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Dense and uniform displays facilitate the detection of salient targets

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ABSTRACT
Increasing the density or uniformity of nontarget stimuli appears to increase the saliency of singleton stimuli. Consequently, search times should be shorter. Surprisingly, however, effects of density or uniformity on search times were not always observed in detection tasks. We re-examined this finding with stimuli having two features, color and shape. Half of the participants indicated the presence or absence of a color singleton, and the other half indicated the presence or absence of a shape singleton. Density was changed by increasing the number of stimuli from 4 to 10. We found that the effects of density were either limited to target-absent trials or to target-present trials, which may explain previous failures to observe these effects. When color was the target feature, we found shorter RTs to dense than sparse displays on target-absent trials, but no difference on target-present trials. When shape was the target feature, it was the opposite. Concerning the uniformity of the nontargets, we found shorter RTs with uniform than mixed displays and this difference was larger on target-absent than target-present trials. These results are mostly consistent with the Guided Search Model.

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Visual search; attentional selection; saliency

Public significance statement

A unique color or shape appears more salient when it is surrounded by many stimuli of the same kind rather than by a few stimuli of several kinds. However, there is only mixed experimental evidence for this intuition so far. Here, we provide evidence by re-examining a search task where observers judged the presence or absence of a salient stimulus.

The visual system is flooded with information each time we open our eyes. As we cannot treat the available information, we are forced to select only a few from the many stimuli for further processing. The question is how selection is controlled. Major theories agree that visual selection is driven by both top-down and bottom-up signals (Desimone & Duncan, 1995; Eimer, 2014; Luck et al., 2021; Schneider, 2013; Wolfe, 2021). Top-down signals arise from the goals of the observer and implicit memory processes, such as inter-trial priming or reward learning. For instance, attention in a grocery store may be guided toward red stimuli because we are currently looking for strawberries (our current goal) or because we just searched for tomatoes (our former goal). Bottom-up signals arise from stimulus saliency (Duncan & Humphreys, 1989; Koch & Ullman, 1985; Nothdurft, 1993). Saliency is largely determined by local feature contrast along basic dimensions such as color, orientation, or size. For instance, a misplaced tomato on a pile of lemons is salient because of its color contrast. A classic finding is that search RTs for salient shape, orientation, and letter targets do not increase when the number of nontarget stimuli is increased (Egeth et al., 1972; Nothdurft, 1993; Sagi & Julesz, 1985; Treisman & Gelade, 1980). Surprisingly, the detection of oriented lines or gratings was even found to improve with the number of nontargets (Sagi, 1990; Zhaoping & Frith, 2011). For color, the situation is similar or even more complicated. Some studies found RTs with salient color targets to be unaffected by set size (Nothdurft, 1993; Treisman & Gelade, 1980), while others found RTs to increase logarithmically (Buetti et al., 2016, 2019) and yet others found RTs to decrease (Bravo & Nakayama, 1992; Rangelov et al., 2017; Song & Nakayama, 2006).

Elusive effects of set size in detection tasks

The different results may be partially explained by the different tasks and designs that were employed. In a

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classic study, Bravo and Nakayama (1992) used a task where participants searched for a stimulus in a color different from the remaining stimuli. In some blocks of trials, the color of this singleton and the color of the nontargets was fixed. With fixed colors, the target feature remained the same from one trial to the next and attention may have been guided to the target by perceptual priming (Ramgir & Lamy, 2022). Therefore, RTs were short and set size did not play a role. In other blocks, singleton and nontarget colors were swapped randomly. With random targets, there was no perceptual priming. Rather, perceptual grouping (Duncan & Humphreys, 1989) was necessary to separate the singleton from the nontarget stimuli (Song & Nakayama, 2006). Reliance on perceptual grouping made search susceptible to effects of set size. Interestingly, RTs decreased with large set sizes (see also Rangelov et al., 2013), probably because perceptual grouping works better for dense stimuli (Julesz, 1986; Koch & Ullman, 1985).

Further, decreasing RTs with increasing set size and color targets were reliably observed with discrimination tasks, but not with detection tasks (Bravo & Nakayama, 1992; Rangelov et al., 2017; Song & Nakayama, 2006). In detection tasks, it is sufficient to indicate the presence or absence of a target feature whereas discrimination tasks require decisions about which target feature is present. RTs are typically longer in discrimination than detection tasks because attention has to be focused on the target (Chan & Hayward, 2009; Nakayama & Mackeben, 1989; Treisman & Gelade, 1980) (but see Töllner et al., 2012). Thus, in Bravo and Nakayama (1992), decreasing RTs with increasing set size only occurred when there was no inter-trial priming and attention needed to be focused on the target (i.e., with random targets and a discrimination task). In contrast, RTs remained unchanged with inter-trial priming and mere detection of a feature discontinuity (i.e., with fixed targets and a detection task). The latter result is surprising because improved perceptual grouping with larger set sizes is expected to directly affect the magnitude of the feature discontinuity and should speed its detection.

In the present contribution, we re-examine the mixed results observed in detection tasks. To this end, we manipulated two variables (see Figure 1). First, we manipulated the set size between 4 and 10 stimuli. With 10 stimuli, density was higher and perceptual grouping is expected to be improved (Julesz, 1986; Koch & Ullman, 1985; Sagi, 1990). Therefore, search RTs are expected to decrease from set size 4–10, which would mean that search slopes are negative. Second, we manipulated the uniformity of the nontargets because similar grouping mechanisms are at play as in manipulations of set size. Nontarget stimuli group more easily when the irrelevant feature is uniform because of increased similarity (Duncan & Humphreys, 1989). Therefore, search RTs are expected to be shorter with uniform than mixed search displays. It should be mentioned that grouping by proximity (resulting from increased set size) and similarity (resulting from uniformity) has also been conceived as iso-feature suppression (Li, 1999), which makes similar predictions as grouping by similarity and proximity. Note, however, that the following analysis shows that the effects of set size and uniformity may be different for target-present and target-absent trials.

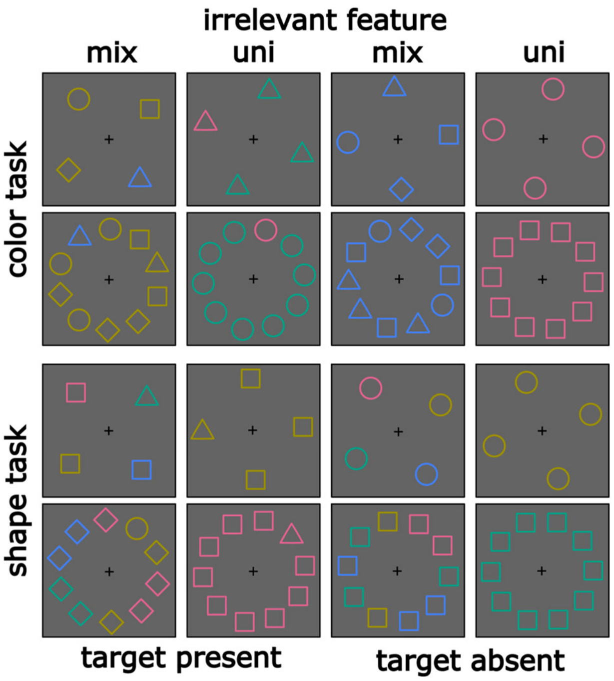

Figure 1. Illustration of the experimental stimuli.

Notes: Half of the participants searched for a color singleton and the other half for a shape singleton (i.e., color and shape tasks). The irrelevant nontarget feature was shape in the color task, and color in the shape task. The nontarget feature was either mixed or uniform. The target was either present or absent and set size was either 4 or 10. mix = mixed, uni = uniform.

The Guided Search Model

To re-examine the mixed results observed in detection tasks, the Guided Search Model (Chun & Wolfe, 1996; Wolfe, 1994) is ideally suited because it has applied ideas from signal detection theory to visual search. That is, it was conceived to model performance specifically in detection tasks. Importantly, Guided Search can accommodate both efficient (parallel) and inefficient (serial) search even though it has been mostly applied to inefficient search. Figure 2 shows an adapted version of the model where search is efficient. The model assumes that nontarget and target stimuli result in variable activations, which can be summarized by two normal distributions, one for nontarget stimuli and the other for target stimuli. The large separation between the distributions indicates that the target is salient and can be detected irrespective of the number of nontarget stimuli (i.e., flat search slopes). In serial search, the two distributions would be closer together, and search RTs would increase with the number of nontargets (i.e., search slopes larger than zero). According to the model, search slopes on target-absent and target-present trials are determined by the activation threshold and the average target activation, respectively. The activation threshold corresponds to the minimal activation of a nontarget stimulus that triggers inspection of this item. On target-absent trials, these items need to be inspected to reach the decision that the target is indeed absent. On target-present trials, nontarget stimuli with activations larger than the average target activation need to be inspected to make sure that they are not the target.

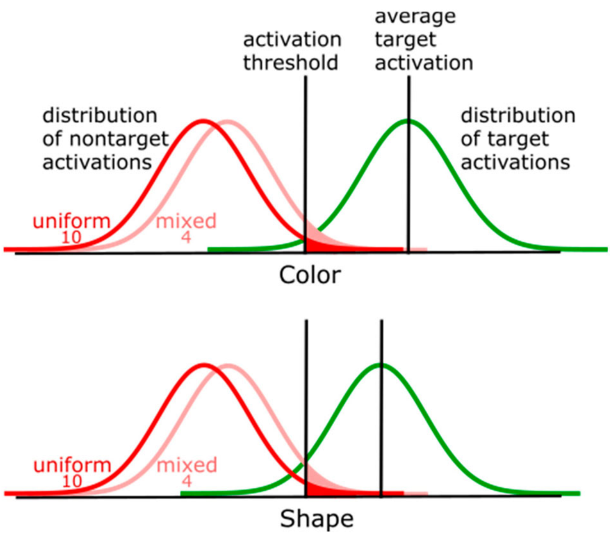

Figure 2. Model of search reaction times for target-present and -absent trials (adapted from Chun & Wolfe, 1996).

Notes: Search RTs on target-absent trials are determined by the part of the distribution of nontarget activations that lies to the right of the activation threshold. We assume that the nontarget activations were lower for set size 10 than set size 4 and for uniform than mixed shapes, which shifts the distribution to the left. The distance between nontarget and target distributions may be larger in the color than the shape task (upper vs. lower panel). Note that the model is simplified because the width of the distribution is likely to vary with the activation level (Chun & Wolfe, 1996; Li, 1999; Wolfe, 1994).

In the model, the proportion of the distribution to the right of the activation threshold determines the search slopes on target-absent trials, whereas the proportion of the distribution to the right of the average target activation determines the search slopes on target-present trials (see Figure 4 in Wolfe, 1994). That is, these slopes would typically determine how much RTs increase from set size 4–10. Here, we expect RTs to decrease from set size 4 to set size 10, which would mean search slopes are negative. These negative search slopes cannot be explained by a single distribution of nontarget activations because the proportion to the right of the activation threshold or average target activation cannot be negative. Therefore, we suggest that nontarget activations are lower with set size 10 or uniform stimuli. The resulting shift of the distribution of nontarget activations would decrease the proportion to the right of the activation threshold or average target activation, which explains the shorter search times with dense or uniform stimuli. Thus, a shift in the distribution of nontarget activations is proposed as an explanation for negative search slopes.

Hypotheses

Inspection of Figure 2 shows that the presumed shift of the distribution of nontarget activations affects target-absent decisions more strongly than target-present decisions. The reason is that the part of the distribution of nontarget activations is larger to the right of the activation threshold than to the right of the average target activation. Therefore, target-absent decisions are expected to be more sensitive to shifts in the distribution of nontarget activations. That is, we expect stronger effects of set size or uniformity on target-absent than target-present trials, which should be visible in interactions of target presence × set size and target presence × uniformity.

We tested these predictions for two feature dimensions using combined shape-color stimuli. In the color task, we presented search displays where the target singleton was defined by color, and shape was irrelevant. In the shape task, it was the other way around.

Both color and shape singletons are expected to result in efficient search, but previous works using similar stimuli found search times to be slower for shape than color singletons (Kerzel & Schonhammer, 2013; Theeuwes, 1992). As can be seen in Figure 2, the target activations may be higher for color than shape. However, predictions regarding target-absent responses are the same because the separation of target and nontarget activations is still large.

Experiment

The task of the participants was to indicate whether a singleton was present or absent. The stimuli in the search arrays had two features: color and shape. In the color task, color was relevant, and participants indicated whether there was a color singleton. In the shape task, shape was relevant, and participants indicated whether there was a shape singleton. The set size was either 4 or 10 stimuli. The irrelevant nontarget feature (i.e., shape in the color task and color in the shape task) could be either mixed or uniform. High set size and uniform nontargets are expected to facilitate the grouping of nontargets, which should decrease the activation by nontarget stimuli. Therefore, we expect RTs to be shorter with high set size (i.e., negative search slopes) and uniform shapes. Importantly, effects of set size and uniformity are expected to be larger on target-absent than target-present trials.

Methods

Participants

First-year psychology students at the University of Geneva participated for class credit. We aimed at a sample size that would allow us to detect medium effect sizes. According to G*Power 3.1 (Faul et al., 2009), a sample size of 32 was sufficient to find effect sizes with Cohen's d_z of 0.51 (power = .80, alpha = .05). Therefore, we aimed at 32 participants per group of participants. In the group performing the color task, one dataset had to be removed because the overall error rate was much higher than in the remaining sample (12% vs. $M = 3.8\%$, $SD = 1.9$), leaving 31 datasets for analysis (2 men; age: $M = 21$, $SD = 5$). In the group performing the shape task, the data from two participants with very long RTs were replaced (826 and 836 ms vs. $M = 519$ ms, $SD = 40$) and one participant was removed because of a very high error rate (11% vs. $M = 4.6\%$, $SD = 1.8$), leaving 31 datasets for analysis (4 men; age: $M = 20$, $SD = 4$). All students reported normal or corrected-to-normal vision. The study was approved by the ethics committee of the Faculty of Psychology and Educational Sciences and was carried out in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki). Informed consent was given before the experiment started.

Apparatus

A 22.5-inch VIEWPixx Lite monitor (100 Hz, 1920 × 1200 pixels, standard backlight; VPixx Technologies Inc., Saint-Bruno, Canada) was used to present the stimuli. Color calibration was based on measurements with an i1Display Pro (VPixx Edition) colorimeter by X-Rite (Grand Rapids, Michigan, United States). Participants responded on a RESPONSEPixx Handheld 5-button response box (VPixx Technologies Inc., Saint-Bruno, Canada) using the left and right buttons. The experiment was run using the Psychtoolbox (Brainard, 1997; Kleiner et al., 2007).

Stimuli

Unless otherwise noted, a light gray fixation cross (0.5° × 0.5°, 48.8 cd/m^2) was shown in the center of the screen. The search displays consisted of 4 or 10 geometric shapes shown at an eccentricity of 3.5°. The shapes were equidistant but rotated randomly around fixation. The shapes were drawn in 0.07°-wide lines. The dimensions of the shapes were as follows. The circle and diamond had diameters of 1.5° and 1.7°, respectively. The triangle and square had side lengths of 1.6° and 1.3°, respectively. Color and luminance of the stimuli are indicated in CIE1931 xyY-coordinates. The xy-coordinates of the stimuli were red = (0.44, 0.27), yellow = (0.45, 0.48), green = (0.19, 0.39), and blue = (0.17, 0.18). The luminance was always Y = 48.8 cd/m^2. The four colors correspond to 0°, 90°, 180°, and 270° of rotation on a color wheel in a CIELAB-based color space with a luminance of L* = 59 and a saturation of 64. The background was gray = (0.31, 0.33) with a luminance of Y = 24.4 cd/m^2.

Procedure

Trials started with a randomly determined fixation period of 750–1250 ms. Then, the search display was presented for 150 ms. Participants were asked to press one of two keys to indicate the presence or absence of a target singleton. They were told to respond as rapidly as possible while keeping the error rate below 10%. Performance feedback was given after blocks of 80 trials in a self-terminated break of at least 2000 ms. Visual error feedback was given immediately after choice errors or RTs outside the response window of 2000 ms.

Design

Three independent variables were within-participants, and one was between participants. For each participant, the target was either present or absent, the set size was either 4 or 10, and the irrelevant feature in the search display was either mixed or uniform. The eight conditions resulting from the combination of the three variables were presented once in each of 120 mini-blocks for a total of 960 trials. The task was manipulated between participants.

One group of participants searched for a color singleton and indicated its presence or absence. Target and nontarget colors were opponents in color space (i.e., red–green, green–red, yellow–blue, and blue–yellow). The irrelevant shape feature could be either mixed or uniform. On trials with mixed shapes, each of the four shapes (circle, square, diamond, and triangle) was presented once when the set size was four and 2–3 times when the set size was ten. On trials with uniform shape, all stimuli were the same shape.

Another group of participants searched for a shape singleton and indicated its presence or absence. To maximize the difference between target and nontarget shapes, we created four shape pairs, in analogy to the opponent colors (i.e., circle–diamond, diamond–circle, triangle–square, and square–triangle). The irrelevant color feature could be either mixed or uniform. On trials with mixed colors, each of the four colors (red, green, yellow, and blue) was presented once when the set size was four and 2–3 times when the set size was ten. On trials with uniform color, all stimuli were the same color.

The irrelevant feature on uniform trials, the distribution of irrelevant features on mixed trials, and the target position on target-present trials were random with the indicated constraints. Finally, the mapping of the left and right response keys to target-absent and -present responses was counterbalanced across participants. At least 40 practice trials were performed before the experiment started.

Results

The data are available in the Open Science Framework at https://osf.io/m87qj/. We removed trials with false alarms (color task: 3.8%, shape task: 4.4%), misses (color task: 3.5%, shape task: 4.8%), and RTs outside the response window of 2000 ms (color task: 0.1%, shape task: 0.1%). Because the analysis of RTs with shape targets was susceptible to outlier removal criteria, we used medians instead of means for all RT analyses. Error percentages were below 5% and were analyzed separately. For these analyses, we considered only the mean percentage of choice errors. To correct the significance of multiple t-tests, we controlled for false discovery rate according to Benjamini and Hochberg (1995). For clarity, we report the uncorrected *p*-values. Significant results remain significant after correction unless otherwise noted.

Reaction times

We conducted a 2 (task: color, shape) × 2 (target presence: present, absent) × 2 (set size: 4, 10) × 2 (uniformity of nontargets: mixed, uniform) mixed ANOVA. We predicted that effects of set size and uniformity should affect target-absent responses more strongly than target-present responses. Statistical support for this hypothesis would come from the following two-way interactions: (1) the interaction between target presence and set size (2) the interaction between target presence and uniformity of the nontargets.

Unexpectedly, the nature of the two-way interaction between target presence and set size changed with the task, as evidenced by a significant three-way interaction (see Figure 3), $F(1, 60) = 14.62$, $p < .001$, $\eta_p^2 = .196$. In the color task, RTs were about the same for set size 4 and 10 when the target was present (475 vs. 476 ms), $t(30) = 0.44$, $p = .660$, Cohen's $d_z = 0.08$, but were 7 ms longer with set size 4 than 10 when the target was absent (478 vs. 471 ms), $t(30) = 3.52$, $p = .001$, $d_z = 0.63$. Stronger effects of set size on target-absent than target-present trials are consistent with predictions of the Guided Search Model. In the shape task, however, RTs were about the same for set sizes 4 and 10 when the target was absent (507 vs. 508 ms), $t(30) = 0.47$, $p = .640$, $d_z = 0.09$, but were 6 ms longer with

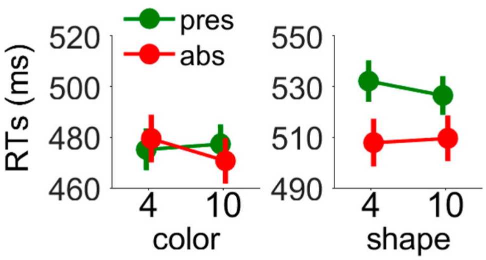

Figure 3. The three-way interaction of task (color, shape), set size (4, 10), and target presence (present, absent).

Notes: The prediction was that reaction times (RTs) are longer with set size 4 than 10 and that this difference is larger on target-absent than -present trials. We found this pattern only in the color task (left graph). In the shape task (right graph), the longer RTs with set size 4 than 10 were observed on target-present trials, but not on target-absent trials. Error bars represent one between-participant standard error. pres = present, abs = absent.

set size 4 than 10 when the target was present (531 vs. 526 ms), $t(30) = 2.46$, $p = .020$, $d_z = 0.44$. This pattern is opposite to the predictions of the Guided Search Model. Thus, effects of set size were expected to be more pronounced on target-absent than -present trials, but we found this pattern only for the color task and the opposite pattern for the shape task.

The two-way interaction of target presence and uniformity of the nontargets was significant (see Figure 4), $F(1, 60) = 4.92$, $p = .030$, $\eta_p^2 = .076$. Unlike in the preceding analysis, the two-way interaction was not further qualified by task, $F(1, 60) = 1.17$, $p = .284$, $\eta_p^2 = .019$. On target-present trials across both tasks, RTs were 6 ms longer with mixed than uniform nontargets (505 vs. 499 ms), $t(61) = 5.00$, $p < .001$, $d_z = 0.55$. This difference was greater (12 ms) on target-absent trials (497 vs. 485 ms), $t(61) = 6.09$, $p < .001$, $d_z = 0.77$, which is consistent with predictions from the Guided Search Model.

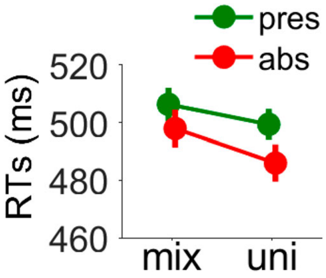

Figure 4. The two-way interaction of uniformity of nontargets (mixed, uniform) with target presence (present, absent).

Notes: The prediction was that reaction times (RTs) are longer with mixed than uniform nontargets and that this difference is larger on target-absent than -present trials. The data confirm this prediction. Error bars represent one between-participant standard error. pres = present, abs = absent, mix = mixed, uni = uniform.

In addition to the results speaking to our experimental hypotheses, there were several other results. The effect of target presence, $F(1, 60) = 10.86$, $p = .002$, $\eta_p^2 = .153$, was modulated by task, $F(1, 60) = 8.56$, $p = .005$, $\eta_p^2 = .125$. In the color task, RTs were about the same on target-present and -absent trials (475 vs. 474 ms), $t(30) = 0.23$, $p = .819$, $d_z = 0.04$. In contrast, in the shape task, RTs were 22 ms shorter on target-absent than -present trials (507 vs. 529 ms), $t(30) = 4.72$, $p < .001$, $d_z = 0.85$, which is odd as RTs are typically longer on target-absent than -present trials. We will return to this result in the General Discussion. Further, RTs in the color task were shorter than in the shape task (476 vs. 519 ms), $F(1, 60) = 14.05$, $p < .001$, $\eta_p^2 = .190$, which is visible in the smaller offset of the y-axis in Figure 3. Also, RTs with set size 4 were longer than with set size 10 (499 vs. 496 ms), $F(1, 60) = 6.12$, $p = .016$, $\eta_p^2 = .093$. Note that the main effects of set size and task as well as the two-way interaction of task and target presence were further qualified by the three-way interaction of task, set size, and target presence, which we described above (see also Figure 3). Further, there was an effect of nontarget uniformity (see also Figure 4), $F(1, 60) = 62.97$, $p < .001$, $\eta_p^2 = .512$, which was modulated by task, $F(1, 60) = 19.38$, $p < .001$, $\eta_p^2 = .244$. In the color task, RTs were 3 ms longer on trials with mixed than uniform nontargets (477 vs. 474 ms), $t(30) = 2.79$, $p = .009$, $d_z = 0.50$. In the shape task, this difference increased to 14 ms (526 vs. 512 ms), $t(30) = 7.71$, $p < .001$, $d_z = 1.38$.

Choice errors

To check for speed-accuracy tradeoff, we conducted the same ANOVA as above on the percentage of choice errors. We found that effects on error percentages were small and mostly mirrored RTs. The relevant three-way interaction of task, set size, and target presence, which we observed in RTs, was not significant in the analysis of errors, $F(1, 60) = 0.75$, $p = .390$, $\eta_p^2 = .012$, ruling out speed-accuracy tradeoff. Concerning the relevant two-way interaction of nontarget uniformity and target presence, we confirmed the same interaction in error percentages as in RTs, $F(1, 60) = 4.90$, $p = .031$, $\eta_p^2 = .075$. Error percentages on target-present trials were about the same with mixed and uniform nontargets (4.1% vs. 4.3%), $t(61) = 1.05$, $p = .300$, $d_z = 0.13$, but on target-absent trials, error percentages were higher with mixed than uniform nontargets (4.4% vs. 3.8%), $t(61) = 2.18$, $p = .033$, $d_z = 0.28$.

In addition to the results speaking to our hypothesis, there were several other results. Consistent with the analysis of RTs, error percentages tended to be lower in the color than in the shape task (3.6% vs. 4.6%), $F(1, 60) = 4.63$, $p = .036$, $\eta_p^2 = .072$. The interaction of target presence and set size, $F(1, 60) = 20.09$, $p < .001$, $\eta_p^2 = .251$, showed that error percentages on target-present trials were lower with set size 4 than 10 (3.7% vs. 4.7%), $t(61) = 3.64$, $p < .001$, $d_z = 0.46$, but on target-absent trials, error percentages were higher with set size 4 than 10 (4.6% vs. 3.6%), $t(61) = -3.15$, $p < .001$, $d_z = 0.40$. The interaction of task and nontarget uniformity, $F(1, 60) = 6.88$, $p = .011$, $\eta_p^2 = .103$, showed that in the color task, error percentages were about the same with mixed and uniform shapes (3.5% vs. 3.8%), $t(30) = 1.15$, $p = .258$, $d_z = 0.21$, whereas in the shape task, error percentages were higher with mixed than uniform colors (4.9% vs. 4.4%), $t(30) = 2.61$, $p = .014$, $d_z = 0.47$.

Discussion

We examined the effects of set size and uniformity on singleton search. Perceptual grouping of nontargets is facilitated with high set size because of increased density (Julesz, 1986; Koch & Ullman, 1985) and with uniformity because of increased similarity (Duncan & Humphreys, 1989). As a result, search times should decrease with high set size or uniform nontargets. However, these effects were not always observed in detection tasks. To better understand the mixed results, we derived more detailed predictions about target-present and -absent trials from the Guided Search Model (Chun & Wolfe, 1996; Wolfe, 1994).

We started from the assumption that the expected decrease of RTs with a high set size was accounted for by a shift in the distribution of nontarget activations. That is, nontarget activations are expected to be lower with a set size of 10 than 4, possibly because of iso-feature suppression (Li, 1999). Similarly, nontarget activations are expected to be lower with uniform than mixed nontargets. According to the Guided Search Model, the effects of a shift in the distribution of nontarget activations should be stronger on target-absent than target-present trials (see Figure 2). That is, RTs are expected to decrease with set size 10 or with uniform nontargets, but more strongly so when the target is absent. Our results were mostly consistent with this prediction. For nontarget uniformity, we found shorter RTs with uniform than mixed nontargets and consistent with our predictions, this difference was more pronounced on target-absent than -present trials. For effects of set size, however, the results were mixed and depended on the task. In the color task, we found shorter RTs with a set size of 10 on target-absent trials, but not on target-present trials, which is consistent with our predictions. In the shape task, however, shorter RTs with a set size of 10 were observed for target-present trials, but not for target-absent trials, which is inconsistent with our predictions. Thus, predictions derived from the Guided Search Model were confirmed with one exception, which is that, in the shape task, the effect of set size was observed on target-present and not on target-absent trials (see Figure 3).

While at odds with the model presented in Figure 2, there may be an explanation related to an anomaly in the search RTs. As reported above, RTs were shorter on target-absent than target-present trials in the task producing the inconsistent result. Shorter RTs on target-absent than -present trials are surprising because if anything, previous research found RTs to be longer on target-absent trials (e. g., Treisman & Gelade, 1980; Wolfe, 1994). Possibly, target-present responses in the shape task required an additional processing stage, namely identification (Eimer, 2014; Wolfe, 2021), contrary to the typical requirements of a detection task. That is, the selected shape singleton had to be compared to an internal template of the target to decide that it was indeed a shape singleton. As a result, RTs increased on target-present trials. Target identification may have been necessary because the color variations in mixed displays were very salient (see the lower part of Figure 1). To avoid false positive responses to variations in color, the shape singleton in the shape task may have been more thoroughly inspected than the color singleton in the color task. If identification is admitted as an explanation for the longer RTs on target-present trials, then the effect of set size on these trials may result from facilitated identification of the shape singleton in dense compared to sparse displays. Possibly, this is the reason why predictions of the Guided Search Model were not confirmed, but the exact mechanisms remain unclear.

Relation to the attentional window account

Further, our results are of interest to the attentional window account. The attentional window account was proposed by Theeuwes (2004) in the context of the additional singleton paradigm. In the original version of the additional singleton paradigm (Theeuwes, 1992), color-shape stimuli as in the current experiment were used. Participants searched for a shape singleton and on some trials, an irrelevant color singleton was presented. Search RTs were found to be longer on trials with a color singleton, suggesting that it captured attention (Theeuwes, 2010). However, interference from the color singleton disappeared when features on the relevant shape dimension were mixed (Bacon & Egeth, 1994), which is referred to as feature search.

The difference between uniform and mixed shapes suggests that interference from the color singleton was restricted to singleton search. However, it may be that feature search was less efficient. That is, the number of stimuli that can be inspected simultaneously may be reduced and the color singleton would be frequently outside the "attentional window," thereby reducing capture (Theeuwes, 2004). However, search slopes were found to be about equal for singleton and feature search (Kerzel & Barras, 2016; see also test phase in Leber & Egeth, 2006) and when singleton and feature search displays appeared unpredictably, search slopes were the same (Kerzel & Huynh Cong, 2024). In the current experiment, features could be mixed on the irrelevant dimension and were always uniform on the relevant dimension, whereas in Bacon and Egeth's (1994) feature search, it was the other way around. Nonetheless, the current results confirm that search slopes for a singleton target are unaffected by uniformity on the irrelevant dimension. There was no increase in search slopes with mixed features, even if mixed features resulted in a large increase in RTs (i.e., shape task). Thus, search did not become more effortful even though additional time was needed to process the stimuli.

Finally, our results speak against the assumption that the saliency of color singletons increases with increasing set size (Stilwell et al., 2022). In the context of the Guided Search Model, this corresponds to a shift of the distribution of target activations to the right, which should decrease RTs to color targets (Töllner et al., 2011). However, we found no effect of set size on target-present trials in the color task. Therefore, our results do not provide support for the idea that denser displays increase the saliency of color singletons. Rather, dense displays facilitate grouping and result in shorter RTs on target-absent trials, at least with color singleton targets and shape as irrelevant dimension.

Conclusions

In sum, we investigated the effects of set size and uniformity on the detection of color or shape singletons. In the color task, we found that RTs were unaffected on target-present trials but were shorter with a large set size on target-absent trials. These results are consistent with the Guided Search model, which considers the difference between activations from nontarget and target stimuli as decisive for search RTs. Subtle differences in the distribution of nontarget activations may affect target-absent trials more strongly than target-present trials. For the shape task, however, we found the opposite. Set size influenced target-present instead of target-absent trials, which is not consistent with the Guided Search Model. However, it may be that this effect is related to the overall increased RTs on target-present trials in the shape task. Finally, we found that effects of uniformity were more pronounced on target-absent than present trials for both tasks, which is again consistent with the Guided Search Model.

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