CrossMark

Fixed-target efficient search has logarithmic efficiency with and without eye movements

Gavin Jun Peng Ng [1] ⬤ · Alejandro Lleras [1] · Simona Buetti [1]

Abstract

Stage 1 processing in visual search (e.g., efficient search) has long been thought to be unaffected by factors such as set size or lure–distractor similarity (or at least to be only minimally affected). Recent research from Buetti, Cronin, Madison, Wang, and Lleras (*Journal of Experimental Psychology: General, 145,* 672–707, 2016) showed that in efficient visual search with a fixed target, reaction times increase logarithmically as a function of set size and, further, that the slope of these logarithmic functions is modulated by target–distractor similarity. This has led to the proposal that the cognitive architecture of Stage 1 processing is parallel, of unlimited capacity, and exhaustive in nature. Such an architecture produces reaction time functions that increase logarithmically with set size (as opposed to being unaffected by it). However, in the previous studies, eye movements were not monitored. It is thus possible that the logarithmicity of the reaction time functions emerged simply as an artifact of eye movements rather than as a reflection of the underlying cognitive architecture. Here we ruled out the possibility that eye movements resulted in the observed logarithmic functions, by asking participants to keep their eyes at fixation while completing fixed-target efficient visual search tasks. The logarithmic RT functions still emerged even when participants were not allowed to make eye movements, thus providing further support for our proposal. Additionally, we found that search efficiency is slightly improved when eye movements are restricted and lure–target similarity is relatively high.

Most models of visual search posit that it is a two-stage process (e.g., Treisman & Gelade, 1980; Wolfe, 1994). The structures of these models are largely similar—Stage 1 of processing is assumed to involve a parallel analysis of the scene, whereas Stage 2 is thought to involve a serial analysis of individual items (or group of items) by focused attention. These models also largely agree that Stage 1 is capacity-unlimited, and they propose that Stage 1 processing times are invariant. Search that relies only on Stage 1 processing is often referred to as *efficient search*, characterized by search slopes of less than 10 ms per item (Treisman & Gelade, 1980; Treisman & Gormican, 1988; Wolfe & Horowitz, 2004). Variability observed in reaction times (RTs) is often thought to arise from the second, capacity-limited stage. Search with RTs that increase with set size and produce slopes of more than 10 ms per item are referred to as *inefficient* (Treisman

& Gelade, 1980; Treisman & Gormican, 1988; Wolfe & Horowitz, 2004). In these models, as well as many others (Bundesen, 1990; Itti & Koch, 1999; Verghese, 2001), attention is thought to influence only Stage 2 of visual processing. Stage 1 is deemed to be *preattentive*—it occurs without (and before) the influence of focused attention, or at best is thought to be minimally influenced by attention, as when top-down goals boost the processing of specific visual features known to belong to the target (e.g., "top-down guidance" to specific features, as in Guided Search; Wolfe, 1994). The majority of research on visual search has focused on Stage 2 processing, since this is where variability in RTs is often observed, and because investigators are naturally interested in gaining a better understanding of cognitive operations whose processing capacity is limited.

Recently, Buetti, Cronin, Madison, Wang, and Lleras (2016) demonstrated that Stage 1 processing times are not invariant, but in fact vary systematically as a function of lure–target similarity and set size. Briefly, *lures* refer to distractors that are sufficiently dissimilar from the target that they can be discarded as potential targets in parallel during Stage 1 processing. Buetti et al. conducted a series of

✉ Gavin Jun Peng Ng
gavin.jp.ng@gmail.com

[1] Department of Psychology, University of Illinois, Urbana, IL, USA

experiments to investigate the nature of parallel processing in Stage 1. In their Experiments 1A and 1B, participants completed an efficient visual search task with a fixed target. The participants were required to discriminate the identity of a triangle target that was oriented to either the left or the right. The display always contained a single target that was accompanied by 0, 1, 4, 9, 19, or 31 homogeneous lures. The lure–target similarity was either high, medium, or low. The results indicated that the RT by set size function was fitted better by a logarithmic function than by a linear one. More importantly, the results showed that the slopes of these log functions increased with lure–target similarity. Critically, the extant models of visual search predict *constant* Stage 1 processing times in those experiments (i.e., similar flat search slopes across all conditions), given that the target was always a unique item in the scene on at least one feature space.

In light of the seminal work by Townsend and Ashby (1983), Buetti et al. (2016) suggested that the logarithmic relation between RTs and set size in efficient search reflects a cognitive architecture of Stage 1 that processes items *exhaustively, in parallel, and with unlimited capacity*. Other forms of cognitive architectures (e.g., self-terminating) produce markedly different RT signatures (Buetti et al., 2016; Townsend & Ashby, 1983). Additionally, this stage is of limited resolution, due to the lossy representation of stimuli in the periphery (Rosenholtz, Huang, Raj, Balas, & Ilie, 2012). Buetti et al. proposed that, upon the onset of the display, a stochastic accumulation of evidence at each item location across the entire display starts once the search display appears. Each location reaches, in an independent manner, a decision threshold regarding whether or not the item is likely to be the target; some accumulators will therefore reach threshold before others. Importantly, this stochastic process of evidence accumulation that occurs in parallel across all locations gives rise to the observed logarithmic functions whenever the stopping rule for the stage is exhaustive. Locations containing lure stimuli are rejected during this first stage. Only locations containing stimuli sufficiently similar to the target are passed on to Stage 2 for further, focused scrutiny. Items at these locations cannot be rejected with high confidence during Stage 1 because of the resolution limitations of peripheral vision (Rosenholtz et al., 2012).

One of the key novel contributions of this model was the proposal that Stage 1 processing is exhaustive in nature, and thus continues even after a location reaches a *target likely* decision. In other words, Stage 1 processing continues until all locations have reached threshold, even after the target location has done so. Note that, although the assumption is often implicit, many previous models assume that Stage 1 processing is *not* exhaustive, but instead self-terminating, in nature (Treisman & Gelade, 1980; Wolfe, 1994). From a theoretical perspective, this follows because these models assume that attention goes directly to the target, wherever it is, as soon as

it is detected. For example, in Wolfe's (1994) Guided Search model, the location containing the target in an efficient search task always has the largest activation on an activation map. Attention, which is proposed to always be directed to the location with the highest activation, is thus always directed to the target, regardless of set size. The search then terminates once the target is found. In addition, from an empirical perspective, the RTs in efficient search studies have been interpreted as being invariant as a function of set size—only self-terminating architectures produce such behavioral signatures (see Buetti et al., 2016, for a more in-depth discussion of this point). Furthermore, previous models used a feature-discontinuity approach to study efficient search tasks, whereby the target would be defined in an almost categorically different fashion (in feature space) from the distractors (i.e., the only red object among green distractors). The target would then "pop out" of the search display, and little, if any, systematic variation of target–distractor similarity *within efficient search ranges* was studied. As a result, target–distractor similarity is a factor that has mostly been thought to affect Stage 2 processing times (Duncan & Humphreys, 1989, 1992), rather than Stage 1. In contrast, Buetti et al. (2016) proposed that even in efficient search tasks, lure–target similarity can have a substantial and systematic impact on processing times, with higher lure–target levels of similarity requiring longer evidence accumulation times to decide that each distractor in the scene is indeed *not* a target. Thus, the evidence decision threshold was proposed to be proportional to each distractor's similarity to the target. Finally, it is worth noting that this systematic variability in Stage 1 processing times is not limited to the simple geometric stimuli used in Buetti et al., since these results have been replicated with photos of real-world objects as the search stimuli (Wang, Buetti, & Lleras, 2017), as well.

In terms of nomenclature, distractor items that are sufficiently distinct from the target, such that they can be rejected during Stage 1 processing, are referred to as *lures*. Locations with items that are sufficiently similar to the target, such that they cannot be rejected during this initial stage of processing, thus require attentive scrutiny and will be passed on to Stage 2 for focused processing. Eye movements and/or focused attention are then deployed to these locations to determine whether or not the item is the target. The distractor items requiring Stage 2 processing are referred to as *candidates* (Neider & Zelinsky, 2008).

In the previous experiments in which logarithmic search slopes were observed (Buetti et al., 2016; Madison, Lleras, & Buetti, 2018; Wang et al., 2017; Wang, Lleras, & Buetti, 2018), however, eye movements were not monitored—participants were instead free to move their eyes to look for the target. It is well known that visual search is often accompanied by eye movements, even in efficient search tasks in which the target seems to be found almost immediately (Findlay &

Gilchrist, 1998; Zelinsky, 2008). Additionally, even when the search task can in principle be completed without eye movements, participants will tend to move their eyes and fixate on or near the target if they are allowed to (Findlay & Gilchrist, 1998). Indeed, the default behavior of participants is to execute eye movements unless they are explicitly instructed not to do so (Zelinsky, 2008).

More directly relevant to the present article, Zelinsky (2008) showed, computationally and behaviorally, that in some search conditions the number of fixations increases with set size in a negatively accelerated fashion. In 2008, Zelinsky introduced his target acquisition model (TAM), a computational model that simulates the retina, complete with a fovea with high visual acuity and a periphery with visual acuity degradations. TAM proposes that the visual scene is first decomposed into features, after which it is compared with the representation of the target. This produces a target map, which indexes the visual similarity between the target and each location in the scene. Eye movements are then executed to a certain location in the scene on the basis of computations on the target map. His results indicated that, in an efficient search task with a fixed target, the number of fixations produced by both human participants and TAM appeared to increase with set size in a negatively accelerating fashion. One could thus argue that this decelerating trend is similar to the log functions observed in Buetti et al. (2016), since logarithmic functions are also negatively accelerated. Thus, it is possible that the trend found in RTs in Buetti et al. may not be an intrinsic characteristic of Stage 1 processing, as was initially proposed, but instead an artifact of eye movements. That is to say, systematic differences in eye movement patterns across search conditions might create RT patterns that look logarithmic. To be clear, it should be noted that Buetti et al. found this pattern in RTs, whereas Zelinsky reported it in terms of the number of eye movements required to find the target. Nevertheless, it is known that when participants are allowed to move their eyes (*free viewing*), RTs can be slower than under *fixed-viewing* conditions, and that increases in the number of eye movements are usually accompanied by increases in overall RTs (Carrasco, McLean, Katz, & Frieder, 1998; Zelinsky & Sheinberg, 1997).

A question thus arises: If eye movements were not allowed in the search task used by Buetti et al. (2016, Exps. 1A and 1B), would RTs no longer increase logarithmically as a function of set size? Perhaps the processing cost indexed by the log curves were associated entirely with eye movements costs. If that were the case, restricting eye movements should eliminate the log functions, or perhaps even completely flatten the RT by set size functions. In contrast, if these log functions were a true signature of the underlying cognitive architecture (i.e., exhaustive processing in Stage 1) as proposed by Buetti et al., log curves should be found even when eye movements were restricted. Thus, it is important to rule out the possibility that the logarithmic relation

between RT and set size is merely the consequence of eye movements. If we were to observe the same logarithmic functions in the absence of eye movements, this would provide strong support in favor of our claim that log functions, which reflect exhaustive parallel processing of the entire search display, are an inherent property of Stage 1 processing. Furthermore, if we were also to observe the modulation of these logarithmic functions by lure–target similarity, we would have further evidence in favor of the model proposed by Buetti et al., in which an item's average processing time increases as a function of its similarity to the target, even when that item is being evaluated in parallel during Stage 1 processing.

In addition, we examined whether search efficiency differed between free- and fixed-viewing conditions. Search that is accompanied with eye movements is generally slower and/or less efficient (Carrasco et al., 1998; Zelinsky & Sheinberg, 1997; but see also Klein & Farrell, 1989). Similarly, information processing has been shown to be at least partially disrupted when eye movements are made (Irwin & Carlson-Radvansky, 1996; Irwin, Carlson-Radvansky, & Andrews, 1995; Matin, Shao, & Boff, 1993). The evidence accumulation process in Stage 1 thus could be disrupted by eye movements. If this is the case, then participants should produce steeper log slopes in the free-viewing than in the fixed-viewing condition as a result of this decreased processing efficiency associated with the execution of eye movements.

Here, Experiment 1A was conducted to determine whether the log functions would still arise when participants completed the task without any eye movements (*fixed-viewing* condition). Experiment 1B was a confirmatory replication of that experiment with a sample size that was derived from a power analysis of Experiment 1A, except for a few changes meant to improve the participants' compliance with the instructions (see General Method section). Experiment 2 was identical to Experiment 1B, except that the target stimulus was changed in order to alter the lure–target similarity relationship used in Experiment 1. This was done to demonstrate that the logarithmic slopes (and, thus, exhaustive processing) that we observed were not simply due to the specific stimuli we chose, but rather to a more general lure–target similarity relationship (as in Exp. 1B; Buetti et al., 2016).

General method

Participants

Undergraduate students from the University of Illinois at Urbana-Champaign participated in the experiment in exchange for either course credit in a psychology class or a payment of $8. All participants had normal or corrected-to-normal vision and were tested as being noncolorblind using the Ishihara color plates before the start of the experiment.

Stimuli and apparatus

The targets were red isosceles triangles that pointed to either the left or the right, whereas the lures were either symmetric blue circles or orange diamonds. Each item was presented at a random location on a concentric "grid" with 36 possible locations equally distributed over three concentric rings with varying eccentricities: 4.17, 7.73, and 14.3 degrees of visual angle. This concentric display was used to minimize crowding, in accordance with Bouma's law (Bouma, 1970; Madison et al., 2018; Pelli & Tillman, 2008). All items, regardless of set size, were distributed equally among the four quadrants of the display (Sample displays are shown in Fig. 1). The search array for each trial was created using the Psychophysics Toolbox for MATLAB (Brainard, 1997) and was then exported as a .png image files and imported into the Experiment Builder environment to be used with the eyetracker.

All stimuli were presented against a black background on a 22-in. (400 × 300 mm) cathode ray tube monitor, with a refresh rate of 85 Hz and a screen resolution of 1,024 × 768 pixels. Each item thus subtended a visual angle of approximately 0.833 deg.

A tower-mounted EyeLink 1000 eyetracker (SR Research, Inc.) was used to record eye movements at a sampling rate of 1000 Hz. Participants placed their heads on a chin rest and viewed the screen at a distance of 59 cm.

Design and procedure

There were three independent variables: viewing condition (free or fixed viewing), set size (1, 4, 12, or 32), and lure–target similarity (high [orange diamonds] vs. low [blue circles]). These produced 38 trials per cell, amounting to a total of 532 trials (266 per viewing condition). It should be noted that there were 14 (instead of 16) different cells, since there were no lures for the target-only (i.e., set size 1) condition [2 × (2 × 3 + 1) = 14].

All trials were fully randomized, but viewing condition was blocked. There were two blocks. The first block of the experiment was always the free-viewing block, in which participants were not instructed to keep their eyes at fixation. The second block was the fixed-viewing condition that we analyze below, in which participants were instructed to maintain fixation throughout the experiment and we monitored eye movements to verify compliance with these instructions. The goal of the first block of trials was to allow us to compare performance in this "free-viewing" condition to that in previous experiments in which eye movements were allowed and not monitored (e.g., Buetti et al., 2016; Wang et al., 2017). We always started with the free-viewing condition so that the performance in that condition would not be influenced by the instructions (and/or performance) in the fixed-viewing condition (e.g., perhaps participants might realize that they were

more efficient if they did not move their eyes, and thus might carry this behavior over into the free-viewing block). Participants were not told that they would be undergoing a fixed-viewing block in the second half of the experiment.

At the start of each experimental block, a pseudorandom 9-point calibration was conducted. A self-paced rest period was administered after every 38 trials, after which a drift correction was performed before the experiment resumed. Participants were allowed to take a short break between the two main experimental blocks. To ensure that participants were fixating the center of the screen before the search array was presented, the experiment was programmed such that recalibration would be performed if the participant was not fixating on the center of the screen after 3 s.

At the start of the *free-viewing block*, participants were told to look at the fixation cross at the center of the screen at the start of every trial. Then, once the search array was presented, they were free to move their eyes. At the start of the *fixed-viewing block*, participants were told to maintain their fixation on the center of the screen throughout the trial (i.e., even when the search array was presented). For both blocks, participants were informed that they were free to move their eyes in order to look around during the interstimulus interval, which was a blank screen. This was intended as a way to reduce the strain on the participants' eyes from fixating on the center of the screen for long periods of time.

Each trial began with a fixation cross presented for 1 s, followed by the presentation of the search array. Participants judged whether the target, which was present on every trial, was pointing (or was oriented) to the left or the right. Participants responded with the "z" key if the target's tip was pointing to the left, and the "/" key if the tip was pointing to the right; the search array remained on the screen until a response was made. Feedback in the form of a loud beep was provided only when participants made an incorrect response. The experimenter verbally notified the participant if there were a large number of trials in which eye movements were detected during the fixed-viewing condition.

Inclusion–exclusion criteria

Only the data from participants who completed both the free- and fixed-viewing block were included in the analyses. Participants were excluded according to the following criteria. First, participants who completed less than 90% of the experiment were excluded. Then, those who had accuracy rates of below 90% were excluded from the analyses. Participants who made eye movements on more than 15% of the trials in the fixed-viewing block were also excluded. Finally, participants who had overall RTs that exceeded two standard deviations of the group mean were excluded. These criteria were planned beforehand and registered on the Open Science Framework.

Data analysis

All reported analyses were pre-registered on the Open Science Framework.[1] Greenhouse–Geisser corrections were applied wherever necessary and are reported with the corrected p values (p_c), as well as with epsilon (ε). Partial omega-squared values (ω_p^2) are also reported. Trials on which participants made any eye movements during the fixed-viewing conditions were excluded from the analyses.

Experiments 1A and 1B: Red target condition

Experiment 1A: Preliminary study

Method

Participants In Experiment 1A, a total of 42 students (28 females, 14 males; mean age = 20) participated in the study. Due to a programming error, there were no data from 11 participants. Due to a computer error (i.e., the computer crashed), the data from two additional participants were excluded. Nine participants were unable to complete more than 90% of the experiment within the allocated time, due to difficulty maintaining fixation at the central point (we addressed this problem by a modification of the procedure in Exp. 1B). Finally, four participants were excluded according to the criteria for eye movements mentioned in the Inclusion–Exclusion Criteria section. The final number of participants included in the analyses was thus 16. These exclusion criteria were determined a priori and were included in the pre-registration of this study.

Stimuli The target was a red triangle pointing to the left or the right (as in Buetti et al., 2016). The high-similarity lures were orange diamonds, and the low-similarity lures were blue circles.

Results

Logarithmic versus linear fits Our primary concern here was to investigate whether the RTs in the fixed-viewing condition were best fitted by logarithmic or linear functions. Thus, we fitted the mean RTs in that condition with both logarithmic and linear functions of set size. The logarithmic fits were better than the linear fits for both the high- and low-similarity lure displays, as indicated by the R^2 and Akaike information criterion (AIC) values (see Table 1).

First, we conducted a repeated measures analysis of variance (ANOVA) on the RTs in the fixed-viewing condition,

with set size (4, 12, 32) and lure type (orange diamonds and blue circles) as factors. The target-only condition was excluded because there were no lures, and therefore no lure type factor, in this condition. The results (Fig. 2A) indicated that RT increased with increasing lure–target similarity, $F(1, 15) = 69.1$, $p < .001$, $\omega_p^2 = 0.8$, as well as with increasing set size, $F(2, 30) = 17.66$, $p < .001$, $\omega_p^2 = 0.502$. The interaction between set size and lure–target similarity was also significant, $F(2, 30) = 13.1$, $p < .001$, $\omega_p^2 = 0.423$. Next, we computed the best-fitting logarithmic function for each participant and each lure type (including the target-only condition). Paired t tests showed that the mean logarithmic slope for orange diamonds (34.13 ms per log unit) was steeper than that for blue circles (7.38 ms per log unit), $t(15) = 7.61$, $p < .001$, $d = 1.903$. Thus, greater lure–target similarity led to steeper logarithmic functions.

Eye movements and search efficiency A second question of interest was whether search efficiency differed between the two viewing conditions. As a manipulation check, we first examined the logarithmic versus linear fits in the free-viewing condition. As in the fixed-viewing condition, the logarithmic fits were once again better than the linear fits for both the high- and low-similarity lure displays (Table 2).

As had been done in the fixed-viewing condition, the logarithmic slopes were then fit to each individual participant for each lure condition. A 2 (viewing condition) × 2 (lure type) repeated measures ANOVA was conducted on these logarithmic slopes. We found main effects of viewing condition, $F(1, 15) = 4.94$, $p = .042$, $\omega_p^2 = 0.188$, and lure type, $F(1, 15) = 80.91$, $p < .001$, $\omega_p^2 = 0.825$. These were qualified by a significant interaction, $F(1, 15) = 11.78$, $p = .0037$, $\omega_p^2 = 0.388$. Follow-up t tests revealed that the logarithmic slopes in the free-viewing condition were significantly steeper than those in the fixed-viewing condition when lure–target similarity was high (61 vs. 37 ms per log unit), $t(15) = 5.11$, $p < .001$, $d = 1.278$, but not when similarity was low (8 ms per log unit in both conditions), $t(15) = 0.13$, $p = .897$, $d = 0.0325$.

Power analysis from Experiment 1A Experiment 1A was the first to examine eye movements during efficient search, specifically looking at the logarithmic relationship between RTs and set size. We planned to replicate the study and also extend it to different stimuli. To do so, we conducted a power analysis on the smallest effect size observed in Experiment 1A ($\eta^2 = .182$). This result indicated that 18 participants would be needed to achieve 90% power at an alpha level of .05.

In Experiment 1B, we also tried to address some of the shortcomings of the methodology in Experiment 1A. First, several participants had had trouble fixating the central location in both the fixed-viewing and the free-viewing conditions (at the start of each trial and before the search array appeared), delaying the starts of trials. This led to a number of participants failing to complete the experiment within the stipulated

---

[1] The analyses presented below in the Results section correspond to Proposed Analysis #1 in our pre-registration of this project on the Open Science Framework (https://osf.io/pve8d/).

Table 1 R^2 and Akaike information criterion (AIC) values for all three experiments in the fixed-viewing condition

Experiment	Measure	High-similarity lures		Low-similarity lures	
		Log	Linear	Log	Linear
1A	R^2	.982	.862	.711	.603
	AIC	31.734	39.789	31.773	33.037
1B	R^2	.96	.81	.917	.828
	AIC	34.793	41.069	24.34	27.264
2	R^2	.959	.944	.839	.998
	AIC	34.698	36.007	33.283	15.901

Higher R^2 values and lower AIC values indicate a better fit. The values for log fits were systematically better than those for linear fits, except for the low-similarity condition in Experiment 2.

Table 2 R^2 and Akaike information criterion (AIC) values for all three experiments in the free-viewing condition

Experiment	Measure	High-similarity lures		Low-similarity lures	
		Log	Linear	Log	Linear
1A	R^2	.988	.859	.798	.435
	AIC	34.771	44.5145	30.353	34.461
1B	R^2	.957	.946	.890	.527
	AIC	40.327	41.291	28.291	34.115
2	R^2	.963	.928	.603	.930
	AIC	34.755	37.360	34.398	27.586

Higher R^2 values and lower AIC values indicate a better fit. The values for log fits were systematically better than those for linear fits, except for the low-similarity condition in Experiment 2.

timeframe. To this end, we implemented a fixation training exercise (Guzman-Martinez, Leung, Franconeri, Grabowecky, & Suzuki, 2009) at the beginning of the experiment. In the fixation training, we presented a display consisting of equal numbers of white and black pixels distributed randomly. This display was rapidly alternated with one that reversed the contrast of each pixel (i.e., black pixels became white, and vice versa). Participants were instructed to fixate at the center of the display. As long as their eyes were kept stationary, the display appeared as a uniform gray due to perceptual averaging. However, whenever an eye movement was made, the break in perceptual averaging would cause a random black-and-white dot pattern to appear. This fixation training took approximately 2 min. We also reduced the number of trials per cell from 38 to 32.
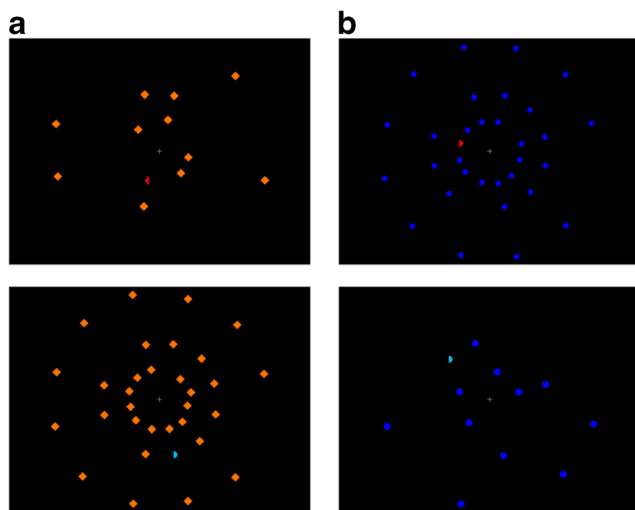

Fig. 1 (Top) Sample displays from Experiments 1A and 1B, showing the red target with high-similarity lures (orange diamonds) on the left, and with low-similarity lures (blue circles) on the right. (Bottom) Sample displays from Experiment 2, with a cyan half-disc target and low-similarity lures (orange diamonds) on the left, and with high-similarity lures (blue circles) on the right. The total set size varied among 1, 4, 12, and 32 items.

Experiment 1B: Confirmatory study

This experiment was also pre-registered on Open Science Framework (https://osf.io/h24u9/)

Method

Participants As indicated by the power analysis, 18 participants were included in the analyses. Twenty-six new participants (21 females, five males; mean age = 20) from the same pool participated in Experiment 1B. The data from one participant were excluded due to a computer error (i.e., the computer crashed). We also excluded two participants who did not complete more than 90% of the experiment, three participants who made eye movements in more than 15% of the trials in the fixed-viewing condition, and two participants with mean RTs that were two standard deviations beyond the group mean. These exclusion criteria were determined a priori and were included in the pre-registration of this study.

Procedure All methods were identical to those in Experiment 1A, except for the following changes. First, the number of trials per cell was reduced from 38 to 32, for a total of 448 trials. Second, a self-paced rest was now given after every 28 instead of 38 trials. This was a result of changing the trial randomization, such that each mini-block (i.e., every 28 trials) had an equal distribution of all conditions (i.e., two trials per condition). Third, fixation training was implemented before the start of the experiment, to familiarize the participants with the feeling of fixating the central fixation location (Guzman-Martinez et al., 2009).

Results

Logarithmic versus linear fits In the fixed-viewing condition, the logarithmic fits were again better than the linear fits for

both the high- and low-similarity lure displays, as indicated by the R^2 and AIC values (Table 1).

The repeated measures ANOVA showed that the RTs in the fixed-viewing condition increased with increasing lure–target similarity, $F(1, 17) = 56.32$, $p < .001$, $\omega_p^2 = 0.744$, and with increasing set size, $F(2, 34) = 24.06$, $p < .001$, $\omega_p^2 = 0.555$. The interaction between set size and lure–target similarity (Fig. 2B) was again significant, $F(2, 34) = 9.73$, $p < .001$, $\omega_p^2 = 0.321$. Paired t tests showed that the logarithmic slope for orange diamonds (33 ms per log unit) was steeper than that for blue circles (6 ms per log unit), $t(17) = 6.53$, $p < .001$, $d = 1.794$.

Eye movements and search efficiency To examine search efficiency in the different viewing conditions, a 2 (viewing condition) × 2 (lure type) repeated measures ANOVA was conducted on the logarithmic slopes. We observed main effects of viewing condition, $F(1, 17) = 15.87$, $p < .001$, $\omega_p^2 = 0.439$, and lure type, $F(1, 17) = 54.06$, $p < .001$, $\omega_p^2 = 0.736$. These were qualified by a significant interaction, $F(1, 17) = 28.73$, $p < .001$, $\omega_p^2 = 0.593$. Follow-up t tests revealed that the logarithmic slopes for the free-viewing condition were significantly steeper than those in the fixed-viewing condition when lure–target similarity was high (65 vs. 35 ms per log unit), $t(17) = 5.41$, $p < .001$, $\omega_p^2 = 1.353$, but not when it was low (9 vs. 6 ms per log unit), $t(17) = 0.75$, $p = .462$, $\omega_p^2 = 0.188$.

Discussion

The results from Experiments 1A and 1B demonstrated that RTs increased logarithmically as a function of set size even when participants maintained central fixation throughout the search trial. Confirming previous findings (Buetti et al., 2016; Wang et al., 2017), this logarithmic relationship between RT and set size was found to be modulated by lure–target similarity: High-similarity lures (orange diamonds) produced steeper logarithmic curves than did low-similarity lures (blue circles). The present results confirm that these logarithmic functions are not an artifact of eye movements. In other words, eye movements are not necessary for the logarithmic relationship between RT and set size to emerge in efficient visual search tasks with fixed targets. In addition, in both Experiments 1A and 1B, it seems that participants were more efficient (i.e., the log slopes were less steep) in the fixed-viewing condition.

Experiment 2: Blue target condition

As we mentioned, the rationale for Experiment 2 was to demonstrate that the steepness of the logarithmic slopes is determined by lure–target similarity, rather than by the specific
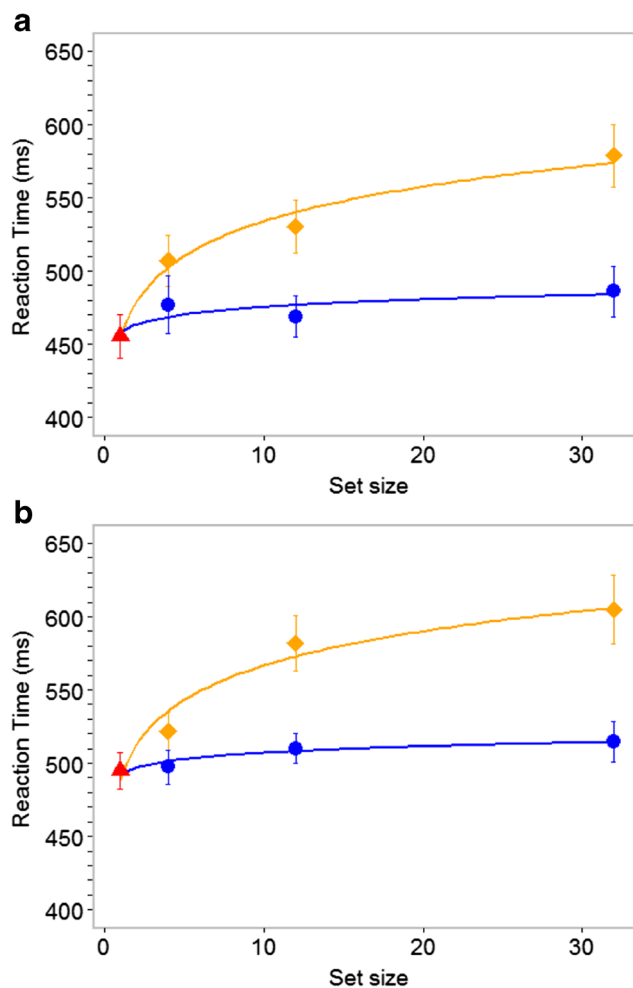

Fig. 2 Reaction times (in milliseconds) in the fixed-viewing condition for Experiments 1A (**A**) and 1B (**B**), respectively, plotted against set size on a linear scale. Orange diamonds were the high-similarity lures, and blue circles were the low-similarity lures in both experiments. Lines show the best-fitting logarithmic trends for each lure condition. Error bars indicate the standard errors of the means.

stimuli we chose. In Experiment 2 we used the same lure stimuli as in Experiments 1A and 1B, but a different target—a cyan half-disc—to reverse the lure–target similarity relationship. As a result, the blue circles now became the high-similarity lures, and the orange diamonds the low-similarity lures. Thus, we now predicted that the blue circles, as high-similarity lures, would produce steeper logarithmic slopes than would the orange diamonds.

In addition, the finding that participants were more efficient in the fixed-viewing condition was inconclusive. This improvement in performance might simply have reflected a practice effect, since participants always completed the fixed-viewing block after the free-viewing block in both experiments. However, the practice effect account would not explain why there was no improved efficiency in the low-similarity condition. Perhaps the performance in the low-similarity condition was so efficient already that it might represent an

effective floor effect, so that increased practice would do little to improve performance. Thus, it was not necessarily clear whether the improvement in efficiency in the fixed-viewing condition for high-similarity lures was due to practice or to a genuine processing advantage for these displays when participants' eyes did not move. In Experiment 2 we sought to examine this in further detail. Here, half the participants completed the free-viewing block first, whereas the other half completed the fixed-viewing block first. If completing the search task without eye movements improves search efficiency (or, in contrast, if completing the search task with eye movements reduces search efficiency), then we should still observe steeper log slopes in the free-viewing block, regardless of block order. However, if the difference in efficiency were due simply to practice, then there should be no effect of viewing condition.

Method

Experiment 2 was identical to Experiment 1B, with the following exceptions.

Participants A total of 36 participants were required for this experiment. Half the participants went through the free-viewing condition first, whereas the other half went through the fixed-viewing condition first. The reason for this change was that in Experiment 1A the results comparing fixed- versus free-viewing conditions (see that experiment above) had indicated that participants were more efficient in the fixed-viewing than in the free-viewing condition. Thus, we wanted to investigate whether this increase in efficiency was due to the absence of eye movements or merely reflected improvements in performance over the length of the experiment (i.e., a practice effect).

To meet the required number of 36 participants, we ran a total of 54 participants (30 females, 24 males; mean age = 20 years) in Experiment 2. We excluded nine participants who did not complete at least 90% of the experiment, two participants who had RTs that were two standard deviations beyond the group mean, and seven participants who made eye movements in more than 20% of the trials in the fixed-viewing block. The rationale for this different criterion was stated beforehand in our pre-registration.[2] As we had planned, a total of 36 participants were included in the analyses, with 18 in each viewing order.

---

[2] According to our pre-registration's inclusion–exclusion criteria, participants who made eye movements in more than 15% of the trials in the fixed-viewing condition were to be excluded from analyses. In the event that the 15% eye movement inclusion criterion were to lead to an unexpectedly high level of participant attrition (i.e., more than 25% of participants rejected), the inclusion criterion was to be relaxed by increasing it in steps of 5% (first to 20%, then to 25%, and then to 30%—but not higher than that).

Stimuli The target was a cyan half disc oriented to the left or right. Thus, the high-similarity lures were now the blue circles, and the low-similarity lures were the orange diamonds.

Results

To verify whether viewing order had an effect of on performance, we conducted a mixed-factorial ANOVA with order (fixed viewing in first block vs. in second block), lure similarity (high [blue circles] vs. low [orange diamonds]), and set size (4, 12, 32) as variables. The results indicated that order had no effect on performance [main effect of order, $F(1, 34) = 0.38$, $p = .543$, $\omega_p^2 = -0.0176$; interaction between order and lure similarity, $F(1, 34) = 0.54$, $p = .467$, $\omega_p^2 = -0.0129$; interaction between order and set size, $F(2, 68) = 0.92$, $p = .403$, $\omega_p^2 = -0.0022$; interaction between order, lure similarity, and set size, $F(2, 68) = 0.87$, $p_c = .397$, $\varepsilon = 0.743$, $\omega_p^2 = -0.00376$]. Thus, the data were collapsed across viewing orders for the logarithmic-versus-linear fit analyses.

Logarithmic versus linear fits The logarithmic fits for the fixed-viewing condition were better than the linear fits for the high-similarity lures, but not for the low-similarity lures, as is indicated by the R^2 and AIC values in Table 1.

The repeated measures ANOVA on RTs in the fixed-viewing condition indicated that they increased with increasing lure–target similarity, $F(1, 35) = 69.58$, $p < .001$, $\omega_p^2 = 0.65$, and with increasing set sizes, $F(2, 70) = 37.33$, $p_c < .001$, $\varepsilon = .847$, $\omega_p^2 = 0.499$. The interaction between set size and lure–target similarity was also significant, $F(2, 70) = 5.02$, $p = .009$, $\omega_p^2 = 0.0994$. Paired t tests showed that the logarithmic slope for high-similarity displays (blue circles: 33 ms per log unit) was steeper than that for low-similarity displays (orange diamonds: 13 ms per log unit), $t(35) = 6.05$, $p < .001$, $d = 1.008$ (Fig. 3).

Search efficiency A 2 (viewing order) × 2 (viewing condition) × 2 (lure type) mixed factorial ANOVA was conducted on the logarithmic slopes. The only significant effect was that of lure type, $F(1, 34) = 65.5$, $p < .001$, $\omega_p^2 = 0.642$. There was no main effect of either viewing order, $F(1, 34) = 1.16$, $p = .288$, $\omega_p^2 = 0.00443$, or viewing condition, $F(1, 34) = 0.97$, $p = .332$, $\omega_p^2 = -0.00083$. None of the two-way interactions were significant: Viewing Order × Viewing Condition, $F(1, 34) = 0.066$, $p = .798$ $\omega_p^2 = -0.0266$, Viewing Order × Lure Type, $F(1, 34) = 0.35$, $p = .557$, $\omega_p^2 = -0.0184$; Viewing Condition × Lure Type, $F(1, 34) = 3.72$, $p = .0621$, $\omega_p^2 = 0.0702$. The three-way interaction also failed to reach significance, $F(1, 34) = 1.47$, $p = .233$, $\omega_p^2 = 0.0129$. That said, the viewing condition by lure type interaction did approach significance. Thus, it is possible that a (small) interaction effect was present and that we failed to detect it with the current sample size. With our sample size and 90% power, we should have been
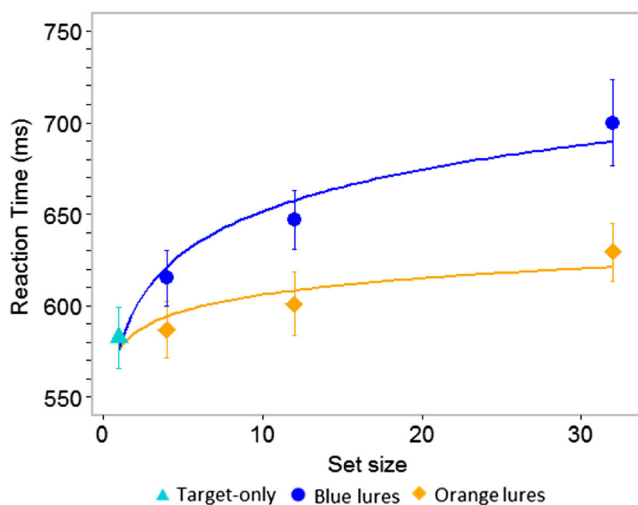
Fig. 3 Reaction times (in milliseconds) in the fixed-viewing condition for Experiment 2, plotted against set size on a linear scale. Blue circles were the high-similarity lures. Lines show the best-fitting logarithmic trend for each lure condition. Errors indicate the standard errors of the means.

able to detect an interaction with an effect size of $\omega_p^2 = 0.08$. Thus, it is possible that a replication of Experiment 2 with a larger sample size might reveal evidence for a small-to-modest viewing condition by lure interaction, similar in direction to the ones observed in Experiments 1A and 1B, though smaller in magnitude. That is, performance may be less efficient when lure similarity is relatively higher and eye movements are allowed, but when lure similarity is low, eye movements appear to have little to no impact on search efficiency.

Discussion

The results of Experiment 2 in the fixed-viewing condition were largely similar to those in Experiments 1A and 1B, except for the fact that, somewhat unexpectedly, the linear fit for the low-similarity (orange) lure condition was better than the logarithmic fit. The perceptual difference between the low-similarity lure and the target in Experiment 2 (a cyan half-disc among orange diamonds) was most likely different from that in Experiment 1 (red triangle among blue circles), but this difference is unlikely to have been responsible for the better linear fit for the low-similarity lures in Experiment 2. We note that this is the first out of 38 conditions studied in our lab, all with varying degrees of lure–target similarity, in which we have found a better linear than a logarithmic fit (14 comparisons tested in Buetti et al., 2016; 12 in Madison et al., 2018; three in Wang et al., 2017; four in Wang et al., 2018; and five others presented in the present article). Furthermore, because of time constraints, we tested fewer lure set-size conditions in the present experiments (three) than in the previous studies (four or five), likely making it more difficult to compare linear with logarithmic functions. So, we are inclined to think that this finding is an exception and likely reflects the fact that even for well-powered

studies, a small proportion of tests (in this case, one out of 38) ought to fail. Nevertheless, it is possible that restricting eye movements influenced the evidence accumulation process; we plan to continue to conduct eyetracking studies to bring more evidence to bear on this question.

General discussion

Recent research has previously demonstrated that, in efficient visual search tasks with a fixed target, Stage 1 processing times are not constant, but instead vary systematically as a function of lure–target similarity (Buetti et al., 2016; Madison et al., 2018; Wang et al., 2017; Wang et al., 2018). Specifically, a logarithmic relationship between RTs and set size was observed. Importantly, such logarithmic (instead of flat or linear) search slopes indicate that processing is *parallel* and *exhaustive* in nature. This is in contrast to current models of search, which predict flat search slopes and/or a self-terminating rule, whereby search ends as soon as the target is found (and often regardless of the number of items in a display). Buetti et al. (2016) proposed that these logarithmic slopes could be interpreted as an index of the efficiency of processing each lure item in parallel across the entire display. The greater the lure–target similarity, the steeper the log slope—indicating less efficient processing (i.e., that a longer evidence accumulation period is needed in order to discard a lure as a nontarget item).

In the present study, we demonstrated that these log functions persisted (in five out of six conditions, log fits outperformed linear fits) even when eye movements were restricted. We further showed that the slopes of these logarithmic functions were also modulated by lure–target similarity in the absence of eye movements. It thus appears that eye movements do not qualitatively change the pattern of results observed in efficient search, therefore providing further evidence in favor of the exhaustive nature of Stage 1 processing (Buetti et al., 2016). This occurs despite the fact that people prefer to move their eyes in efficient search tasks (Findlay & Gilchrist, 1998; Zelinsky, 2008). Several studies have also suggested that free- and fixed-viewing search are not qualitatively different (e.g., Klein & Farrell, 1989; Zelinsky & Sheinberg, 1997). In addition, although Zelinsky's (2008) target acquisition model showed that the number of fixations increased with set size in a negatively accelerating function, we can now confidently conclude that this effect is independent of RTs. Nevertheless, Zelinsky's (2008) results do suggest that eye movements may be an additional source of (negatively accelerating) nonlinearity in RT functions.

Our present results thus suggest that logarithmic functions are an inherent signature of the cognitive architecture of Stage 1 processing, and not simply an artifact of eye movements. When participants have to discriminate a fixed target in an efficient visual search task, their behavior is best characterized

by a cognitive architecture that accumulates evidence at each location in the display, in order to determine which locations are unlikely to contain the target, and which ones might. Evidence accumulates across all locations in parallel, with unlimited capacity and in an exhaustive fashion, as evidenced by the observed log functions (Buetti et al., 2016; Madison et al., 2018; Wang et al., 2017; Wang et al., 2018). Furthermore, the time taken to accumulate the necessary evidence to reject an item increases as lure–target similarity increases. This is reflected in the modulation of the logarithmic functions by lure–target similarity.

In recent work, we have also ruled out crowding (Madison et al., 2018), target eccentricity, and cortical magnification (Wang et al., 2018) as potential causes of the logarithmic functions. In sum, the evidence suggests that the logarithmic shape of the RT by set size functions in fixed-target efficient search tasks is indeed a characteristic of the underlying exhaustive processing required to find the target in these displays. Furthermore, this cognitive architecture is not limited solely to efficient visual search tasks. In fact, we propose that it is an inherent property of Stage 1 processing and, as we have shown here, not simply an artifact of eye movements. In inefficient visual search tasks with a fixed target, the presence of lures of different numbers and different lure–target similarities produces the same logarithmic patterns seen in efficient search, even when the number of candidates (items that are sufficiently similar to the target and thus require further scrutiny) is held constant (Buetti et al., 2016, Exps. 3A–3D). That is, lures nevertheless contribute to processing times, even when they are sufficiently dissimilar from the target and any other candidate stimuli present in the scene (and thus require no further scrutiny). To be clear, these findings and this proposal stand in contrast to previous models of visual search (Treisman & Gelade, 1980; Wolfe, 1994). For example, in Guided Search (Wolfe, 1994), attention is thought to visit locations with the highest activation value. The greater the visual similarity of an item to the target (among other factors), the greater the activation value. If that location does not contain the target, attention moves to the location with the next highest activation value. These models (Treisman & Gelade, 1980; Wolfe, 1994) predict that lures, which are very dissimilar from the target, will not contribute to processing times at all, due to their extreme dissimilarity from the target, and even less so when they are presented in the context of candidates.

In addition, our results suggest that search was less efficient in the free-viewing than in the fixed-viewing condition, but only when lure–target similarity was relatively high. The lack of a significant change in search efficiency in low lure–target similarity displays could have been due to the fact that search was very efficient with these lures, thus providing little opportunity (and/or need) for eye movements to impact search performance. Our results could thus possibly explain the disparate findings in the literature regarding the influence of eye

movements on efficient visual search. It may be that studies that have shown little to no significant difference in RTs between fixed- and free-viewing conditions (e.g., Klein & Farrell, 1989; Treisman & Gormican, 1988; Zelinsky & Sheinberg, 1997) used lower levels of lure–target similarity than have studies in which eye movements did reduce search efficiency in free- as compared to fixed-viewing conditions (e.g., Carrasco et al., 1998).

In sum, our results suggest that (i) fixed-target efficient search functions are logarithmic, even when eye movements are not allowed; (ii) there are no strong practice effects on search efficiency in these efficient search tasks; and (iii) viewing condition has at most a small interaction effect with lure type on search efficiency (as we observed in Exps. 1A and 1B), such that efficiency is improved when eye movements are restricted, but only when the lure–target similarity is relatively high.

Constraints on generalizability

One caveat of our findings is that the best-fitting logarithmic functions were derived from averaged data across all participants. This was necessary because individual-level data are rather noisy, due to the relatively low number of observations per condition, the relatively large variability in terms of possible display arrangements per condition, and the mere stochastic nature of the underlying accumulation processes. These factors only average out with larger numbers. For instance, when we consider individual-level fits, the average R^2 values for the log versus linear curves (e.g., in Exp. 1A, those values are .862 vs. .774 for the high-similarity lure curves, and .596 vs. .534 for the low-similarity lure curves) are substantially lower than the group R^2 values. Thus, it seems important to follow up this research with a more psychophysical approach in order to study the role of individual differences in efficient visual search.

In addition, we removed participants who made excessive eye movements from our analysis. These participants could have had a lower level of inhibitory control in response to the appearance of the search display (i.e., more reflexive eye movements). Watson, Brennan, Kingstone, and Enns (2010) reported that eye movements can be influenced by search strategies. Participants who engaged in a passive strategy, in which they allowed the target to "pop" into awareness, waited longer before moving their eyes than did those who adopted an active strategy of guiding attention. Perhaps those who were having difficulty completing our search task without eye movements were "active" searchers who might have shown a different pattern of results. Unfortunately, this set of experiments did not allow us to examine the influence of individual differences in search strategies in the context of our model. This would be an interesting avenue for further research.

We believe that our results will be generalizable to other stimuli of different shapes, colors, and complexity, as well as to images of real-world objects (e.g., Wang et al., 2017). By

using the same lures but different targets (and thus different lure–target similarities), we have shown that our results depend on lure–target similarity instead of on a specific set of stimuli (see also Buetti et al., 2016). Other results from our laboratory (manuscript in preparation) show that these logarithmic functions are observed even when lure–target similarity is based on shape alone (i.e., when all stimuli are the same color), suggesting that logarithmic functions are not exclusively the result of color differences between lures and target.

The nature of the search task, however, is important. We have previously shown that in an oddball task in which the target identity is not fixed from trial to trial, Stage 1 processing is qualitatively different than it is in fixed-target searches (as we studied here): Evidence about the distractor (i.e., the repeated color) must first be accumulated before the target color (and therefore the target itself) can be selected (Buetti et al., 2016). In such cases (oddball searches), logarithmic curves do not emerge. Instead, RTs then decrease as a power function of set size. Aside from these factors, we have no reason to believe that our results will depend on other characteristics of the materials or context.

References

Bouma, H. (1970). Interaction effects in parafoveal letter recognition. *Nature*, *226*, 177–178. https://doi.org/10.1038/226177a0

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision*, *10*, 433–436. https://doi.org/10.1163/156856897x00357

Buetti, S., Cronin, D. A., Madison, A. M., Wang, Z., & Lleras, A. (2016). Towards a better understanding of parallel visual processing in human vision: Evidence for exhaustive analysis of visual information. *Journal of Experimental Psychology: General*, *145*, 672–707. https://doi.org/10.1037/xge0000163

Bundesen, C. (1990). A theory of visual attention. *Psychological Review*, *97*, 523–547. https://doi.org/10.1037/0033-295X.97.4.523

Carrasco, M., McLean, T. L., Katz, S. M., & Frieder, K. S. (1998). Feature asymmetries in visual search: Effects of display duration, target eccentricity, orientation and spatial frequency. *Vision Research*, *38*, 347–374. https://doi.org/10.1016/S0042-6989(97)00152-1

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*, 433–458. https://doi.org/10.1037/0033-295X.96.3.433

Duncan, J., & Humphreys, G. W. (1992). Beyond the search surface: Visual search and attentional engagement. *Journal of Experimental Psychology: Human Perception and Performance*, *18*, 578–588. https://doi.org/10.1037/0096-1523.18.2.578

Findlay, J. M., & Gilchrist, I. D. (1998). Eye guidance and visual search. In *Eye guidance in reading, driving and scene perception* (pp. 295–312). Oxford, UK: Elsevier. Retrieved from https://community.dur.ac.uk/j.m.findlay/UnChap.pdf

Guzman-Martinez, E., Leung, P., Franconeri, S., Grabowecky, M., & Suzuki, S. (2009). Rapid eye-fixation training without eyetracking. *Psychonomic Bulletin & Review*, *16*, 491–496. https://doi.org/10.3758/PBR.16.3.491

Irwin, D. E., & Carlson-Radvansky, L. A. (1996). Cognitive suppression during saccadic eye movements. *Psychological Science*, *7*, 83–88. https://doi.org/10.1111/j.1467-9280.1996.tb00334.x

Irwin, D. E., Carlson-Radvansky, L. A., & Andrews, R. V. (1995). Information processing during saccadic eye movements. *Acta Psychologica*, *90*, 261–273. https://doi.org/10.1016/0001-6918(95)00024-O

Itti, L., & Koch, C. (1999). Feature combination strategies for saliency-based visual attention systems. In *Proceedings of SPIE: Human Vision and Electronic Imaging IV (HVEI '99), San Jose, CA* (Vol. 3664, pp. 473–482). Bellingham, WA: SPIE Press. https://doi.org/10.1117/1.1333677

Klein, R., & Farrell, M. (1989). Search performance without eye movements. *Perception & Psychophysics*, *46*, 476–482. https://doi.org/10.3758/BF03210863

Madison, A., Lleras, A., & Buetti, S. (2018). The role of crowding in parallel search: Peripheral pooling is not responsible for logarithmic efficiency in parallel search. *Attention, Perception, & Psychophysics*, *80*, 352–373. https://doi.org/10.3758/s13414-017-1441-3

Matin, E., Shao, K. C., & Boff, K. R. (1993). Saccadic overhead: Information processing time with and without saccades. *Perception & Psychophysics*, *53*, 372–380. https://doi.org/10.3758/BF03206780

Neider, M. B., & Zelinsky, G. J. (2008). Exploring set size effects in scenes: Identifying the objects of search. *Visual Cognition*, *16*, 1–10. https://doi.org/10.1080/13506280701381691

Pelli, D. G., & Tillman, K. A. (2008). The uncrowded window of object recognition. *Nature Neuroscience*, *11*, 1129–1135. https://doi.org/10.1038/nn.2187

Rosenholtz, R., Huang, J., Raj, A., Balas, B. J., & Ilie, L. (2012). A summary statistic representation in peripheral vision explains visual search. *Journal of Vision*, *12*(4), 14. https://doi.org/10.1167/12.4.14

Townsend, J. T., & Ashby, F. G. (1983). *The stochastic modeling of elementary psychological processes*. Cambridge, UK: Cambridge University Press. https://doi.org/10.2307/1422636

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*, 97–136. https://doi.org/10.1016/0010-0285(80)90005-5

Treisman, A. M., & Gormican, S. (1988). Feature analysis in early vision: Evidence from search asymmetries. *Psychological Review*, *95*, 15–48. https://doi.org/10.1037/0033-295X.95.1.15

Verghese, P. (2001). Visual search and attention: A signal detection theory approach. *Neuron*, *31*, 523–535. https://doi.org/10.1016/S0896-6273(01)00392-0

Wang, Z., Buetti, S., & Lleras, A. (2017). Predicting search performance in heterogeneous visual search scenes with real-world objects. *Collabra: Psychology*, *3*, 1–23. https://doi.org/10.1525/collabra.53

Wang, Z., Lleras, A., & Buetti, S. (2018). Parallel, exhaustive processing underlies logarithmic search functions: Visual search with cortical magnification. *Psychonomic Bulletin & Review*. Advance online publication. https://doi.org/10.3758/s13423-018-1466-1

Watson, M. R., Brennan, A. A., Kingstone, A., & Enns, J. T. (2010). Looking versus seeing: Strategies alter eye movements during visual search. *Psychonomic Bulletin & Review*, *17*, 543–549. https://doi.org/10.3758/PBR.17.4.543

Wolfe, J. M. (1994). Guided search 2.0: A revised model of visual search. *Psychonomic Bulletin & Review*, *1*, 202–238. https://doi.org/10.3758/BF03200774

Wolfe, J. M., & Horowitz, T. S. (2004). What attributes guide the deployment of visual attention and how do they do it? *Nature Reviews Neuroscience*, *5*, 495–501. https://doi.org/10.1038/nrn1411

Zelinsky, G. J. (2008). A theory of eye movements during target acquisition. *Psychological Review*, *115*, 787–835. https://doi.org/10.1037/a0013118

Zelinsky, G. J., & Sheinberg, D. L. (1997). Eye movements during parallel-serial visual search. *Journal of Experimental Psychology: Human Perception and Performance*, *23*, 244–262. https://doi.org/10.1037/0096-1523.23.1.244