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Complex Background Information Slows Down Parallel Search Efficiency by Reducing the Strength of Interitem Interactions

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In the laboratory, visual search is often studied using uniform backgrounds. This contrasts with search in daily life, where potential search items appear against more complex backgrounds. In the present study, we examined the effects of background complexity on a parallel visual search under conditions where objects are easily segregated from the background. Target–distractor similarity was sufficiently low such that search could unfold in parallel, as indexed by reaction times that increase logarithmically with set size. The results indicate that when backgrounds are relatively simple (sandy beach with water elements), search efficiency is comparable to search using a solid background. When backgrounds are more complex (child bedroom or checkerboard), logarithmic search slopes increase compared to search on solid backgrounds, especially at higher levels of target–distractor similarity. The results are discussed in terms of different theories of visual search. It is proposed that the complex visual information occurring in between distractors slows down individual distractor rejection times by weakening the strength of interitem interactions.

Public Significance Statement

We compare how quickly human observers search through objects in an environment while manipulating the complexity of the background surfaces on which those objects rest. Our results demonstrate that, when the search task is relatively easy, the complexity of the visual information that is present in between objects can significantly slow down the speed at which observers search through that environment, even when those objects are easily distinguishable from the backgrounds on which they appear. These results suggest that future studies should study more carefully the perceptual interactions between nontarget objects, and the factors that impact the strength of those interactions.

Keywords: visual search, parallel search, search efficiency, background complexity, interitem interactions

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In daily life, we search for objects in different contexts, such as when searching for car keys on a counter or searching for a carton of milk of a certain brand on the supermarket shelf. Most of the time, these objects are embedded in more complex backgrounds than the ones used in classic laboratory search paradigms, which are typically uniform in color (e.g., Alexander & Zelinsky, 2011; Farmer & Taylor, 1980; Rosenholtz et al., 2004; Wang et al., 2017). Backgrounds have been shown to impact search performance on several fronts. For instance, backgrounds can reduce the visibility of objects (camouflaging effect), which can slow down search dramatically (e.g., Boot et al., 2009; De Vries et al., 2013; Geisler & Chou, 1995; Neider et al., 2010).

Background information can also guide attention, impacting search behavior. Torralba et al. (2006; see also Pereira & Castelhano, 2019) famously proposed a new model of guidance that combines both contextual guidance (i.e., prior knowledge of the likely locations of objects in daily scenes) with a more traditional bottom-up salience analysis of the scene. Torralba et al.'s model predicts eye fixations of participants searching for targets on real-life images to a greater extent than salience alone. For example, when searching for a painting, the model predicts that people will inspect vertical surfaces where paintings are typically hung, whereas when searching for a coffee mug, it predicts people will inspect kitchen counters or tables. More recently, Wolfe's Guided Search 6.0 (2021) incorporates a "nonselective pathway" that enables visual awareness of the entire field of view and allows for the rapid extraction of scene gist and ensemble statistics without requiring selective attention. The nonselective pathway carries much of the information responsible for scene guidance effects such as scene meaning

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(e.g., Henderson & Hayes, 2017), consistent object–scene location associations (e.g., Torralba et al., 2006), and consistent object–object associations (Võ, 2021).

In addition to potential camouflaging and semantic/context guidance effects, background information might also impact search behavior by altering the type and/or quality of the perceptual representations that the visual system has access to when searching. Indeed, in recent years, there has been a growing realization that visual search theories ought to better incorporate the known processing characteristics of peripheral vision into their mechanistic accounts of guidance in complex scenes (e.g., Hulleman & Olivers, 2017; Lleras et al., 2022; Rosenholtz, Huang, & Ehinger, 2012). The most sophisticated account of peripheral vision's impact on search is the texture tiling model (TTM) put forward by Rosenholtz and colleagues (Chang & Rosenholtz, 2016; Rosenholtz, Huang, & Ehinger, 2012; Rosenholtz, Huang, Raj, et al., 2012; Zhang et al., 2015). TTM proposes that in the periphery, processing unfolds in a pooled fashion: some 30 or so visual properties are computed over regions that increase in area as their eccentricity increases. These statistical properties computed over that region are the ones used by Portilla and Simoncelli (2000) in their model of textural effects in the vision. The statistics range in complexity from fairly simple ones (like mean, variance, and range of luminance in the patch) to increasingly more complex ones (such as autocorrelations, magnitude correlations, and relative phase statistics; for more, see Balas et al., 2009). The key point here is that perceptual representations in the periphery are not "object" or "feature" centered necessarily, but rather represent statistics computed over the entirety of each pooling region. Rosenholtz, Huang, Raj, et al. (2012) demonstrated that visual search efficiency for any target–distractor pair of stimuli can be predicted by the visual system's ability to discriminate peripheral patches that contain the target (plus some distractor stimuli) from those that only contain distractors.

One current unknown regarding the TTM is that the model was developed based on data from experiments with uniform backgrounds; thus, it is difficult to know what the model would predict would happen when objects are placed in complex backgrounds. Does the computation of pooled statistics in the periphery blend, in a way, the visual characteristics of the search stimuli with that of the background? If so, one can make the prediction that the presence of complex visual signals in the background will necessarily slow down search, if for no other reason that these features will basically decrease the target signal, or in TTM's terminology, background will decrease the discriminability between pooling regions contain the target (+background and potentially some distractors) from those that only contain distractors (+background).

Alternatively, it is possible that the pooled statistics in TTM might be computed after figure/ground segmentation has occurred or that, at the very least, some subset of visual properties that describe the objects is sufficiently distinct from the corresponding subset that is present in the background image that search might still be able to unfold guided by information along these subsets of complex features. If so, background information might in fact not have much of an impact on search, provided that the objects in the scene have features that do not overlap much with those in the background (i.e., that there is no camouflage). Is there reason to believe that such a result might obtain? That is, is there any empirical evidence that searching for a target in a complex scene might unfold with identical efficiency when objects are presented over complex backgrounds compared to uniform, simple backgrounds? There is. Wolfe et al. (2011) first examined the impact of backgrounds on visual search using easily visible (noncamouflaged) objects occurring in real-life scenes. The stimuli consisted of photos of real-life scenes, annotated to count the number of itemsand with labels for each object in the scene. In Experiment 5, the authors compared performance across three main background conditions: (a) the original background (indoor scenes), (b) the black background (where the individual objects in the scene were maintained and the background surfaces were cut out and replaced by a black uniform surface), and (c) the noise background condition (where the background surfaces were replaced with a black-and-white phase-scrambled version of the scene). Participants were asked to find an object in the scene. Somewhat surprisingly, the results indicated that the background manipulation did not impact search performance: reaction times (RTs) were the same irrespective of the background condition. Furthermore, the search was efficient across several experiments using these types of real-world scenes, suggesting observers can search in parallel through complex scenes without there being much cost associated with the information content in the background (or variations therein).

While Wolfe et al. (2011) was a great first study of search in real-life environments, there are several limitations that impact the generalizability of the results. First, there was no attempt at characterizing whether contextual guidance was at play in these scenes because only naturally occurring object arrangements were used. It is likely that many contextual cues were present in every search scene (e.g., Torralba et al., 2006; Võ, 2021). For instance, a desktop computer was presented on a desk where it would typically be found. Perhaps the background had no effect and the search was very efficient in these scenes due to very strong scene guidance effects. Second, because the search scenes were images of real-life environments, distractor set size could not be easily manipulated within a given scene/target combination. Therefore, the main measure in the study was overall RT rather than search efficiency, which is the true index of search performance. Third, the similarity relations between the target and all the other objects in the scene were difficult to establish. Thus, it is also possible that the search may have been overly easy simply because the chosen targets might have been extremely visually different from all distractors. This would also reduce the likelihood of observing any background effects on search performance.

Current Study

The present study focuses on evaluating the impact of scene backgrounds on search efficiency under easy-to-segregate and arbitrarily positioned conditions. Indeed, in daily life, there are many situations where objects are not camouflaged by the background and are also randomly placed in the environment. For instance, imagine searching for an easily visible toy in a child's bedroom. The toy might appear at many possible locations, such as on shelves, furniture, or on the ground, with little systematicity. In such situations, contextual guidance will not direct the observers toward the target, and only knowledge of the target features can guide the search.

To expand on the findings in Wolfe et al. (2011) findings, the present work examined the effects of background complexity under more controlled conditions. Like Wolfe et al. (2011), we focused on a relatively efficient search. In that study, search efficiency was estimated to be in the range of 3–10 ms/item in experiments with backgrounds, which are values traditionally associated with efficient search. To have a better estimate of search efficiency, we directly manipulated set size (as opposed to trying to infer its value in a natural scene). We also directly varied target–distractor similarity to evaluate search efficiency at various levels of processing efficiency.

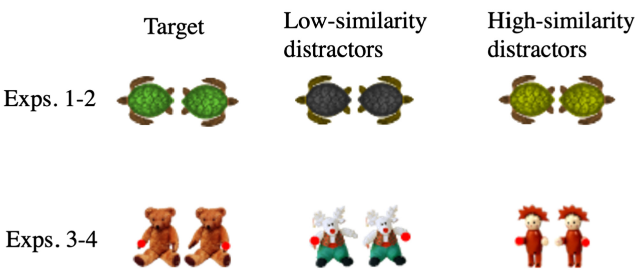
Finally, we utilized two types of background complexity: an unstructured background (sandy beach) in Experiments 1A, 1B, and 2, and a structured background (child bedroom) in Experiments 3A–C. The results from these two experiments suggested a new hypothesis regarding the role background information plays during efficient search, which was tested in a final experiment (Experiment 4) with a new background (checkerboard).

We must acknowledge that the stimuli we chose to occupy a midpoint between traditional, simple geometric motifs more typically associated with the search and attention literature (e.g., searching for a red triangle among blue circles on a white background) and the naturalistic photo scenes used in Wolfe et al. (2011). The background scene in Experiments 1 and 2 was a picture of a beach, slightly edited, and the background scene in Experiment 3 was a child's bedroom with furniture generated in a 3D environment. The scene respected perspective rules, but the furniture was not photorealistic. The search stimuli themselves also varied in terms of complexity (see Figure 1). In Experiments 1 and 2, we used colorful images of small turtles, and in Experiments 3 and 4, we used photos of small toys. With both sets of stimuli, we had a titrated similarity manipulation that would ensure that the search would unfold in an efficient manner (at least in the uniform background condition) because we had used them successfully in past studies (e.g., Lleras et al., 2019; Wang et al., 2017). Thus, we knew participants would be able to use peripheral vision and perform a search in parallel to the scene with these stimuli.

In sum, the stimuli and scenes in the current study live somewhere in between the real and the artificial. Yet, they clearly represent a step up from traditional lab studies in terms of image complexity/realism. They also allow us to effectively manipulate several variables of interest (set size and target–distractor similarity). And finally, the scenes and stimuli were chosen such that we could pretty much place the objects almost anywhere in the background (with some minimal constraints in Experiment 3), allowing us to sidestep the potential problems associated with strong contextual guidance effects that might be evident when using real objects presented in the location where they are most expected (e.g., a computed being presented on a desk). Overall, the aim was to build on the findings in Wolfe et al. (2011) to get a more precise characterization of the impact of backgrounds under efficient search conditions. The study of the impact of backgrounds on inefficient search was not examined here.

Different patterns of results were possible in these experiments. On the one hand, search might unfold at a processing stage that happens sometime *after* figure-ground segmentation in the scene has been completed, particularly given that we had chosen search stimuli that were easily segregated from the background (i.e., a noncamouflage condition). If this is the case, search might unfold with identical efficiency, irrespective of the background information. It is also possible that, if our stimuli somehow tap into the same mechanisms that allowed search to be efficient and unaffected by the background as was observed in Wolfe et al. (2011), then, again, we might fail to find much of an impact of background information on search efficiency. On the other hand, there is also an a priori reason to expect an effect. Indeed, with this type of stimulus, it is known that some low-level effects like crowding (Madison et al., 2018) and stimulus size (Wang et al., 2018) impact search efficiency. Thus, one might expect that background information to be yet another such low-level factor that might, for instance, slow down the rate of evidence accumulation for items presented in the periphery. This would be akin to complex background information decreasing the signal quality at each location where an object appears compared to solid background information. Such a result would certainly be consistent with a TTM account, whereby pooled statistic representations would be less discriminable when complex backgrounds are used. Finally, it is possible that the effect (if one is found) might lie at yet a different level of processing: one important factor that determines search efficiency is our visual system's ability to notice that nearby items are similar to one another (i.e., that they perceptually group together, e.g., Duncan & Humphreys, 1989; Lleras et al., 2019). Indeed, when nearby distractors are similar to each other, rejection of those distractors is multiplicatively faster than when nearby distractors are different from one another (Lleras et al., 2019). Thus, it is possible that the presence of complex visual information in the space in between items might make it more difficult for our visual system to ascertain that Object 1 at location [$x1$, $y1$] is the same as Object 2 at nearby location [$x2$, $y2$]. If that were to occur, search efficiency would suffer compared to conditions with little or no intervening visual information simply because nearby identical distractors would be less able to facilitate each other's rejection. The current results will eventually lead us to favor this latter possibility.

Figure 1
Stimuli Used in the Study



Note. The top row shows the stimuli used in Experiments 1A–B and 2. The target was a green turtle pointing either to the left or right. Participants reported the direction of the target. The distractors in the low similarity conditions were back turtles and the distractors in the high similarity condition were yellow–greenish turtles. The distractors were manipulated between-subjects in Experiment 1 (1A: low similarity condition; 1B: high similarity condition) and within subjects in Experiment 2. The bottom row shows the stimuli used in Experiments 3 and 4. The target was a teddy bear with a red dot on the left or right side, and participants reported the side of the red dot. The distractors in the low similarity conditions were white reindeers and the distractors in the high similarity conditions were red dolls. The distractors were manipulated between-subjects in Experiments 3A and 3B (3A: low similarity condition; 3B: high similarity condition) and within-subjects in Experiments 3C and 4. See the online article for the color version of this figure.

Experiment 1

In Experiment 1, we evaluated the effects of an unstructured background with little visual or semantic structure on search efficiency. A sandy beach scene with water elements was used as the background, and participants searched for a green turtle among black turtles (low similarity distractors, Experiment 1A) or among yellowish–green turtles (high similarity distractors, Experiment 1B). Search efficiency for the same target and distractors was also evaluated with two other backgrounds. A solid background was created by averaging the RGB values of the naturalistic background scene. This background condition provided us with a baseline for searching for the same items when no scene information is present, which is also the most often encountered condition in laboratory studies of search. Finally, a phase-scrambled background was created from the naturalistic beach background (e.g., Caddigan et al., 2017). This background maintained similar first-order image statistics as the beach background but scrambled the recognition of the elements in the scene (sand, wave, water), which allowed us to evaluate the effect of low-level features on search efficiency.

Based on previous findings on efficient search, we expected to observe a logarithmic relationship between RTs and set size (Buetti et al., 2016; Lleras et al., 2020; Madison et al., 2018; Ng et al., 2018; Wang et al., 2018). We also expected the logarithmic slopes to be sensitive to the similarity relationship between the target and distractors. Specifically, the slopes should be steeper in the high similarity than in the low similarity search condition.

Regarding the effect of background on search performance, there are several possible ways in which background could impact search performance. With respect to search-related processes, it is possible that backgrounds will have no meaningful effects on search efficiency (see Wolfe et al., 2011). As mentioned earlier, it is also possible that complex backgrounds might slow down search efficiency, similar to how crowding and stimulus size have been shown to impact search efficiency (Madison et al., 2018; Wang et al., 2018). This would result in inflated logarithmic slopes in the more complex background conditions compared to the solid background conditions. If recognition of the elements that make up the background image drives this effect, the increase in the logarithmic slopes should only be observed in the beach but not in the phase-scrambled background because, by design, the phase-scrambled image has no recognizable visual elements. If it is the presence of more complex visual features that drives the effect, then the increase in slopes should be observed with both backgrounds.

It is also possible that background impacts nonsearch-related processes, such as the overall time required to identify the target in the absence of any distractors. These types of effects will be observed at the level of the intercepts of the logarithmic functions fitted to each participant's performance. Of note, the analyses of the intercepts closely correspond to analyses of the RTs in the target-only condition. This follows because in the equation, $RT = a + b \times \ln$ (Set Size) when Set Size = 1 (as in the target-only condition), $\ln(1) = 0$. As a result, RT(target-only) = a. The key to remember is that moving forward, analyses of the intercept of the search function will be indexing the impact of the various backgrounds on nonsearch-related processes (e.g., encoding, response preparation, response execution), whereas analyses of the logarithmic search slopes will be indexing the impact of the various backgrounds on search-related processes (e.g., distractor rejection processes).

Method

Participants

Experiment 1 was preregistered on Open Science Framework (Ballew et al., 2019; https://doi.org/10.17605/OSF.IO/NAFE2). Note that because of the COVID-19 pandemic, all experiments were run online instead of in the laboratory. Participants in Experiments 1A and 1B were recruited from the subject pool at the University of Illinois at Urbana-Champaign and were given course credits for their participation. Only participants who self-reported to have normal or corrected-to-normal vision and normal color vision were allowed to take part in the experiment. The sample size had to be adapted because of the increased noise associated with online data collection, as described below. A power analysis performed on the data collected in Experiment 1A revealed that 31 participants would be required to detect a within-subject effect size of $\eta_p^2 = .065$ for the main effect of background at 80% power, with the variability observed in online data collection. So, in general, we tried to reach a sample size of 31 participants, but because of the nature of online data collection, we often ended up collecting a few more participants.

Thirty-seven participants completed Experiment 1A (26 female, 10 male, 1 other; $M_{age} = 20$); 36 participants completed Experiment 1B (25 female, 11 male; $M_{age} = 20.7$).

The criteria for inclusion were based on accuracy, and analyses were conducted on correct trials only. Trials in which the wrong button was pressed (incorrect trials), no response was provided after 2.5 s (time-out trials), or with RTs that exceeded two standard deviations (SDs) of the mean RT for that participant in each condition were excluded.

After data collection, participants' data were excluded if the time-out rate was greater than 15% or if overall accuracy (including incorrect trials but not time-out trials) was lower than 90%. Four participants were excluded from Experiment 1A (three of them were excluded because of low accuracy and one because of a high time-out rate) and three from Experiment 1B (two of them were excluded because of low accuracy and one because of a high time-out rate). The data analysis included 33 participants in Experiment 1A and 33 participants in Experiment 1B.

Stimuli and Materials

Due to COVID-19, participants completed the experiments online using their own devices. All experiments were programmed in JavaScript and conducted on Pavlovia. Using information about each participant's screen resolution and pixel width, search items were designed to cover approximately 0.8 cm × 1 cm and were placed on a 19.5 cm × 14.5 cm background. In Experiments 1A and 1B, the search stimuli were placed randomly with jitter (the jitter was randomly generated, with a maximum being 25 pixels horizontally or vertically from the standard grid positions) within a 6 × 6 rectangular grid that occupied an area of 14.7 cm × 10.5 cm. This size was chosen to make sure participants who have screens as small as 12.5 in. could see the full display.

In Experiments 1A and 1B, the stimuli were turtles (Figure 1) presented on one of three backgrounds that varied in complexity and meaning. The three backgrounds were a naturalistic scene of a beach with sand and water, a solid color background obtained by averaging the RGB values of the naturalistic background scene, and a phase-scrambled version of the naturalistic background scene (Figure 2). All three backgrounds had equal mean RGB values, which ensured the same low-level salience across the different backgrounds. In Experiment 1A, the color similarity between the target and distractors was low. The target was a green turtle, and the distractors were black turtles. In Experiment 1B, the color similarity between the target and distractors was high. The target was a green turtle, and the distractors were yellow–greenish turtles. The turtle's head could point to the left or right, and participants reported the orientation of the target turtle. The stimuli in Experiments 1A and 1B were placed in a subset of the 32 evenly spaced locations within the 6×6 grid (the four central locations around the fixation point were left empty, Figure 2).

Design and Procedure

The similarity between target and distractors was manipulated between subjects. Backgrounds were manipulated within subjects and presented in a random fashion. The set size was the number of objects against the background and included the target item. There were four different set sizes: 1, 5, 10, 20. The experimental session was expected to last approximately 45 min. There were 50 trials per condition. Thus, across the three backgrounds and four different set sizes (including one target-only condition), there were a total of 600 trials. A mandatory rest period took place after every 150 trials.

Each trial proceeded as follows. In Experiments 1A and 1B, there was a practice block of 6 trials before each experiment. There was a white fixation cross in the center of the screen before the search display presented for 500 ms. Participants were asked to search for the target and report which side (left or right) the target turtle was heading by pressing the left or right arrow key on their keyboards, respectively. Each display was presented for 2.5 s or until the participants pressed the response key. A visual feedback statement ("Correct!" or "Wrong!") was given after each trial. In all experiments, the trial ended with a black background shown for a random interval lasting 0.5 s.

Transparency and Openness

We reported how we determined our sample size, all data exclusions, all manipulations, and all measures in this and later experiments, and we followed JARS (Kazak, 2018) on methods, data availability, and prospective power analysis. The data, materials, and code for this and later experiments are publicly available on OSF (https://osf.io/n4s85/). Data were analyzed using R Version 4.1.2 (R Core Team, 2021) and the package ggplot2, Version 3.3.6. Experiment 1 and Experiment 3 were preregistered on Open Science Framework (Ballew et al., 2019). The data in this and later experiments were collected between 2020 and 2022.

Analyses

In all experiments, analyses were performed on the correct trials only and were conducted in R (Version 4.0.2). For each participant, we computed a logarithmic slope for each background and similarity condition. A two-way analysis of variance (ANOVA) with background as a within-subject factor and target–distractor similarity as a between-subject factor was then conducted on the logarithmic slope value. We also conducted an ANOVA with background as a within-subject factor on the intercepts of the logarithmic functions to evaluate the overall baseline differences.

Results

The data analysis included 33 participants in Experiment 1A (group accuracy = .963, $SD = .034$) and 33 participants in Experiment 1B (group accuracy = .958, $SD = .027$). Figure 3A and B show the results from Experiment 1. The results from Experiment 1 are shown in Figure 3A and B. Only RTs in correct trials were included in the subsequent analyses.

As a reminder, we analyzed two different parameters obtained from search performance evaluation: intercepts and search slopes of the logarithmic search functions that were fitted to each individual participant in each search condition. The intercept indexes the time taken to complete nonsearch-related processes, whereas the search slope indexes the efficiency at which search processes unfold. Intercept and search slope should be influenced by different factors. For example, manipulations that impact the target-response mapping ought to uniquely impact the intercept: on all search trials, irrespective of search difficulty, and irrespective of the number of distractors, eventually participants will find the target, and once they do, they will have to identify which response maps to its identity on the current trial. Some mappings might be easier than others, leading to faster response decisions and thus smaller intercepts. In contrast, manipulations like target–distractor similarity should only impact the efficiency at which the search unfolds but not the intercept. That is because lower levels of target–distractor similarity make it easier to determine that a distractor is not the target, speeding up how search unfolds compared to when target–distractor similarity is comparatively higher. That said, in both cases, once distractors have been rejected and the target has been found, our attention is fully engaged with the target, and the processes for choosing the correct response should be identical from that moment on.

Intercept Analysis. The results from the ANOVA with background as within-subject the intercepts revealed a significant main effect of background, $F(2, 128) = 23.62$, $p < .001$, $\eta_p^2 = .270$. Intercepts were smaller with the solid background (694 ms), followed by the phase-scrambled background (707 ms) and by the beach background (717 ms). Follow-up paired t tests revealed that the intercepts differed significantly between any two of the backgrounds, beach vs. phase-scrambled background: $t(65) = 2.79$, $p = .007$, 95% CI: [2.69, 16.32]; beach vs. solid background: $t(65) = 7.64$, $p < .001$, 95% CI: [16.61, 28.36]; phase-scrambled vs. solid background: $t(65) = 3.61$, $p < .001$, 95% CI: [5.81, 20.15].

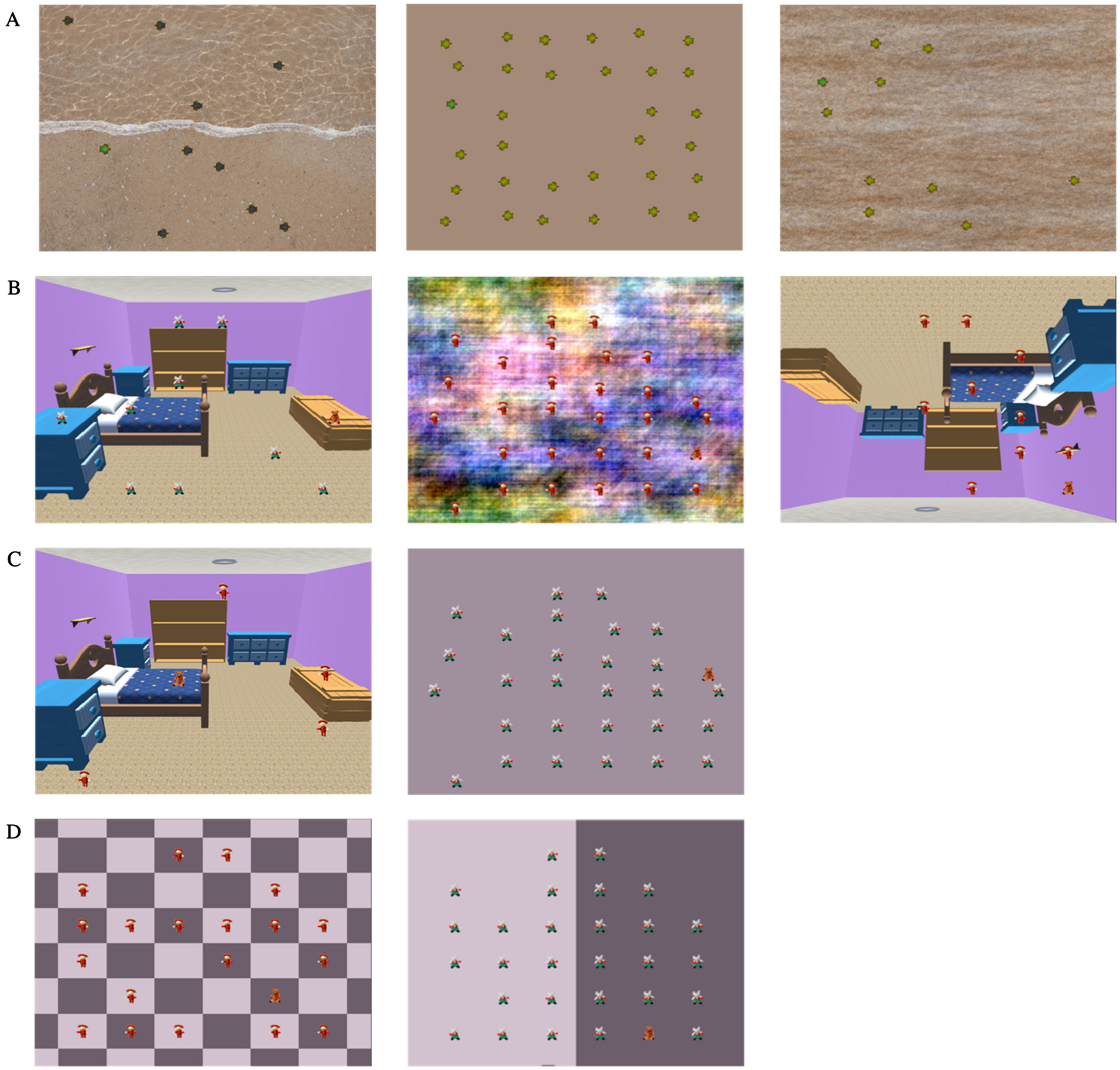
Slope Analysis. The results from the two-way ANOVA with background as a within-subject factor and similarity as a between-subject factor on the logarithmic slope revealed a significant main effect of similarity, $F(1, 64) = 185.197$, $p < .001$, $\eta_p^2 = .743$. The slopes observed for low similarity distractors were significantly shallower than the slopes for high similarity distractors (23 vs. 75 ms/log unit of set size, see Figure 3B). The main effect of the background was not significant, $F(2, 128) = 2.30$, $p = .10$, $\eta_p^2 = .035$, but the interaction between background and similarity was significant, $F(2, 128) = 3.37$, $p = .038$, $\eta_p^2 = .050$. A follow-up ANOVA on each experiment separately indicated that the effect of background was not significant in the low similarity group (Experiment 1A), $F(2, 64) = 2.23$, $p = .116$, $\eta_p^2 = .065$, and was marginally significant in the high similarity group (Experiment 1B), $F(2, 64) = 3.02$, $p = .056$, $\eta_p^2 = .086$.

Discussion

Experiment 1 showed that the different backgrounds impacted nonsearch processing times, as indicated by the significant effect

Figure 2

Illustration of the Backgrounds and Stimulus Placement in Experiments 1–4



Note. Total set size was varied across trials (1, 5, 10, 20) and the target was always present. Background was manipulated within-subjects and the different background types were intermixed during the experiment. In Experiment 1 (Panel A), three backgrounds were used: a naturalistic scene of a beach with sand and water (left); a solid color background, obtained by averaging the RGB values of the naturalistic background scene (middle); and a phase-scrambled version of the naturalistic background scene (right). In Experiment 2, only the beach and solid backgrounds were used (Panel A, left and middle). In Experiments 3A and 3B (Panel B), three backgrounds were used: a child bedroom scene (left), a phase-scrambled version of the bedroom (middle), and an upside-down version of the bedroom (right). In Experiment 3C (Panel C), the bedroom and solid backgrounds were used. In Experiment 4 (Panel D), a checkerboard (left) and semisolid backgrounds (right) were used as backgrounds. For illustration purposes, the second image on each panel visualizes all possible stimuli locations in these scenes, but note that in the experiments, the highest set size was 20, so during the experiments, there were many empty locations on every search display, with the majority of trials containing no more than 10 stimuli (set size conditions 1, 5, and 10). See the online article for the color version of this figure.

of background on the intercepts, with the more complex backgrounds delaying the most detection of the target.

Furthermore, the pattern of the data confirmed that as target–distractor similarity increases, search efficiency is reduced (Duncan & Humphreys, 1989; Lleras et al., 2020).

The results also showed that, compared to a solid background, unstructured backgrounds (beach and phase-scrambled) had a very small effect on search performance, with a larger impact when target–distractor similarity was high compared to low. This result suggests that the presence of a more visually complex background might reduce search efficiency to a modest extent. However, it is possible that the between-subject design might have introduced noise making it difficult to truly evaluate the similarity by background interaction. To better evaluate the presence of this background by similarity interaction, we reran this experiment using a within-subject design.

Experiment 2

In Experiment 2, we tested the impact of background on search processes within subjects to increase statistical power. Given the absence of a difference between the beach and phase-scrambled backgrounds in Experiment 1 and given the time constraints to run the experiment (50-min limit), in Experiment 2, we only tested two levels of target–distractor similarity (low vs. high) and two levels of background (solid vs. beach).

Participants

Participants in Experiment 2 were recruited from the subject pool at the University of Illinois at Urbana Champaign in the same way as Experiments 1A and 1B. Forty-four participants completed Experiment 2 (33 female, 10 male, 1 other; $M_{age} = 19.48$). Only participants who self-reported to have a normal or corrected-to-normal vision and normal color vision were allowed to take part in the experiment. The criteria for data inclusion were identical to those in Experiments 1A and 1B. After data collection, two participants were excluded from Experiment 2 (because of low accuracy). Thus, the data analysis included 42 participants in Experiment 2.

Design and Procedures and Analyses

The same design and procedure as in Experiment 1 were used, except that at the beginning of the experiment, participants were asked to rescale an image of a credit card to match the size of a credit card in real life (for a similar procedure, see Li et al., 2020). This scaling procedure was used in all subsequent experiments as well. This procedure allowed us to make sure that the search stimuli had the same physical size irrespective of the display size. Search items were 0.8 cm × 1 cm and were placed on a 21.8 cm × 17.5 cm background. The same analyses as in Experiment 1 were conducted. Experiment 2 was identical to Experiment 1 except that here we aimed to compare search performance *within subjects* across two different backgrounds (solid vs. beach) and two levels of similarity (low vs. high).

Results

As a reminder, in design, the data analysis included 42 participants in Experiment 2 (group accuracy = .952, SD = .039). The results from Experiment 2 are shown in Figure 3C and D.

Intercept Analysis

The results from the ANOVA with the background as within-subject on the intercepts revealed a significant main effect of background, $F(1, 41) = 11.78$, $p = .0014$, $\eta_p^2 = .223$. Intercepts were smaller in the solid (680 ms) than in the beach (697 ms) condition.

Slope Analysis

The two-way ANOVA with background and similarity as within-subject factors on the logarithmic slope revealed a significant main effect of similarity, $F(1, 41) = 375.68$, $p < .001$, $\eta_p^2 = .902$. The slopes in the low similarity condition were significantly shallower than the slopes in the high similarity condition (24 vs. 68 ms/log unit of set size, see Figure 3D). The slopes did not vary significantly as a function of background, $F(1,41) = 0.85$, $p = .36$, $\eta_p^2 = .020$. The interaction between background and similarity was not significant, $F(1, 41) = 0.18$, $p = .67$, $\eta_p^2 = .0044$.

Discussion

Experiment 2 confirmed that the complexity of the background impacted target detection times but did not produce a significant slowdown in search efficiency. Thus, we can conclude that search times are only minimally affected when unstructured images with little visual or semantic structure are used as background. On the other hand, we confirmed that the more complex background was associated with larger search intercepts, suggesting that this more complex background makes it harder for participants to figure out which direction (left or right) the target turtle is pointing, once the target has been found. This is a clear example of manipulation only impacting nonsearch-related processes.

Experiment 3

In Experiment 3, we evaluated the effects of a structured background on search efficiency. An indoor scene of a child's bedroom was used as background and participants searched for a target toy (teddy bear) among other toys—white reindeer dolls (low similarity) or red dolls (high similarity). As in Experiment 1, Experiments 3A and 3B compared search performance across three different backgrounds under conditions of low (Experiment 3A) and high (Experiment 3B) target–distractor similarity. The bedroom background was compared to two additional backgrounds that allowed us to evaluate the impact of structural and semantic information present in the background image on search processes. First, a phase-scrambled background obtained from the bedroom scene was used to evaluate the effect of complex low-level features, in the absence of structural information. Second, an upside-down version of the bedroom was used, which maintained the low-level features and structural information present in the image while minimizing semantic effects.

Similar to Experiment 2, Experiment 3C was a follow-up to 3A and 3B that provided us with a comparison between a solid background and the bedroom background, in a within-subject design, and thus, with increased statistical power.

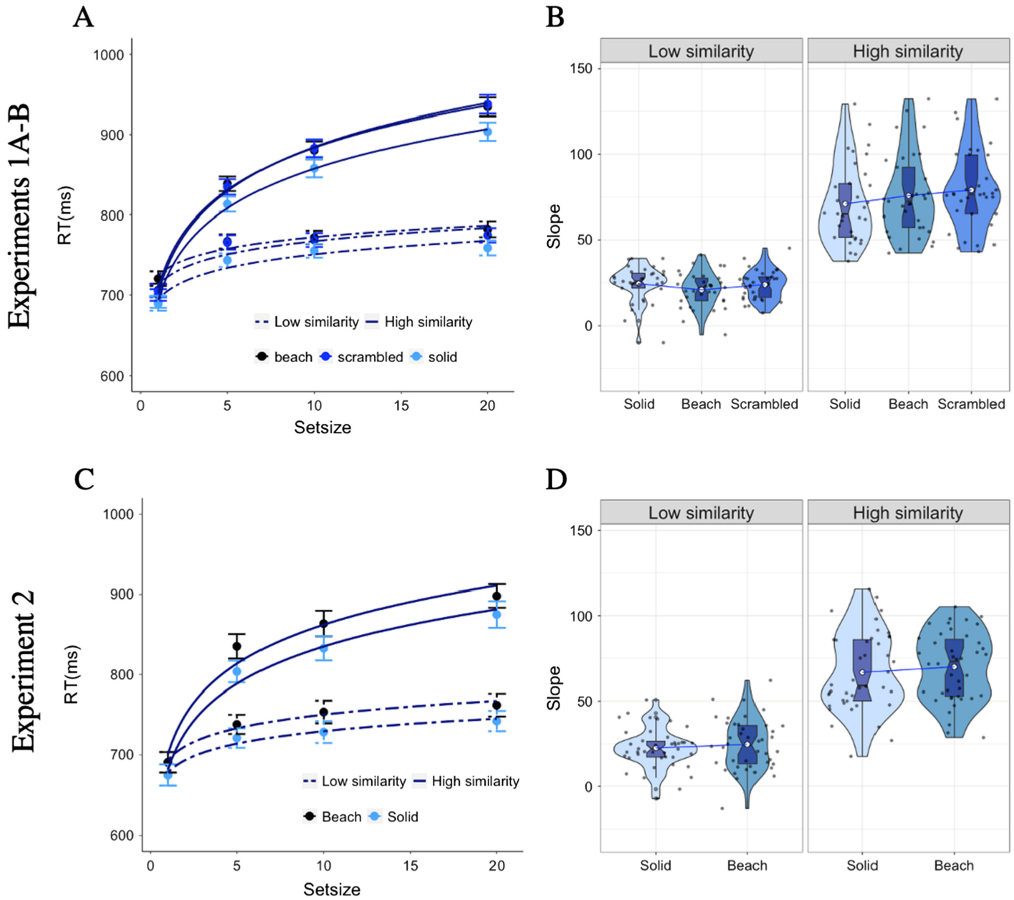
Method

Participants

Experiment 3 was preregistered on Open Science Framework (Ballew et al., 2019). In Experiments 3A and 3B, participants were recruited from the subject pool at the University of Illinois at Urbana-Champaign and were given course credit for their participation. Only participants who self-reported to have normal or corrected-to-normal vision and normal color vision were allowed to take part in the experiment. Thirty-five participants completed Experiment 3A (28 female, 7 male; $M_{age} = 19.1$), and 37 participants completed Experiment 3B (27 female, 9 male, 1 other;

Figure 3

Logarithmic Slopes in Experiments 1 (Panels A and B) and 2 (Panels C and D)



Note. Target–distractor similarity was manipulated between-subjects in Experiment 1 (1A: low similarity; 1B: high similarity) and within-subjects in Experiment 2. Panels A and C: Search RTs increased as a logarithmic function of set size both in Experiment 1 and 2, respectively. Error bars indicate one standard error of the mean. Panels B and D: Slope values displayed in violin plots. Each violin plot represents the slopes (ms/log unit of set size) of all participants in that condition. In the notched boxplots, the boxes indicate the interquartile range, the horizontal markers indicate the median, and the white circles indicate the mean with blue lines connecting them. The dark gray circles represent individual data points and the shaded areas show the probability density of the data. RT : reaction time. See the online article for the color version of this figure.

$M_{age} = 18.8$). Forty-one participants completed Experiment 3C (25 female, 16 male; $M_{age} = 21.4$). Out of the 41 participants, 21 were recruited from the subject pool at the University of Illinois at Urbana-Champaign and were given course credit for their participation. The remaining 20 participants were recruited from Prolific and a monetary reward was given in compensation for their time ($6 for 50 min).

The criteria for data inclusion were identical to those in Experiment 1. After data collection, one participant was excluded from Experiment 3A (low accuracy), four participants were excluded from Experiment 3B (two of them were excluded because of low accuracy and the other two because of high time-out rates), and six participants were excluded from Experiment 3C (because of low accuracy). Thus, the data analysis included 34 participants in Experiment 3A, 33 participants in Experiment 3B, and 35 participants in Experiment 3C.

Stimuli and Materials

At the beginning of the experiment, participants were asked to rescale an image of a credit card to match the size of a credit card in real life. In Experiment 3, the stimuli were toy objects positioned against one of the three different backgrounds that varied in the degree of structural and meaning information they carried (Figure 2). In Experiments 3A and 3B, the three backgrounds were a naturalistic (right-side-up) scene of a child's bedroom, a phase-scrambled version, and an upside-down version of the same scene. All three backgrounds had equal mean RGB values, which ensured the same low-level salience across the different backgrounds. In Experiment 3C, we compared the bedroom background to a solid color background obtained by averaging the RGB values of the bedroom background (Figure 2).

In Experiment 3A (low target–distractor similarity condition), the target was a teddy bear and the distractors were white reindeer dolls

(Figure 1). In Experiment 3B (high target–distractor similarity condition), the target was a teddy bear and the distractors were red-top dolls (Figure 1). In Experiment 3C, both low- and high similarity stimuli were shown.

The toy stimuli were shown with a red dot on either their right or left side, and participants used the left/right location of the dot on the target stimulus as the response-defining feature. The placement of stimuli in Experiment 3 was similar to that in Experiment 1, except that because toys could not be placed just anywhere in the background (the toys had to appear to be supported by a horizontal surface), the stimuli in Experiment 3 were placed in a subset of 29 locations within the 6×6 grid (Figure 2). The placement of each stimulus was adjusted slightly along the x–y axes as needed so that the stimuli and background objects lined up naturalistically. On the other two background conditions, the same set of locations was used.

Design and Procedure

The design and procedure in Experiments 3A and 3B were identical to those in Experiment 1 and the design and procedure in Experiment 3C were identical to those in Experiment 2.

Results

Experiments 3A and 3B

The data analysis included 34 participants in Experiment 3A (group accuracy = .970, $SD = .022$), and 33 participants in Experiment 3B (group accuracy = .942, $SD = .034$). The results from Experiments 3A and 3B are shown in Figure 4A and B.

Intercept Analysis. The ANOVA with background as a within-subject factor and similarity as a between-subject factor on the intercepts of the logarithmic search functions indicated a main effect of background, $F(2, 130) = 14.68$, $p < .001$, $\eta_p^2 = .184$. Intercepts were smaller in the bedroom background (769 ms), followed by the phase-scrambled condition (772 ms) and the upside-down condition (789 ms). Follow-up paired t tests revealed that the intercepts differed significantly between the upside-down and the other two conditions, bedroom versus phase-scrambled background: $t(66) = -0.71$, $p = .48$, 95% CI: [−10.55, 5.02]; bedroom versus upside-down background: $t(66) = -5.36$, $p < .001$, 95% CI: [−26.84, −12.27]; phase-scrambled versus upside-down background: $t(66) = -4.03$, $p < .001$, 95% CI: [−25.09, −8.48].

Slope Analysis. The two-way ANOVA with background as a within-subject factor and similarity as a between-subject factor on the logarithmic slope revealed a significant main effect of similarity, $F(1, 65) = 366.11$, $p < .001$, $\eta_p^2 = .849$. The slopes observed for low similarity distractors were significantly shallower than the slopes for high similarity distractors (38 vs. 98 ms/log unit of set size, see Figure 4B). Slopes did not significantly vary as a function of background (right-side-up, phase-scrambled, and upside-down), $F(2, 130) = 0.90$, $p = .41$, $\eta_p^2 = .014$. The interaction between background and similarity was not significant, $F(2, 130) = 1.33$, $p = .27$, $\eta_p^2 = .020$.

Experiment 3C

The data analysis included 35 participants in Experiment 3 (group accuracy = .961, $SD = .028$). The results from Experiment 3C are shown in Figure 4C and D.

Intercept Analysis. The ANOVA on the intercepts with background as a within-subject factor showed a main effect of background, $F(1, 34) = 113.47$, $p < .001$, $\eta_p^2 = .769$, with intercepts being smaller in the solid condition compared to the bedroom condition (718 vs. 782 ms).

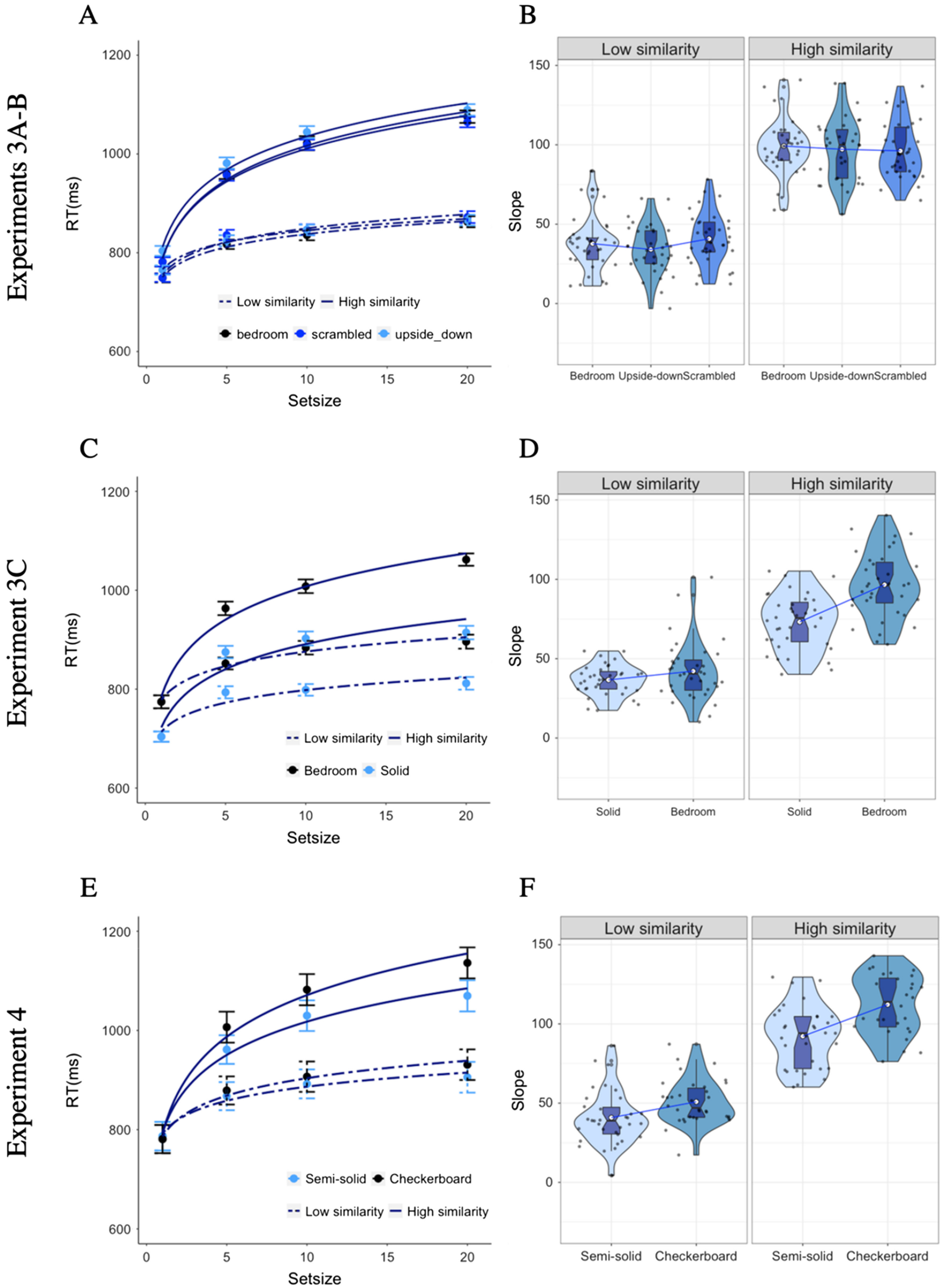
Slope Analysis. The two-way ANOVA with background and similarity as within-subject factors on the logarithmic slope revealed a significant main effect of similarity, $F(1, 34) = 334.64$, $p < .001$, $\eta_p^2 = .908$. The slopes in the low similarity condition were significantly shallower than the slopes in the high similarity condition (40 vs. 85 ms/log unit of set size, see Figure 4D). The slopes also varied significantly as a function of background, $F(1, 34) = 32.43$, $p < .001$, $\eta_p^2 = .488$, with shallower slopes in the solid than in the bedroom background condition (55 vs. 70 ms/log unit of set size). The interaction between background and similarity was also significant, $F(1, 34) = 24.72$, $p < .001$, $\eta_p^2 = .421$. In the low similarity group, follow-up one-sample t-tests revealed similar search slopes in the solid and bedroom background condition (37 vs. 42 ms/log unit of set size), $t(34) = -1.83$, $p = .08$, 95% CI: [−11.69, 0.62]. In the high similarity condition, search efficiency was significantly faster in the solid than in the bedroom background condition (73 vs. 97 ms/log unit of set size), $t(34) = -7.32$, $p < .001$, 95% CI: [−29.99, −16.95].

Discussion

In Experiment 3, search slopes were impacted by target–distractor similarity in all experiments, with slopes that increased as target–distractor similarity increased. In Experiments 3A and 3B, the interaction between background and similarity was not observed, indicating that the three complex backgrounds (normal, phase-scrambled, and upside-down bedroom) had similar effects on search efficiency. Compared to the normal bedroom scene, the phase-scrambled scene shared the same low-level features in the absence of any structural information and the upside-down bedroom scene shared the same structure but did not carry the same meaning. Therefore, neither the structural nor the semantic information present in the background had a strong impact on search efficiency. In contrast, in Experiment 3C, participants searched more efficiently on the solid than bedroom background, and this effect was modulated by target–distractor similarity: search efficiency improved by 6 ms per log unit in the low similarity condition and by 23 ms per log unit in the high similarity condition when searching on the solid compared to the bedroom background. Together, the results from Experiment 3 seem to indicate that it was the mere presence of complex low-level features that slowed down search efficiency in complex backgrounds.

Previous research has shown that a key factor in determining search efficiency is the degree to which nearby distractors can facilitate one another's rejection (Duncan & Humphreys, 1989; Lleras et al., 2019; Xu et al., 2021). Those studies were conducted using a solid background. When local distractor heterogeneity is low (i.e., when all nearby distractors are identical), distractor rejection is facilitated compared to situations where local distractor heterogeneity is high (i.e., when nearby distractors are different from one another). Furthermore, Lleras et al. (2019) showed that the search efficiency in distractor-homogeneous displays (e.g., searching for the teddy bear among reindeers or for the teddy bear among the red dolls) was identical to the search efficiency in distractor-heterogeneous

Figure 4
Logarithmic Slopes in Experiments 3A–C and 4



Note. Left panels: the RTs increased as a logarithmic function of set size both in Experiment 1 and 2. Error bars indicate one standard error of the mean. Right panels: Slopes displayed in violin plots. Each violin plot represents the slopes (ms/log unit of set size) of all participants in that condition. In the notched boxplots, the boxes indicate the interquartile range, the horizontal markers indicate the median, and the white circles indicate the mean with blue lines connecting them. The dark gray circles represent individual data points and the shaded areas show the probability density of the data. RT: reaction time. See the online article for the color version of this figure.

displays when distractors were segregated on different parts of the displays (e.g., reindeers on the right vs. red dolls on the left). In contrast, search was significantly slowed down when the reindeer and orange dolls were intermixed on the display. The authors concluded that the rejection of distractors is facilitated when nearby distractors are identical. The results from Experiment 3C seem to suggest that the presence of visually complex information in the background between identical distractors might weaken the strength of these local, distractor–distractor interactions in a similar way. This hypothesis was tested in Experiment 4, using minimal manipulation of the background information.

Finally, the findings observed at the level of the intercepts suggest once again that differences across backgrounds continue to produce nonsearch-related effects, with some backgrounds slowing down the detection of the target. In Experiments 3A and 3B, the upside-down background appears to particularly slow down overall response times, perhaps because it is unexpected to observe a familiar background presented from an unusual perspective.

Experiment 4

In the visual search literature, there are two well-known factors that impact search efficiency (Duncan & Humphreys, 1989, 1992; Lleras et al., 2019). One is target–distractor similarity, which explains why search is slowed down when the similarity between target and distractors increases. The other factor is distractor–distractor similarity, sometimes also conceptualized as distractor heterogeneity. Specifically, when distractors are more visually distinct from one another, search efficiency is reduced. In the present experiment, we tested whether the presence of visually complex information in the background between identical distractors slows down the processing of those distractors compared to situations where more uniform visual information is present (i.e., solid background).

We manipulated the global background information in the display while keeping the local background information surrounding each stimulus the same across background conditions (Figure 2). In the checkerboard condition, the background consisted of a grid of alternating rectangles (that were created by adding or subtracting 50 from the RGB value of the solid background in Experiment 3C). In the semisolid condition, the same rectangles were organized so that the darker rectangles were all on one side of the screen and the lighter rectangles on the other side, creating two regions of uniform background color. This manipulation preserved the overall background luminance in the checkerboard and semisolid conditions. The backgrounds in Experiment 4 differ from the complex backgrounds used in Experiments 1–3 because, in the previous experiments, the local information surrounding each search item varied as a function of location in the display as well as across background images.

If variation in the local background information around the stimuli weakens the strength of the local interactions between distractors, then search efficiency should be slowed down in the checkerboard compared to the semisolid condition. Furthermore, in Experiment 3C, target–distractor similarity interacted with background complexity, showing that the facilitatory effect of the solid background compared to more complex backgrounds was substantially larger when target–distractor similarity was high compared to when it was low. Thus, in the present experiment, we also expected the background manipulation to have larger effects when target–distractor similarity is high.

Finally, we will also compare search efficiency across Experiments 3C and 4. This will allow us to get a sense of whether the minimal manipulation of the local background in Experiment 4 produced similar slowing effects as those observed in Experiment 3C, with much more complex background information.

Method

Participants

Participants in Experiment 4 were recruited from Prolific. A monetary reward was given in compensation for their time ($6 for 50 min). Only participants who self-reported to have normal or corrected-to-normal vision and normal color vision were allowed to take part in the experiment. Thirty-six participants completed Experiment 4 (11 female, 22 male, 3 other; $M_{age} = 24.8$). The criteria for data inclusion were identical to those in Experiment 1. After data collection, two participants were excluded from Experiment 4 (accuracy lower than 90%). The data analysis included 34 participants (group accuracy = .954, $SD = .029$).

Stimuli and Materials

The same search stimuli as in Experiment 3 (toy objects) were used in Experiment 4. The stimuli were positioned on two backgrounds. The checkerboard background consisted of a grid of alternating rectangles. The lighter rectangles were obtained by adding 50 to the RGB value of the solid background in Experiment 3; the darker rectangles were obtained by subtracting 50 from it. The semisolid background contained the same light and dark rectangles as the checkerboard background, but they were spatially organized by lightness on each side of the display (The lighter background was on the left, and the darker background was on the right, Figure 2).

Design and Procedure

The design and procedure were identical to those in Experiment 3. Trials with semisolid and checkerboard backgrounds were pseudo-randomly intermixed.

Analyses and Results

The data analysis included 34 participants (group accuracy = .954, $SD = .029$). The results from Experiment 4 are shown in Figure 4E and F.

Intercept Analysis

The ANOVA with background within-subject factors on the intercepts indicated that the main effect of background was not significant, $F(1, 33) = 1.00$, $p = .32$, $\eta_p^2 = .0294$. The intercepts in the semisolid and checkerboard conditions were 794 and 790 ms, respectively.

Slope Analysis

The two-way ANOVA with background and similarity as two within-subject factors on the logarithmic slope revealed a significant main effect of similarity, $F(1, 33) = 336.66$, $p < .001$, $\eta_p^2 = .911$. The slopes in the low similarity condition were significantly shallower than the slopes in the high similarity condition (45.9 vs.

108.9 ms/log unit of set size). The slopes in the semisolid condition were significantly shallower than the slopes in the checkerboard condition (68.9 vs. 85.9 ms/log unit of set size, see Figure 4F), $F(1, 33) = 58.11$, $p < .001$, $\eta_p^2 = .638$. Finally, the interaction between similarity and background was significant, $F(1, 33) = 15.64$, $p < .001$, $\eta_p^2 = .322$.In the low similarity condition, search efficiency slowed down from 41 to 51 ms/log unit of set size in the checkerboard compared to the semisolid condition, $t(33) = -4.71$, $p < .001$, 95% CI: [−14.29, −5.67]. In the high similarity condition, search efficiency slowed further down from 97 to 121 ms/log unit of set size in the checkerboard condition compared to the semisolid condition, $t(33) = -6.99$, $p < .001$, 95% CI: [−31.15, −17.10].

Between Experiment Comparison

To compare the patterns of results across Experiments 3C and 4, we conducted an ANOVA on search slopes with similarity (low vs. high) and background (simple vs. complex) as within-subjects factors and experiment as a between-subjects factor. The results showed that the interaction between the experiment and background complexity was not significant, $F(1, 67) = 0.565$, $p = .455$, $\eta_p^2 = .0084$. This indicated that across low and high similarity conditions, there was no significant difference in the slowing down effect arising from complex backgrounds between Experiment 4 (checkerboard) and Experiment 3C (bedroom), compared to search on the simpler, uniform backgrounds. The results also showed that a three-way interaction term “background complexity by similarity by experiment” was not significant, $F(1, 67) = 0.554$, $p = .459$, $\eta_p^2 = .0082$. This indicated that the two-way interaction term “background complexity by similarity” did not differ significantly between Experiment 4 (checkerboard) and Experiment 3C (bedroom).

Finally, we ran a Bayes factors (BFs) analysis using “anovaBF” function in the package “BayesFactor” (Morey & Rouder, 2021) to evaluate the strength of evidence in favor of the latter null hypothesis, that is, that the slowdown effect arising from background complexity and the two-way interaction term “background by similarity” in both experiments was similar. Model 1 was a model consisting of all the factors with significant effects in the above ANOVA analysis (background complexity, distractor similarity, experiment, the interaction term between background complexity and distractor similarity, and the interaction term between experiment and distractor similarity). Model 2 was a model with the interaction term between experiment and background complexity in addition to what was included in Model 1. Model 3 was a model with a three-way interaction term among background complexity, distractor similarity, and experiment, in addition to what was included in Model 2. A model comparison between Model 1 and Model 2 should reveal how much evidence there is in favor of Model 1 in the data. In particular, this comparison will tell us how much evidence there is to support the absence of meaningful interaction between background complexity and experiment. A model comparison between Model 1 and Model 3 should reveal how much evidence there is in favor of Model 1 and, in particular, how much evidence there is to support the absence of a meaningful three-way interaction term among background complexity, distractor similarity, and experiment. We followed Jeffreys (1998) to interpret the strength of evidence as a function of BF magnitude. There was moderate evidence in favor of Model 1 over Model 2 ($BF_{12} = 4.070$), indicating that the minimal background manipulation in Experiment 4 (checkerboard) and the more complex background manipulation in Experiment 3C (bedroom) produced similar slowdown effects compared to the more uniform backgrounds in both low and high similarity conditions. In addition, there was strong evidence in favor of Model 1 over Model 3 ($BF_{13} = 14.348$), suggesting that the three-way interaction term (Complexity × Similarity × Experiment) was indeed meaningfully nonsignificant. This suggests that there is strong evidence that the pattern of results of Experiment 3C (Figure 4D) and the pattern of results of Experiment 4 (Figure 4F) are indeed identical. In other words, the search slowed down to the same extent in the high similarity condition compared to the low similarity condition when comparing search in complex versus uniform backgrounds.

Discussion

The results from Experiment 4 showed that the global background configuration of alternating light and dark rectangles in the checkerboard condition did not impact the response time needed to identify the target when it was alone in the display, as evidenced by nearly identical intercepts between the checkerboard and semisolid conditions. This suggests that what determines how quickly observers find an isolated target is the visual complexity in the local region immediately surrounding the target, not the global arrangement of the background.

With regard to search-specific processes, the global configuration of the background impacted search efficiency, as evidenced by the slowdown in search efficiency observed in the checkerboard arrangement compared to the semisolid background. This suggests that when the local background alternates between nearby items, distractor rejection will occur at a slower pace than when distractors are presented on uniform backgrounds (on each half of the display). The pattern of results in Experiment 4 also mirrored the ones in Experiment 3, suggesting that, in general, when visually complex information is present in the intervening background regions between distractors, distractor–distractor interactions are weakened.

General Discussion

The goal of the present study was to evaluate the effects of background complexity on efficient search. The target was always present and target–distractor similarity was manipulated, along with different types of backgrounds. We focused on conditions where all search items were easily segregated from the background (i.e., clearly outside of background camouflage effects). Experiments 1 and 2 investigated backgrounds that were visually simple: They were variations of a sandy beach image, with little visual or semantic structure. Experiments 3 and 4 investigated more structured backgrounds (child bedroom, checkerboard).

With respect to the intercepts of the logarithmic search functions, the results showed that, in the absence of any distractors, it takes longer to respond to the target when the background is complex compared to when a solid background is used (Experiments 1–3). In Experiment 4, no difference in the intercepts was found when the local complexity was matched between the simple (semisolid) and complex (checkerboard) backgrounds, but the global complexity varied between the two conditions. Thus, we propose that the intercept effects observed in Experiments 1–3 are driven by the presence of visual complexity in the area immediately surrounding the target (i.e., local complexity), rather than by the complexity of the entire scene (i.e., global complexity). Local complexity around the target can make it harder for participants to evaluate what the correct response to the target is (i.e., to identify the response-defining feature of the target).

Turning now to the results on search efficiency, we found the expected effect of target–distractor similarity on search efficiency across all experiments (e.g., Buetti et al., 2016; Lleras et al., 2020). Higher target–distractor similarity conditions produced steeper logarithmic search functions than lower target–distractor similarity conditions. Importantly, the search functions were always logarithmic in nature in both simple and complex backgrounds. This indicates that background complexity does not fundamentally alter how observers search for the target in these scenes: all search items are processed in parallel using peripheral vision until the target is found, with minimal serial inspection of individual objects in the scene.

Furthermore, the results indicated that background complexity can have an impact on search efficiency. Relatively simple backgrounds in terms of their visual complexity do not tend to have much of an impact on search efficiency. This was evidenced by similar search efficiencies between the solid and the sandy beach backgrounds for both levels of target–distractor similarity (Experiments 1–2). In contrast, compared to a solid background, more complex backgrounds reduced search efficiency (Experiments 3–4), and this was more pronounced when the target–distractor similarity was high. The comparison between the normal bedroom scene, the phase-scrambled version of that scene, and the upside-down background suggested that the effect was driven by the simple presence of more complex visual features intervening between the stimuli. Indeed, no difference on search efficiency was found between these three types of background, indicating that it was neither structural information nor semantic information that impacted search efficiency.

Overall, the findings on search efficiency suggest that the rejection of identical nearby distractors is facilitated when the intervening background between distractors is as simple as possible, as in the solid and semisolid backgrounds we tested. This is consistent with the results showing that search efficiency was equivalent between solid and sandy background conditions (Experiments 1 and 2). Indeed, the sand and water elements in the scene created a rather uniform and homogenous background (Figure 2). In contrast, the rejection of identical nearby distractors is slowed down when intervening background information between distractors is varied (Experiment 4) or more visually complex (Experiment 3).

Relations to Other Theories

The present study adds to the literature on distractor rejection during visual search. Duncan and Humphreys (1989) famously proposed that search becomes harder (as indexed by search efficiency) as distractor heterogeneity increases. This proposal was based on comparing performance on displays with multiple types of distractors with performance on displays with identical distractors. Duncan and Humphreys proposed a "spreading suppression" mechanism whereby nearby identical distractors form structural units (i.e., a type of grouping mechanism). Distractor rejection then unfolds en masse, by rejecting structural units rather than individual items. Duncan and Humphreys' findings and the present results on search efficiency can both be understood in terms of the degree to which local "horizontal" connections between items in the display facilitate or impede distractor rejection. Distractor rejection is facilitated (even over relatively long distances, Gilbert & Li, 2013; Ramalingam et al., 2013) when there is little to no information in the intervening space between two identical distractors. Distractor rejection is slowed down when there is complex visual information in the intervening space between two identical items, be it a different distractor or complex visual variations in the background. From the perspective of Duncan and Humphreys, it is as if background information modulates the strength at which spreading suppression operates, or more simply, the likelihood that identical distractors will group into structural units.

More recently, Lleras et al. (2019) advanced our understanding of distractor heterogeneity effects by demonstrating that identical distractors are rejected at the individual level, rather than as structural groups. Indeed, the logarithmic nature of the response time function supports the idea that each additional item on a display adds a cost, even when all distractors are identical. Thus, distractors are rejected individually and in parallel. Furthermore, Lleras et al. (2019) tested different spatial arrangements of distractors to compare the rejection times of individual items in distractor-heterogeneous displays to the ones found in distractor-homogeneous displays. When two types of distractors are present in the display but are spatially segregated such that distractors of the same type appear on the same side of the display, individual distractor rejection times are the same as when only one type of distractor is present in the display (i.e., a homogeneous search condition). However, when the two types of distractors are spatially intermixed, individual distractor rejection times are multiplicatively longer. In sum, we propose that search efficiency will suffer (i.e., individual rejection times become longer) whenever there is complex visual information (in the form of a different distractor or varied background information) in the intervening space between identical distractors.

Other possible mechanisms might underlie the slowdown in search efficiency observed in complex backgrounds. First, it is possible that the local neighborhood around each distractor might be a part of the representation that the visual system uses when evaluating in parallel all the items in the scene. This possibility follows the recent proposals by Rosenholtz and colleagues (Chang & Rosenholtz, 2016; Rosenholtz, Huang, & Ehinger, 2012; Rosenholtz, Huang, Raj, et al., 2012; Zhang et al., 2015) arguing that visual search in the periphery is not mediated by individual object representations but rather by summary statistic representations that code all the visual features present inside peripheral pooling regions. Although Rosenholtz and colleagues have not directly discussed the issue of figure-ground segmentation in their papers (i.e., they have only studied search with solid backgrounds), it seems that peripheral pooling regions might not distinguish between featural information coming from the object and that coming from the background. As a result, background features would contribute to the summary statistics of all item-containing regions in the display, thereby reducing the signal-to-noise ratio between the regions of the image containing the target and those containing the distractors. And, as the authors demonstrated, smaller discriminability between target-present and target-absent regions is associated with slower search (Balas et al., 2009; Rosenholtz, Huang, & Ehinger, 2012; Rosenholtz, Huang, Raj, et al., 2012).

More research is needed to directly test the summary statistics account, but there is at least one aspect of our data that casts doubt on this account. If parallel, peripheral search was supported by summary pooled representations, it is difficult to understand why the background manipulation in Experiment 4 did not produce an intercept effect. Indeed, target identification times should have been slower in the checkerboard pattern compared to the semisolid pattern because the checkerboard pattern information ought to have impacted the pooled representation of the target-present region, making the target less distinguishable and producing a slower response (much like all the complex backgrounds in Experiments 1–3). Although tentative, this observation suggests that, somehow, search is unfolding after figure-ground segmentation is completed, and not before, at least, at this easy level of object-background segmentation (this is likely quite different than under camouflage conditions).

A final possibility is that the slowdown in search associated with complex backgrounds might arise from an interaction between search and figure-ground segmentation mechanisms. Because the manipulation of background complexity and target–distractor similarity produced a statistical interaction, according to additive factors logic (Donders, 1868; Sternberg, 1969), these two manipulations might be affecting the same stage of information processing. However, the nature of that interaction is unclear. The results of Experiment 4 suggest that the effect of background complexity on search efficiency, whatever it is, might come after figure-ground segmentation is achieved. This follows because the search slowdown in the complex background in the experiment (the checkerboard) was observed in spite of the fact that figure-ground segmentation of individual items was equally easy across simple and complex backgrounds: in both conditions, search items were presented overlaid on top of a uniform surface. And, as mentioned before, evidence that figure-ground segmentation was equally easy across both conditions comes directly from the observation that search intercepts were identical across the two conditions. Thus, it was not harder to segment and find the target in the checkerboard compared to the semisolid background. That said, further research is needed at this point to better disentangle these three possibilities.

Limits on Generalizability

First, we should acknowledge that the present study used a limited number of backgrounds (beach and bedroom, and variations of those, plus checkerboard). This was done because evaluating logarithmic search efficiency on a given condition requires a large number of observations over multiple set sizes. Second, for the same reason, the stimuli used are also limited in nature. As mentioned before, our goal was to study visual search in more visually complex contexts than those used in traditional lab studies (e.g., colored geometric shapes against a uniform black background). Some of our stimuli were photos of real-world objects and backgrounds (beach, toys), but not all. Third, it could be argued that the bedroom search condition in Experiment 3 was a bit artificial because we did not titrate stimulus size to height on the plane, as would be the case in a 3D scene. That is to say, if the toys had actually been placed inside the scene, the toys that are placed far in the scene would have to have a smaller physical size, to reflect that the farther an object is from the observer, the smaller its retinal projection becomes. While this is true, we did run a control experiment (see online supplemental material) to evaluate whether the bedroom scene was creating an illusion of size on the toys, such that the toys that appear higher on the plane would be perceived as being larger (given that they have the same retinal size). The results showed that indeed, participants experienced a size illusion, with toys appearing larger the higher in the plane (i.e., the farther in the bedroom) they appeared. This can also be seen by looking at Figure 2. Fourth, our results are constrained to parallel peripheral search with a fixed target under easy-to-segregate conditions and arbitrarily positioned items. For example, background complexity might not impact search when strong contextual cues point the observer toward the direction of the target. This might have been the case in Wolfe et al. (2011). Indeed, if observers know that a keyboard (the target) always appears just below a computer monitor, it is likely that the color and textures of the walls and other objects in the scene will not impact how quickly observers take to find the target. This form of strong contextual cueing was likely present in Wolfe et al. (2011) because the authors used photos of representative indoor scenes. Finally, there are many instances when search unfolds in a more serial manner due to crowding, high target–distractor similarity, or near-camouflaged conditions. Our findings are unlikely to inform search under these different conditions.

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