# Serial Attention Mechanisms in Visual Search: A Direct Behavioral Demonstration

**Emanuela Bricolo[1,2], Tiziana Gianesini[1], Alessandra Fanini[1], Claus Bundesen[3], and Leonardo Chelazzi[1]**

## Abstract

■ In visual search, inefficient performance of human observers is typically characterized by a steady increase in reaction time with the number of array elements—the so-called set-size effect. In general, set-size effects are taken to indicate that processing of the array elements depends on limited-capacity resources, that is, it involves attention. Contrasting theories have been proposed to account for this attentional involvement, however. While some theories have attributed set-size effects to the intervention of serial attention mechanisms, others have explained set-size effects in terms of parallel, competitive architectures. Conclusive evidence in favor of one or the other notion is still lacking. Especially in view of the wide use of visual search paradigms to explore the functional neuroanatomy of attentional mechanisms in the primate brain,

it becomes essential that the nature of the attentional involvement in these paradigms be clearly defined at the behavioral level. Here we report a series of experiments showing that highly inefficient search indeed recruits serial attention deployment to the individual array elements. In addition, we describe a number of behavioral signatures of serial attention in visual search that can be used in future investigations to attest a similar involvement of serial attention in other search paradigms. We claim that only after having recognized these signatures can one be confident that truly serial mechanisms are engaged in a given visual search task, thus making it amenable for exploring the functional neuroanatomy underlying its performance. ■

## INTRODUCTION

In a typical visual search paradigm, human observers are asked to report whether or not an array of multiple elements contains a prespecified target. Usually collected responses are manual key presses, and the experimenter measures their accuracy and reaction time (RT). Visual search paradigms have long provided cognitive psychologists with a powerful tool to investigate the computational stages of human vision and to infer the underlying neuronal mechanisms. One main objective has been to define the extent to which perceptual analysis of a given search array depends on focal attention (Chelazzi, 1999). More recently, visual search paradigms have also gained increasing popularity among cognitive neuroscientists, and a number of influential papers have appeared using a variety of methods, including functional neuroimaging (Donner et al., 2000; Hopf et al., 2000; Leonards, Sunaert, Van Hecke, & Orban, 2000; Corbetta, Shulman, Miezin, & Petersen, 1995), the scalp recording of event-related potentials (ERPs; Woodman & Luck, 1999; Luck & Hillyard, 1995), and transcranial magnetic stimulation (TMS; Ashbridge,

Walsh, & Cowey, 1997). In these studies, visual search has mainly been used as a means to unveil the functional neuroanatomy of attentional deployment in complex visual displays. While the use of neuroscience methods will undoubtedly help clarify the perceptual processes and underlying mechanisms of visual search, and particularly the role played by selective attention, it is essential that visual search be first thoroughly characterized at the behavioral level. The present report represents an attempt to gain a deeper understanding at the behavioral level of one class of visual search task—"inefficient" search, thus making it amenable to systematic exploration with the various neuroscience methods.

Difficulty of search can be manipulated by varying the nature of the target with respect to the nature of the nontargets, that is, by controlling the visual similarity of the target to the nontargets, and by varying the number of elements in the array (the set size; Bundesen, 1990; Duncan & Humphreys, 1989). At one extreme of search efficiency lie the so-called pop-out tasks, in which the target is detected without effort from the multitude of nontargets and the average RT remains constant over large variations in set size, yielding a flat search function. Pop-out can be obtained with targets differing from the nontargets by a highly discriminable stimulus feature (e.g., a red patch among green ones). Under these

---

[1]University of Verona, [2]University of Milano Bicocca, [3]University of Copenhagen

conditions, search is thought to proceed in parallel throughout the display area, and perceptual analysis is thought to be preattentive in nature (Treisman & Gelade, 1980). While there is general consensus over the interpretation of flat search functions, students of visual perception have long disputed over the interpretation of nonflat functions, which in general attest that search proceeds less efficiently. Slopes of nonflat search functions can vary between a few tens to over one hundred milliseconds (Wolfe, 1998; Treisman & Gormican, 1988). Nearly everybody agrees that nonflat search functions must reflect involvement of limited capacity (i.e., attentional) resources, yet different authors have offered contrasting views concerning the nature of the attentional involvement. One such view, originally put forward by Treisman and Gelade (1980), claims that nonflat functions reflect the intervention of a serial mechanism. Under conditions where search is less efficient, for instance, when the target is defined by a conjunction of features (e.g., a red horizontal bar among red vertical and green horizontal bars), focal attention will have to be deployed to individual elements in turn to aid perceptual analysis, perhaps to allow correct binding of the elemental stimulus features. As a consequence, RT will increase monotonically with set size. Although subsequent versions have incorporated new properties into the original scheme to accommodate for a number of experimental findings (Wolfe, Cave, & Franzel, 1989; Wolfe, 1994; Treisman & Sato, 1990), this theoretical framework has retained the essential notion that nonflat search functions are the manifestation of a serial attention component. In contrast, other authors have claimed that increasing RTs with set size need not reflect the participation of serial mechanisms (McElree & Carrasco, 1999; Palmer, 1995; Humphreys & Müller, 1993; Townsend, 1990; Duncan & Humphreys, 1989; Ward & McClelland, 1989; see Bundesen, 1996, for a review). Duncan and Humphreys (1989), for instance, have argued that nonflat search functions can result from a competitive mechanism, whereby search is performed in parallel throughout the entire stimulus array by comparing an internal representation of the relevant target properties (target template) to the perceptual description of each stimulus in the array. Under the proper task conditions, RTs will increase with set size, other factors being constant, because the total amount of computational resources aiding perceptual analysis of the array will be fractionated by the number of array elements. Each array element will receive a progressively thinner share of the total pool of resources as set size increases.

Given this unresolved controversy in interpreting nonflat search functions, it becomes unclear what set of cognitive operations people have actually explored when applying neuroscience methods to investigate the neuronal underpinnings of inefficient search (Donner et al., 2000; Hopf et al., 2000; Leonards et al., 2000;

Woodman & Luck, 1999; Ashbridge et al., 1997; Corbetta et al., 1995; Luck & Hillyard, 1995).

In essence, the critical questions asked by the present study are: (1) Does visual search performance "ever" depend on truly serial attention mechanisms? (2) Can one rely on a specific set of behavioral signatures to decide that a given search task does require serial scrutiny of the array elements? In the following, we will provide direct evidence that (1) a properly designed search paradigm does indeed recruit serial attention mechanisms and (2) a set of stringent criteria can be used as diagnostic of the involvement of serial attention in a given search paradigm.

# RESULTS

## Effects of Set Size

Since our goal was to directly demonstrate the role of serial attention in visual search, and to define a set of diagnostic criteria to attest its involvement, the first step was to devise a highly controlled search paradigm producing very steep search functions. Following a long phase of pilot testing using a large variety of experimental conditions and array stimuli, the task of choice was the one schematically shown in Figure 1a. In brief, search arrays were drawn in light gray against a dark background and consisted of identical T-shaped elements presented in any of four possible orientations: 0° (upright), +90°, 180°, and −90°. Throughout each experimental session, one specific orientation (all but upright) defined the target for that session, while all other orientations (including upright) defined the nontargets. A target was present in 50% of the trials. Set size could take one of four values: 2, 4, 6, and 8. A set size of 8 filled all the available stimulus locations in the array. Array elements were presented along an imaginary hemicircle centered on fixation. Regardless of the set size for a given trial, array elements were always presented at contiguous locations along the hemicircle. In different trial blocks, the stimulus array was confined either to the right or left visual hemifield. Stimulus arrays across the vertical midline were not used to avoid the potential confounds due to the direct involvement of both hemispheres and the anatomical discontinuity of the brain commissures. Subjects were asked to press a key to indicate that a target was present, and a different key to indicate that it was absent. In addition, subjects were instructed to maintain fixation on a central light gray dot throughout the trial. We measured accuracy and RT of their responses as functions of set size, separately for target-present and target-absent trials.

Figure 1b shows the performance of one example observer. Average RTs for this observer increased linearly with set size, while percentage of errors was low in all conditions. The slope of the search function, averaged across hemifields, was 99.9 msec for the target-present

**Figure 1.** Our search task produced a very large effect of set size. (a) Example of target-present stimulus array containing six elements, with the target represented by the T-shaped element tilted to the right (+90° orientation). (b) Accuracy and RT data for one observer (IL) are presented separately for each set size and for each hemifield (square symbol for the right hemifield, circle symbol for the left hemifield), in the target-present (empty symbols) and target-absent (filled symbols) conditions. (c) Accuracy and RT data averaged across the group of 17 subjects for the target-present (empty symbols) and target-absent (filled symbols) conditions. Here results for the left and right hemifields have been collapsed.
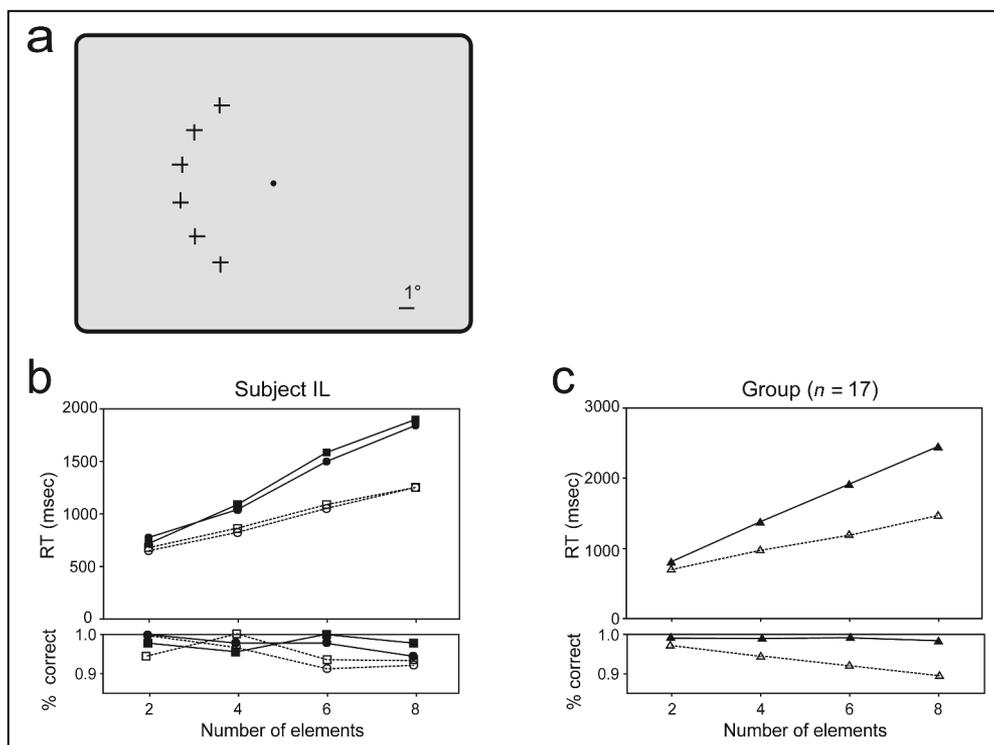


trials and 195.4 msec for the target-absent trials (correlation coefficient $r > .90$ in both cases). The high value of the slopes indicates that search was very inefficient under these conditions. The slope was about twice as steep for the target-absent as for the target-present trials, consistent with a serial, self-terminating strategy (search is interrupted upon locating the target). The same experiment was performed on 16 additional observers. Figure 1c shows the average performance across the group of 17 subjects. Since the two visual hemifields produced comparable results in all subjects, data shown in Figure 1c have been collapsed across the right and left hemifield. Similar to the results for the individual observer, performance across the 17 individuals indicates that under our testing conditions search was highly inefficient. Average search slopes were 273.6 and 126.0 msec for the target-absent and target-present trials, respectively, resulting in an average ratio of 2.11. Across the population of subjects, slopes ranged between 93.7 and 604.8 msec for the target-absent trials, and between 55.1 and 231.5 msec for the target-present trials. The ratios between the two values ranged between 1.70 and 2.93. Finally, the correlation coefficients $r$ of the linear regressions ranged between .91 and 1.00. All the observers performed the task with an accuracy of at least 74.0% in every condition.

## Eye Movement Control

The results of the initial experiment indicate that we were able to devise a paradigm for highly inefficient search that might depend critically on serial, attentional scrutiny of the individual array elements. One might argue, however, that the steep slopes reflected sequential eye movements toward the individual stimuli, rather than sequential, covert shifts of attention toward the stimuli. In other words, perceptual analysis might have been so difficult in peripheral vision that subjects had to foveate the individual stimuli to attain an adequate level of performance. This possibility seemed to us particularly plausible given that the measured slopes were in the same order of magnitude as the typical saccadic latency (Leigh & Zee, 1999). In a subsequent experiment, we thus measured eye movements from six observers performing the same visual search task as before, except that only search arrays confined to the left visual hemifield were used. Accuracy and RT data were analyzed as in the previous experiment. Our main concern here was to demonstrate that similar search slopes could be obtained from trials in which maintenance of central fixation was directly established. Collected trials were first sorted depending on whether or not eye position was kept within a $\pm 2°$ by $\pm 2°$ window centered on the fixation target during the entire course of the trial. Figure 2 shows the results of this experiment for one example observer.

Panel (a) of the figure displays the eye position records from trials in which the fixation criterion was satisfied. For this observer, trials with adequate fixation amounted to 84.3% of the total (after excluding all trials with an incorrect key press response, 6.8%). Panel (b) of the same figure shows the RT data for the trials shown in (a). As in the previous experiment, average RT increased monotonically with set size, with a slope of 272.9 msec

for the target-absent and 130.9 msec for the target-present trials (the ratio was 2.08 and the correlation coefficient $r$ was .99). Panel (c) of the figure shows the eye position records from trials in which the eyes moved outside the fixation window at least once during the course of the trial. These amounted to 13.9% of the total. It was important to determine the pattern of eye movements and RTs in these trials as well. As shown in Figure 2c, even though central fixation was broken in these trials, it is clear that the observer was not sequentially foveating individual stimuli while performing the task. A detailed account of the pattern of eye movements from these trials would be beyond the scope of the present report. Panel (d) of the figure shows the RT data for the trials shown in (c). Although the average RT measured in these trials tended to increase with set size, there were too few samples for each data point to allow any direct comparison with the data shown in (b). Finally, 1.8% of the total trials were contaminated by an artifact produced by eye blinks, sometimes in combination with occasional eye movements (not shown).

This pattern of results was confirmed in five additional observers. In these observers, the slope of the search function computed on trials with correct fixation (between 70% and 92% of the total, across individuals) was well within the range of values computed in our initial experiment, varying between 100.7 and 471.7 msec in the target-absent condition. We can conclude that the steep slopes yielded by our search paradigm are not due to sequential eye movements toward the individual array elements. Rather, we may hypothesize that the search slopes measured under our task conditions reflect covert shifts of attention to the locations of the individual stimuli.

## RT Distributions

After we were able to establish that our paradigm is apt to produce very steep search slopes, and that eye movements are not responsible for the effect, we next decided to acquire further evidence in favor of serial scrutiny of the array elements by exploring the entire distribution of RTs. As mentioned earlier, a 2:1 ratio between the slope in the target-absent and target-present trials is in perfect accordance with a serial self-terminating model. In target-absent trials, observers can decide that no target is present only after assessing all the elements in the array. In contrast, in target-present trials, a target

**Figure 2.** The effect of set size was not caused by sequential eye movements toward the individual array elements. (a) Eye position records for one observer (AT) from trials in which the eyes remained within a ±2° × ±2° window centered on the fixation target (after excluding trials with an incorrect key press response). The color scale encodes the frequency with which the eye position signal matched a specific coordinate on the computer monitor (5 × 5 pixels resolution, or about 0.2° in each direction). In light gray, the eye positions that occurred less than 0.02% of the total samples. For reference, the figure shows the locations in the left hemifield where array elements could be presented. (b) RT data for trials shown in (a), separately for target-present (empty symbols) and target-absent (filled symbols) conditions. (c) Eye position records for subject AT from trials in which the eyes moved outside the fixation window at least once during the course of the trial (after excluding trials with an incorrect key press response). Color coding as in (a). (d) RT data for trials shown in (c).
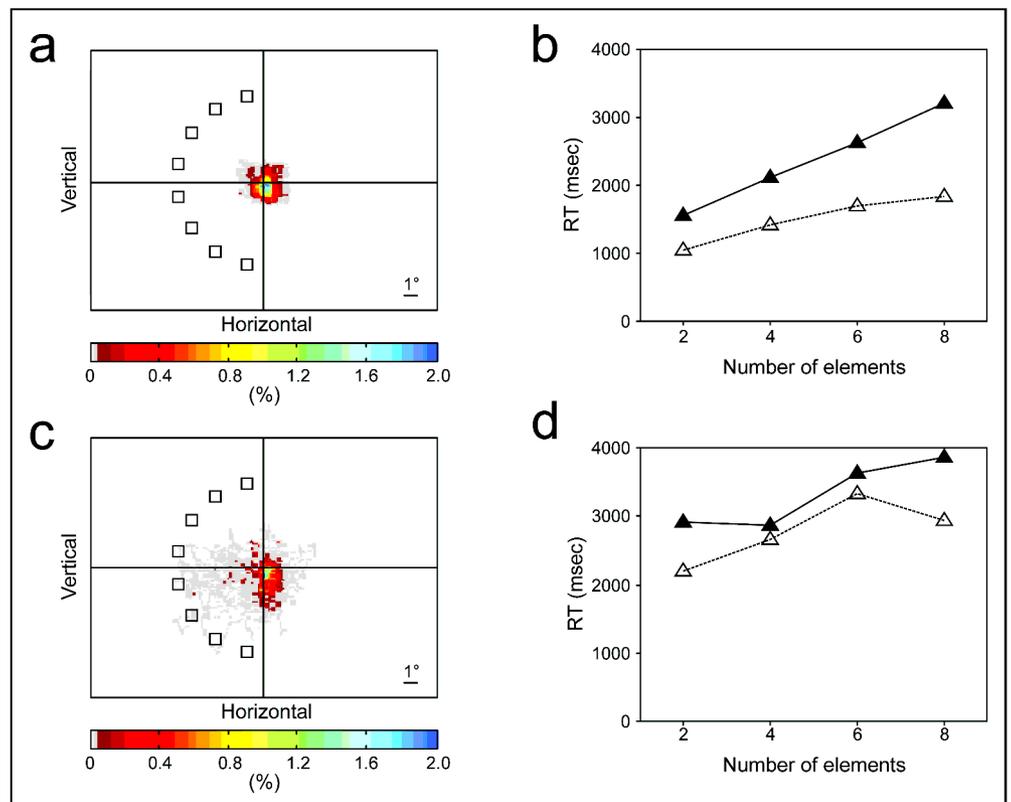
will be found after assessing on average only half of the nontargets. The same logic, however, prompts additional predictions concerning the distribution of RTs in the two conditions. In particular, according to the model, the RT distributions should change in different ways for target-present and target-absent trials as a function of set size. In target-present trials, the RT distribution for any given set size should be a mixture of underlying distributions, where each contributing distribution corresponds to trials in which the target was found at the $n$th cycle of the search process, with $n$ ranging between 1 and the number of array elements in the trial. For example, the distribution obtained with a set size of 4 ought to be a mixture of four contributing distributions: one from trials in which the target was located at the first cycle of the search process, one from trials in which it was located at the second cycle, one from trials in which it was located at the third cycle and, finally, one from trials in which it was located at the fourth cycle. As a consequence, the minima of the RT distributions for the target-present trials should be little affected by set size. The lower sector of the distribution should mostly reflect cases where the target happened to be found at the first cycle of the search process, regardless of the total number of array elements. In addition, the RT distributions for the target-present trials should show an increasing variance as a function of set size, in accordance with a greater variability in the number of search cycles required to perform the task (see Yantis, Meyer, & Smith, 1991). A different pattern of results should be expected for the target-absent trials. Here, one can predict that the minima of the RT distributions should increase substantially with set size, consistent with the notion that for any given set-

size subjects can decide in favor of the absent response only after assessing all the array elements. In other words, RT distributions for progressively larger set sizes should be shifted with respect to one another, with a less dramatic increase in variance. To test these predictions, we constructed cumulative RT distributions for the subjects tested in our initial experiment, separately for each set size and for target-present and target-absent trials. The results of these analyses are illustrated in Figure 3.

Panel (a) of Figure 3 shows the results for one observer, while panel (b) shows the corresponding results for the group of subjects. Because we were setting out to test the validity of the serial self-terminating model in a strictly quantitative way, and a ratio of 2:1 between search slopes in target-absent and target-present trials is the hallmark of the model to be tested, for this analysis, we excluded individual subjects whose performance deviated substantially from this ratio. From the total of 17 observers tested in the first experiment, we thus eliminated four subjects whose performance yielded slope ratios more than 1 standard deviation away from the grand-average ratio computed across the entire group of 17 subjects (see below). The average ratio across the remaining 13 subjects was 2.06.

As shown in the cumulative distributions of panels (a) and (b) of Figure 3, for the single observer and for the whole population, respectively, the results are at least qualitatively consistent with the predictions of the serial self-terminating model outlined above. In particular, the minima of the distributions for the target-present trials were only slightly affected by set size, certainly much less than the minima of the distributions for the target-absent conditions. Across the 13 observers, the minima



**Figure 3.** Cumulative distributions of RTs reveal different effects of set size for target-present and target-absent trials. (a) Cumulative distributions of RTs collected from one example observer (IL) in the different conditions of the experiment. Target-present RTs in red, target-absent RTs in blue. (b) Average cumulative distributions across the group of 13 observers. Color coding as in (a). (c) Standard deviation computed over the different distributions shown in (b), after normalizing by the average RT of the same distributions. Data for the target-present trials are shown in red, data for the target-absent trials are in blue.
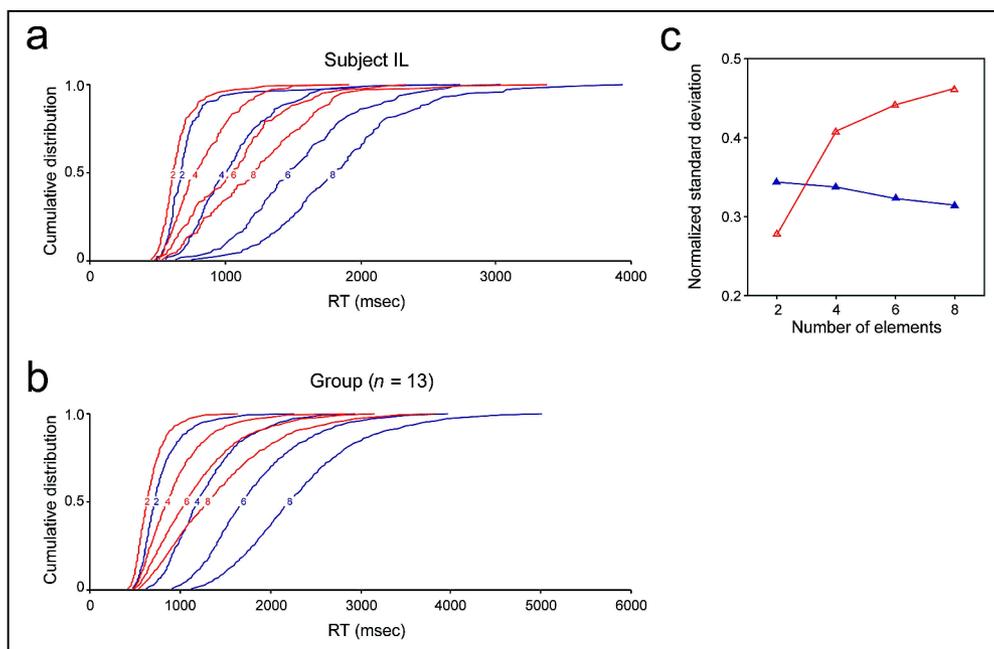
for the set sizes of 2, 4, 6, and 8 in the target-present trials were 416, 467, 486, and 529 msec, while in the target-absent trials they were 464, 606, 888, and 1093 msec. This trend was confirmed by a repeated-measures two-factor ANOVA, with Target (present vs. absent) and Set Size (2, 4, 6, and 8) as main factors, and the minimum of the RT distribution as the dependent variable. Both main effects were significant [Target, $F(1,12) = 28.8$, $p < .001$; Set Size, $F(3,12) = 13.0$, $p < .001$), and, most importantly, so was their interaction [$F(3,12) = 12.6$, $p < .001$]. We also performed separate one-way ANOVAs for the target-present and target-absent trials with Set Size as the only factor, and they both revealed a significant effect [target-present, $F(3,12) = 12.6$, $p < .001$; target-absent, $F(3,12) = 19.7$, $p < .001$]. Thus, even in the target-present condition, the minimum RT showed some increase with set size. This finding can be explained by the fact that the probability that the target was found at the first search cycle decreased as set size increased. For instance, there was a probability of 1/2 for the target to be found at the first cycle with a set size of 2, but this probability dropped to only 1/8 with a set size of 8.

The overall pattern of results for the target-present and target-absent conditions was consistent with the serial self-terminating model. In particular, while the distributions for the target-present trials had roughly the same origin and progressively diverged as a function of set size, the latter affected the distributions for the target-absent trials mainly by causing a progressive horizontal shift toward the right, that is, toward longer RTs. The standard deviation (SD) of the cumulative distributions computed across the group of subjects for the different conditions confirmed this pattern. However, since the variance of an RT distribution normally increases with its mean, and mean RTs differed across the conditions of the experiment (particularly between target-present and target-absent conditions), we divided (normalized) the SD value computed in each condition by the average RT in the same condition. The results of this analysis are shown in Figure 3c. While normalized SD increased substantially with set size in the target-present condition, it decreased with set size in the target-absent condition. The decrease relates to the fact that the variance of a sum of independent random variables (durations of successive cycles of the search process) equals the sum of their variances (cf. Yantis et al., 1991), so the variance of the duration of N (independent, identically distributed) successive cycles is proportional to N, and hence, to the mean. Thus, the variance divided by the mean should be a constant, whence the normalized SD should decrease as N is increased. In contrast, in target-present trials, where performance should reflect a probability mixture of cases with 1, 2, . . . , N cycles, the variance should be a function of both the means and the variances of the contributing basis distributions (see Yantis et al., 1991),

and the value of this function should increase disproportionately more than the mean as N is increased.

Close inspection of the performance scores of all our subjects provided likely explanations for why 4 of the total 17 subjects tended to deviate from the model (i.e., their slope ratios were substantially less or more than 2). In particular, two of these subjects had ratios of 1.7 and 1.8, respectively, while the remaining two had ratios of 2.8 and 2.9, respectively. The two subjects with slope ratios of less than 2 had the two shallowest slopes in both the target-absent and target-present conditions, and the two fastest average RTs across all conditions. Also, and perhaps most importantly, one of them had the highest error rate that was measured in the target-present condition (19%), while the other had the third highest error rate in the same condition (12%). Together, these data suggest that these subjects emphasized speed at the expense of accuracy, a manifestation of speed–accuracy tradeoff, combined with a bias to produce absent responses (they made virtually no errors in the target-absent condition). In essence, they seem to have had a tendency to interrupt search before having inspected all the array elements, with the consequence of missing the target on some occasions. This led to a number of errors (misses) in the target-present condition (especially with larger set sizes) and, likely, a number of correct (and fast) absent responses produced by chance.

A completely different pattern of results has emerged for the two subjects with the highest slope ratios. They had the two steepest slopes in the target-absent condition, the second and third steepest slopes in the target-present condition, and the two slowest average RTs across all conditions. Also, both of them showed virtually errorless performance in all conditions. Opposite to the two subjects discussed above, these two subjects appear to have adopted a very conservative criterion, emphasizing accuracy rather than speed. Perhaps, their slope ratios of more than 2 may indicate that they inspected some of the nontargets more than once when facing target-absent arrays.

## Monte Carlo Simulations

The analyses reported thus far on the RT distributions provide suggestive evidence in favor of the serial self-terminating model. As a further and more stringent test of the model, we next decided to perform a quantitative simulation of the empirical data by explicitly implementing the model to be tested. The general mathematical equation to simulate the data was obtained by performing a convolution between a gaussian function and a variable number of exponential functions (Hockley, 1984; Ashby & Townsend, 1980; Ratcliff & Murdock, 1976). The former was incorporated to accommodate for the set of processes that occur only once during the course of a trial (e.g., early-level visual processing,

response selection, motor preparation, key pressing); the latter to accommodate for the predicted number of search cycles in the different conditions. Under the assumption that these underlying stages are independent, the overall RT distributions can be reproduced by convolution of the functions. The simulation was performed separately for the target-present and target-absent trials, with the only constraint that the parameter of the exponential function ($\lambda$) be the same for the two sets of data (but see below). Finally, the $\lambda$ parameter of the exponential function, and the mean ($\mu$) and standard deviation ($\sigma$) of the gaussian function were estimated by a best-fitting procedure, which minimized the residual (mean square) error of the simulated distributions relative to the empirical data (see Methods for further details).

Figure 4 shows the results of the simulation, separately for the target-absent (panel a) and target-present trials (panel b). Let us consider the target-absent trials first. As shown in panel (a) of the figure, our simulation provided an excellent fit of the behavioral data, as confirmed by the nonsignificance of a Kolmogorov–Smirnoff one-sample test ($p > .1$; Siegel, 1956). However, the equation that minimized the residual error had to be modified in two important respects relative to our a priori model. First, we discovered that the number of exponentials needed to obtain a reasonably good fit for the different set sizes was not 2, 4, 6, and 8, as we had anticipated, but 1, 3, 5, and 7. Likely, this is because processing of the first element proceeds faster than processing of the subsequent ones, as the former does not suffer from the refractoriness generated by having just processed another element (cf. demonstrations of ''blinks'' of attention; Ward, Duncan, & Shapiro, 1996; Duncan, Ward, & Shapiro, 1994; Raymond, Shapiro, & Arnell, 1992). We then considered two alternative ways of accounting for this faster search cycle. One was to assume that the first cycle is incorporated into the gaussian function. The second one was to model the first search cycle with a separate exponential function. Pilot simulations revealed that the most satisfactory fit was obtained by the latter approach, with the free parameter $\lambda_2$ corresponding to the first search cycle and the free parameter $\lambda_1$ corresponding to all other cycles. Thus, the equation that minimized the residual error had the following parameters: $\lambda_1 = 252.9$ msec, $\lambda_2 = 26.1$ msec, $\sigma = 36.6$ msec, $\mu = 514.1$ msec. Not surprisingly, the $\lambda_1$ parameter was very close to the average slope of the search function measured across the same subjects in the target-absent condition (257.5 msec). In spite of this modification to the original scheme, it appears that the empirical data for the increasing set sizes can be successfully simulated by mathematical equations directly derived from a strictly serial notion. Similar results were obtained for the individual observers, except that their RT distributions were noisier than those for the group.
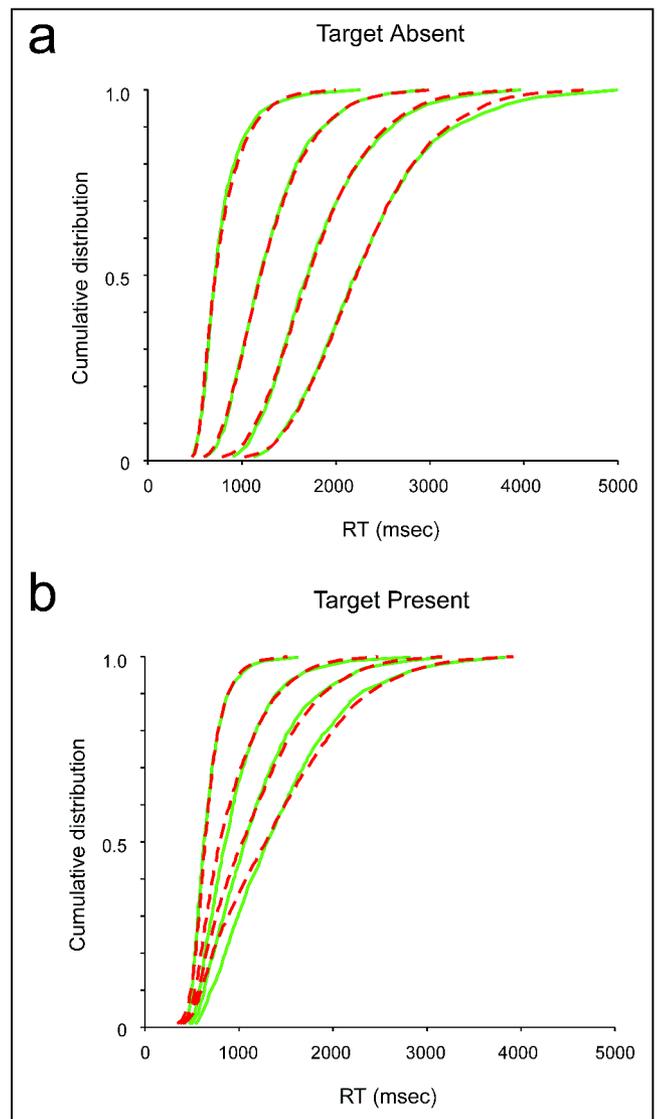


**Figure 4.** RT data from experimental subjects can be well approximated by mathematical equations that implement a serial, self-terminating model of search. (a) The plot shows the average cumulative distributions of RTs computed across 13 subjects for the target-absent trials (in green) and the theoretical distributions created through the Monte Carlo simulation for the same condition (in red). (b) Same as in (a), except that here experimental RT data (in green) and theoretical distributions (in red) are shown for the target-present condition.

Figure 4b shows the results of the simulation for the target-present condition. Again, the theoretical distributions provided a good fit to the empirical data, as confirmed by the nonsignificance of a Kolmogorov–Smirnoff one-sample test ($p > .1$). Here, however, another modification was necessary to optimize fit. Namely, while we maintained the $\lambda_2$ and $\lambda_1$ exponential functions to simulate processing of the nontargets at the first and subsequent cycles, respectively, a third exponential function with parameter $\lambda_3$ had to be included to model processing of the target element, that is, to model the last cycle of search. The $\lambda_1$ and $\lambda_2$

parameters were assigned the same value as for the target-absent simulation. The free parameter $\lambda_3$ of the additional exponential function and the free parameters of the gaussian function that minimized the residual error took the following values: $\lambda_3 = 176.1$ msec, $\sigma = 94.7$ msec, $\mu = 564.2$ msec. Processing of the target thus appears to proceed faster than processing of the nontargets, perhaps as a result of the direct match between the target element and the active mental template of its distinguishing properties (Duncan & Humphreys, 1989). Unlike for the target-absent condition, the number of exponentials necessary for a given set size was not fixed in the target-present condition. Rather, it was varied with equal probability between 1 and the number of array elements. As an example, to simulate the RT distribution for the set size of 4, we generated four underlying distributions, each contributing 1/4 of the overall distribution: The distribution for the case in which the target was located at the first search cycle was obtained by convolving the gaussian function with a $\lambda_2$ exponential function; the distribution for the case in which the target was located at the second cycle was obtained by convolving the gaussian function with one $\lambda_2$ and one $\lambda_3$ exponential function; the distribution for the case in which the target was located at the third cycle was obtained by convolving the gaussian function with one $\lambda_2$, one $\lambda_1$ and one $\lambda_3$ exponential function; finally, the distribution for the case in which the target was located at the fourth cycle was obtained by convolving the gaussian function with one $\lambda_2$, two $\lambda_1$, and one $\lambda_3$ exponential function. The same logic was applied to simulate the distributions for the other set sizes. It should be noted that to simulate cases in which the target was located at the first cycle, a better fit was obtained by using the $\lambda_2$ rather than the $\lambda_3$ exponential function. Of course, we could have included yet another exponential function to model this special case.

In conclusion, although the fit of the empirical data obtained from the target-present condition is less close than that for the target-absent condition, overall it appears that our simulation was highly successful at modeling the entire distribution of RTs, thus lending strong support to the notion that our search task relies on serial shifts of focal attention.

## A Position Effect

To further reinforce the conclusion that our search task depends on serial scrutiny of the array elements, we finally devised a paradigm in which, instead of varying the number of elements across trials, we systematically varied the position of the target within arrays of constant size (Harris, Shaw, & Altom, 1985; Hockley, 1984; Townsend & Roos, 1973; Atkinson, Holmgren, & Juola, 1969). If the set-size effect in our previous experiments was due to sequential shifts of covert attention to the individual array elements, then one should observe a similar RT increase as a function of the number of search cycles to be performed before intersecting the target in arrays of constant size. In other words, one should be able to induce a similar increase in the number of search cycles either by increasing the total number of array elements, as in our previous experiments, or by increasing the number of nontargets to be inspected before the target is found, while keeping the set size constant.

The stimuli for this experiment and their positioning in the visual field were identical to those used previously, except that the stimulus arrays always contained eight elements. A target was present in 50% of the trials. Subjects were cued to start search from one end of the array by informing them that the target, when present, had a higher probability (51%) of being at the corresponding array location, and a lower probability of being at any of the remaining seven locations (7% for each, 49% in total). The cued location was the lower location for arrays in the left hemifield and the upper location for arrays in the right hemifield. Our hypothesis was that subjects would tend to search for the target in an orderly progression starting from the cued location and moving toward the opposite end of the array. Nine observers were tested. RT and accuracy were measured as functions of the location of the target within the array, that is, as functions of the hypothetical number of search cycles subjects would have to perform before encountering the target along the path. The goal of the experiment was to demonstrate a large position effect, that is, a linear RT increase as a function of the location of the target relative to the cued end of the array, of a magnitude similar to the slopes obtained in our initial experiment with varying set size.

Figure 5a and b illustrates the results for one example observer and for the group of nine subjects, respectively. As shown in both panels, RT tended to increase monotonically as a function of the location of the target relative to the cued location within arrays of constant size, and this increase was, on average, 151.7 msec per location (the correlation coefficient $r$ calculated on group average RTs was .99). The slope of this position effect is within the range of the slope values measured in the target-absent trials of our initial set-size experiment (i.e., between 93.7 and 604.8 msec). In turn, this suggests that the two effects reflect the same underlying process, that is, sequential deployment of focal attention onto individual array elements. The only difference would be that in the set-size experiment, the number of search cycles was determined by the number of elements in the array, while in the position experiment, it was determined by the number of locations subjects had to visit before intersecting the target. It is possible that subjects in the position experiment sometimes searched the array in another order than the normal one (e.g., starting from the opposite end of the array or

**Figure 5.** Using the same type of search arrays, a position effect can be obtained of about the same magnitude as the set-size effect described previously. (a) Accuracy and RT data for one example observer (LM) as a function of the location of the target within arrays containing eight elements. (b) Accuracy and RT data averaged across the nine observers tested. Both in (a) and (b) data from the two hemifields have been collapsed.
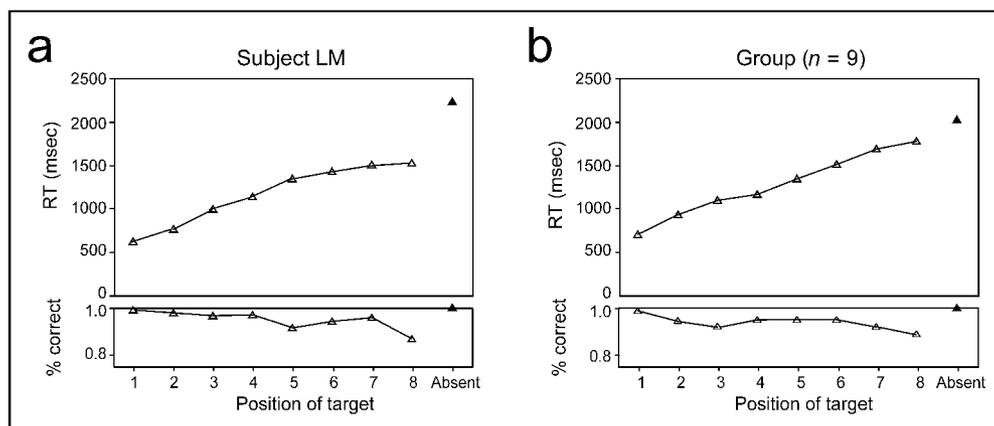


randomly). This possibility may account for the fact that, although the slopes were the same in order of magnitude, the mean slope in the position experiment (151.7 msec) was somewhat lower than the mean slope for the target-absent trials in the initial set-size experiment (273.6 msec).

As a control, we measured eye movements of three additional subjects performing the same task. A clear position effect of roughly the same magnitude was obtained in these subjects from trials in which central fixation could be directly established.

## DISCUSSION

The aim of the present study was to develop a paradigm for highly inefficient visual search yielding very large effects of set size, and then test whether these effects were due to a serial attention mechanism. A first experiment demonstrated that under our testing conditions, search for the target through the stimulus array proceeded very slowly, with a linear increase in average RT as a function of set size and a slope of this linear increase of over 200 msec per element in the target-absent condition. Although this figure is higher than with most inefficient search paradigms, very large effects of set size have been shown in previous studies (Wolfe, 1998; Treisman & Gormican, 1988). In addition, the experiment revealed a ratio between target-absent and target-present trials very close to 2:1, a further indication of serial, self-terminating strategy. A subsequent experiment showed that such slow rates of search were not determined by a need to produce eye shifts toward individual array elements.

Analysis of the RT distributions from the initial set-size experiment provided additional, qualitative evidence in favor of a serial, self-terminating mechanism in our task. The minima of the RT distributions increased strongly as a function of set size in the target-absent condition, while a much more modest increase of the minima with set size was observed in the target-present condition. Also, normalized variance increased with set size in the target-present, but not in the target-absent, condition.

Most importantly, the RT distributions could be successfully simulated by a direct implementation of the serial, self-terminating model. Only two rather minor modifications of the model were necessary to achieve an excellent fit to the empirical data. Namely, two special exponential functions had to be included in the equation, one to account for the processing of the first array element in a given trial, and one to account for the processing of the target.

Finally, a position effect of the same order of magnitude as the original set-size effect was obtained by systematically varying the location of the target within arrays of constant size, again suggesting that the set-size effect in our initial experiment reflects serial deployment of attention toward individual array elements (Harris et al., 1985; Hockley, 1984; Townsend & Roos, 1973; Atkinson et al., 1969). Together, these results strongly support the notion that at least a highly inefficient visual search depends critically on serial attention.

Of course, the notion that inefficient search tasks engage serial attention mechanisms is not new, and it forms the core of several theories, notably Feature Integration Theory and its subsequent developments (Wolfe et al., 1989; Wolfe, 1994; Treisman & Gelade, 1980; Treisman & Sato, 1990). However, the experimental evidence on which this notion usually rests—a positive slope of the search function and a 2:1 ratio of the slope for the target-absent and target-present trials, has not been considered compelling enough (McElree & Carrasco, 1999; Palmer, 1995; Townsend, 1990; Duncan & Humphreys, 1989; Ward & McClelland, 1989). Here, we have provided a set of more stringent criteria upon which the notion of seriality can now rely. Future explorations of the neurocognitive mechanisms underlying visual search performance, both in humans and nonhuman primates, could profitably use these criteria to establish the nature of the attentional involvement in a given search paradigm.

The results of the reported experiments are well described by our serial model. Yet a crucial question still remains. Could the same results be fitted by parallel-processing models? The predictions by the serial model

for the set-size experiment can be mimicked by a parallel model with a strong serial component (a series of reallocations of processing capacity; Townsend & Ashby, 1983). In the parallel model, a limited amount of processing capacity ($1/\lambda_1$) is evenly distributed among those elements in the search array that have not yet been processed. If and when an element completes processing by being classified as a target, a target-present response is made. If and when all elements have been classified as nontargets, a target-absent response is made. Otherwise, whenever an element completes processing by being classified as a nontarget, the processing capacity allocated to that element is reallocated so that it becomes evenly distributed among the elements that remain to be processed. If the time taken to process an element is exponentially distributed with a rate parameter equal to the amount of processing capacity allocated to the element, predictions by this model are identical to predictions by a serial model with exponentially distributed processing times.

To predict faster processing of the very first element in a display, one must assume that the total amount of processing capacity is greater ($1/\lambda_2$) in the beginning of the search process until the first element has completed processing. As in the serial model, base RT on target-absent trials should follow a gaussian distribution. To mimic the effect of the serial model's assumption that the target-processing cycle is special (for elements other than the first element completing processing), one could assume that the base RT on target-present trials follows a gaussian distribution convolved with a fast ($\lambda_3$) exponential and deconvolved with a slow ($\lambda_1$) exponential, so that base RT plus ($\lambda_1$-exponentially distributed) target-processing time becomes distributed as the gaussian convolved with the fast ($\lambda_3$) exponential.

The predictions by the serial model for the position experiment can be mimicked by a parallel model with fixed processing capacity if one makes some special assumptions. Let the consecutive stimulus positions be numbered from 1 up to 8, so that position 1 is the position at which the target is most likely to occur. Assume that the total processing capacity is distributed across the eight elements in a display in proportion to attention weights, and assume that the attention weight of the element located at position $i$ is equal to $1/i$. Further, assume that during the processing of the display the distribution of processing capacity is kept constant (i.e., reallocation of processing capacity does not occur). Then the mean time taken to complete processing of the item at position $i$ should be directly proportional to $i$. Hence, as also predicted by the serial model, the time taken to find a target at position $i$ should be a linearly increasing function of $i$.

It is interesting that the predictions by the serial model can be mimicked by parallel models (Townsend & Ashby, 1983), but it is noteworthy that the parallel models for the two experiments are mutually inconsistent. Whereas the parallel model for the set-size experiment assumes that processing capacity is reallocated whenever an element completes processing by being classified as a nontarget, the parallel model for the position experiment makes the opposite assumption. It seems impossible to account for both experiments by a single, reasonably simple parallel model.

Although the present study appears to demonstrate that some search arrays indeed require the intervention of serial attention mechanisms, this demonstration should not be taken to imply that any reliable effect of set size in visual search is due to serial mechanisms. For example, Bundesen (1990, 1998a, 1998b) suggested that only very large effects of set size, of the same order of magnitude as those shown in the present report, reflect serial deployment of attention to individual array elements, while smaller set-size effects are the result of parallel, competitive mechanisms (see also Ward & McClelland, 1989) or of a combination of parallel competitive and serial mechanisms (e.g., search that is parallel within groups of array elements, but serial between groups; Pashler, 1987). It will be our next objective to assess whether search tasks producing set-size effects in the order of a few tens of milliseconds per added element also draw upon serial attention.

## METHODS

### General Methods

Stimulus displays were generated on a CRT monitor (640 by 480 pixels, 60 Hz refresh rate) controlled by a PC. Search arrays were drawn in light gray (14.8 cd/m$^2$) against a dark background (<0.1 cd/m$^2$) and consisted of T-shaped elements presented in any of four possible orientations: 0° (upright), +90°, −90°, and 180°. Each element was made of two identical segments, 0.85° in length and 0.08° in width, with the center of one segment intersecting the other at 0.25° off its center. One specific orientation (except the upright orientation) defined the target throughout an experimental session, while all the remaining orientations (including upright) were used for the nontargets. Targets in the upright orientation were excluded after pilot testing had demonstrated that they yielded a substantially better performance than targets in any other orientation. A target was present in 50% of the trials. Array elements were presented along an imaginary hemicircle centered on fixation at an eccentricity of 6.7°. In different trial blocks, the search array was confined to the right or left visual hemifield. In each hemifield, there were eight locations where an element could appear, with an angular distance between them of 2.2°. When fewer than eight elements formed an array, they were always presented at adjacent locations along the hemicircle. Elements were shown with a jitter of ±0.2° in the horizontal and vertical

direction. Three aspects of the stimuli that we used should be emphasized. First, target and nontargets had an identical shape, the only distinguishing property being their relative orientation. Second, during pilot testing, we were able to progressively increase the perceptual difficulty of the task by making one stimulus segment intersect the other closer and closer to its midline. This gave us a virtually continuous control of search (in)efficiency. In the extreme case, if the two segments were to cross each other at the exact midline, then there would be no difference at all between target and nontargets. Third, again during pilot testing, we could move stimulus arrays progressively further out in the periphery of the visual field in order to maximally challenge their discriminability, while ensuring that our observers could perform the task without making eye movements.

Subjects were seated in a dimly illuminated room at a viewing distance of 57 cm from the computer monitor which, at this distance, subtended 21° by 28° of the visual angle. They were instructed to press a key to indicate that a target was present, and a different key to indicate that it was absent. Key pressing was performed with the index and middle fingers of the hand ipsilateral to the stimulated hemifield. In addition, subjects were instructed to maintain fixation on a central light gray dot throughout the trial.

At the start of each trial, the fixation dot was presented for 500 msec, after which the search array appeared and remained visible until the subject's response or until 10 sec had elapsed. An auditory feedback was provided on error trials. We measured accuracy and RT of key presses as functions of set size, separately for target-present and target-absent trials. Stimulus presentation and collection of key presses were controlled by the commercial software MEL2 (Psychology Software Tools, 1995).

## Set-Size Experiment

Seventeen students at the University of Verona (between 20 and 30 years of age, 5 men), with normal or corrected-to-normal vision, were paid to take part in this experiment. They were all naïve with respect to the purpose of the study. Set size could take one of four values: 2, 4, 6, and 8. A set size of 8 filled all the available stimulus locations in the array. The experiment comprised three 1-hr sessions run on consecutive days, one for each target orientation. Each session comprised 10 blocks of trials, 5 for the left hemifield followed by 5 for the right hemifield, or vice versa. Ten subjects started their sessions with arrays in the left hemifield, while the reverse order was followed for the remaining subjects. The first block of 60 trials for each hemifield was considered training and the data were discarded from further analyses. The remaining four blocks of 60 trials each provided the data reported in this study. Thus, 480

trials were run per session for each subject, or a total of 1440 trials across sessions. Each block was initiated by the subject with a key press, while subsequent trials were automatically administered by the computer program. An interval of 1 sec was allowed between consecutive trials.

## Eye Movement Control Experiment

Six students at the University of Verona (between 21 and 30 years of age, 3 men), with normal or corrected-to-normal vision, were paid to take part in this experiment. They were all naïve with respect to the purpose of the study. The experiment was identical to the previous one except for the following. Only search arrays confined to the left visual hemifield were used. Eye position was measured binocularly with the aid of a video-based system (EyeLink, SR Research Ltd., Toronto, Canada; SensoMotoric Instruments GmbH, Teltow, Germany). Horizontal and vertical position of each eye was sampled and stored at a rate of 250 Hz. In addition, the system measured the 3-D position of the head with respect to the computer monitor, which allowed to compensate for slight head movements. Eye position could be measured with a resolution of at least 0.1°. In order to ensure this high level of performance, calibration and drift correction of the eye tracker were repeated every 10–20 trials. Each subject participated in three sessions on consecutive days. The first 64-trial block of each session was used to familiarize the subject with the task and with the eye movement recording procedures. In each of the three sessions, subjects then performed four blocks of 60 trials.

## Position Experiment

Nine students at the University of Verona (between 20 and 30 years of age, 1 man), with normal or corrected-to-normal vision, were paid to take part in this experiment. They were all naïve with respect to the purpose of the study. The experiment was identical to the initial one except for the following. Search arrays contained eight elements in all trials. Subjects were informed that a target was present in 50% of the trials and that, when present, it had a much higher (51%) probability of being at one specific end-location of the array. This was the upper location for arrays confined to the right hemifield and the lower location for arrays confined to the left hemifield. The remaining 49% target-present trials had a target at any of the other seven locations, with a 7% probability at each location. Subjects performed three sessions on consecutive days. Each session comprised 18 blocks of trials, nine for the left and nine for the right hemifield. Order of hemifield testing was counterbalanced across subjects. The first block of 60 trials for each hemifield was used as training. The remaining eight blocks of 60 trials each provided the experimental data.

## Cumulative Distributions and Monte Carlo Simulations

We first computed the centized cumulative RT distributions for each subject (one for each set size, separately for target-present and target-absent trials), and then averaged the resulting distributions across subjects (Ratcliff, 1979). We therefore obtained eight group cumulative distributions, four for target-present and four for target-absent trials.

Next, we explored the possibility that, according to the serial, self-terminating model, each of the eight distributions under consideration could be described by the convolution of a number ($N$) of exponential distributions $f(x)$, all with the same parameter $\lambda$, and a normal distribution $g(x)$ with parameters $\mu$ and $\sigma$, where

$$f(x) = (1/\lambda)e^{-x/\lambda}$$

and

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\}$$

Each exponential distribution would represent one cycle of the serial process, while the normal distribution would represent the set of processes that occur only once during the course of a trial (e.g., early-level visual processing, response selection, motor preparation, key pressing).

Each one of the eight distributions can therefore be described by four parameters: $N$, $\lambda$, $\mu$, and $\sigma$. The parameter $\lambda$ should be identical in all conditions (target present and target absent, for all set sizes), while in order to account for the different number of search cycles, the number $N$ of exponential functions should increase as predicted by the number of elements to be analyzed. For instance, in the case of target-absent trials with two elements, two cycles need to be performed on each trial, since both elements must be analyzed before the subject can produce a response. Therefore, this type of trial should be simulated by performing a convolution of one gaussian and two exponential distributions. On the contrary, in the case of target-present trials with two elements, the target will be found after inspecting only one element in 50% of the trials and after inspecting both elements in the remaining 50%. Therefore, this type of trial should be simulated by a mixture of underlying distributions: one consisting of a gaussian and one exponential function, the other consisting of a gaussian and two exponential functions. In other words, the number $N$ of exponential functions for the simulation should depend on the number of array elements but in two different ways for target-absent and target-present trials. For target-absent trials, it indicates the actual number of exponential functions convolved in the equation, while for target-present trials, it indicates the maximum number of exponential functions convolved

in the equation. Contrary to this simple scheme, we actually discovered that two special cases had to be added to the model, each corresponding to an exponential function with a separate $\lambda$ parameter: one ($\lambda_2$) exponential function for the first cycle of search and one ($\lambda_3$) exponential function for the search cycle in which the target is found.

Parameters $\mu$ and $\sigma$ need not be exactly the same for the target-present and target-absent conditions.

In conclusion, we needed to estimate the three $\lambda$ parameters and two sets of parameters $\mu$ and $\sigma$, one for the target-present and one for the target-absent condition, while the values of parameter $N$ for the eight conditions were imposed according to the model. In order to estimate these parameters, we used the method of Monte Carlo simulation. Starting from randomly chosen values of the parameters $\lambda_1$, $\lambda_2$, $\lambda_3$, $\mu$, and $\sigma$, the theoretical distributions were computed and compared to the experimental ones. The magnitude of the residual error (mean square error) was used to correct the parameter estimation. This procedure was repeated a large number of times in order to reach a satisfactory goodness of fit.

In practice, we first estimated the parameters for the four target-absent conditions together. Since there was a strong hypothesis equating the number of cycles to the number of elements, we did not try to estimate the number $N$ of exponential functions, and parameter $N$ was fixed to be equal to the number of elements in the array. However, after pilot simulation of the empirical data, we discovered that the first cycle of search had to be modeled as a separate exponential function with free parameter $\lambda_2$. Therefore, we first randomly picked initial values $\mu_0$, $\sigma_0$, $\lambda_{10}$, and $\lambda_{20}$ for the free parameters. Using these parameters, we generated four theoretical group RT distributions by sampling 10,000 times four theoretical distributions each with a gaussian and 2, 4, 6, and 8 exponentials, respectively. Of the $N$ exponential functions, one was always a $\lambda_2$ exponential and $N-1$ were $\lambda_1$ exponentials. Once these distributions were obtained and centized, the average mean square error between each theoretical distribution and the corresponding experimental distribution was computed. The error, averaged across the four distributions, was used to update the values of the free parameters, as described above. This procedure was repeated a large number of times. In order to assess whether the values obtained for the parameters were acceptable, once the simulation had converged, we also assessed the goodness of fit of each theoretical distribution to the corresponding empirical distribution by means of the Kolmogorov–Smirnoff one-sample test (Siegel, 1956).

In the case of target-present trials, we proceeded to estimate only some of the parameters to generate the artificial RT distributions, under the theoretical hypothesis that the $\lambda_1$ and $\lambda_2$ parameters of the exponential functions and the maximum number $N$ of cycles for a

given set size should be the same as for the target-absent condition. The only free parameters in the simulations were thus the two parameters of the gaussian distribution and the $\lambda_3$ parameter of the exponential function that had to be included to simulate the search cycle in which the target is found.

## Acknowledgments

## REFERENCES

Ashbridge, E., Walsh, V., & Cowey, A. (1997). Temporal aspects of visual search studied by transcranial magnetic stimulation. *Neuropsychologia, 35,* 1121–1131.

Ashby, F. G., & Townsend, J. T. (1980). Decomposing the reaction time distribution: Pure insertion and selective influence revisited. *Journal of Mathematical Psychology, 21,* 93–123.

Atkinson, R. C., Holmgren, J. E., & Juola, J. F. (1969). Processing time as influenced by the number of elements in a visual display. *Perception and Psychophysics, 6,* 321–326.

Bundesen, C. (1990). A theory of visual attention. *Psychological Review, 97,* 523–547.

Bundesen, C. (1996). Formal models of visual attention: A tutorial review. In A. F. Kramer, M. G. H. Coles, & G. D. Logan (Eds.), *Converging operations in the study of visual selective attention* (pp. 1–43). Washington, DC: American Psychological Association.

Bundesen, C. (1998a). Visual selective attention: Outlines of a choice model, a race model and a computational theory. *Visual Cognition, 5,* 287–309.

Bundesen, C. (1998b). A computational theory of visual attention. *Philosophical Transactions of the Royal Society of London, Series B, 353,* 1271–1281.

Chelazzi, L. (1999). Serial attention mechanisms in visual search: A critical look at the evidence. *Psychological Research, 62,* 195–219.

Corbetta, M., Shulman, G., Miezin, F., & Petersen, S. (1995). Superior parietal cortex activation during spatial attention shifts and visual feature conjunction. *Science, 270,* 802–805.

Donner, T., Kettermann, A., Diesch, E., Ostendorf, F., Villringer, A., & Brandt, S. A. (2000). Involvement of the human frontal eye field and multiple parietal areas in covert visual selection during conjunction search. *European Journal of Neuroscience, 12,* 3407–3414.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review, 96,* 433–458.

Duncan, J., Ward, R., & Shapiro, K. L. (1994). Direct measurement of attentional dwell time in human vision. *Nature, 369,* 313–315.

Harris, J. R., Shaw, M. L., & Altom, M. J. (1985). Serial-position curves for reaction time and accuracy in visual search: Tests of a model of overlapping processing. *Perception and Psychophysics, 38,* 178–187.

Hockley, W. E. (1984). Analysis of response time distributions in the study of cognitive processes. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 10,* 598–615.

Hopf, J. M., Luck, S. J., Girelli, M., Hagner, T., Mangun, G. R., Scheich, H., & Heinze, H. J. (2000). Neural sources of focused attention in visual search. *Cerebral Cortex, 10,* 1233–1241.

Humphreys, G. W., & Müller, H. J. (1993). SEarch via Recursive Rejection (SERR): A connectionist model of visual search. *Cognitive Psychology, 25,* 43–110.

Leigh, R. J., & Zee, D. S. (1999). *The neurology of eye movements* (3rd ed.). New York: Oxford University Press.

Leonards, U., Sunaert, S., Van Hecke, P., & Orban, G. A. (2000). Attention mechanisms in visual search—An fMRI study. *Journal of Cognitive Neuroscience, 12* (Suppl. 2), 61–75.

Luck, S. J., & Hillyard, S. A. (1995). The role of attention in feature detection and conjunction discrimination: An electrophysiological analysis. *International Journal of Neuroscience, 80,* 281–297.

McElree, B., & Carrasco, M. (1999). The temporal dynamics of visual search: Evidence for parallel processing in feature and conjunction searches. *Journal of Experimental Psychology. Human Perception and Performance, 25,* 1517–1539.

Palmer, J. (1995). Attention in visual search: Distinguishing four causes of a set-size effect. *Current Directions in Psychological Science, 4,* 118–122.

Pashler, H. (1987). Detecting conjunctions of color and form: Reassessing the serial search hypothesis. *Perception and Psychophysics, 41,* 191–201.

Ratcliff, R. (1979). Group reaction time distributions and an analysis of distribution statistics. *Psychological Bulletin, 86,* 446–461.

Ratcliff, R., & Murdock, B. B. J. (1976). Retrieval processes in recognition memory. *Psychological Review, 83,* 190–214.

Raymond, J. E., Shapiro, K. L., & Arnell, K. M. (1992). Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of Experimental Psychology. Human Perception and Performance, 18,* 849–860.

Siegel, S. (1956). *Nonparametric statistics for the behavioral sciences.* New York: McGraw-Hill.

Townsend, J. T. (1990). Truth and consequences of ordinal differences in statistical distributions: Toward a theory of hierarchical inference. *Psychological Bulletin, 108,* 551–567.

Townsend, J. T., & Ashby, F. G. (1983). *The stochastic modeling of elementary psychological processes.* Cambridge: Cambridge University Press.

Townsend, J. T., & Roos, R. N. (1973). Search reaction time for single targets in multiletter stimuli with brief visual displays. *Memory and Cognition, 1,* 319–332.

Treisman, A., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12,* 97–136.

Treisman, A., & Gormican, S. (1988). Feature analysis in early vision: Evidence from search asymmetries. *Psychological Review, 95,* 15–48.

Treisman, A., & Sato, S. (1990). Conjunction search revisited. *Journal of Experimental Psychology. Human Perception and Performance, 16,* 459–478.

Ward, R., Duncan, J., & Shapiro, K. L. (1996). The slow time-course of visual attention. *Cognitive Psychology, 30,* 79–109.

Ward, R., & McClelland, J. L. (1989). Conjunctive search for one and two identical targets. *Journal of Experimental Psychology. Human Perception and Performance, 15,* 664–672.

Wolfe, J. M. (1994). Guided search 2.0: A revised model of visual search. *Psychonomic Bulletin and Review, 1,* 202–238.

Wolfe, J. M. (1998). Visual search: A review. In H. Pashler (Ed.), *Attention* (pp. 13–73). London: University College London Press.

Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology. Human Perception and Performance, 15,* 419–433.

Woodman, G. F., & Luck, S. J. (1999). Electrophysiological measurements of rapid shifts of attention during visual search. *Nature, 400,* 867–869.

Yantis, S., Meyer, D. E., & Smith, J. E. K. (1991). Analyses of multinomial mixture distributions: New tests for stochastic models of cognition and action. *Psychological Bulletin, 110,* 350–374.