thus, they are likely to be RTs for trials in which pop-out finishes before interruption. We sorted the RTs and sampled only from those that were less than the median RT. We sampled from the entire difficult search distribution, as in the original simulations. Note that this model is not identical to the simple convex model introduced earlier, because our sampling of the pop-out control distribution is biased, rather than random. However, we considered it because it is a reasonable hypothesis of how processing might occur in our task. In the simulation, this biased sampling of the pop-out distribution produced only a small change, relative to unbiased sampling, and the λ s remained close to coinciding. This makes intuitive sense, because the pop-out distribution is narrow, as compared with the difficult search distribution. In fact, the slight difference that we see is that, with this biased sampling, the λ s were slightly shifted toward the direction *opposite* that for the pattern of our data. That is, such a model also cannot account for our data.

GENERAL DISCUSSION

We have shown that partial pop-out assists difficult search. What models of search processing do our results rule out? We have considered a simple convex model and several plausible modifications of this model as explanations of concurrent processing by multiple, noninteracting mechanisms. Our data cannot be explained by these models. For example, one plausible mixture model proposes that the difficult search mechanism might commence processing only if the pop-out process fails (e.g., when the second set of distractors is added). As our simulation results show, this mixture model predicts that λ s derived from lower moments should approach pop-out values faster than λ s derived from higher moments (by a

Figure 2. (A) Frequency distributions for hit response time (RT) for the different stimulus onset asynchrony (SOA) conditions. (B) λ_s derived from the first four moments of the hit RT distributions for each SOA condition.

very small amount; see Figure 3B). This prediction is contrary to our data, and thus our results rule out this model, as well as the other models we tested above. It is a strength of our technique that it provides data that allow us to reject a wide range of models. We conclude that the processes do, in fact, interact and, furthermore, that partial pop-out information is used by difficult search processes.

Note that in Figure 2A, there are no pop-out RTs in the SOA = 50 RT distribution (the maximum pop-out RT is 694 msec, and the minimum RT for the SOA = 50 condition is 715 msec). However, despite this lack of overlap, the mean of the SOA = 50 RT distribution is less than the mean of the SOA = 0 RT distribution. This reduction in mean RT at the 50-msec SOA (compared with mean RT

Figure 3. (A) λ s calculated for simulated intermediate response time (RT) distributions, according to the race model, based on difficult and pop-out search control data from observer E.O. The x-axis represents percent sampling from the pop-out control RT distribution (as opposed to the difficult search control distribution); thus, the control distributions are located at 0% (difficult search) and 100% (pop-out search) along this axis. The simulated distribution, containing 50% points from pop-out and 50% points from difficult search, is located at 50% along the x-axis. Please see the text for a further description of the procedure. (B) λ s calculated from simulated intermediate RT distribution, according to the mixture model. The delay imposed on the difficult search RTs is 100 msec. (C) λ s calculated from a simulated intermediate RT distribution, according to the mixture model. The delay imposed on the difficult search RTs is 600 msec.

at the 0-msec SOA) is not caused by inclusion of RTs drawn from the pop-out distribution. This is strong additional evidence for the claim that the processes responsible for difficult search are being assisted by information from *failed* pop-out.³

Several mechanisms described in the visual search literature can explain the facilitation of difficult search by incomplete pop-out. For example, if bottom-up feature detection influences the order of difficult search (Wolfe, 1994) by priming more likely target locations, information gathered during incomplete pop-out provides incomplete, but still useful, assistance. Another model (Watson & Humphreys, 1997) suggests that early processing guides search by eliminating from consideration loca-

tions at which the target is unlikely to appear. If any locations at all are eliminated by incomplete pop-out, there is facilitation of difficult search. These models were suggested by experimental paradigms that differ from ours, but their search guidance mechanisms can explain the interaction we found.

The arguments given above show that incomplete pop-out search can provide information that assists difficult search. What form does this information take? To answer this question, we separated trials by target position. Radial distance from fixation had a significant effect on hit RT [$F(3,1429) = 27.2$, $MS_e = 249,866$, $p < .0001$]. In Figure 1B, this effect is shown, with target positions grouped into four circular orbits of roughly 0.8°, 1.9°, 2.9°, and 3.9°.

and 3.4° eccentricity from fixation. In addition, the interaction of SOA and orbit was significant [$F(24,1429) = 6.9$, $MS_e = 249,866$, $p < .0001$].

Targets take longer to detect the farther they appear from fixation (the *eccentricity effect*: Carrasco et al., 1995; Carrasco & Frieder, 1997; Wolfe et al., 1998).⁴ Our technique allows us to demonstrate the advantage of detection for targets near fixation in a new way. This advantage is evident from the faster development of pop-out search (decrease in RT with increase in SOA) for targets nearer fixation than for those farther from fixation. Without interrupting pop-out partway through, we could not have shown this differential development. We can calculate the rate at which pop-out processing progresses from fixation outward by measuring the displacement between the Orbit 1 and Orbit 4 hit RT curves. At SOA = 50, Orbit 1 RT is about 1,500 msec, whereas Orbit 4 requires about 50 msec more SOA (SOA = 100) to achieve the same RT. We divide 50 msec (the increase in SOA needed for equivalent RT) by 2.6° (the difference in eccentricity between Orbit 1 and Orbit 4) and estimate that pop-out proceeds outward from fixation to periphery at about 20 msec per degree. This value is very similar to values reported for color/orientation conjunction search, a very different visual task (Carrasco & Frieder, 1997; Wolfe et al., 1998). We regard this agreement as suggestive of important directions for future research.

Radial spread in pop-out has several possible explanations. For example, signal might build up more slowly in the periphery because photoreceptor and neural densities are lower. Or, the searchlight of attention may widen its beam as processing proceeds. The present results only show that processing spreads radially during the 200 msec in which pop-out processing occurs, with processing time halved in the fovea within 50 msec, well before any sign of processing exists at 3.4° from fixation. A better understanding of the neural correlates of this phenomenon will certainly provide important constraints for theories of early vision.

Independent of the origin of radial spread is its contribution to information transfer from pop-out to difficult search. Figure 1B shows that if the target has not popped out at 50-msec SOA, it is unlikely to be in the innermost orbit, allowing difficult search processes to eliminate that part of the display from consideration. We suspected that the information provided by partial pop-out to difficult search involves the location of the target. In a variant of the experiment described here, we changed the target position when the second set of distractors appeared, at the SOA (Olds et al., 2000). We expected this change to prevent partial pop-out from assisting difficult search, and this is indeed what occurred. That is, the λ s derived from different moments coincided, rather than displaying the pattern shown in Figure 2B. This result illustrates empirically that the pattern in the λ s in the present data is not an inevitable artifact of the statistics of the moments

(e.g., instability in measurements of higher moments). The nature of this information transfer can be further specified by continuing to dissect the spatiotemporal character of pop-out search. The resolution of these questions has important consequences for models of early vision.

We have replicated the pattern of results reported here in other observers (Olds et al., 2000). We have also replicated the results in several variations on this procedure. For example, it could be argued that the blocking of trials by SOA allows observers to use strategies particular to each SOA; however, we have found the same pattern of results for a replication of the experiment that used intermixed SOAs (Olds et al., 2000).

To summarize, spatial position influences search time, and it interacts with temporal factors. Pop-out search spreads from fixation outward, and difficult search is guided by information from failed pop-out search. Specific time scales vary from one observer to another, but not the general properties described in this paper. A continuing exploration of this methodology, for linearly separable color stimuli and for other visual relationships, will further elucidate the mechanisms underlying visual selection and visual search.

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NOTES

1. There was very little difference in the pattern of λ s between the screened and the original data.

2. This value was chosen because pop-out search takes about 200 msec; given that pop-out is said to fail on half the trials in this artificial intermediate distribution, perhaps the SOA is in the range of 100 msec. However, this choice is arbitrary and does not affect the results.

3. It might seem that a control condition with 100 msec exposure to the first portion of the display, for example, followed by a mask, would be a useful demonstration of the amount of pop-out processing completed in 100 msec. Pilot data indicate that error rates are too high in such a condition to warrant comparison of RTs (which is crucial for our method). The observed poor performance in this condition indicates that little pop-out processing is complete in 100 msec. Thus, the improvements at SOA = 100 in our experiment must be due to *partial* pop-out assisting difficult search, rather than to *completed* pop-out. However, despite this suggestive result, we believe that uncontrolled strategic effects related to high error rates make this an inappropriate control condition.

4. This observer does not show strong traditional eccentricity effects for pop-out (SOA = ∞) or difficult search (SOA = 0). However, other subjects do, in a variety of contexts (see Olds et al., 2000).

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