Visual search with negative slopes: The statistical power of numerosity guides attention

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Four experiments were performed to examine the hypothesis that abstract, nonspatial, statistical representations of object numerosity can be used for attentional guidance in a feature search task. Participants searched for an odd-colored target among distractors of one, two, or three other colors. An enduring advantage of large over small sets (i.e., negative slopes of search functions) was found, and this advantage grew with the number of colored subsets among distractors. The results of Experiments 1 and 2 showed that the negative slopes cannot be ascribed to the spatial grouping between distractors but can be partially explained by the spatial density of the visual sets. Hence, it appears that observers relied on numerosity of subsets to guide attention. Experiments 3a and 3b tested the processes within and between color subsets of distractors more precisely. It was found that the visual system collects numerosity statistics that can be used for guidance within each subset independently. However, each subset representation should be serially selected by attention. As attention shifts from one subset to another, the "statistical power" effects from every single subset are accumulated to provide a more pronounced negative slope.

Introduction

When using the visual search task in studies of visual attention, researchers often focus on the slopes of the resulting search functions that relate the reaction time (RT), or sometimes accuracy rates, to the number of items in a display (set size). The slopes of the search functions are important for making distinctions between two basic modes of search behavior: efficient and inefficient searches. The search for a target item among multiple distractors is typically considered efficient if the RT does not increase substantially with the number of items in a display. This concept is supported by the shallow slopes of the search functions that are observed under these conditions. In contrast, a visual search is considered inefficient when the RT increases with the number of items in a display. In the latter case, substantial positive slopes of the search functions are observed.

A more unusual visual search pattern was reported in the early 1990s by Bacon and Egeth (1991) and Bravo and Nakayama (1992). In both studies, observers had to detect an odd-colored target among a variable number of distractors of another color. In addition, in some conditions of their experiments, Bravo and Nakayama required observers to report either the color or the shape of the odd element. Finally, Bravo and Nakayama compared variable-mapping tasks (when the color of an odd element changed unpredictably from trial to trial) and consistent-mapping tasks (when the color of an odd element remained constant from trial to trial). Both studies found similar results, with RTs that decreased as the number of distractors increased. Remarkably, the most dramatic decline of the function was found within relatively small set sizes. In large sets, the RTs remained far more constant. This trend, therefore, can be characterized by *search functions with decelerating negative slopes*. It is noteworthy that in Bravo and Nakayama's study, a negative slope was found only in a shape-discrimination task under variable-mapping conditions while in the experiment by Bacon and Egeth, it was documented for a color-detection task.

The principal explanation for the negative slopes, which was supported in both studies, relies on the spatial organization of the displays, which can be treated as a factor *guiding attention* to an odd feature. However, the specific mechanisms behind this guidance suggested by Bacon and Egeth (1991) differ from those suggested by Bravo and Nakayama (1992). According to a hypothesis advocated by Bravo and Nakayama, this guidance is provided by local retinotopic interactions between all neighboring features. Two versions of this interaction are discussed by Bravo and Nakayama. One version suggests that the neighboring features are the subjects of local comparison and contrast compu-

Citation: Utochkin, I. S. (2013). Visual search with negative slopes: The statistical power of numerosity guides attention. *Journal of Vision*, *13*(3):18, 1–14, http://www.journalofvision.org/content/13/3/18, doi:10.1167/13.3.18.

doi: 10.1167/13.3.18 Received December 6, 2012; published July 23, 2013 ISSN 1534-7362 © 2013 ARVO

tations (Sagi & Julesz, 1987). The highest local contrast between a singleton and distractors immediately guides attention to an odd feature. This version of a bottom-up guidance mechanism was later supported by Wolfe (1994) in his influential guided-search model of attention. The other version suggests that there is mutual inhibition between neighboring similar items because they are represented within the same preattentive feature map. As soon as a singleton is represented in a different feature map and stands apart from the inhibitory interactions between distractors, it easily wins the competition for prior attentional selection (Koch & Ullman, 1985). In both versions, the local interactions are supposed to increase as the spatial separation between neighbors decreases. The spatial density of elements, therefore, appears to be critical for salience. Because visual search displays are typically presented within a constant visual angle, increasing the number of items causes the density to increase as well. This is most likely the simplest explanation for the negative slopes observed by Bacon and Egeth and Bravo and Nakayama.

However, Bacon and Egeth (1991) provided arguments against the explanation for negative slopes based on target-distractor local contrasts. They manipulated the target-distractor spatial separation independently from the set size and observed no effect on the slopes. However, when Bacon and Egeth arranged the distractors in a manner that maintained a constant distractor-distractor separation for any set size, they observed the elimination of the negative slopes. Similar results were obtained by the authors for the detection of orientation singletons. Bacon and Egeth concluded that the guidance principle is spatial by nature, but the mechanism is based on the proximity grouping between distractors rather than the target-nontarget spatial separation. The significance of the spatial grouping of distractors for search efficiency was demonstrated in numerous other experiments with feature and conjunction targets (Humphreys, Quinlan, & Riddoch, 1989; Poisson & Wilkinson, 1992; Treisman, 1982).

Certainly, spatial arrangements of items and local interactions within these arrangements are very important and biologically significant determinants of representing textures, surfaces, and objects that can guide attention through the environment. However, it appears that the visual system has a powerful tool to represent large groups of objects in an abstract, nonspatial way. Recent studies within an explosively evolving ensemble-representation paradigm have established that observers are rather good at judging the summary statistics for large sets of objects seen in a momentary glance (Ariely, 2001; Chong & Treisman, 2003). At least two types of basic statistics are available to the observer, namely the *average* values across different dimensions (Ariely, 2001; Bauer, 2009; Dakin & Watt, 1997; Watamaniuk & Duchon, 1992) and the *numerosity* (Burr & Ross, 2008; Chong & Evans, 2011; Whalen, Gallistel, & Gelman, 1999). Perhaps the most beneficial effect of summary statistics is that they allow the observers to overcome attention and working memory limitations (Cowan, 2001; Luck & Vogel, 1997; Pylyshyn & Storm, 1988) and rapidly judge the properties of multiple objects without paying attention to individuals. Moreover, it appears that this type of judgment may be more precise and reliable than one based on few sample objects (Alvarez, 2011; Chong, Joo, Emmanouil, & Treisman, 2008).

The main point of the present paper is that using abstract ensemble statistics can be an effective strategy for guiding attention through a visual search, especially when spatial organization does not help. There are at least three basic properties of ensemble summary statistics that can make them useful for an efficient visual search. The properties are applicable to both average and numerosity estimations. *First,* the summary statistics are extracted rapidly (Chong & Treisman, 2003, but see Whiting and Oriet, 2011) and mostly in parallel with equal efficiency for all set sizes (Ariely, 2001). In fact, statistical judgments may even benefit slightly from larger sets (Chong et al., 2008; Robitaille & Harris, 2011). *Second,* both the average (Alvarez, 2011; Chong & Treisman, 2005a; de Fockert & Marchant, 2008) and the numerosity (Chong & Evans, 2011) can be better represented with broadly distributed, rather than focused, attention. This is consistent with the finding that an efficient visual search also requires distributed attention (Joseph, Chun, & Nakayama, 1997). *Third* (and perhaps most important), the visual system is able to compute the averages (Chong & Treisman, 2005b) and numerosities (Halberda, Sires, & Feigenson, 2006; Treisman, 2006) for different feature-marked subsets. This ability is quite good for both spatially grouped and spatially overlapped subsets (Chong & Treisman, 2005b) although it appears to be limited to approximately three subsets at one time (Halberda et al., 2006). In other words, differently featured items can be represented as *separate* and *arrangement-independent* statistical entities or distributions. This notion can be used for thinking about visual search. If the visual system represents differently featured items as different distributions, then the search for a feature singleton can be performed as a direct comparison among these distributions.

So how can this statistically based strategy explain the negative slopes of search functions? The answer most likely lies in the statistical concept of numerosity. In statistical terms, the visual search for a singleton is akin to testing a hypothesis in which only one feature-marked subset consists of a single member. Because multiple-subset enumeration can be processed in parallel, although with some limitations (Halberda et

al., 2006), the visual system can then directly compare numerosities. When discriminating the numerosities of two distinct subsets, their ratio is a powerful determinant of discrimination speed and accuracy (Barth, Kanwisher, & Spelke, 2003). If there is a large difference in the number of items between subsets, then it is easier to decide that the smallest one is perhaps a singleton. Certainly, I do not assume that a visual search is the same thing as an enumeration task, but I hypothesize that the global contrast between the numerosities of distracting and target subsets can be used to guide a visual search along with, or sometimes instead of, local feature relationships.

This hypothesis was tested in the series of experiments described below. The main point of these experiments was to demonstrate that numerosity contributes to the negative slopes of search functions when both the local contrast (Bravo & Nakayama, 1992; Sagi & Julesz, 1987; Wolfe, 1994) and the between-distractors spatial grouping (Bacon & Egeth, 1991) are less useful. Two factors were manipulated across and within the experiments to test this hypothesis. First, I manipulated the density of sets across two pairs of experiments. In Experiments 1 and 3a, the density varied with the set size, like in standard visual search displays. In Experiments 2 and 3b, the density remained the same for all set sizes, so local contrasts remained constant. The other factor manipulated in all of the experiments was the number of colors among the distractors. Colors were intermixed so that they formed overlapping subsets. When a singleton target is surrounded by homogeneous one-colored distractors, such as in experiments by Bacon and Egeth (1991) and Bravo and Nakayama (1992), both the local contrast around the target and the between-distractor grouping are high. Therefore, the typical search strategies described by those authors seem plausible under these conditions. However, when the target is surrounded by heterogeneous, multicolored distractors, these guidance strategies appear to be less useful for two reasons. First, there are many more regions with high local contrasts than in homogeneous displays. Second, the between-distractor grouping is weakened under multicolor conditions. Both of these circumstances predict the reduction of guidance tendencies based on spatial arrangement. Consequently, the negative slopes should also decrease. However, in accordance with the numerosity-based hypothesis, the negative slopes should remain intact or even increase with the number of colors because the visual system is supposed to be able to compare an abstract number of representations of color subsets, regardless of their spatial arrangement (Halberda et al., 2006). It is also necessary to prove that multicolor displays are indeed treated as separate, overlapping subsets rather than a unitary, heterogeneous superset. Otherwise, the numerosity-based hypothesis makes no sense. Clear evidence in favor of separating dissimilar colors into distinct subsets and the serial attendance toward each subset will be presented in all experiments. In addition, Experiments 3a and 3b clarify the nature of within- and between-subset interactions that eventually contribute to attentional guidance.

Experiment 1

Experiment 1 was aimed at two main goals. The first goal was the replication of the negative slope pattern reported by Bacon and Egeth (1991) and Bravo and Nakayama (1992). A variable-mapping color search task was used as in the mentioned studies. The reference condition was to include distractors of only one color. The second goal was the investigation of grouping processes within displays and their role in attentional guidance. The manipulation of the grouping factors was achieved by adding colors to distracting sets. As was mentioned above, the spatial mixture of heterogeneous elements increases the local contrasts at multiple locations and diminishes the similarity grouping between distractors. The theoretical considerations of Bacon and Egeth (1991) and Bravo and Nakayama (1992) imply that both grouping reduction and increasing contrasts should eliminate negative slopes. The current experiment tests this prediction.

Methods

Observers

Seventeen undergraduate students of the Higher School of Economics participated in this experiment for extra credits in their general psychology lab classes. All students reported having normal or corrected-to-normal color vision and no neurological problems.

Apparatus and stimuli

The stimulation was developed and presented through the StimMake for Windows (authors A.N. Gusev and A.E. Kremlev, UMK "Psychology," Ltd., Moscow, Russia, 1999–2012). The stimuli were presented on a standard VGA-monitor with a refresh frequency of 85 Hz and a spatial resolution of 800 × 600 pixels. To register the responses, a parallel port–compatible control pad for RT experiments was used. The construction of the control panel provided a short distance between the top (unpressed) and the bottom (pressed) key positions. This provided an RT measurement with a precision of no less than ±2 ms.

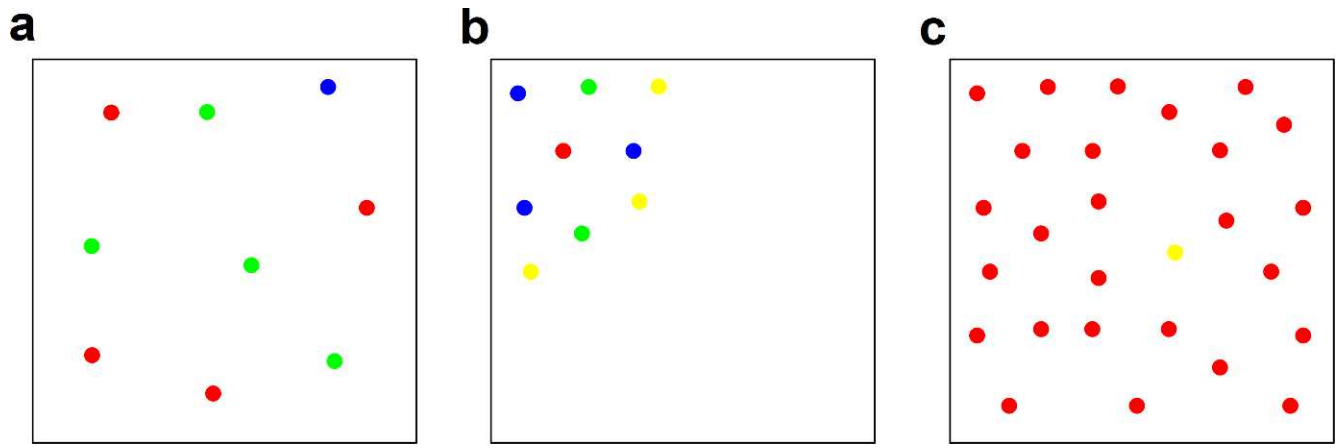

Figure 1. Examples of stimulus displays used in Experiments 1 and 2. (a) Set size = nine, sparse arrangement (Experiment 1); (b) set size = nine, dense arrangement (Experiment 2); (c) set size = 27, dense arrangement (both experiments).

The stimuli were presented on a homogenous 15° × 15° white field. It was divided into 3 × 3 = 9 imaginary squares. These imaginary squares were considered to be possible target locations. A target could appear at a random location within a square, but its appearance frequency was strictly uniform across squares. This provided a globally uniform spatial distribution of a given target over the field during the entire experiment.

The displayed items were colored dots, .6° in diameter. Four colors—red, green, blue, and yellow—were used for coloring the items. One to three colors could be presented as distractors in negative trials (where no target was presented). In positive trials, color singletons were added to sets as targets. All colors were equally likely to be presented as targets in each of the nine spatial positions. All colors were also equally likely to be presented as distractors in the one-, two-, and three-color conditions. All possible color combinations were used with equal frequencies. Two set sizes, nine and 27 dots, were used to test the general RT trend. The minimum set size was larger than those used by Bacon and Egeth (1991) and Bravo and Nakayama (1992), but it was chosen intentionally to provide for the further division of sets into smaller subsets. The failure to test small set sizes was compensated for in Experiments 3a and 3b. The dots were distributed over the field so that small sets were sparser than large sets. The average between-dot distance was approximately 4.4° (ranging from 3.1° to 5.2°) for small sets and approximately 3.1° (ranging from 1.3° to 4.4°) for large sets. Examples of small and large sets are presented in Figure 1a and 1c, respectively.

Observers were seated approximately 65 cm from the monitor. A typical trial began with a 500-ms fixation on a small black cross at the center of the white field. Immediately following the fixation period, a stimulus array appeared. Observers were asked to rapidly report the presence or absence of a singleton target in the array by pressing one of two specially assigned keys on the control panel. Half of the trials were positive, and the other half of the trials were negative. The array remained on the screen until a response was made or disappeared if a response had not been made within 3000 ms. The intervals between the trials varied in length between 1000 and 1500 ms, and a blank white field was presented during these intervals. Three 1-min breaks were given during the experiment. In total, the experimental design included three numbers of subsets × two set sizes × nine target positions (imaginary squares) × four target colors × two types of trials (positive or negative) = 432 trials per observer. Twenty-four randomly chosen trials were used during a training session that preceded the main block of trials. All conditions were arranged in a random sequence with the restriction that there could be no more than three positive or negative trials in a row.

Results and discussion

The data from two observers were excluded from the analysis due to their large error percentages (more than 10%). For the rest of the data, only the trials with a correct response were analyzed for RT.

The experimental effects of the number of subsets and the set size on the RT were tested with a within-subjects ANOVA. In the ANOVA model, the set size and the number of subsets were defined as fixed factors. To handle individual differences in performance among observers, the model also included the observer's identity as a random factor.

The results of Experiment 1 are summarized in Figure 2 in the left panel. The effect of the number of subsets on the RT was found to be significant, $F(2, 28) = 114.88$, $p < 0.001$, $\eta^2_p = .89$. As seen from the plot, the RT tended to increase with the number of subsets in

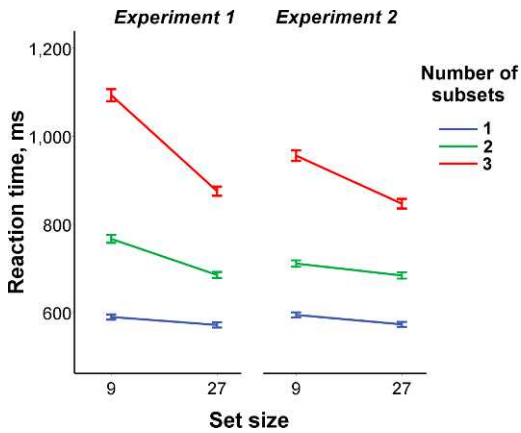

Figure 2. Reaction times for Experiments 1 and 2. Error bars denote ±1 *SEM*.

a display. The set size also had a significant effect on the RT, $F(1, 14) = 67.37$, $p < 0.001$, $\eta^2_p = .83$, producing negative slope functions similar to those described earlier for variable-mapping feature detection tasks (Bacon & Egeth, 1991; Bravo & Nakayama, 1992). The series of post-hoc t tests revealed that this set size effect is maintained in all numbers of subsets ($t = 2.19$, $p < 0.05$ for the one-color condition; $t = 7.29$, $p < 0.001$ for the two-color condition; and $t = 12.72$, $p < 0.001$ for the three-color condition). Finally, the interaction between the set size and the number of subsets also had a significant effect on the RT, $F(2, 28) = 63.13$, $p < 0.001$, $\eta^2_p = .81$, indicating that the absolute value of the slope increases with the number of subsets.

The experiment has succeeded in replicating the negative slope effect under standard conditions, which required the search for an odd target among one-colored distractors, that were the most similar to the task used by Bacon and Egeth (1991). The finding that the overall performance tended to decrease with the number of distracting colors is in agreement with the results obtained by Bundesen and Pedersen (1983) and Santhi and Reeves (2004).

However, the most remarkable result of Experiment 1 is the character of interaction between the number of subsets and the set size. Paradoxically, it appears that visual search becomes slower in general but guidance becomes stronger as the number of subsets increases. I shall further refer to this pattern as the *crescent slope* effect. At first glance, this finding seems discouraging. As the number of overlapping colors increases, both the local contrast and the grouping tendencies between distractors are reduced, which is predicted to result in a reduction in target salience. This reduction in target salience appears to be the case in terms of overall performance. However, these conditions are also predicted to result in an impairment in the bottom-up guidance while assuming that guidance relies solely on the parallel preattentive discrimination between groups and textures (Bacon & Egeth, 1991; Bravo & Nakayama, 1992; Sagi & Julesz, 1987; Wolfe, 1994).

The results, however, become clearer if we presume that a limited-capacity process, typically referred to as attention, is involved in this type of visual search. One might argue that limited-capacity attention should produce positively, rather than negatively, sloped search functions because attention serially switches from one location occupied by an object or a group to another. However, as was previously mentioned, attention can also select spatially overlapping, feature-marked subsets (e.g., Halberda et al., 2006). This type of selection implies that the RT should increase with the number of subsets rather than number of items. The results of the current experiment suggest that such a subset-oriented type of attentional selection may be involved in this task. Given the serial character of attending to subsets, a further presumption can be made regarding the crescent slopes observed. According to this presumption, separate guiding processes are being launched within each subset. Taken together, these processes provide a more efficient overall guidance effect or *cumulative guidance*. The idea of the accumulation of several guidance processes, provided by several separable features, was earlier suggested by Wolfe, Cave, and Franzel (1989) for conjunction-search tasks. I hypothesize that, in my feature-search task, this cumulative guidance effect may be caused by a numerosity comparison between subsets. However, the present experiment does not provide sufficient data to test this hypothesis because subset numerosities were incomparable for one-, two-, and three-color conditions. This hypothesis will be properly addressed below in Experiments 3a and 3b.

Experiment 2

As was mentioned in the Introduction, the reasoning regarding bottom-up attentional guidance is typically based on the concepts of density and proximity. In other words, a prevailing significance is given to the spatial factors of display organization. Increasing the number of items is thought to produce a negative slope only as far as it is positively related to density and proximity. Alternatively, numerosity can be considered to be an independent factor affecting guidance. Experiment 2 tests whether the negative slopes observed in Experiment 1 were the result of spatial density or numerosity. In this experiment, the spatial density for small and large sets was identical. A density-oriented hypothesis predicts a shallow-slope pattern for singleton detection because guidance tendencies are equated in small and large sets. In contrast, a

numerosity-oriented hypothesis predicts the maintenance of a negative slope despite the density manipulations.

Methods

Observers

Sixteen undergraduate students of the Higher School of Economics participated in this experiment for extra credits in their general psychology lab classes. All students reported having normal or corrected-to-normal color vision and no neurological problems. None of the observers that participated in this experiment participated in Experiment 1.

Stimuli and procedure

The stimulation and procedures used were identical to those used in Experiment 1. The only exception concerned the spatial arrangement of small sets. The density of these sets was equated with that of the large sets, and both were the same as the large set densities from Experiment 1. In this experiment, the small sets were organized as compact groups occupying approximately 20% of the "working" field. To provide a uniform distribution of the target locations during this experiment, these small sets were centered along each of the nine imaginary squares of the visual field with equal frequencies. An example of a dense small set used in this experiment is provided in Figure 1b.

Results and discussion

The data from one observer were excluded from the analysis due to the large error percentage (more than 10%). The method of analyzing the RT and the statistics used were the same as those used in Experiment 1.

The number of subsets had a significant effect on the RT, $F(2, 28) = 66.99$, $p < 0.001$, $\eta^2_p = .83$, indicating that the search efficiency decreased with the number of presented colors. The effect of the set size was also significant, $F(1, 14) = 18.24$, $p = 0.001$, $\eta^2_p = .57$), indicating the global maintenance of negative slopes. The series of post-hoc t tests indicated that the slopes were negative in all conditions ($t = 2.69$, $p < 0.01$ for the one-color condition; $t = 2.66$, $p < 0.01$ for the two-color condition; and $t = 6.88$, $p < 0.001$ for the three-color condition). Finally, the interaction between the set size and the number of subsets also had a significant effect on the RT, $F(2, 28) = 10.46$, $p < 0.001$, $\eta^2_p = .43$, demonstrating a crescent slope trend similar to the one observed in Experiment 1. As seen from the effect size estimates, the effect of the number of subsets remained largely identical to that observed in Experiment 1. However, the effect sizes were reduced for both the set size and the set size × number of subsets interaction when compared with Experiment 1. Indeed, as seen from the plot (Figure 2, right panel) the negative slope functions are shallower than those observed in Experiment 1 at least for the two- and three-subset conditions.

As predicted by traditional accounts regarding bottom-up guidance (Bacon & Egeth, 1991; Bravo & Nakayama, 1992; Sagi & Julesz, 1987; Wolfe, 1994), the spatial densification of visual elements in small sets made the visual search for a feature singleton more efficient. However, this manipulation failed to remove the negative slopes and the crescent slope trend completely. This result is also in agreement with the previous finding that the effect of spatial density on a feature search is limited (Cohen & Ivry, 1991). Theoretically, there could be an alternative interpretation for this pattern. This interpretation is based on the notion that perceiving small but dense sets requires the additional operation of narrowing attention. Indeed, in Experiment 2, the set size varied randomly from trial to trial, so observers did not know which region would be occupied until the dots appeared. This could result in the adoption of a strategy of using a wide attentional window with subsequent narrowing as needed. This narrowing operation could yield an additional cost in the RT that resulted in negative slopes. This narrowing of attention is a plausible strategy but is still unable to explain the crescent slope effect. If the narrowing strategy acts alone, then its effect on the slopes should be independent of the number of subsets because the region occupied by small sets was always the same. Hence, the remaining factor that could contribute to the crescent slope pattern is numerosity.

To label this link between numerosity and search efficiency, I use the term "*statistical power effect*." This term is prompted by a statistical rule that states that an increasing sample size (numerosity) typically lowers the threshold value of a statistical test sufficient for confirming or rejecting an H1 hypothesis. In visual search for a singleton, the visual system tests the hypothesis that the size of any of subset is equal to one. In a general statistical sense, the task is akin to testing a proportion hypotheses (chi-square hypotheses). I found that the visual system makes decisions regarding search outcomes faster with larger sets. Larger differences between numerosities make the differences between subsets more evident; therefore, hypotheses are being confirmed or rejected more readily. However, the notion of statistical power does not limit the possible mechanisms of guidance by direct numerosity comparisons. The other mechanism that can mediate search facilitation is variance reduction. In statistics, with an increasing number of items, a population of similar

items tends to its mean, and the observed variance tends to be reduced. A recent finding by Robitaille and Harris (2011) supports the notion that this statistical rule acts in judging ensemble summary statistics in human observers. In a visual search, a variance reduction can be directed at diminishing the noisy interactions between subset representations and enhancing discrimination. Both direct numerosity comparisons and variance reduction are plausible mechanisms of the statistical power effect. Future experiments will be needed to clarify their possible contributions to negative slopes. In the present paper, I mainly highlight the apparent similarity between the statistical power rule and the observed RT patterns to justify the use of the term "statistical power effect." In my opinion, the statistical power effect is useful when thinking about visual sets as statistically represented entities.

Experiments 3a and 3b

In the discussion of Experiment 1, a hypothesis was presented that separate guidance processes are being generated by each color subset and accumulated in a visual search once attention is paid to a subsequent subset. This hypothesis could likely explain the crescent slope trends observed in Experiments 1 and 2. However, the above experiments do not provide enough data to conclude whether this hypothesis is correct due to the inability to separate the set size and the subset size. In standard set-size manipulations, the total number of items is an endpoint of an experimental condition. However, if the set is then divided into equal or nearly equal subsets, the number of items per subset is reduced. For example, in a positive trial of a nine-item set, we have eight items in one distracting subset; four and four items in two distracting subsets; or three, three, and two items in three distracting subsets. The guidance tendencies within subsets cannot be compared under these conditions. As was clearly demonstrated in the experiments conducted by Bacon and Egeth (1991) and Bravo and Nakayama (1992), the negative slope is a decelerating function of the number of items. This deceleration can provide an alternative explanation for the crescent slope trend: As the number of subsets increases, the subset numerosity is reduced, and this results in the sharpening of guidance processes within each subset. In summary, two alternative hypotheses should be considered regarding the guidance processes underlying the crescent slope trend. In accordance with the first hypothesis, independent guidance processes that evolve within each subset are being serially accumulated as soon as attention is directed to other subsets in a serial manner. This hypothesis supports the

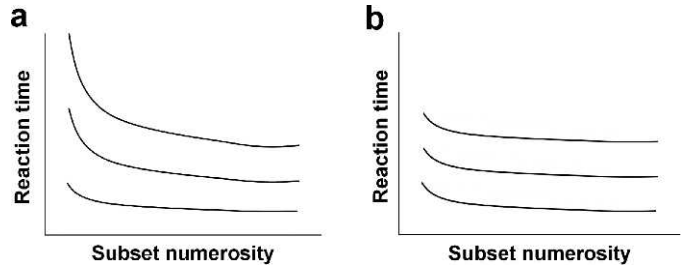

Figure 3. Two predictions regarding between-subset interactions in providing attentional guidance by subset numerosity: (a) cumulative guidance or (b) noncumulative guidance.

concept of *cumulative guidance* as suggested above. The second hypothesis asserts that there is no serial accumulation of numerical information. Rather, it appears that information is being accumulated in parallel within all subsets but is only accessible when attention is paid to a particular subset. In this case, the RT slopes should not be dependent on the number of subsets. Note that both hypotheses assume that attention inspects the subsets serially as was demonstrated in Experiments 1 and 2.

Experiments 3a and 3b address these hypotheses and provide advanced investigations into the within- and between-subset processes that result in bottom-up guidance. The subset numerosities were controlled in these experiments rather than the set sizes. The conditions of the subset numerosity factor were termed "*iso-numerosity points*." An iso-numerosity point is a visual set in which the number of items per subset remains constant regardless of the number of subsets. To assert that spatial proximity is not an exclusive factor affecting bottom-up guidance, the density manipulations from Experiments 1 and 2 were replicated with iso-numerosity stimuli. Thus, the item density was manipulated across Experiments 3a and 3b.

Given the serial character of attending to subsets (as Experiments 1 and 2 revealed), two predictions can be made regarding the results when considering the above hypotheses. If the guidance processes are being accumulated from subsets with serial shifts of attention, then the absolute slope should increase with the number of subsets (*cumulative guidance* hypothesis). If the guidance processes are being generated in parallel prior to attending to a particular set, then the slopes should remain the same, regardless of the number of subsets (*noncumulative guidance* hypothesis). These two predictions are summarized in Figure 3a and 3b, respectively. Moreover, Experiments 3a and 3b test the shape of the numerosity–RT function in greater detail than in Experiments 1 and 2, in which only two points were used. Based on the results reported by Bacon and Egeth (1991) and Bravo and Nakayama (1992) for one-color–condition experiments, I predict a rapidly decelerating shape for the numerosity–RT function as the

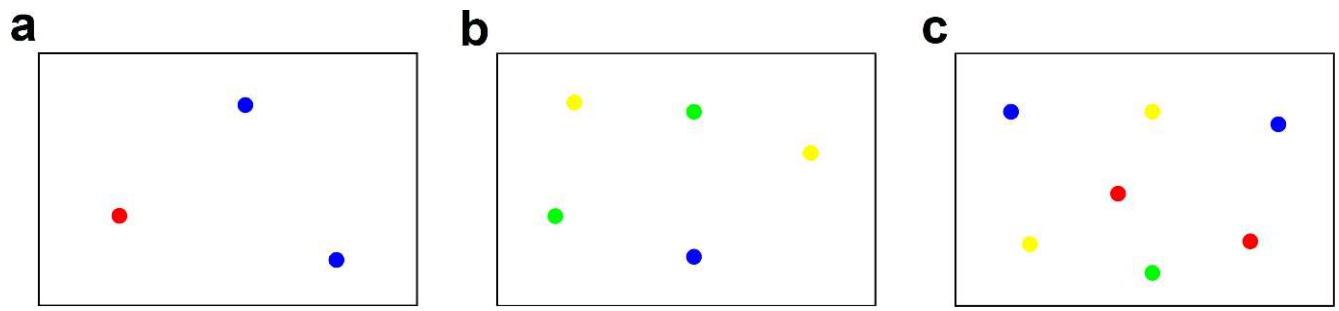

Figure 4. Examples of stimulus displays used in Experiment 3a demonstrating iso-numerosity manipulation. All panels depict the same iso-numerosity condition, namely the two-item condition; that is, there are always two items of the same color regardless of the total number of colors. This causes the overall set size to increase but keeps subset numerosity constant: (a) one-subset condition: two blue distractors + red target = three items; (b) two-subset condition: two green distractors + two yellow distractors + blue target = five items; (c) three-subset condition: two red distractors + two blue distractors + two yellow distractors + green target = seven items.

number of items per subset increases. Figure 3 takes this prediction into account.

Methods

Observers

Nineteen and 18 undergraduate students of the Higher School of Economics participated in Experiments 3a and 3b, respectively, for extra credits in their psychology courses. All students reported having normal or corrected-to-normal color vision and no neurological problems. Observers did not overlap between the two experiments, and none of them participated in Experiments 1 or 2.

Stimuli and procedure

The stimulation and procedures for both experiments were similar to those used in Experiments 1 and 2. However, there were several important differences.

The "working" visual field was 15° × 9.7°. The field was divided into six imaginary squares, serving as spatial positions for the targets, and the sizes of the squares were the same as in Experiments 1 and 2. It can be seen that the total size of the field and the number of imaginary squares were reduced as compared to the above experiments. This change was caused by changes in set size range brought by iso-numerosity manipulations. In Experiment 1, only two set sizes, nine and 27 items, were used that provided two items per square on average across conditions. In Experiments 3a and 3b, the set size ranged from three to 37 items, depending on the number of subsets and subset numerosity (see detailed set size calculations below). Using a six-square field provided an average density of about 2.2 items per square that was closer to Experiment 1 than using a nine-square field (1.5 items per square). As in Experiment 1, the targets appeared with equal frequencies in all imaginary squares during the experiments. The same four colors and rules for coloring targets and distractors were implemented as were used in the previous experiments.

To investigate the role of subset numerosity in attentional guidance, four iso-numerosity points were used. The iso-numerosity points were two, four, eight, and 12 items per subset. The total set size included the number of subsets multiplied by the iso-numerosity point value, and one item was reserved to be a target in positive trials (Figure 4). In negative trials, an additional member of a randomly chosen distractor subset was presented instead of the target. The total set sizes, consequently, were $2 + 1 = 3$, $4 + 1 = 5$, $8 + 1 = 9$, and $12 + 1 = 13$ for the one-distractor subsets; $2 \times 2 + 1 = 5$, $2 \times 4 + 1 = 9$, $2 \times 8 + 1 = 17$, and $2 \times 12 + 1 = 25$ for the two-distractor subsets; and $3 \times 2 + 1 = 7$, $3 \times 4 + 1 = 13$, $3 \times 8 + 1 = 25$, and $3 \times 12 + 1 = 37$ for the three-distractor subsets. In Experiment 3a, the items were uniformly distributed across the field in all set sizes as described in Experiment 1. Consequently, the average density of all items varied with the set size. However, the average within-subset density remained constant for any given iso-numerosity point. In Experiment 3b, the densities were equated for all set sizes as described in Experiment 2.

In total, the designs of Experiments 3a and 3b included three numbers of subsets × four subset numerosities (iso-numerosity points) × six target positions (conditional squares) × four target colors × two types of trials (positive or negative) = 576 trials per observer. Trials of different types were intermixed in a random order with the restriction that there could be no more than three positive or negative trials in a row. Five breaks were provided during the main session of the experiments. Twenty-four randomly chosen trials were used during a training block that preceded the main session. All of the other conditions were identical to those used in the previous experiments.

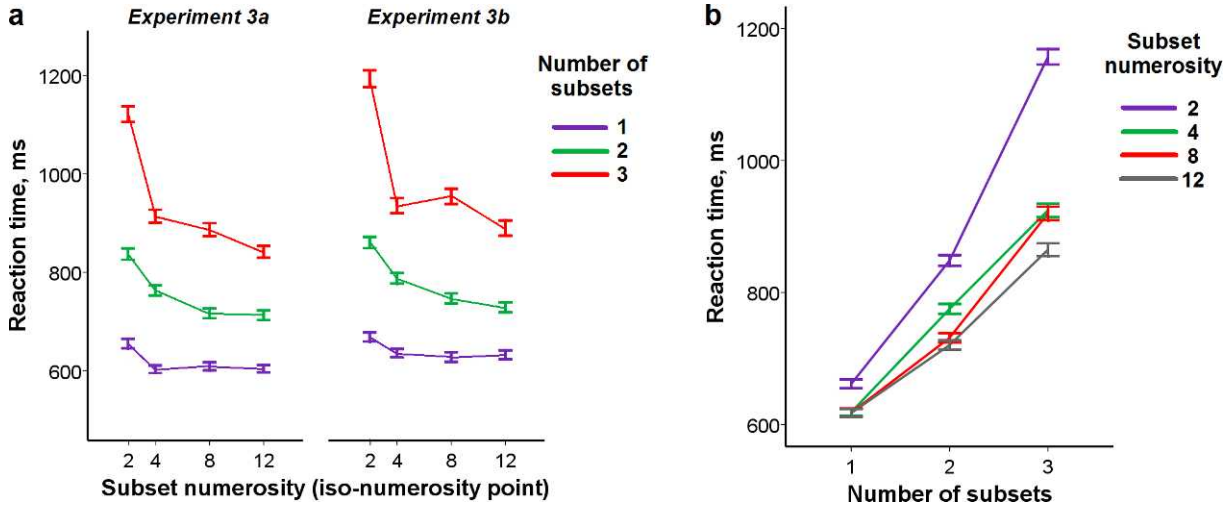

Figure 5. RTs for Experiments 3a and 3b (a) as a function of subset numerosity (iso-numerosity points). The functions are characterized by negative slopes with deceleration. The absolute RT tends to increase with the number of subsets as depicted by separate lines, but the absolute slopes are showed to increase as the number of subsets increases, demonstrating the *crescent slope trend*. (b) The same results averaged across experiments and replotted using alternative coordinates (x-axis depicts the number of subsets) to emphasize an effect of subset numerosity (separate lines) on serial search among subsets. As the numerosity increases, the slope tends to be reduced, indicating attentional guidance. Error bars denote ±1 *SEM*.

Results and discussion

The data from one observer who participated in Experiment 3b was excluded from analysis due to the large error percentage (more than 10%). The methods for analyzing the RTs and the statistics used were identical to those described in previous experiments.

The results of Experiment 3a are plotted in Figure 5a, in the left panel. The effect of the number of subsets was significant, $F(2, 36) = 117.61$, $p < 0.001$, $\eta^2_p = .87$, indicating that the addition of subsets yielded an increase in the RT as observed in the previous experiments. The second principal result was that the RT function gradually declined as the subset numerosity increased from two to 12 items, $F(3, 78) = 69.17$, $p < 0.001$, $\eta^2_p = .79$, which replicated the negative slope function observed in the previous experiments. A regression analysis was applied to determine which shape of the function fit the experimental data better. Five function shapes were tested, including linear, inverse, logarithmic, quadratic, power, and exponential. The best fit was provided by the inverse function, $R^2 = .25$, $F(1) = 268.01$, $p < 0.001$, and the power function with the absolute exponent less than one, $R^2 = .25$, $F(1) = 260.79$, $p < 0.001$. Both functions are decelerating. The worst fit was provided by the linear function, $R^2 = .18$, $F(1) = 185.54$, $p < 0.001$. Therefore, it was more likely that the general trend was slightly decelerated, which is consistent with that reported by Bacon and Egeth (1991) and Bravo and Nakayama (1992). The most dramatic difference was obtained in the transition from the iso-numerosity points of two to four items. Remarkably, in the one-subset condition, this transition was also accompanied by the slight facilitation of performance, followed by a flat RT function at all other numerosities. This inhibition of response to the target in the presence of only two one-colored distractors could be due to a strong competition between the three items. Both local contrast and between-distractor grouping appear to be insufficient for guiding attention under this condition.

The absolute slope of the function tended to increase with the number of subsets (subset numerosity × number of subsets interaction, $F(6, 108) = 20.84$, $p < 0.001$, $\eta^2_p = .54$), replicating the crescent slope trend observed in the previous experiments. Yet the effect size estimate was reduced when compared with Experiment 1 because the uncertainty regarding the influence of the number of subsets and the subset numerosity, described above, was removed.

The results of Experiment 3b are plotted in Figure 5a in the right panel. As seen from the plot, the results do not differ substantially from those observed in Experiment 3a. Again, the effect of the number of subsets was significant, $F(2, 32) = 86.41$, $p < 0.001$, $\eta^2_p = .85$. The effect of subset numerosity was also significant, $F(3, 48) = 67.31$, $p < 0.001$, $\eta^2_p = .81$, demonstrating overall negative slope. The results of the regression analysis of the search function general shape yielded substantially the same results as for Experiment 3a. The best fit was provided by the power function with the exponent less than one, $R^2 = .26$, $F = 256.60$, $p < 0.001$, and the worst fit was provided by the linear function, $R^2 = .16$, $F = 160.84$, $p < 0.001$, indicating that the slope tends to decelerate as subset numerosity increases. Finally, the

crescent slope trend was retained in the present experiment, subset numerosity × number of subsets interaction, $F(6, 96) = 31.75$, $p < 0.001$, $\eta^2_p = .66$.

As in Experiments 1 and 2, the strongest statistical effect was observed for the number of subsets. Note that in Experiments 3a and 3b the set sizes increased proportionally to the number of subsets while in Experiments 1 and 2 the set sizes remained constant and the subset numerosities were variable. Yet the subset-related increments in the RT were nearly identical for all of the experiments, which leads to an important conclusion that this effect is only marginally dependent on the manipulations of the set size. Rather, changes in the RT appear to be dependent on the subset numerosities. These results provide evidence that, in my task, attention operates serially with subsets rather than with single items or with the whole set at once (otherwise the RT should not be dependent on the number of subsets).

Strikingly, Experiments 3a and 3b showed no substantial effects of the item density on the slopes while substantial effects of item density were observed in Experiments 1 and 2. There is unlikely to be a stimulus variable that could interfere with density between the two pairs of experiments because they all used principally the same stimuli. However, there could be a procedural difference responsible for this discrepancy. In Experiments 1 and 2, observers were exposed to only two set sizes while in Experiments 3a and 3b there were four iso-numerosity points, which, in turn, produced an even greater variety of set sizes. The random mixture of all these set sizes in a trial sequence resulted in a greater level of unpredictability, which may have complicated the spatial adaptation to smaller sets. In other words, it became quite difficult to predict which visual angle would be occupied by informative items in any given trial and, therefore, to adjust the proper size and resolution of an attentional window. This hypothesis should definitely be tested properly in future experiments. The most important result, in the context of the present paper, is the finding that density manipulations appear to have a more volatile effect on search performance than subset numerosities do.

The main goals of Experiments 3a and 3b were to examine the roles of within- and between-subset processes in attentional guidance. First, I obtained a more precise numerosity–RT function due to the increased number of iso-numerosity points. Moreover, my numerosity manipulations concerned the most guidance-sensitive span that did not exceed 12 items per subset. In general, the shapes of the functions (decelerating and negatively sloped lines) were similar to those reported by Bacon and Egeth (1991) and Bravo and Nakayama (1992). Given the difficulties in deriving a purely spatial explanation for the guidance effect, the latter similarity appears to be rather important. Presumably, both types of functions can reflect the statistical power effect, which is the facilitation of reaching a decision regarding the entire ensemble as the number of items increases. A more detailed view of the statistical power effect and its role in guidance will be given in the General discussion section.

I also sought to understand whether the guidance effects caused by each subset were being accumulated during a visual search or not. As seen from the results, the crescent slope trend was maintained with iso-numerosity manipulations. Consequently, the results of these experiments correspond with the prediction inferred from the "cumulative" hypothesis. It appears that independent guidance processes generated by individual subset statistics are then accumulated as attention switches from one subset to another.

In Figure 5b, results of Experiments 3a and 3b are replotted in an alternative coordinate system to make the guidance effects of statistical power more evident. It can be seen from the plot that additional subsets result in a linear increase in the RT as was predicted by the standard, serial, item-by-item attentional deployment hypothesis (Treisman & Gelade, 1980). A similar linear effect of additional color subsets on search performance was reported by Bundesen and Pedersen (1983). The statistical power of subsets has little effect on the linearity but reduces the slopes of the functions, which can serve as a criterion for attentional guidance (Friedman-Hill & Wolfe, 1995).

General discussion

Attentional guidance by statistical power

Attentional guidance is an adaptive mechanism that facilitates the visual search for various targets. It appears that this mechanism is served by numerous processes. In the present study, I tested one such mechanism, namely using the statistical power of numerosity for detecting feature singletons. It is important to emphasize that I consider this numerosity-based method of guidance to be an additional strategy that the visual system can utilize to control detection. Both local contrast comparisons and spatial grouping are the major tools used for guiding visual search (Bacon & Egeth, 1991; Bravo & Nakayama, 1992; Sagi & Julesz, 1987; Treisman, 1982; Poisson & Wilkinson, 1992; Wolfe, 1994), especially in highly regular or homogeneous displays. However, when different elements are arranged in an irregular manner (which is typical for many natural textures, objects, and scenes), other tools can aid visual search. These tools, however,

should be less dependent on spatial arrangement to provide effective guidance.

My experimental manipulations were based on the notion that arrangement-based and numerosity-based strategies should yield different effects on the slopes of the search functions when grouping and density are manipulated. Increasing the number of colors among distractors made arrangement-based strategies less useful for guiding attention because there were too many concurrent discontinuity regions in the visual field. These conditions should abolish the guidance patterns that are manifested as negative slopes when only arrangement-based strategies are used. However, observers demonstrated an opposite pattern, the crescent slope effect, which demonstrated that the power of guidance tended to increase with the number of heterogeneous colors. At the same time, density manipulations had only a limited effect on the slopes observed in Experiment 2 and no substantial effect was observed in Experiments 3a and 3b. This led me to conclude that observers rely on the numerosities of spatially overlapping color subsets to judge whether a singleton is present or absent. This *statistical power* effect was found to have the properties of a guiding factor.

The notion of statistical power implies that there can be an analogy between a visual search and a statistical decision. This analogy is a natural extension of the previous ideas regarding the global ensemble representation as summary statistics (Alvarez, 2011; Ariely, 2001; Chong & Treisman, 2003; Treisman, 2006). If the visual system is indeed able to rapidly extract rather compact statistical descriptions from an image instead of representing every feature and every item, why can't it use such descriptions to distinguish between different ensembles? As summary statistics for feature-marked subsets are collected independently (Chong & Treisman, 2005b; Halberda et al., 2006) and in parallel from the entire visual field (Chong et al., 2008), then direct comparisons among statistical properties (numerosities, averages, etc.) can be a more economic strategy than local feature comparisons among all neighboring items.

Attentional selection of statistical subsets

The second important and very articulated result of the present study is the finding that the visual system appears to be unable to process all subsets at a time, and processing is likely to require attentional selection. Furthermore, it appears that attentional switching between subsets was being performed in a strictly serial manner as the RT tends to increase linearly with the number of subsets (Experiments 3a and 3b). This finding is in agreement with those reported by Bundesen and Pedersen (1983). Yet Bundesen and Pedersen understood that subsets are spatial groups determined by the combination of proximity and similarity. They found that the search time positively correlates with the number of subjectively perceived groups. A somewhat similar conclusion was made by Treisman (1982) for conjunction searches. My results, however, provide an alternative explanation for their results. When all of the elements of one color were spatially grouped, the average distance between them was shorter than in a mixed arrangement. We can see from Experiment 2 that the densification of visual sets facilitated the visual search performance to some degree, but it appears that attention, nevertheless, operates with the whole subset rather than its spatially separated fragments. Otherwise, no statistical power effect could be observed.

The other reference for an increase in RT with an increasing number of subsets is the framework provided by Duncan and Humphreys (1989). According to their theory, the efficiency of a visual search decreases as the heterogeneity of distractors increases. However, this rule appears to apply only if the target is similar to the distractors; otherwise, the distractor heterogeneity has no effect on efficiency. As only basic colors were used in the experiments, the targets were always dissimilar from the distractors and, hence, could not produce a substantial loss in efficiency; this is exactly what was found in other color detection tasks (Duncan, 1989; Smallman & Boynton, 1990). However, the Duncan and Humphreys' theory implies that a target template in working memory controls the allocation of attention in a visual search. In studies by both Duncan and Smallman and Boynton, observers had such templates. In my variable-mapping experiments, there was no definite template for a target color, and therefore, attention selected subsets one by one.

The notion that attention is able to operate with subsets of spatially distributed objects sharing a common feature as single units is not novel. The ensemble representation paradigm provides examples of the representation of global features of color subsets independently of spatially overlapping subsets (Chong & Treisman, 2005b; Halberda et al., 2006; Treisman, 2006). More remarkable, in the context of my study, is an example from visual search. In conjunction-search experiments, Friedman-Hill and Wolfe (1995) demonstrated that observers can produce flat search functions more typical for feature searches. Once an observer selects a subset of all commonly featured items (for instance, attends to all red items, ignoring all green items), the task transforms into a trivial feature search (a target is the only differently oriented item in that subset). An interesting observation, made by Friedman-Hill and Wolfe, is that the serial or parallel character of a conjunction search depends on the set size: The more items that are presented in a display, the

more the slope tends to zero. This is considered to be a manifestation of attentional guidance. This observation is important in light of the statistical power effect discussed in this paper. As proposed by Friedman-Hill and Wolfe and Michod, Wolfe, and Horowitz (2004), the failure of guidance for small set sizes can be ascribed to the slow speed of subset selection. It takes approximately 250–300 ms for this type of guidance to develop, but visual searches with small sets typically finish faster (Michod et al., 2004). This is the likely explanation for the failure of guidance with small sets, given recent estimates of the time required for representing ensemble properties (Whiting & Oriet, 2011). However, this notion does not explain the advantage of large sets found in my color detection experiments. As the visual search in a large set is finished faster than in a small set, the guidance effect develops before a singleton is found in a small set. Again, only the statistical power of numerosity appears to provide a satisfactory explanation. What the present experiments add to the knowledge of subset-oriented attention is the notion that *attention appears to have access to the statistical representation of subsets to guide visual search, not merely a simple feature map* (otherwise numerosity could not be taken into account).

Cumulative guidance

The final point of my analysis concerns the interaction between the processes responsible for the statistical representation within subsets and the allocation of attention between subsets. Taken together, these processes yield an unusual combination of total search efficiency and attentional guidance. As attention is required for the serial selection of subsets, the RT tended to increase with the number of subsets. At the same time, the statistical power effect became stronger with the number of subsets. I concluded, hence, that the guidance processes generated by every individual subset are simply accumulated (or summated) as the search progresses.

The model of such accumulation is based on the discrimination hypothesis, proposed above, for the likely mechanism of statistical guidance. I suggested that discrimination between a target and distractors becomes easier in large sets (due to numerosity contrast or decreasing variance). My results demonstrated that attention likely switches from one subset to another to provide discrimination. As more subsets are attended to in a visual search, more serial discrimination operations are performed. It is obvious that there should be a more relative benefit from two, serial, easy discriminations than from only one such discrimination. As a result, the crescent slope trend is observed as the number of subsets increases. In other words, *numerosity statistics are being collected within each subset independently, but only when attention is paid to a subset does it enact subset statistics to guide the visual search.*

Conclusion

Recent studies have convincingly shown that statistical features are being rapidly encoded from large displays by a broad attentional window like many other features. The central idea of the present study was that the basic statistical properties of ensembles (such as numerosity) can guide attention when searching for a unique target. In the present study, I found that numerosity statistics affect the bottom-up type of guidance and yield negative slopes of search functions. I referred to this effect as the statistical power effect and demonstrated that it is more than simply spatial retinotopic interactions between targets and distractors. Finally, I showed the critical role of attention in the selection of statistical representations and the accumulation of guidance effects during a visual search. The results of the present study can be considered to be a step in bridging the gap between the two aspects of perceiving objects and scenes, the ensemble representation, and the visual search for an individual member of that ensemble.

Keywords: visual search, attention, feature search, ensemble representation, numerosity

Acknowledgments

The study was implemented in the framework of the Basic Research Program at the National Research University Higher School of Economics in 2012. The author thanks Yulia Stakina for her assistance in collecting experimental data.

Commercial relationships: none.
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