

# Distractors slow information accumulation in simple feature search

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M. Carrasco and B. McElree (2001) presented a speed–accuracy trade-off experiment, investigating covert attention in visual search. One of the conclusions from Carrasco and McElree was that adding distractors to a single feature search does not decrease the speed with which information is accumulated about target identity. We present a reanalysis of the relevant data from Carrasco and McElree in which we demonstrate that their conclusion was incomplete and we demonstrate a processing speed advantage for single feature search displays with no distractors compared with displays with distractors. This finding is confirmed in a new speed–accuracy trade-off experiment presented here. Further, we demonstrate that increasing the display duration increases the processing speed of displays with distractors but not for displays without distractors. We discuss these results in relation to theories of visual attention and the debate between graded and fixed architecture accounts for attentional allocation.

Keywords: attention, speed–accuracy trade-off, visual search, graded attention, attention allocation

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## Introduction

Covert attention, the ability to preferentially process information from objects that are not foveated, has been extensively studied (see a recent review by Carrasco, 2011) and is at the center of models of a wide range of visual behaviors including reading (e.g., Henderson & Ferreira, 1990), visual search (e.g., Treisman, 1988), and multiple object tracking (e.g., Fehd & Seiffert, 2008). However, what is less clear is exactly what covert attention does to enhance perception. Over the last 20 years, the mechanisms by which covert attention enhances perception have become clearer. Covert attention can increase the precision with which objects are represented (Howard & Holcombe, 2008; Prinzmetal, Amiri, Allen, & Edwards, 1998). Equivalently to increasing precision, others have shown attention to give rise to signal enhancement (increasing the signal-to-noise ratio), with a similar effect to an increase in contrast of stimuli (Cameron, Tai, & Carrasco, 2002; Carrasco, Penpeci-Talgar, & Eckstein, 2000; Lu & Doshier, 1998). Covert attention can also help filter out task-irrelevant stimuli, even when these stimuli function to add noise at the location where the target signal is presented (Lu, Lesmes, & Doshier, 2002). Additionally, covert attention has been shown, under some circumstances, to increase the speed with which stimuli are processed (Carrasco & McElree, 2001). This article focuses on this last benefit of covert attention and explores the effect that additional distractors

have on the speed of information accumulation from a target.

In particular, we examine the speed of information accumulation when the number of distracting stimuli is small ( $\leq 3$ ) as, traditionally, processing in simple detection<sup>1</sup> tasks with few distractors has been thought not to benefit from focal attention and so not affected by the addition of distractors (e.g., Carrasco, McElree, Denisova, & Giordano, 2003; Henderickx, Maetens, Geerinck, & Soetens, 2009; Lee, Kock, & Braun, 1997; Treisman & Gelade, 1980).

Evidence from multiple object tracking tasks and subitizing tasks suggests that up to around four spatially distinct objects can be very efficiently processed (e.g., Pylyshyn & Storm, 1988; Trick & Pylyshyn, 1994). Converging evidence for a limit of around four objects comes from visual short-term memory studies (Cowan, 2001; Luck & Vogel, 1997). Originally, the mechanism underlying the limited focus of attention was assumed to be a fixed architecture system in which a limited number of discrete, independent, attentional foci are allocated to objects, as exemplified in the FINST model (e.g., Pylyshyn, 1989; Pylyshyn & Storm, 1988; Trick & Pylyshyn, 1994). However, more recent evidence has suggested that the focus of attention is a more graded, flexible resource (e.g., Alvarez & Franconeri, 2007; Howard & Holcombe, 2008; Iordanescu, Grabowecky, & Suzuki, 2009; Shim, Alvarez, Vickery, & Jaing, 2010; Tombu & Seiffert, 2008; Vetter, Butterworth, & Bahrami, 2008). According to a graded resource account, attention is allocated on a

demand basis, in line with the principles of cognitive load (Lavie, 2005). Crucially, a graded resource account claims that there is no fixed number of items that can be attended but that the demands of the task (including stimulus properties) determine the amount of attention that can be allocated to each item, with loads greater than around four items demanding more resources than those available, resulting in a decrement in performance (at least those typically used in visual attention studies, see, e.g., Horowitz et al., 2007). For moving objects, factors such as spatial density and object speed can affect the number of items that can be tracked (e.g., Shim et al., 2010). Critically, a resource-based model of attention predicts a more gradual decline in performance as more items requiring attention are added to the task. Such a gradual decline is clearly evident in the data of Alvarez and Franconeri (2007) when the number of items to track is plotted against either the speed at which objects can move or the minimum distance separating objects. An attentional mechanism based on a number of independent attentional foci (e.g., a fixed slot-based architecture, e.g., Pylyshyn & Storm, 1988) does not in and of itself predict gradual decreases between one and four items (e.g., Shim et al., 2010).

In contrast, visual search tasks have focused on the continuum of processing between rapid efficient search, in which a target item is defined by a single unique feature and “pops out” among distractors, and a slower inefficient search, in which a target item is defined by a unique combination of features that are shared by distractors (conjunction search). The typical finding is that efficient search results in a search slope between 0 and 10 ms per item and that in inefficient searches, slopes above 20 ms per item (e.g., Duncan & Humphreys, 1989; Treisman & Souther, 1985). It has been argued that efficient search requires only limited focal attention and that either attention is allocated diffusely across the whole search area or the target is detected by a “pre-attentive” process, similar to the proposed mechanisms involved in subitization or multiple object tracking. In contrast, inefficient search may require some element of serial allocation of attention (covert or overt) to items in the display. Evidence suggests that with a homogenous set of distractors, each additional new distracting item is not treated as unique, and all distracting identical items are treated as a single distracting item, through perceptual grouping (e.g., Duncan & Humphreys, 1989). Thus, efficient search (single feature search) is apparently unaffected by the number of distractors.

While in many of these attentional tasks speed is stressed as important to participants in verbal instructions (e.g., “Please respond as quickly and accurately as possible”), the participant is still able to respond when they feel ready. The participant presumably makes an implicit calculation of the relative importance of speed and accuracy on the task and uses this metric to make their response after an appropriate amount of processing

has occurred. In other words, the participant determines where to respond along the speed–accuracy trade-off (SAT) continuum, between chance responding for relatively fast responses and asymptotic performance for relatively slow responses. Thus, whereas instructions to respond quickly may result in faster responding than instructions giving more weighting to accuracy (or no instruction), the exact trade-off is unknown, and only a single point on the SAT continuum is measured. One major problem with the typical instructions used in the above literature is that we cannot know the relative effects of attention on speed and accuracy, and subtle differences may be hidden. For example, when a task places relatively little demand on attention, for instance, when searching for a simple feature among a small number of distractors, search may occur very rapidly. However, if the efficient task is mixed with inefficient tasks (or take place in the same testing session), participants may set a conservative criterion for accuracy (i.e., they only respond when they are very confident that they will be correct) to ensure they maximize accuracy for both efficient and inefficient trials. This would result in slower responding than could be achieved for a similar level of accuracy for efficient trials. It could obscure differences between smaller set sizes that may have been apparent with a more liberal response criterion (i.e., respond as quickly as possible). A clue that this may be the case is seen in the typically low error rates (<5% errors). Such a situation would result in minimal differences in RTs for set sizes that have similar levels of accuracy, especially when search displays are left on screen until a participant makes a response (allowing continued stimulus sampling for the more inefficient trials). Thus, the typical instructions given to participants may hide differences in the speed at which processing can occur between set sizes in a simple detection task and therefore any differences in the demand on attention. In an important and influential article, Carrasco and McElree (2001) used a SAT paradigm (designed to provide a measure of the dynamics of information accumulation; Reed, 1973) and demonstrated that covert attention not only increases discriminability but also speeds the rate at which information is extracted from an attended object in a search task. Importantly, the speed of processing was unaffected by an increase in the number of distractors in a simple feature (orientation singleton) search, in line with results from respond-when-ready studies, suggesting that simple efficient feature search does not place a significant demand on covert attention.

A series of articles followed in which Carrasco, McElree, and Giordano (Carrasco, Giordano, & McElree, 2004, 2006; Carrasco & McElree, 2001; Carrasco et al., 2003; Giordano, McElree, & Carrasco, 2009) further investigated the nature and time course of covert attention using the SAT procedure in a simple 2AFC discrimination task (left or right 30° oriented Gabor patch among vertically aligned distractors). The main findings from Carrasco and McElree (2001) included: (i) increasing the

number of distractors decreased discriminability of targets both for feature and conjunction searches; (ii) spatial cuing of target location increased discriminability of targets both in feature and conjunction searches; (iii) cuing decreased processing time for both feature and conjunction searches; (iv) however, reducing the number of distractors increased processing speed for conjunction searches but not for feature searches. For their single feature (orientation singleton) search, when set sizes 1, 4, and 8 were investigated, Carrasco et al. (2003, p. 1) reported that “Set size did not affect processing speed, indicating that all items are processed in parallel.” It is this claim that we investigate in detail in this article.

Apparently, parallel search for a simple feature or “pop-out” is typical of a great many experiments that do not use the SAT methodology. It is still perhaps surprising however that an increase from no distractors to three distractors or even seven distractors failed to have an impact on the speed at which information was accumulated given that processing speed for a single item can be sped further by cuing, suggesting that there is some spare capacity in the system, which could be utilized when there is less uncertainty as to the target location. It therefore seems plausible that there should be a difference in processing speed between set sizes 1, 4, and 8 in Carrasco and McElree’s (2001) data. Critically, Carrasco and McElree do not report the crucial pairwise comparisons for whether there is a rate difference between set sizes 1, 4, and 8. We therefore reanalyzed their data to explore more fully whether there was a constant rate in single feature search between displays that only contain the target and those containing the target plus distractors.

## Reanalysis of Carrasco and McElree (2001)

We now briefly outline the SAT procedure and the method used to analyze data from such experiments, before detailing the reanalysis of Carrasco and McElree’s (2001) data. The SAT procedure is used to investigate the full time course of processing, while avoiding strategic processes that can occur during standard respond-when-ready paradigms. On any trial, participants are *a priori* unaware of how much time they will be allowed to process the stimulus and respond. On a trial, some time after stimulus onset (usually between tens of milliseconds and up to several seconds), a signal is given (e.g., a loud tone) at which point the (trained) observer is required to respond within a small time frame, usually around 300 ms after the signal. A number of signal intervals are used such that performance can be mapped from chance responding (at very short signal intervals) to asymptotic performance (at longer intervals). Task performance (typically  $d'$  for a two-choice task) is plotted as a function of processing

time  $t$  (signal interval plus response lag) for each condition of the experiment. A simple shifted exponential-rise-to-asymptote function is then fit to the SAT data:

$$d'(t) = \lambda(1 - e^{-\beta(t - \delta)}), \text{ for } t > \delta, \text{ else } 0, \quad (1)$$

in which  $\lambda$  is the asymptotic level of discriminability,  $\beta$  is the rate at which discriminability rises from guessing ( $d' = 0$ ) to asymptote, and  $\delta$  is the intercept—the time at which responding is no longer at chance (the “takeoff” point).<sup>2</sup> Typically, a hierarchical model testing approach is used to find the optimal model (in terms of goodness of fit and the numbers of free parameters) starting with the fully restricted null model (with only the three free parameters for all conditions) moving toward the fully saturated model (three free parameters:  $\lambda$ ,  $\beta$ , and  $\delta$ , for each condition of the experiment). Figure 1 plots idealized SAT curves for a two-condition experiment. The top panel shows the case where two conditions differ in asymptote,

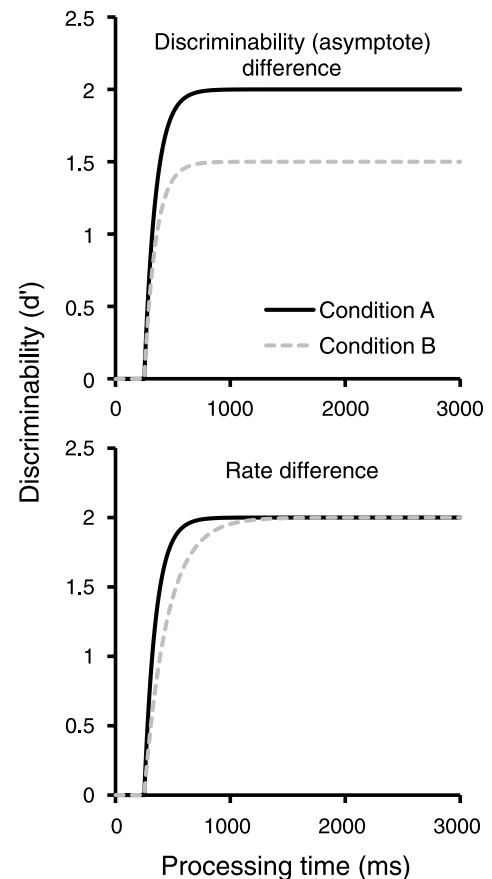


Figure 1. Idealized speed–accuracy trade-off functions using Equation 1. The top panel demonstrates a difference in asymptotes for Condition A ( $\lambda = 2$ ) and Condition B ( $\lambda = 1.5$ ). The bottom panel demonstrates a difference in rate between Condition A ( $\beta = 100$  ms) and Condition B ( $\beta = 200$  ms). All takeoff parameters,  $\delta$ , = 250 ms. Processing time refers to the time of the signal to respond plus the lag in responding.

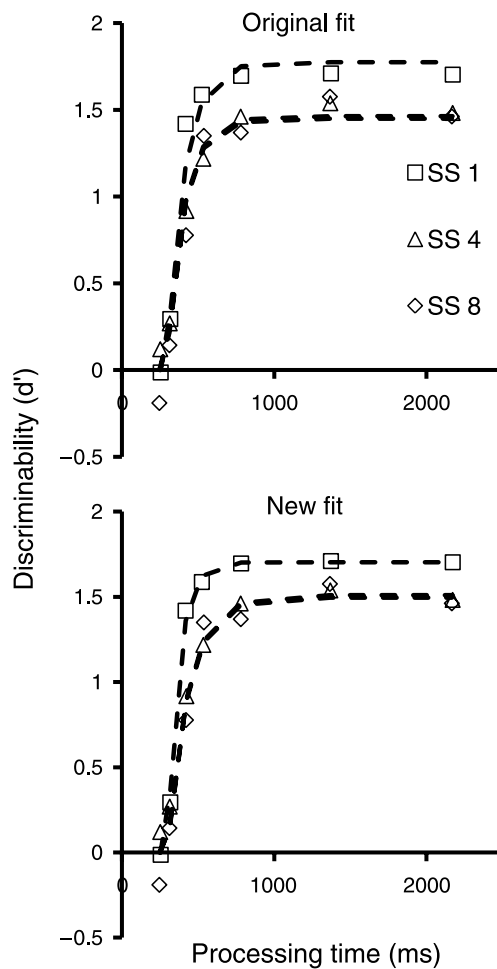


Figure 2. Data from the single feature search task, neutral cue, condition of Carrasco and McElree (2001). The top panel shows the original ( $3\lambda-1\beta-1\delta$ ) model fits, and the bottom panel shows the new ( $3\lambda-2\beta-1\delta$ ) model fits. SS = set size. Processing time refers to the time of the signal to respond plus the lag in responding.

whereas the bottom panel shows the case where the two conditions differ in rate (a difference in takeoff is not shown but would simply involve shifting one of the SAT curves to the left or right).

In our reanalysis of Carrasco and McElree's (2001) data, we are interested only in the single feature search data and focus only on the central (non-informative) cue condition, thus we do not consider the conjunction search or cued data. Figure 2 (top panel) shows the data and original SAT function fits from Carrasco and McElree's single feature search condition (Table 1 gives the SAT parameters). The data show the typical pattern of initial guessing, followed by a rapid increase in discriminability up until an asymptotic level of discriminability. A fully saturated model of the data has 9 free parameters: 3 (set size: 1, 4, 8)  $\times$  3 (parameters:  $\lambda$ ,  $\beta$ , and  $\delta$ ), denoted as  $3\lambda-3\beta-3\delta$ . Carrasco and McElree reported that they used three criteria for determining which model was most

appropriate: (i) the value of an  $R^2$  statistic adjusted for the number of free parameters:

$$R^2 = 1 - \frac{\sum_{i=1}^n (d_i - \hat{d}_i)^2 / (n - k)}{\sum_{i=1}^n (d_i - \bar{d})^2 / (n - 1)}, \quad (2)$$

in which  $d_i$  is the observed data,  $\hat{d}_i$  is the predicted value,  $\bar{d}$  is the observed mean,  $n$  is the number of data points, and  $k$  is the number of free parameters; (ii) the consistency of the parameter estimates across all three observers; and (iii) whether any fit left any systematic residuals that could be captured by additional free parameters. Carrasco and McElree ultimately ended up declaring a  $3\lambda-1\beta-1\delta$  model as the best to describe their data ( $R^2 = 0.970$ ). This model only allows the asymptotic levels of performance to vary across set sizes, with equal takeoff and rate parameters; Carrasco and McElree state: "For the *neutral* feature search, processing time was unaffected by set size. Model fits that varied intercept or rate as a function of set size reduced the adjusted- $R^2$  for each observer and for the average data, indicating that the additional parameters were not accounting for systematic variance in the data" (p. 5365). However, it is unclear whether the authors attempted to fit models that allowed rates to vary between set sizes other than in an all-or-none fashion and whether the reduced fit was due to combining attempts to fit the neutral cue condition and the peripherally cued condition simultaneously.

In our reanalysis, we applied the same basic model as Carrasco and McElree (starting with the  $3\lambda-1\beta-1\delta$ ) but allowed the individual rate parameters to vary by set size. In addition, we also fit the data using maximum likelihood criteria (in effect minimizing log-likelihood,  $\text{Ln}(L)$ , as well as the adjusted- $R^2$  value) that allow us to statistically test differences in goodness of fit between nested models. Both statistics gave the same results in terms of model selection. Like Carrasco and McElree, we also fit the

Parameter	Original	New
<i>Discriminability (<math>\lambda</math> in <math>d'</math> units)</i>		
Set size 1	1.78	1.70
Set size 4	1.46	1.51
Set size 8	1.45	1.50
<i>Rate (<math>\beta</math> in ms units)</i>		
Set size 1	114	74
Set sizes 4 and 8		137
<i>Intercept (<math>\delta</math> in ms units)</i>		
All set sizes	293	299

Table 1. Parameter estimates for the original ( $3\lambda-1\beta-1\delta$ ) and new ( $3\lambda-2\beta-1\delta$ ) models fit to single feature search, neutral cue condition, of Carrasco and McElree (2001).

model to individual participants and the averaged data (presented) that gave largely consistent patterns of results. The  $3\lambda-1\beta-1\delta$  model gives an  $R^2$  value of 0.970,  $\text{Ln}(L) = 16.712$ . However, a close inspection of Figure 2 (top panel) reveals that the model fit for the set size 1 condition slightly overestimates the asymptote and underestimates several of the data points critical for estimating the rate parameter. Thus, we fit a model that included a separate free rate parameter for set size 1,  $3\lambda-2\beta-1\delta$ , which resulted in a significantly better fit,  $R^2 = 0.982$ ,  $\text{Ln}(L) = 19.09$  (a likelihood ratio test comparing the  $3\lambda-1\beta-1\delta$  and  $3\lambda-2\beta-1\delta$  models confirmed the improved fit,  $X^2(1) = 4.756$ ,  $p = 0.029$ ). All other models (varying both  $\beta$  and  $\delta$ ) failed to improve upon this fit. The  $3\lambda-2\beta-1\delta$  model fits can be seen in Figure 2 (bottom panel); the model now more closely captures the data for set size 1. The new parameter values are given in Table 1. As well as better capturing the rise to asymptote, by allowing the rate parameter for set size 1 to vary, the asymptote parameter has also been reduced, enabling the model to capture the asymptote, which before was overestimated. The set size 1 rate is now faster at 74 ms (instead of 114 ms as estimated originally) than the rate for set sizes 4 and 8 at 137 ms. Thus, as well as leading to greater asymptotic accuracy, having only one object displayed leads to significantly faster visual information accumulation, indeed much closer to the estimated 69 ms for the peripherally cued condition (Carrasco & McElree, 2001, Table 1, p. 5366), suggesting that cuing and removing distractors reduce the demand on attention to a similar degree. This finding is consistent with the idea that attention bestows greater discriminability but also a faster rate of information accumulation when there are no distractors present than when distractors are present, similar to the effect of cuing.

Our experiment was designed to replicate and further test the idea that processing speed is reduced by introducing distractors. When there are few distractors, all of the displayed items may potentially be within the visual focus of attention (if we assume capacity limit of approximately four items). One reason for the difference between set size 1 and set size 4 in Carrasco and McElree's data may have been that set size 4 was at or above the capacity for the limited focus of covert attention, and therefore, smaller set sizes (set size 2 and set size 3) within the limited focus of attention may be more similar to set size 1 than set size 4. Our experiment directly tested this possibility.

In addition to manipulating the number of distractors, we also manipulated display duration. Our motivation for manipulating the display duration stemmed from the observation that for single item identification tasks, very brief stimulus presentation (around 50–100 ms) could result in asymptotic accuracy that was not further increased with additional stimulus presentation time (e.g., Guest, Kent, & Adelman, 2010; Ludwig & Davies, 2011). Thus, it appears that the formation of a reliable representation is rapid for single stimulus displays (e.g., Ratcliff & Smith, 2010; Smith & Ratcliff, 2009), consistent with our

reanalysis of Carrasco and McElree's (2001) data. Carrasco and McElree only used a 40-ms presentation time that is on the lower end of estimates of the time it takes to form a sufficient representation (see Bays, Gorgorptis, Wee, Marshall, & Husain, 2011, for evidence linking exposure duration to representational variability). It has been argued that the rate of information processing is affected by the amount of attention directed at an item whereas the asymptote is affected by the quality of the stimulus, e.g., the contrast of the stimulus and the stimulus exposure time (Carrasco & McElree, 2001; Liu, Wolfgang, & Smith, 2009; Smith & Wolfgang, 2004). These in turn affect the representation (e.g., Ratcliff & Smith, 2010; Smith & Ratcliff, 2009). Therefore, if 40 ms is not long enough to form a complete representation, increasing the stimulus duration above around 100 ms (in this case to 140 ms) should result in a more complete representation and an increase in asymptotic performance. However, increases in the display duration may also increase the rate of information processing as information accumulation from a noisy representation will be slower than a less noisy representation. We expect a lower accumulation rate and asymptote in the set size 4 condition compared with the set size 1 condition, as in Carrasco and McElree's data, and that the longer stimulus duration should increase both the rate and asymptote for displays with distractors to a greater extent than compared with set size 1, as information may be sampled from the distractors when the representation is poor (under the 40-ms condition), which is not the case for set size 1 (no distractors). One difference between studies that manipulate stimulus exposure duration (e.g., Bays et al., 2011; Guest et al., 2010; Liu et al., 2009; Ratcliff & Smith, 2010; Smith & Wolfgang, 2004) and Carrasco and McElree's experiment and our experiment is the use of post-stimulus masks to prevent stimulus sampling after stimulus offset. Without using a mask, it is impossible to know whether stimulus duration *per se* (or, for example, increased perceived stimulus contrast) is affecting a change in performance. In order to maintain comparability to Carrasco and McElree's experiment, we do not use masks in our experiment. Regardless of the underlying process, increasing exposure duration in our task (with other factors held constant) should result in a more reliable stimulus representation (cuing appears to be more effective for masked than non-masked stimuli; see Kerzel, Gauch, & Buetti, 2010, and since masking may shorten the information accrual period, there is clearly no simple relationship between accrual time and performance).

The experiment closely followed the design of Carrasco and McElree's (2001) single feature search neutral cue condition with the following differences: (i) the current experiment included four distractor set sizes (zero, one, two, and three); (ii) the current experiment consisted of only single feature (orientation) search; (iii) we used only the neutral cue condition and no informative cue conditions; and (iv) stimuli were presented for either 40 ms or 140 ms.

## Methods

### Participants

Three participants completed the experiment; two of the authors (CK and CH) and one naive participant who was paid £8 per hour for her time.

### Stimuli and procedure

Stimuli were presented on a 19" Cathode Ray Tube monitor at  $1024 \times 768$  and a refresh rate of 120 Hz. The display background remained a uniform gray throughout the experiment. Stimuli were Gabor patches (sinusoidal luminance gratings vignettted by a Gaussian envelope) of 2 cpd presented at 10% contrast subtending approximately  $2^\circ$  of visual angle (with a 57-cm viewing distance) with a standard deviation of  $0.88^\circ$  of visual angle. Target stimuli were oriented either  $30^\circ$  to the left of vertical or  $30^\circ$  to the right of vertical. Target stimuli were either displayed with zero, one, two, or three distracting stimuli (vertically oriented Gabor patches). On each trial, stimuli were randomly allocated without replacement to one of four positions on a polar grid ( $45^\circ$ ,  $135^\circ$ ,  $225^\circ$ , and  $315^\circ$ ) at  $4^\circ$  eccentricity from a small black fixation cross.

At the start of each trial, a fixation cross was presented at the center of the screen for 1,000 ms. The cross was then replaced by an uninformative cue (a small black circle) for 67 ms to ensure consistency with Carrasco and McElree (2001). The cross then reappeared and remained on-screen for the remaining duration of the trial. There was a 53-ms gap between cue offset and stimulus presentation. The stimulus remained on-screen for either 40 ms or 140 ms. Participants were required to respond with a button on a gamepad under either their left or right

index finger depending on the stimulus orientation. Participants were trained to respond within 300 ms of the onset of a response signal (a 2120-Hz 100-ms tone). Response signals were randomly presented on each trial at 17, 34, 67, 100, 150, 250, 500, or 1,000 ms after stimulus onset. Feedback was given: If responses were made before the response signal, the message "Too Fast" was displayed; if responses were made after the response window, the message "Too Slow" was displayed; if the response was within the window and correct, the message "Correct" was displayed; and if the response was within the window and incorrect, the message "Wrong" was displayed. All feedback were presented at the center of the screen for 1,000 ms. A schematic of a trial is presented in Figure 3. At the end of the experimental block, proportion correct and proportion of responses within the window were displayed to the participant.

Participants completed 26 experimental blocks (each participant was given training until they were comfortable with the procedure, consisting of at least four full blocks). Each block consisted of 640 trials, containing 10 completely randomized replications of each cell of the design (collapsing across left and right stimulus orientations). Thus, each participant underwent 16,640 trials in the experiment. Participants were allowed a short break every 64 trials.

## Results

Figure 4 shows the averaged data from the three participants for the four set sizes in the 40- (top panel) and 140-ms (bottom panel) conditions. All set sizes showed the typical rise to asymptote pattern. We conducted a hierarchical model analysis using the same techniques and criteria as our reanalysis of Carrasco and

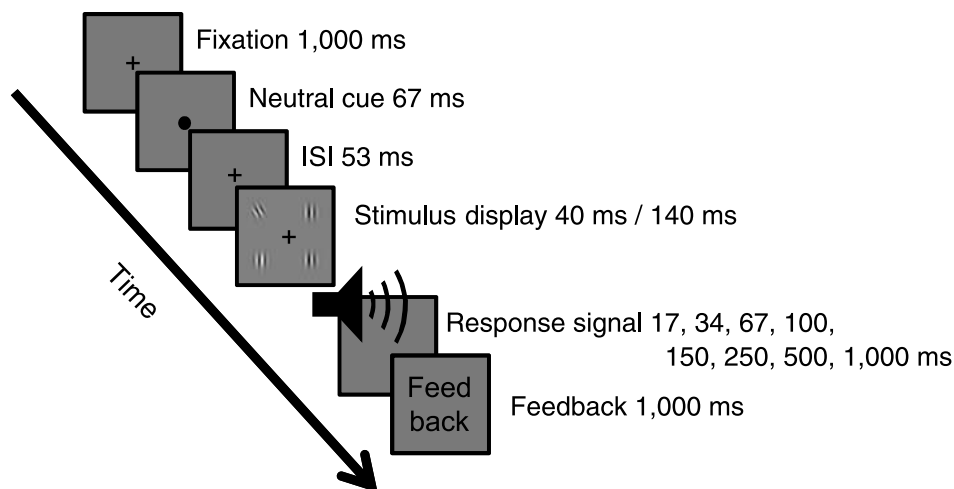


Figure 3. Trial structure used in the experiment, based on Carrasco and McElree (2001). Stimulus displays consisted of the target and 0, 1, 2, or 3 distractors. Objects could appear in 1 of 4 locations as shown (not to scale).

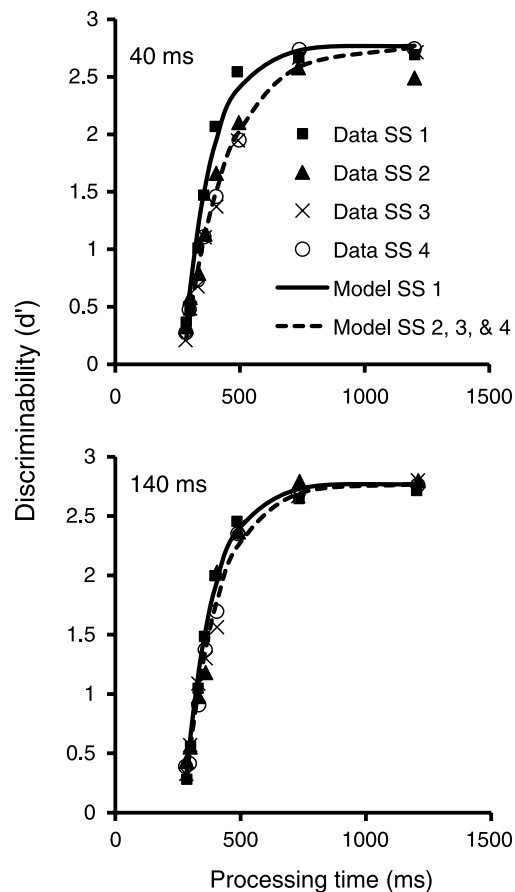


Figure 4. Markers are averaged data points from the three participants from the experiment; lines show the best fitting  $1\lambda-3\beta-1\delta$  model predictions for the 40- (top panel) and 140-ms (bottom panel) stimulus duration conditions. SS = set size. Processing time refers to the time of the signal to respond plus the lag in responding.

McElree (2001). The design is 2 (stimulus exposure duration)  $\times$  4 (set size) ignoring the response intervals. We start by exploring possible parametric differences between stimulus exposure duration (which could have a maximum of six free parameters associated with it:  $2\lambda + 2\beta + 2\delta$ ) and then look at parametric differences due to set size (which could have a maximum of 12 free parameters associated with it:  $4\lambda + 4\beta + 4\delta$ ). Thus, the saturated model (allowing parametric variance between all stimulus exposure durations and set sizes) would be  $8\lambda-8\beta-8\delta$ . We started with the null model,  $1\lambda-1\beta-1\delta$ , that assumes no parametric differences between any of the set sizes or stimulus exposure durations, which provided a baseline goodness of fit to judge other models against,  $R^2 = 0.966$ ,  $\text{Ln}(L) = 14.955$ . Next, we allowed either the asymptotes ( $2\lambda-1\beta-1\delta$ ), rates ( $1\lambda-2\beta-1\delta$ ), or takeoffs ( $1\lambda-1\beta-2\delta$ ) to vary by stimulus duration. The largest improvement in fit was seen by allowing the rates to vary ( $1\lambda-2\beta-1\delta$ ),  $R^2 = 0.972$ ,  $\text{Ln}(L) = 26.41$  ( $X^2(1) = 22.91$ ,  $p < 0.001$ ), compared to  $R^2 = 0.971$ ,  $\text{Ln}(L) = 23.99$  ( $X^2(1) = 18.07$ ,  $p < 0.001$ )

and  $R^2 = 0.969$ ,  $\text{Ln}(L) = 20.49$  ( $X^2(1) = 11.07$ ,  $p < 0.001$ ) for when the asymptotes ( $2\lambda-1\beta-1\delta$ ) or takeoffs ( $1\lambda-1\beta-2\delta$ ), respectively, were allowed to vary. The relative likelihood for allowing asymptotes to vary over rates is 0.09 and for the takeoffs over rates, 0.003. Allowing rates and asymptotes and/or takeoffs to vary with stimulus duration resulted in little improvement in fit (indeed the most general version,  $2\lambda-2\beta-2\delta$ ,  $R^2 = 0.971$ ,  $\text{Ln}(L) = 27.161$ , resulted in no significant improvement compared with the  $1\lambda-2\beta-1\delta$  model,  $X^2(2) = 1.502$ ,  $p = 0.47$ ). As the likelihood of a rate difference between stimulus durations is greatest, we chose this model as the basis for future model comparisons.

Next, we tested whether there were any parametric differences due to set size. From our reanalysis of Carrasco and McElree's (2001) data, we predicted that there would at least be a difference between the set size 1 and set size 4 conditions. The most general rate model,  $1\lambda-8\beta-1\delta$ , fit our data very well,  $R^2 = 0.984$ ,  $\text{Ln}(L) = 53.90$ , suggesting a differences in rates due to set size ( $X^2(6) = 54.98$ ,  $p < 0.001$ ). The  $1\lambda-8\beta-1\delta$  rate model fit our data better than allowing asymptotes ( $4\lambda-2\beta-1\delta$ ,  $R^2 = 0.975$ ,  $\text{Ln}(L) = 34.912$ , a relative likelihood ratio of  $<0.001$  compared with allowing rates to vary) or takeoffs ( $1\lambda-2\beta-4\delta$ ,  $R^2 = 0.974$ ,  $\text{Ln}(L) = 33.370$ , a relative likelihood ratio of  $<0.001$  compared with allowing rates to vary) to vary by set size. The comparable model to that supported in the reanalysis of Carrasco and McElree's data,  $1\lambda-4\beta-1\delta$  model ( $R^2 = 98.5$ ,  $\text{Ln}(L) = 52.06$ ), which allows variability in processing rates between the two exposure durations and between set size 1 and set sizes 2, 3, and 4, did not fit the data significantly less well than the more general  $1\lambda-8\beta-1\delta$  model ( $X^2(4) = 3.68$ ,  $p = 0.45$ ), which allowed all the set sizes to vary from each other and between stimulus exposure durations. Comparing the  $1\lambda-4\beta-1\delta$  model to one in which there is no parametric variability in rates due to set sizes, the  $1\lambda-2\beta-1\delta$  model, demonstrates the differences between set size 1 and set sizes 2, 3, and 4, replicating the effect demonstrated in Carrasco and McElree's data ( $X^2(2) = 51.28$ ,  $p < 0.001$ ). Finally, we tested whether all set sizes resulted in different processing rates and whether all set sizes differed between stimulus durations. For brevity, out of all possible model combinations, the optimal model was  $1\lambda-3\beta-1\delta$ ,  $R^2 = 0.985$ ,  $\text{Ln}(L) = 52.052$ , which did not result in a significantly poorer fit than the most general  $1\lambda-8\beta-1\delta$  model in which all set sizes could vary from each other and between stimulus exposure durations, despite having five fewer free parameters ( $X^2(5) = 3.69$ ,  $p = 0.59$ ). This model only had parametric variability between the 40- and 140-ms conditions for the rate parameters for set size 2, set size 3, and set size 4, which all had a shared slower rate than set size 1.<sup>3</sup> The fits of this model can be seen in Figure 4, and the parameters are given in Table 2. In summary, we found no evidence of either the takeoffs or asymptotes varying between stimulus duration and set size. The processing rate was fastest when only one item

Parameter	40 ms	140 ms
<i>Discriminability (<math>\lambda</math> in <math>d'</math> units)</i>		
All set sizes		2.77
<i>Rate (<math>\beta</math> in ms units)</i>		
Set size 1		111
Set sizes 2, 3, and 4	172	131
<i>Intercept (<math>\delta</math> in ms units)</i>		
All set sizes		270

Table 2. Parameter estimates for the best fitting ( $1\lambda-3\beta-1\delta$ ) model from the experiment for the 40- and 140-ms conditions.

was presented, and stimulus duration did not affect this rate. However, when more than one item was present, processing was slower than when there were no distractors, but processing speed increased with increased stimulus duration.

## Discussion

We found that when only one object was present, processing of visual information proceeded more rapidly than when other distracting objects were present. We argue that the effect of attention was to speed processing and that this effect was reduced when there was more than one object present because attentional resources were split between the target and distractors. That attention acts to speed the processing of visual information is consistent with the results of Carrasco and McElree (2001). They did not, however, report a processing speed difference between conditions containing one object and those containing more than one object in a simple feature search. In our reanalysis of their data, we found the same result as for the data presented here—namely, that the effect of attention to speed information accumulation is greater when attending to one item than when attending to two or more items in a simple search. We found no evidence for differences in asymptotic performance (discriminability) between set sizes, contrary to Carrasco and McElree, who found a decrease in discriminability between set size 1 and set size 4; we note that performance for our participants was closer to ceiling asymptotic performance and that this may make it more difficult to detect any set size effect on asymptotic performance. We also did not find an effect of exposure duration on discriminability, contrary to our predictions; again, this could be due to the overall high asymptotic level of performance of our participants. Similarly to Carrasco and McElree, we found no evidence for differences in takeoff time by set size; stimulus duration also did not impact on takeoff time. Increasing the display duration had little or no effect on the processing rate for a single item but increased the speed of processing in displays with multiple items. This is consistent with the claim that stimulus

duration does not affect the rate at which information is abstracted for single item detection (e.g., Smith & Ratcliff, 2009).

Why should stimulus duration affect the rate for displays including distractors but not for single item displays? One might expect that for displays with distractors, there would be a higher proportion of trials on which the participant incorrectly identifies a distractor as the target. This could be the case even if objects are equally discriminable in displays with and without distractors. Rather, simply having more ways of misidentifying which object is the target can increase the probability of these false alarms. A greater false alarm rate would mean that occasionally the participant is responding at chance to the target orientation, and this would have a negative impact on target discriminability estimates. Longer display durations would allow for recovery from false alarms, since attention has a longer time to move from the falsely identified target to the actual target. However, we found no differences in asymptotic discriminability between short and long duration displays, which makes this explanation unlikely (albeit with asymptotes near ceiling). Another explanation could lie in partial hemifield independence of attentional resources (Alvarez & Cavanagh, 2005). Alvarez and Cavanagh suggested that targets only compete for attention when placed in the same hemifield as each other. Targets in different hemifields might then draw from different attentional resources. Perhaps longer stimulus durations allow for attention to switch between targets when they are in the same hemifield, as is of course only the case for object numbers greater than one here. Why this did not impact on target discriminability here however is not clear, although, again, asymptotic accuracy was near ceiling. Most likely, when only one item is present, any signal information will tend to increase the evidence for a correct response; however, when distracting evidence is present, information may be accumulated from a distracting item, thus accumulating evidence for the correct response more slowly. We argue that this process is mediated by forming a stronger internal representation (by increasing stimulus exposure duration, see Bays et al., 2011).

The fact that processing proceeds more rapidly when there are no distractors than when distractors are present has important implications for attention capacity. Estimates of capacity derived from several experimental paradigms are based on the number of objects to be processed. For example, for spatial attention, measured using the multiple object tracking task, a four-object limit was originally proposed by Pylyshyn and Storm (1988). Under this conception, there are four independent attentional resources, FINSTs, which can each be allocated to one target for tracking. Hence, the model predicts a sharp drop-off in performance once participants are asked to track more than four targets. More recently, however, this type of model, where targets are either discretely tracked or not tracked, has been challenged. Instead, it appears



that tracking is performed by a single resource that can be flexibly allocated to few or many objects (Alvarez & Franconeri, 2007). In this conceptualization, the resource can be allocated entirely to one object or spread progressively more and more “thinly” when allocated to greater numbers of objects. In terms of multiple object tracking, the more resource is applied to a target, the less likely it is that the participant will lose track of the target (Franconeri, Alvarez, & Enns 2007; Howard & Holcombe, 2008). If attention to space and attention to object features (as measured by visual search and in the experiment presented here) share a common architecture, then we would expect flexible allocation of attention to objects here. We found that attention improves the speed of processing of objects and that decrements in performance are seen even when comparing the action of attention to one object and its action on two objects (one target and one distractor). This is not consistent with a limit based on a fixed number of objects of around four. It is however consistent with a model in which attention is flexibly allocated between objects. Moreover, this flexible attentional resource that acts to speed the accumulation of object information is caused to slow down when shared even between as few as two objects.

If the attentional resource can be flexibly allocated to one or several objects, one might expect a gradual decrease in performance with each additional object added to the attentional load. Neither we here nor Carrasco et al. find a cost for every individual addition to the number of objects in both speed and discriminability measures. Several possibilities may explain this. First, there may, in fact, be underlying set size costs, but both studies may have lacked sufficient statistical power to uncover them. Second, the performance cost with each additional object need not be linear, and as such, each additional object added to the load may produce progressively smaller performance decrements. Third, it is possible that the cost going from one to two objects is both qualitatively and quantitatively different from successive load increments. For instance, attending to two objects in two locations may require an additional comparison operation between the two perceived features, which is not required in the single object condition. Another possibility is that the additional spatial uncertainty when there is more than one object causes a performance decrement over and above the need for attention to operate on the features of more than one object. There may have been a cost associated with filtering out the distractors (Kahneman, Treisman, & Burkell, 1983), but it is unclear why this would have led to a slower rate of information accrual without a dependence on the *number* of distractors (and not a change in the takeoff time). Most likely, since we used homogenous distractors, there is the possibility of distractors being grouped perceptually (Humphreys, Quinlan, & Riddoch, 1989). Using a set of distractors that do not lead to perceptual grouping in a simple detection task might

produce a gradual decline in processing speed between one and four items. Indeed, evidence from Bricolo, Ganesini, Fanini, Bundesen, and Chelazzi (2002) suggests that with heterogeneous distractors (in a very inefficient search task) there are processing rate differences between set sizes of two, four, six, and eight items. However, Bricolo et al. did not use a SAT procedure and instead estimated cumulative distribution curves from free RTs (see their Figure 3, p. 985) and used a traditional detection search task. Nonetheless, the pattern of data from Bricolo et al. suggests that a heterogeneous set of distractors may lead to rate differences between set sizes of two, three, and four items. Indeed, in Carrasco and McElree’s (2001) conjunction search, with heterogeneous distractors, there is a clear difference in processing rates between set sizes of 1, 4, and 8.

We did not find a cost in discriminability for spreading attention over two objects compared to attending to a single object. This is not consistent with some previous studies that show a decrease in discriminability when attending to the features of two objects as compared to one (Greenlee & Magnussen, 1998; Howard & Holcombe, 2008; Magnussen & Greenlee, 1997). It is possible that speed of processing (like overall RT) is a more sensitive measure than discriminability (overall accuracy), which could explain the disparity between studies. If this is the case, then the discriminability differences found previously may actually be due to differences in processing speed; indeed, this is the main reason for using SAT studies over respond-when-ready studies. If processing is disrupted in some way during a task (perhaps due to target offsets or competing attentional demands), then the faster the processing, the greater quality of representation will be achieved before the disruption. That spreading attention over two objects reduces the speed with which features are processed may, in fact, go some way to explaining the pattern of temporal lags observed by Howard and Holcombe (2008). Howard and Holcombe asked observers to attempt to keep track of the changing features (changing orientations, changing locations, or changing spatial frequencies) of one or several objects. They found that when observers were asked to report the final feature of one of the tracked objects, reports were more similar to previous values of the object than its final value. Moreover, the magnitude of this temporal lag increased with the number of objects tracked. If processing speed is slowed by additions to the number of attended objects, then the temporal lag will also increase.

What is the role of visual short-term memory (VSTM) in producing the pattern of data? Understanding the capacity limits on VSTM has followed a similar trajectory to conceptualizations of attention resources for tracking. At first, it was thought that there may be a limit based on a number of objects of around four (Luck & Vogel, 1997). More recently, it has been shown that this capacity for visual features may be limited by a graded and flexible

resource, set by the amount of visual information encoded about objects (Alvarez & Cavanagh, 2004; Bays et al., 2011; Bays & Husain, 2008; Wilken & Ma, 2004). If VSTM encoding is predicted to process one object better than two objects in terms of the complexity or quality of object representations (e.g., Bays et al., 2011), then it is possible that encoding also occurs faster for one object than for two or more objects. This may have contributed to the effects on processing speed reported here. Of course, it will also take longer to accumulate information from VSTM about target identity if the representation is noisy: More samples will be needed as noise or information from distractors is accumulated. Both set size and stimulus duration impact the noise in a VSTM representation (Bays et al., 2011). Longer stimulus durations may allow the displays with distractors to be processed faster than shorter durations, because a less noisy representation is created in VSTM and less information is therefore accumulated from distractors. Overall, there appears to be growing evidence for an overlap in architecture between encoding and storage processes.

Simple search or detection has traditionally been thought of as a parallel process that is largely unaffected by the number of distractors. However, the evidence presented here suggests a more complex picture whereby processing of single item displays proceeds more rapidly than when attention must be split (displays with distractors). In the latter case, there is a constant cost in processing (at least for two to four items, the cost may increase for larger set sizes, but this was not evident in Carrasco & McElree's, 2001, data when comparing set size 4 with set size 8). We suspect that this constant cost might partly reflect the fact that the distractors were homogenous and, therefore, may have been grouped as a single object (Humphreys et al., 1989). Future theories will need to specify the exact mechanism through which attention speeds the rate of information accumulation in single item displays, cued displays, and multiple item displays with additional duration, which this article has clarified.

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## Footnotes

<sup>1</sup>Although we focus on 2AFC orientation discrimination tasks, it has been demonstrated that contrast thresholds in yes/no detection and orientation discrimination are identical (Thomas & Gille, 1979), and discrimination has, therefore, been used by many authors (e.g., Cameron et al., 2002; Lee et al., 1997; Smith & Ratcliff, 2009) to make inferences about detection.

<sup>2</sup>Sometimes the takeoff and rate are combined into one measure of processing dynamics as they can be difficult to tease apart (e.g., Carrasco et al., 2004; Liu et al., 2009). However, the parameters are well behaved and clearly identifiable in both Carrasco and McElree's (2001) data and our data.

<sup>3</sup>For one participant, the set size 1 rate also varied between 40 and 140, with the 140-ms rate being slower than the 40-ms rate. One participant also showed set size differences between all set sizes, except set size 3 and set size 4 in the 140-ms condition (in addition for this participant, set size 4 was faster than set size 3 in the 40-ms condition). All participants demonstrated faster processing for set size 1 than any other set sizes.

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