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Visual Enumeration of Spatially Overlapping Subsets

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Abstract. Observers are able to extract summary statistical properties, such as numerosity or the average, from spatially overlapping subsets of visuals objects. However, this ability is limited to about two subsets at a time, which may be primarily caused by the limited capacity of parallel representation of those subsets. In our study, we addressed several issues regarding subset representation. In four experiments, we presented observers with arrays of dots of one to six colors and instructed them to judge the number of colors. We measured both speed and accuracy of those judgments. Following standard criteria used for the interpretation of object enumeration data, we recognized two modes of subset representation: a) parallel, effortless and strategy-independent representation of no more than two subsets, and b) serial representation modulated by different attentional strategies and a working memory template. We also found an advantage of large sets over small ones, demonstrating that subset representation can be formed based on some statistical accumulation of information from individual objects.

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Introduction

Numerous studies have demonstrated that access to visual information is severely limited by the natural capacities of our attention or visual working memory. That is, one is normally able to be clearly aware of and to store only about three to four items at a time (Luck & Vogel, 1997; Pylyshyn & Storm, 1988). However, our everyday perceptual experience tells us that we continuously see many more than just a few objects at a time. One way to overcome the strict limitations of attention and visual working memory is to encode multiple objects as a single unit, or *ensemble*, using the broad settings of the attentional window (Navon, 1977; Treisman, 2006). The results of the past dozen years of research in this field show that the visual system can effectively compress rather variable features of individual objects to achieve an economic description of an entire ensemble in a set of summary statistics such as the average along different dimensions (Ariely, 2001; Bauer, 2009; Dakin & Watt, 1997; Watamaniuk & Duchon, 1992) or their numerosity (Chong & Evans, 2011). These summary statistics can be very useful for representing the gist of a scene and for making rapid decisions. For instance, consider picking raspberries from a bush (the example is inspired by a recent analysis of visual foraging by Wolfe, 2013). When moving from one branch to another, one must visually estimate whether it is worth his or her efforts (especially if some branches are difficult to reach). Instead of serial inspection of every individual berry (some of which cannot be seen), the picker can judge the “goodness” of the branch based on the approximate number of items that resemble berries and the average “redness” of those items.

Representing Multiple Overlapping Sets

However, encoding all objects in the visual field as an indivisible ensemble is not always useful. Looking at a raspberry bush, the picker would see berries interspersed with leaves. If the “redness” statistics had been extracted from all bush elements it would have been spoiled enormously by the “greenness” of the leaves which are typically far more numerous than berries. Therefore, the benefits of ensemble representation appear to be incomplete without *segmentation* of spatially grouped or overlapping subsets and subsequent selection of such subsets. In a set of refined laboratory studies, it was found that observers are in fact able to extract summary statistics from spatially overlapping subsets. Chong and Treisman (2005b) found that their observers were able to estimate the average size of briefly presented and spatially mixed subsets of colored circles. The observers reported the average size of a subset almost as accurately as when only one set was presented. That led Chong and Treisman to conclude that statistical representations of subsets are independent of each other and based on a preattentive feature segregation process. The authors argued that it is the same process as the one responsible for attentional guidance in efficient visual searches for conjunction targets (e.g., Wolfe, Cave, & Franzel, 1989; Friedman-Hill & Wolfe, 1995). Moreover, the performance shown by Chong and Treisman's participants was equally good when a relevant subset was both precued and postcued, suggesting that at least two subsets can be statistically processed *in parallel*.

In another experiment, Treisman (2006) tested the ability to estimate the proportion of subset members among a whole ensemble (a kind of numerosity judgment). Her participants succeeded in parallel estimation of such statistics as long as a relevant subset was defined by a single feature (a color or a letter shape). In contrast, when a relevant subset was defined by a color-letter conjunction, performance deteriorated dramatically.

However, the seemingly parallel statistical representation of multiple ensembles is not truly free of limitations. Halberda, Sires, and Feigenson (2006) studied absolute numerosity judgments for spatially overlapping subsets. They briefly presented their observers with one to six variably-sized subsets of colored dots and precued or postcued a relevant color. The observers had to report the number of dots of the cued color. Halberda et al. (2006) found that, regardless of the number of subsets, observers could estimate numerosity with unchanging precision when the relevant subset was precued — that is, attended. However, when the relevant subset is postcued, only two subsets and the superset could be enumerated with the same precision as the precued ones. This conclusion limits the generalization by Chong and Treisman (2005b) about the parallel and preattentive character of subset representation. Rather, results by Halberda et al. (2006) suggest that operating with subsets requires limited attentional or working-memory capacity that had been earlier estimated for single-item units (Alvarez & Cavanagh, 2004; Cowan, 2001; Luck & Vogel, 1997; Pylyshyn & Storm, 1988).

More recently, Poltoratski and Xu (2013) tried to determine whether the limited capacity of parallel statistical representation found by Halberda et al. (2006) is a limit of the statistical "processor" per se. It is possible that the restrictions for statistical processing are imposed by a more basic limitation such as an ability to represent subsets ensembles in parallel. First, Poltoratski and Xu (2013) replicated Halberda et al.'s (2006) finding that parallel enumeration is limited to a capacity of less than three. Then, using the same stimuli, they ran a partial report working memory test: they presented various numbers of overlapping color subsets followed after some delay by a color probe, and asked whether a subset having this color has been presented. Again, they found that fewer than three colors can be perfectly stored in memory for such stimuli. Poltoratski and Xu (2013) concluded that the ability to extract numerosity statistics from subsets is constrained by the limits of working memory for subsets. This estimate is consistent with that provided by Watson, Maylor, and Bruce (2005).

Limited Capacity and Enumeration of Objects

The limited capacity of the processing bottleneck is one of the cornerstone issues of vision theory. It is tightly associated with the "magic number problem" (Cowan, 2001): the search for the boundary condition delimitating the maximum number of structural units that can be processed and stored without loss in parallel, with numbers exceeding this maximum involving some loss in processing.

One straightforward approach to establishing the boundary conditions for the "magic number" of processing capacity familiar since early experimental psychology (Jevons, 1871) is based on using enumeration. What can enumeration behavior tell us about the representation of subsets? In the standard enumeration paradigm, observers have to report the number of distinct items, presented either briefly or until a response is given. Two modes of enumeration — subitizing and counting — are typically differentiated. *Subitizing* refers to an ability to enumerate objects effortlessly and perfectly at a brief glance. It is limited to up to four items at one time. If the accuracy of enumeration is measured, then the error will be always zero within the subitizing range, even for brief presentations. If the reaction time (RT) is measured within that range, then the slope of the set size-RT function is rather shallow (about 40–120 ms/item), indicating fast and almost parallel number representation (Mandler & Shebo, 1982; Trick & Pylyshyn, 1993) that, nonetheless, requires some attentional resources (Burr, Turi, & Anobile, 2010; Vetter, Butterworth, & Bahrami, 2008) or at least a limited-capacity preattentive process (Trick & Pylyshyn, 1994). Numbers exceeding four cannot be subitized and are subject to *counting*. Counting is slower than subitizing (about 250–350 ms/item) (Trick & Pylyshyn, 1993) because large numbers can be accurately represented only with serial shifts of attention and they require clear awareness of each individual item and its distinctiveness from other individual items (Chong & Evans, 2011; Trick & Pylyshyn, 1993). Alternatively, large numbers can be *estimated* more rapidly but somewhat approximately when items are presented briefly or are crowded during presentation. Chong and Evans (2011) suggested that slow but accurate counting and fast but approximate estimation are the different attentional strategies of representing large sets of objects. Whichever strategy is used, the presentation of large sets typically causes a substantial drop in enumeration performance (the error magnitude, the RT, or both) as compared to the presentation of small sets. Therefore, the differences between subitizing and counting yield a specific shape of the performance vs. set size function of enumeration. It consists of a flat region of easy and almost error-free performance followed by an abrupt decline of the function that indicates more difficult and error-prone enumeration. Moreover, both the error magnitude and the RT typically correlate with the number of items to be enumerated, so the function tends to become steeper after the abrupt decrement. The "break point" between the flat and the steep regions (normally about four items) is the limit of subitizing capacity.

The Present Study

We propose here that a similar logic can be applied to subset representation. If summary statistics can be extracted from at least two to three overlapping subsets without loss (Chong & Treisman, 2005b; Halberda et al., 2006; Poltoratski & Xu, 2013), then at least the same number of subsets can be subitized. Thus, the subset enumeration task can be considered to be a converging way to measure the capacity of effortless subset representation. Given a finding that spatially embedded objects cannot be subitized (Trick & Pylyshyn, 1993, Experiment 1), our claim about subitizing spatially overlapping subsets seems challenging. However, subset subitizing does not necessarily involve the same underlying mechanisms as object subitizing. Enumeration of objects requires their spatial individuation by boundaries in physical space. In contrast, individual boundaries can be discarded in the subset enumeration task as these boundaries are not informative. Once the subitizing boundary is exceeded, the enumeration task permits probing of the "fate" of subset representation beyond this boundary. Do observers see just the "colored stuff" when overlapping color subsets cannot be subitized? Or are they perhaps still able to represent the components of such "stuff" to some degree? In the former case, we can expect a decline in enumeration performance with no correlation to an actual number of subsets. In the latter case, we also expect a drop in performance but it should correlate with that number.

Watson, Maylor, and Bruce (2005) addressed some of these points. They presented their participants with variable numbers of color sets that could be spatially grouped or overlapped. The observers were asked to report the number of colors presented, and their reaction times were measured. Watson et al. (2005) found a breakpoint in reaction times resembling the subitizing-counting breakpoint for individual objects in 2- and 3-subset conditions. They also reported that the enumeration of overlapping subsets was far less efficient than that of grouped subsets both in the subitizing and counting ranges. This suggests that it is somewhat problematic for the visual system to extract a subset by mere parallel selection of a feature shared by all subset members (Treisman, 2006). Instead, Watson et al. (2005) propose that a limited-capacity mechanism related to indexing potential objects can be related to subset enumeration (Trick & Pylyshyn, 1993, 1994).

In our study we addressed some novel aspects of subset representation that have not been addressed in previous studies such as those of Watson et al. (2005) or Poltoratski and Xu (2013). First, Poltoratski and Xu (2006) as well as Halberda et al. (2006) as predecessors were focused on merely establishing a boundary condition for parallel subset representation and encoding their statistical properties. In our study, we tried to determine the "fate" of perceived subsets beyond this boundary condition, so we probed different numbers of subsets more rigorously using both speed and accuracy indices. Special focus was applied to the strategies that can mediate subset representation. Second, we investigated some issues of subset formation across the visual field. Specifically, we tested whether observers judge the presence of a particular subset based on all members in parallel or on a sort of limited-capacity strategy, such as sampling.

Our general experimental approach is based on the subset enumeration task which is similar to that used by Watson et al. (2005). Unlike standard object enumeration tasks (e.g., Halberda et al., 2006; Trick & Pylyshyn, 1993, 1994), subset enumeration considers a group of similar items (such as a group of same-color dots among different-color dots) as a unit of enumeration. It allows estimation of a somewhat "pure" ability to represent and process subsets as holistic units without paying attention to their constituents. Watson et al. (2005) used subset enumeration directly and registered the reaction time (RT) to distinguish between parallel and serial stages of subset processing. A similar ability was tested by Poltoratski and Xu (2013) using a working memory task. Their participants had to detect the presence or absence of a postcued color in a set of differently colored dots regardless of the number of dots. The authors used hit and false alarm rates to calculate the capacity of working memory that had been the end point of their measurements. Our experiments combine some aspects of both Poltoratski and Xu's paradigm (brief presentation) and Watson et al.'s paradigm (long presentation and RT measurement) for elaborative probing of the visual processing of subsets.

In all of our experiments, we presented arrays of differently colored dots and asked our observers to respond with how many colors they have just seen. We also varied the set size of the arrays, which caused corresponding changes in the number of items per subset. This manipulation was aimed at probing how subset representation is formed from individual items. We measured both the accuracy and the speed of responses to obtain a more detailed behavioral pattern and a time course of subset enumeration. In Experiment 1, we tested the general ability of observers to enumerate spatially overlapping color subsets at a brief presentation. In Experiment 2, we tested whether subset enumeration can be accomplished via a limited-capacity sampling strategy. In Experiment 3, we used the same stimulation as in Experiment 1 with the exception that observers could see the dots until responding and, thus, could inspect them thoroughly. Finally, Experiment 4 was aimed at clarifying the nature of an unusual effect discovered in Experiments 1–3, namely, facilitated enumeration of larger numbers of subsets.

Experiment 1

Experiment 1 was designed to investigate the ability to enumerate spatially overlapping color subsets. Observers were briefly presented with arrays of dots of one to six colors randomly distributed in the space. The observers had to determine how many colors had been presented. The maximum number of colors was chosen to exceed any possible visual capacity estimates (e.g., Alvarez & Cavanagh, 2004). This allowed us to probe subset representation processes both within and beyond the subitizing range. We also varied the set size of arrays that allowed us to study how the subset representation is formed from individual items. If subset information is extracted from all items at once, then subset enumeration performance should not depend or even benefit from larger numbers of items in that subset (Robitaille & Harris, 2011). Contrastively, if extracting a subset requires focusing on individual items, then performance should decrease as the set size increases. There is a third possibility that a reported number of subsets can be approximated based upon a few sample items without worsening performance. This possibility will be addressed specifically in Experiment 2.

Method

Participants. Fourteen undergraduate psychology students of the Higher School of Economics (nine female, age range between 18 and 20 years, M = 18.9, SD = .73) participated in the experiment for extra credit in their general psychology lab classes or as volunteers. All participants were naïve with respect to the goals of the experiment. All reported having normal or corrected to normal visual acuity, normal color vision and no neurological problems.

Apparatus and stimuli. Stimulation items were developed and presented through the StimMake software (authors A.N. Gusev and A.E. Kremlev). Stimuli were presented on a standard VGA-monitor with a refresh frequency of 85 Hz and spatial resolution of 800 × 600 pixels. The "working space" for displaying arrays was a 9 × 14 degree gray field in the center of the screen. The rest of the screen space was black and was not used for presentation.

Arrays of colored dots were made for the subset enumeration task. The dots were approximately .57 degrees in diameter. The total number of dots in an array could be 6, 12, or 36 (see Figure 1a). The dots were uniformly distributed over the field, with the average between-dot distance in small sets being greater than in large sets. Six colors were used for coloring the dots: black (RGB (0, 0, 0); CIE XYZ (0, 0, 0)), white (RGB (255, 255, 255); CIE XYZ (95, 100, 109)), red (RGB (255, 0, 0); CIE XYZ (41.24, 21.26, 1.93)), green (RGB (0, 255, 0); CIE XYZ (35.76, 71.52, 11.92)), blue (RGB (0, 0, 255); CIE XYZ (18.05, 7.22, 95.05)), and yellow (RGB (255, 255, 0); CIE XYZ (77, 92.78, 13.85)). One to six colors could be present in an array. All colors were equally likely to be included in the arrays. All possible color combinations were used with equal frequency. So, one combination of colors was used in the six-subset condition, six combinations were used in the one- and the five-subset conditions, 15 combinations were used in the two- and four-subset conditions, and 20 combinations were used in the three-subset condition. Colors were uniformly divided between the subsets of dots using the simple N/n fraction, where N is the total number of dots and n is the number of colors. When perfect equality was impossible (e.g., dividing four colors between six dots) a closest-to-equal proportion was used instead (e.g., 1, 1, 2, and 2 items). Dots of different colors were randomly mixed in the space in a way that prevented same-color dots from grouping by proximity (see Figure 1a). Likewise, differently colored adjacent dots were placed in a way that precluded spatial regularity as much as possible. This provided maximum spatial overlap between color subsets.

Procedure and design. Experimental sessions were conducted in a darkened room with groups of one to three participants. Observers were seated about 70 cm from a monitor. A typical trial began with a 500-ms fixation on a small black cross at the center of the screen. Immediately after fixation, a stimulus array appeared for 50 ms followed by a question mark at the center that remained on the screen until a response was provided. Participants had to decide as quickly as possible how many colors they had just seen. They were informed that the number of colors would vary from one to six per trial. Responses were entered using the numeric pad of a standard computer keyboard.

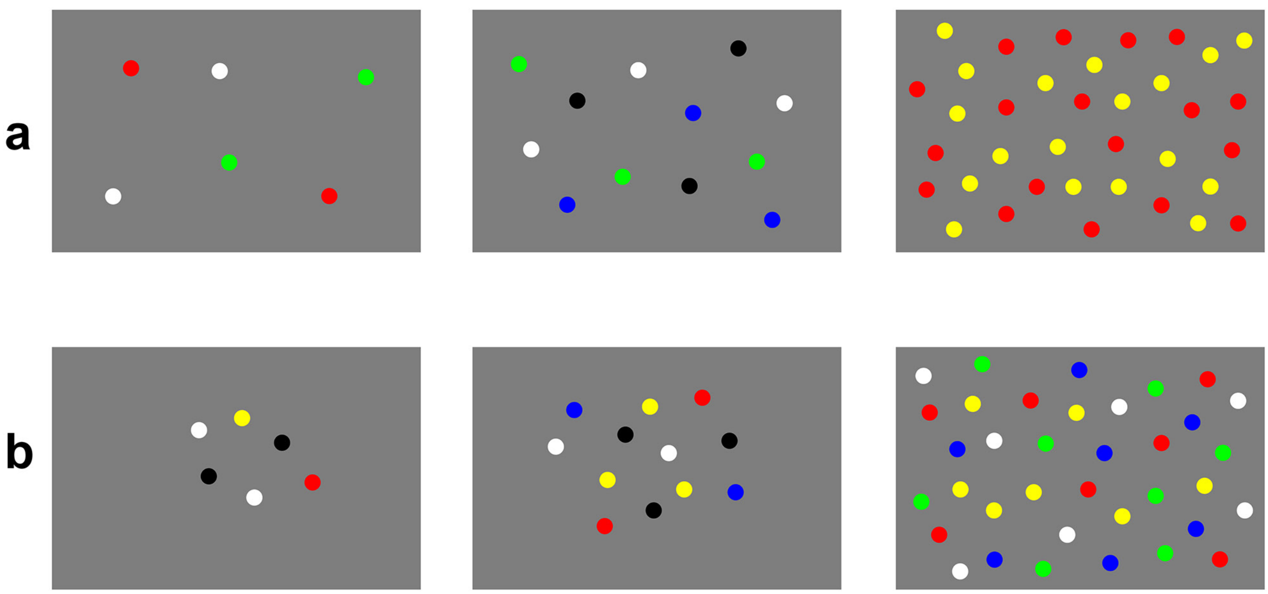

Figure 1. Examples of stimuli with set sizes of 6, 12, and 36 items used in (a) Experiment 1 and (b) Experiment 2.

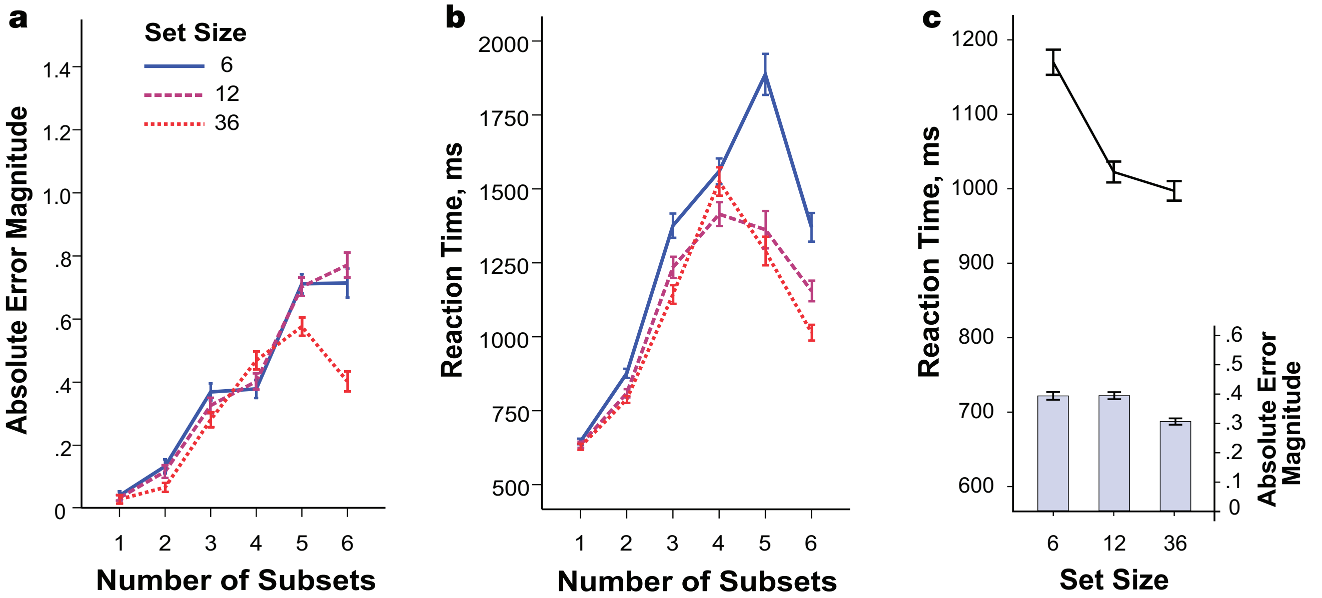

Figure 2. The results of Experiment 1: (a) – (b) the effect of Number of Subsets and Set Size on the error magnitude and the RT and (c) the effect of Set Size on the error magnitude and the RT. Error bars denote ± 1 *S.E.M.*

To obtain reliable statistics of errors and reaction times (RT), 30 trials were presented in each experimental condition. The entire experimental design included six conditions of the Number of Subsets (one to six concurrently presented colors) × three Set Sizes (6, 12, and 36 dots) × 30 trials = 540 trials per observer. Five rest breaks were given, one after every 90 trials. A training session consisting of 18 randomly chosen trials was presented prior to the main session of 540 trials. The results of the training session were excluded from analysis.

Results and Discussion

Absolute differences between the actual and estimated number of colors were computed on each trial as an error magnitude measure. Average RTs were computed only on trials with correct responses. Experimental effects were tested using a within-subjects ANOVA including the Number of Subsets and Set Size as fixed factors. To handle individual differences between observers, the model also included observers' identity as a random factor. A series of post-hoc t-tests were performed to establish pairwise differences providing overall experimental effects.

The effect of the Number of Subsets on the error magnitude was significant ($F(5, 65) = 29.05$, $p < .001$, $\eta^2_p = .69$). Differences between the pairs of neighboring conditions of the Numbers of Subsets were significant (p's $< .001$, Bonferroni corrected), demonstrating gradually increasing errors with the number of subsets (see Figure 2a). The only exception was a non-significant difference between the 5- and 6-color conditions. The effect of Set Size was also significant ($F(2, 26) = 12.51$, $p < .001$, $\eta^2_p = .49$), demonstrating the overall advantage of 36-item sets over 6-item and 12-item sets (p's $< .001$, Bonferroni corrected) (see Figure 2c). Finally, the effect of the Number of Subsets × Set Size on the error magnitude was significant ($F(10, 130) = 5.88$, $p < .001$, $\eta^2_p = .31$). Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 65) = 18.52$, $p < .001$, $\eta^2_p = .59$; set size = 12, $F(5, 65) = 33.73$, $p < .001$, $\eta^2_p = .72$; set size = 36, $F(5, 65) = 19.71$, $p < .001$, $\eta^2_p = .60$). In all set sizes, there was no difference between the 1- and 2-color conditions. In set sizes of 6 and 12, there was no difference between the 3- and 4-color conditions. Finally, there was no difference between the 5- and 6-color conditions in the set size of 12. All of the other comparisons of neighboring pairs regarding the number of colors were significant within each set size (p's $< .05$, Bonferroni corrected).

The effect of the Number of Subsets on the RT was significant ($F(5, 66) = 38.86$, $p < .001$, $\eta^2_p = .75$). All pairwise differences between neighboring conditions were significant (p's $< .001$, Bonferroni corrected), except for the difference between the 4- and 5-color conditions. As can be seen from Figure 2b, the 4-color condition is a point where the general positive trend in the RT breaks down and subsequently reverses. The effect of Set Size was significant ($F(2, 28) = 27.53$, $p < .001$, $\eta^2_p = .66$), demonstrating the advantage of 12- and 36-item sets over 6-item sets (p's $< .001$, Bonferroni corrected, Figure 2c). The effect of Number of Subsets × Set Size on the RT was also significant ($F(10, 146) = 6.59$, $p < .001$, $\eta^2_p = .31$). Within each Set Size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 67) = 39.30$, $p < .001$, $\eta^2_p = .75$; set size = 12, $F(5, 67) = 25.81$, $p < .001$, $\eta^2_p = .66$; set size = 36, $F(5, 67) = 32.10$, $p < .001$, $\eta^2_p = .71$). The effect is predominantly provided by the increasing larger set advantage as a function of the number of subsets. All of the between-neighbor pairwise comparisons regarding the number of colors were significant within each set size (p's $< .05$, Bonferroni corrected).

Three results of Experiment 1 deserve attention in light of our topic. First, we found that both the error magnitude and the RT tended to increase with the number of color subsets (except the terminal numbers; this effect will be discussed below). It appears that decisions become more difficult as the global variation of an ensemble increases. This finding has two important theoretical consequences. The first consequence is that subset representation is not free from limitations, which is consistent with the general conclusions of Halberda et al. (2006), Poltoratski and Xu (2013), and Watson et al. (2005). Our results allow us to conclude that there is a boundary condition defining those limitations. This boundary is likely to be no more than two subsets. This result differs from the estimate for object subitizing (e.g., Mandler & Shebo, 1982; Trick & Pylyshyn, 1993, 1994). However, it seems to be in line with other estimates for parallel subset representation (Poltoratski & Xu, 2013; Watson et al., 2005). We found that the error magnitude in the 2-subset condition is only slightly different than that in the 1-subset condition (see Figure 2a). At the same time, a more dramatic increment in the error magnitude is found between the 2- and 3-subset conditions. In theory, this incremental difference may indicate a transition from easy and near perfect enumeration (subitizing) to a more difficult and error-prone method (counting or estimation). The second criterion of subitizing is a rather flat (40–120 ms/item) RT function (Mandler & Shebo, 1982; Trick & Pylyshyn, 1993, 1994). The criterion of the boundary condition between subitizing and counting is an abrupt change in the slope of the RT function, which becomes steeper. In our experiment, the initial slope of the function (187 ms/subset) between the 1- and 2-subset conditions is larger than that required for conforming to the standard subitizing criterion although slightly smaller than that for counting (250–350 ms/item). However, there is also a remarkable slope increment observed between the 2- and 3-subset conditions (424 ms/subset). The slope ratio between the regions is, therefore, about 2.3. This ratio is substantial but a bit lower than that reported in the standard object enumeration paradigm (~2.9–8.3) (Trick & Pylyshyn, 1993). We suppose that in our experiment the ratio could be deflated because of the brief presentation duration. This possibly prevents our observers from reliably counting, which takes a lot of time per unit. As observers did not have that time because of the brief presentation, they probably relied on more rapid and imprecise judgments. In Experiment 3, we retest the slope ratio between the 1–2 and 2–3 subset regions with an unlimited duration of presentation.

In summary, so far our 2-subset estimate of the boundary condition of subset subitizing is in many ways preliminary. This preliminary approximation will be retested in further experiments.

The second consequence of our finding is that subsets are somehow represented beyond the subitizing range. This conclusion is based on systematic changes that occur in both the error magnitude and RT with the number of subsets. Otherwise, enumeration performance would have looked like random guessing with no difference between conditions. Note that the average error magnitude did not exceed .7 even in the most difficult conditions (see Figure 2a), and the analysis of frequencies showed that observers rarely underestimated or overestimated the number of subsets by more than one or two. Some additional data about the “fate” of subset representation beyond the subitizing boundary will be reported in Experiments 3 and 4. Another finding that looks unusual is the striking acceleration of enumeration at the terminal points of the RT function, accompanied by the relative stabilization of the error magnitude. Moreover, the points where the reversal of the function takes place varies for different set sizes (see Figure 2a and 2b). In larger sets the advantage of terminal positions starts with the 5-subset condition, while in small sets it is found only in the 6-subset condition. Given the incremental character of the function at the previous positions, this reversal pattern is discouraging and needs careful replication and explanation. The replication of the effect will be reported in Experiments 2 and 3 using independent groups of observers. In Experiment 4, we will address two possible mechanisms underlying this pattern.

The third important finding from Experiment 1 is the systematic advantage of larger sets over small ones. It appears that subset representation somehow benefits from increasing the number of items in that subset (which was proportional to the set size in Experiment 1). This conclusion is not surprising given growing experimental evidence that ensemble summary statistics also benefit from larger sets (Chong, Joo, Emmanouil, & Treisman, 2008, Experiment 2; Robitaille & Harris, 2011). A more important conclusion from this result is that the visual system does not need to serially inspect all subset members to collect a subset representation, despite their spatial separation by other items. However, this result of Experiment 1 does not necessarily imply a parallel mode of subset formation. The point is that the same pattern of results can be provided by two completely different mechanisms: *exhaustive processing* of all 1-color items at one time vs. *limited-capacity sampling*. These two hypothetical mechanisms will be explained in detail and dissociated in Experiment 2.

Experiment 2

As was mentioned above, two hypotheses can be considered about the mechanisms providing the larger subset advantage observed in Experiment 1. The first hypothetical mechanism implies that all subset members are being processed in a parallel and cumulative manner, which somehow collects evidence from individual items and eventually improves their representation as a whole subset. The second hypothetical mechanism explains the pattern without reference to a parallel process. The advantage can theoretically be achieved by selectively focusing attention on a few dots, or *sampling* (Myczek & Simons, 2008). Consider a typical display in Experiment 1 (see Figure 1a). How many dots should one inspect to reliably judge the number of colors in the entire set? The rules of array composition (see Apparatus and Stimuli) allowed such a judgment based upon a randomly chosen group of about six adjacent dots. In statistical terms, any random sample of six neighboring items was representative of the color distribution among all items presented. A very plausible strategy in this case is inspecting a sample of six items closest to the fovea where color vision is the best. In large sets, the sample occurs in close proximity to the center of fixation due to the high density of dots. In contrast, the sample items in small sets are farther from that center, yielding poorer discrimination and involving additional costs in moving spatial attention (Tsal, 1983).

To clarify whether subset formation is being carried out over all items in parallel or by focusing attention on a sample of foveal items, we made all visual sets equal in density and centered them around the fixation point (which made sets subtending different total areas in the visual field). On the one hand, if a foveal sampling strategy is involved this manipulation would eliminate

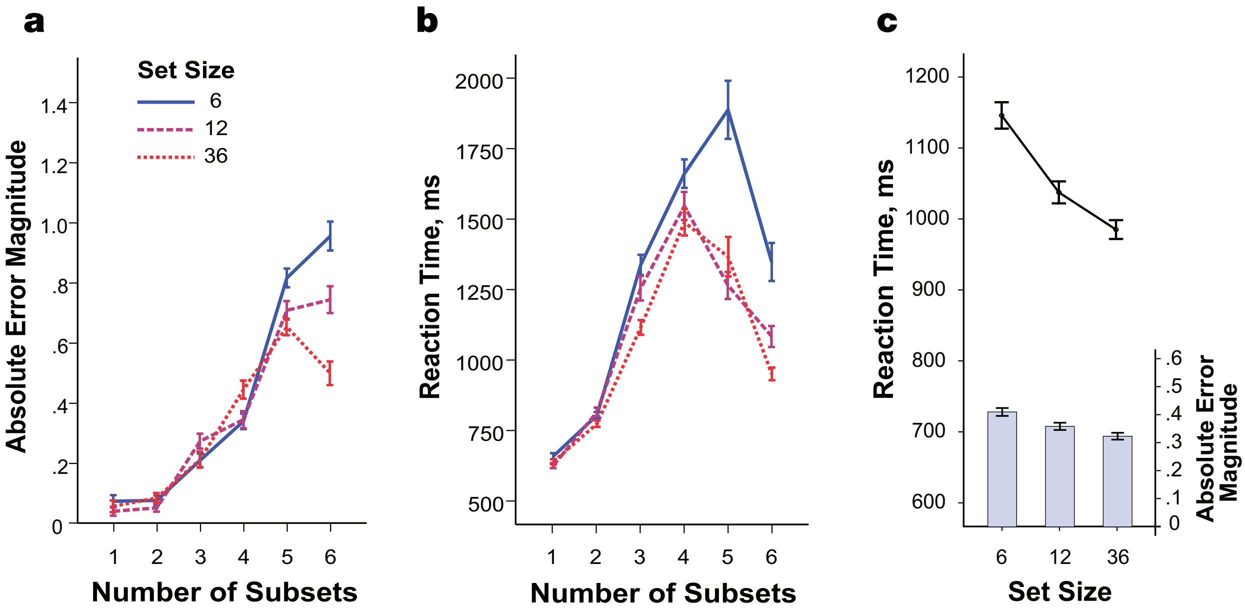

Figure 3. The results of Experiment 2: (a) – (b) the effect of Number of Subsets and Set Size on the error magnitude and the RT and (c) the effect of Set Size on the error magnitude and the RT. Error bars denote ± 1 *S.E.M.*

the large set advantage. Enumeration would be even more precise in the small 6-item sets, as they are complete representative samples of themselves, while in large sets the representativeness of a small sample varies from trial to trial. So, we can expect better performance with small sets if observers indeed rely on the foveal sampling strategy. On the other hand, if all items contribute to the formation of a subset representation then density manipulation would have no effect on that advantage.

Method

Participants. Thirteen undergraduate students and professors of the Higher School of Economics (six female, age range between 18 and 37 years, M = 20.3, SD = 5.03) participated in the experiment for extra credit in their general psychology lab classes or as volunteers. All participants were naïve about the goals of the experiment. All reported having normal or corrected to normal visual acuity, normal color vision and no neurological problems. None had participated in Experiment 1.

Apparatus and stimuli. The apparatus was identical to that used in Experiment 1. Stimuli were very similar to those used in Experiment 1; the only exception concerned the spatial arrangement of dots in the arrays. In all sets, the average distance between dots was about 1.6 degrees (the same value was used in Experiment 1 for the sets with 36 dots), providing approximately constant density for all set sizes. Therefore, a visual angle occupied by a set of dots grew proportionally to the set size. All sets were located around the center of the screen in a way that the average spatial position of the dots was always at the fixation point.

Procedure and design. The procedure and design were identical to those used in Experiment 1.

Results and Discussion

The results of Experiment 2 are summarized in Figure 3. The methods used to compute the error magnitude and the RT, as well as the statistical procedures, were the same as in Experiment 1.

The effect of the Number of Subsets on the error magnitude was significant (F(5, 55) = 24.98, p < .001, η^2_p = .69). The difference between the 1- and 2-color conditions was non-significant. The difference between the 5- and 6-color conditions was also non-significant, replicating the finding from Experiment 1. All other between-neighbor pairwise differences along the number of subsets were significant (p's < .001, Bonferroni corrected), demonstrating that errors gradually increased with the number of subsets (see Figure 3a). The effect of the Set Size was nearly significant (F(2, 22) = 3.33, p = .055, η^2_p = .23). However, the pairwise difference between the 6-item sets and two other conditions was significant (p = .001, Bonferroni corrected), demonstrating the relative advantage of larger sets (see Figure 3c). The effect of the Number of Subsets × Set Size on the error magnitude was also significant (F(10, 110) = 4.13, p < .001, η^2_p = .27). Within each set size, the effect of the Number of Subsets was significant (set size = 6, F(5, 55) = 28.47, p < .001, η^2_p = .72; set size = 12, F(5, 55) = 17.95, p < .001, η^2_p = .62; set size = 36, F(5, 55) = 10.23, p < .001, η^2_p = .48). In all set sizes, there was no difference between the 1- and 2-color conditions. In set sizes of 12 and 36, there was no difference between the 5- and 6-color conditions. Finally, there was no difference between the 3- and 4-color conditions in the set size of 12. The rest of the comparisons of neighboring pairs regarding the number of colors were significant within each set size (p's < .05, Bonferroni corrected).

The effect of the Number of Subsets on the RT was significant (F(5, 56) = 25.75, p < .001, η^2_p = .70). All pairwise differences were significant (p's < .001, Bonferroni corrected) except the difference between the 4- and 5-color conditions. As can be seen in Figure 3b, the reversal of the RT vs. Number of Subsets function starts at the 4-color condition, similar to what was found in Experiment 1. The effect of the Set Size was also significant (F(2, 28) = 27.53, p < .001, η^2_p = .66), with all pairwise differences being significant (p's ≤ .01). As can be seen in Figure 3b, the RT tended to decrease as the set size increased. The effect of the Number of Subsets × Set Size on the RT was also significant ($F(10, 146) = 6.59$, $p < .001$, $\eta^2_p = .31$). This effect is predominantly provided by the increasing larger set advantage as a function of the number of subsets. Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 55) = 20.19$, $p < .001$, $\eta^2_p = .65$; set size = 12, $F(5, 55) = 23.87$, $p < .001$, $\eta^2_p = .68$; set size = 36, $F(5, 55) = 22.13$, $p < .001$, $\eta^2_p = .67$). All comparisons of neighboring pairs regarding the number of colors were significant within each set size (p's < .05, Bonferroni corrected).

As can be seen from the results, our density manipulation had a very limited effect on performance as compared to Experiment 1. Indeed, we found a local reduction in the advantage of larger over smaller sets in the error magnitude. This could be partially explained by improved color processing at the fovea. However, the effect appears insufficient for accepting the foveal sampling hypothesis. If observers perfectly attended to only a few sample items around the center, they probably would have been able to filter out the rest of the items and our density manipulation would have eliminated any large set advantages. Moreover, we expected even more accurate enumeration in small sets due to their greater representativeness. In contrast to this expectation, the general trend remained the same as in Experiment 1, suggesting that foveal sampling is an implausible strategy for subset enumeration. In addition, the large set advantage was kept in the RT domain as well. It appears, consequently, that all items are processed in parallel across the entire visual field to provide a cumulative, redundant effect on subset representation. Our results here are similar to those reported by Chong et al. (2008, Experiment 2), who found that the reliability of ensemble representation benefits from larger numbers of items independently of their spatial arrangement. Other findings reporting a facilitating effect of large sets in averaging tasks (Chong et al., 2008; Robitaille & Harris, 2011) support numerosity as a strong factor providing the quality of ensemble encoding.

What did Experiment 2 add to our estimate of subset subitizing capacity made in Experiment 1? Primarily, the experiment confirmed the stated boundary of about two subsets in an independent population of observers, which is in line with Poltoratski and Xu's (2013) and Watson et al.'s (2005) reports. As can be seen in the plot in Figure 3a, two subsets are enumerated as accurately as one subset but the error magnitude gradually increases in the other conditions (except the 6-subset condition). The pattern corresponds in general to the subitizing-counting pattern. This boundary is supported by the RT data, which show a substantial break in slopes between the 2- and 3-subset conditions (156 ms/subset for the 1–2 subsets region and 452 ms/subset for the 2–3 subsets region). Therefore, the slope ratio between the regions is about 2.9, close to the minimum difference sufficient to distinguish between subitizing and counting. In Experiment 3, additional evidence will be provided that a substantial break in the RT occurs between the 2- and 3-subset conditions.

Finally, the unusual RT reversal pattern observed in Experiment 1 was completely replicated in Experiment 2, which demonstrates the robustness of that pattern. In Experiment 4, this pattern will be considered in detail.

Experiment 3

In Experiment 3, we used an unlimited duration of stimuli presentation (Watson et al., 2005) instead of the brief duration allowed in Experiments 1 and 2. This manipulation had two goals. First, we sought to prove that the results of Experiments 1 and 2 were not due to a lack of encoding time. Specifically, we asked whether the "subitizible" number of subsets can be more than two when encoding time is unlimited. The brief presentation of stimuli in Experiments 1 and 2 required observers to enumerate subsets approximately, using an estimation strategy as termed by Chong and Evans (2011). In contrast, unlimited presentation time allows observers to enumerate subsets more thoroughly, slowly and precisely, using a true counting strategy. What should remain insensitive to duration manipulation is subitizing. We expect, therefore, that both the error magnitude and the RT should not differ substantially within the subitizing range as compared to those observed in Experiments 1 and 2. In contrast, more drastic changes are expected beyond the boundary condition of subitizing. Specifically, we expect an overall decrement in the error magnitude and an increment in the RT as compared to Experiments 1 and 2, since the true counting strategy is now available. This relative change along with the "break point" described above may eventually provide the reliable value of the boundary condition. Furthermore, the principal availability of the counting strategy is expected to make the time course of subset enumeration more pronounced.

Method

Participants. Fifteen undergraduate students and professors of the Higher School of Economics (seven female, age range between 18 and 45 years, $M = 23.6$, $SD = 8.67$) participated in the experiment for extra credit in their general psychology lab classes or as volunteers. All participants were unaware of the goals of the experiment. All reported having normal or corrected to normal visual acuity, normal color vision and no neurological problems. None had participated in Experiments 1 or 2.

Apparatus and stimuli. Apparatus and stimuli were identical to those used in Experiment 1.

Procedure and design. The procedure and design were similar to those used in Experiment 1. The only exception was that the duration of display presentation was prolonged as compared to the former experiment. Stimulus sets remained on the screen until a response or for 7,000 ms if no response followed. The design was the same as in two previous experiments.

Results and Discussion

The results of Experiment 3 are summarized in Figure 4. The methods used to compute the error magnitude and the RT were the same as in Experiment 1, as were the statistical procedures.

The effect of the Number of Subsets on the absolute error was significant ($F(5, 65) = 24.82$, $p < .001$, $\eta^2_p = .65$). The pairwise differences between the 1- and 2-color conditions and between the 5- and 6-color conditions were non-significant, replicating the finding from Experiment 2. All other pairwise differences between the numbers of subsets were significant (p's < .001, Bonferroni corrected)

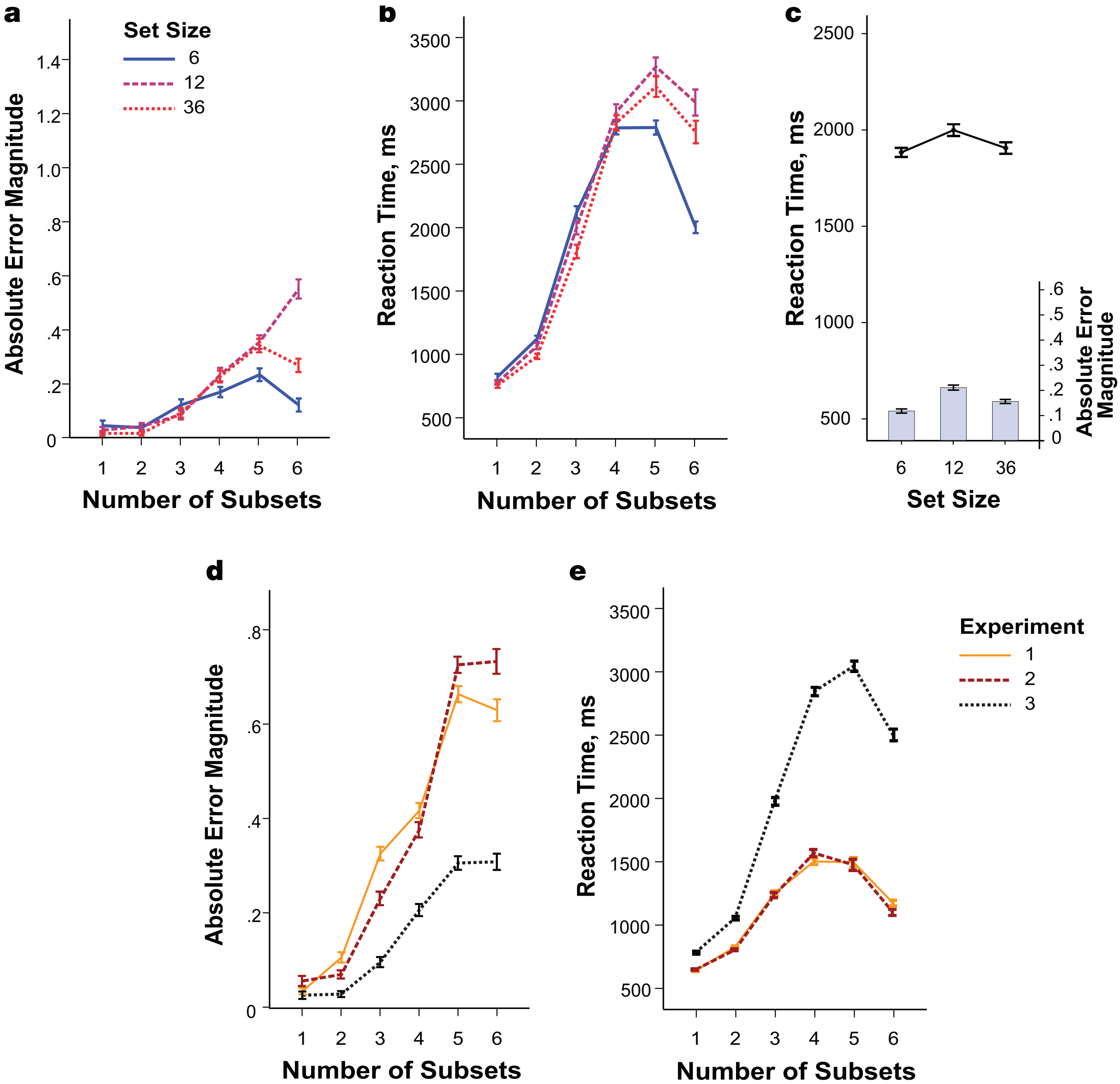

Figure 4. The results of Experiment 3: (a) – (b) the effect of Number of Subsets and Set Size on the error magnitude and the RT and (c) the effect of Set Size on the error magnitude and the RT; and cross-experimental comparison (Experiments 1–3) of Number of Subsets effects on (d) the error magnitude and (e) the RT. Error bars denote ± 1 *S.E.M.*

demonstrating gradually increasing errors with the number of subsets (see Figure 4a). The effect of the Set Size was also significant ($F(2, 26) = 10.56$, $p < .001$, $\eta^2_p = .45$), with all pairwise differences being significant (p's < .01, Bonferroni corrected). In contrast to Experiments 1 and 2, the error magnitude changed non-monotonically with the set size, as depicted in Figure 4c. The non-monotonic character of this effect can perhaps be explained by a complex Number of Subsets × Set Size interaction ($F(10, 130) = 11.38$, $p < .001$, $\eta^2_p = .47$) indicating some range-specificity of set size effects. Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 65) = 10.67$, $p < .001$, $\eta^2_p = .45$; set size = 12, $F(5, 65) = 22.13$, $p < .001$, $\eta^2_p = .63$; set size = 36, $F(5, 65) = 18.34$, $p < .001$, $\eta^2_p = .59$). In all set sizes, there was no difference between 1- and 2-color conditions. In the set size of 6, there was no difference between 3- and 4-color conditions, nor was there a difference between 4- and 5-color conditions. In the set size of 12, there was also no difference between 2- and 3-color conditions. Finally, there was no difference between 5- and 6-color conditions in the set size of 36. All of the other comparisons of neighboring pairs regarding the number of colors were significant within each set size (p's < .05, Bonferroni corrected).

The effect of the Number of Subsets on the RT was significant ($F(5, 65) = 97.37$, $p < .001$, $\eta^2_p = .88$), as shown by significant pairwise differences between all conditions (p's < .001, Bonferroni corrected). As can be seen in Figure 4b, the shape of the function basically replicates those from Experiments 1 and 2. The effect of the Set Size was also significant ($F(2, 26) = 15.83$, $p < .001$, $\eta^2_p = .53$) demonstrating the advantage of 6-item and 36-item sets over 12-item sets (p's < .05, Bonferroni corrected). Again, the effect is non-monotonic (see Figure 4c), as was found in the error domain. We propose that it can be explained by a more complex Number of Subsets × Set Size interaction

($F(10, 130) = 13.37, p < .001, \eta^2_p = .51$). As in the previous case, the interaction is provided by the range specificity of set-size advantages. For the “low” range (one to three subsets), post-hoc tests revealed the advantage of 36-item sets over smaller ones. Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 65) = 90.68$, $p < .001$, $\eta^2_p = .87$; set size = 12, $F(5, 65) = 85.54$, $p < .001$, $\eta^2_p = .87$; set size = 36, $F(5, 65) = 55.15$, p’s $< .001$, $\eta^2_p = .80$). All between-neighbor differences were significant in all set sizes (p’s $< .05$, Bonferroni corrected) except for the difference between 4- and 5-color conditions in the set size of 6, and between 5- and 6- color conditions in set sizes of 12 and 36.

One of the main goals of Experiment 3 was to compare two duration conditions — brief vs. unlimited presentation — that are likely to induce different prevailing enumeration strategies, namely estimation and counting (Chong & Evans, 2011). We supposed that a substantial strategic effect on performance would be found for those subsets that cannot be subitized. In Figures 4d and 4e, we plotted enumeration functions from Experiments 1–3 that were averaged across set sizes. As can be seen from the plots, both the error (Figure 4d) and the RT (Figure 4e) functions have rather similar shapes in all experiments, indicating the robustness of subset enumeration behavior regardless of spatiotemporal conditions such as density (Experiment 1 vs. 2) or duration (Experiment 1 vs. 3). However, the slopes of the functions differ between Experiments 1 and 2 versus Experiment 3. We suggest that these differences reflect the predominant use of the two different strategies mentioned above. Specifically, in Experiment 3 observers could rely on true counting that yielded a simultaneous decrement in the error magnitude per subset and an increment in the RT per subset.

However, the dramatic change in slopes did not take place along entire functions. The regions between the 1- and 2-subset conditions maintain almost the same slopes as in Experiments 1 and 2. For the error magnitude, this region is flat, so two subsets were likely to be enumerated as precisely as one subset. For the RT, the slope of this region is 272 ms/subset. It is about 1.6 times as steep as the average slope found in Experiments 1 and 2 within the same region. This can be partially explained by the general tendency to respond slower when provided an unlimited duration of presentation, which is consistent with other ensemble representation data (Robitaille & Harris, 2011). Moreover, the 1.6-time difference is smaller than that required for being ascribed to critically different modes of enumeration (Trick & Pylyshyn, 1993). Besides, the ratio was even smaller than those found between the 2- and 3-subset conditions of Experiments 1 and 2. We conclude, therefore, that both the error magnitude and the RT functions reflect a rather rapid and efficient process of subitizing.

A more dramatic difference between Experiments 1 and 2 versus Experiment 3 appears at the 3-subset condition. This is well depicted in Figures 4d and 4e, where a small between-function gap at the beginning is followed by a progressively increasing gap after the 2-subset condition. As was mentioned above, we argue that the latter gap is explained by the difference between the estimation and counting strategies (Chong & Evans, 2011) acting beyond the subitizing boundary. We consider this gap to be additional evidence that no more than two spatially overlapping subsets can be effortlessly represented and enumerated at a time.

The results of Experiment 3 also provide several important observations about subset representation beyond the boundary condition of subitizing. First, our RT data show that observers were likely to count subsets. This claim is supported by the steep slope of the RT function at the 2–3 subset region (955 ms/subset, about 3.5 times as steep as at the “subitizable” 1–2 subset region), followed by a very steep increment in subsequent conditions (except the 6-subset condition). This shows that slow serial selection is likely to be required for perceiving and enumerating each additional subset. Second, we found that subset enumeration is more difficult than object enumeration, even with a longer duration of presentation. When we count individual items one by one, our accuracy is normally close to perfect. In contrast, Experiment 3 showed that even if one has an opportunity to count color subsets, accuracy diminishes gradually with the number of subsets. There are several possible explanations for this pattern. On the one hand, the increasing variety of colors may cause difficulties with segregation of one subset from the others. However, experimental data show that a relevant subset can be easily segregated from the multicolor environment and represented in statistical terms if that subset is properly attended to (Halberda et al., 2006). As counting requires focusing attention on each enumerated unit (Chong & Evans, 2011), we rule out this explanation based on poor subset segregation. On the other hand, during slow and serial counting observers might sometimes forget which subsets have already been counted and which have not. Obviously, the number of subsets to count increases with the total number of subsets, and so does the number of subsets that can be forgotten as counting progresses. This can explain the incremental character of the error function in Experiment 3. Certainly, this explanation is speculative and needs careful testing in future research.

An interesting observation was made about the effect of the set size on enumeration performance, and it can also be related to the error-proneness of subset counting. For the “low” range of subset numbers, the pattern replicated the large sets’ advantage from Experiments 1 and 2, indicating that a subset representation is formed upon all subset members in parallel. Taken together, these patterns indicate that subset formation is independent of spatial (Experiments 1 vs. 2) and temporal (Experiments 1 vs. 3) conditions. However, for the “high” range of subset numbers, the pattern changes in favor of small sets. The advantage of small over large sets is well known from the literature on visual search, and is often explained by focused attention that shifts serially from one occupied location to another (Treisman & Gelade, 1980). We suppose that our participants were able to use a sort of focused attention strategy at the “high” range. In other words, they could perform color enumeration of individual items instead of (or maybe along with) counting subsets as wholes. Although a color subset can be easily individuated as a whole from a multicolored ensemble at a brief glance (Halberda et al., 2006), this does not mean that observers did not pay attention to individual items when the presentation time was unlimited. During brief stimulus presentations (such as in Experiments 1 and 2), enumeration is likely to be accomplished only with coarsely distributed attention as it spreads to all items momentarily. Of course, decisions can be rather intuitive and imprecise under distributed attention, but it aids the encoding of global ensemble features (Chong & Treisman, 2005a; Treisman, 2006) which, in turn, would benefit from larger set sizes (Chong et al., 2008; Robitaille & Harris, 2011). That is exactly what was observed in Experiments 1 and 2. In contrast, focused attention is more available during longer stimulus presentations due to its slow serial deployment. It yields more confident, precise, and somewhat rational decisions but impairs global feature encoding (Chong & Treisman, 2005a) and grants an advantage of small sets over large ones. That was the case in Experiment 3.

Finally, the reversal pattern of performance in the terminal subset numbers was replicated again with the independent group of observers and modified conditions in Experiment 3. This led us to conclude that the pattern is more than an occasional feature of particular observers or specific stimulus conditions. Experiment 4 addresses the nature of this pattern.

Experiment 4

Two possible explanations for the reversal enumeration pattern were suggested in the discussion of Experiment 1, and will now be considered in detail. First, we presumed that observers could rely on a "full set" memory template when distinguishing between the large numbers of subsets. The benefit of templates of this kind can be explained using inverted U-shaped functions as shown in Figure 5. The functions relate the number of particular color combinations to the total number of possible colors. Given the limited color possibilities in Experiments 1–3, the lowest number of combinations is achieved in the 6-subset condition (see Figure 5, dotted line). That is the only possible combination that includes the entire range of colors. It can be easily stored as a template for representing a gist. When a large number of colors are presented at once, it is obviously easier to compare a display with the template than to count colors one by one.

However, there is a second and more mundane explanation for the observed pattern in terms of the "ceiling effect". This is based on a simple bias toward terminal response categories, such as the 6-color response. While seeing large numbers of colors, observers may choose the 6-color category more readily because it has no neighboring categories from the upper side, while other responses do. For instance, when four or five colors are presented, the nearest uncertainty zone incorporates two additional alternatives: above and below the correct response. In the 6-color condition, the nearest uncertainty zone incorporates only one alternative, which can impose an easier decision. The inevitable consequence of such organization of the response choices is a more accurate and fast response (since decisions are predominantly distributed around two instead of three adjacent categories). The same strategy can apply to the 1-color condition as well (the "floor effect"), but near perfect performance makes it almost useless. Note that this ceiling strategy nevertheless implies that some discrimination between subsets does in fact exist in the 4- to 6-color range, for otherwise observers would respond randomly in all conditions and no bias could be observed.

Experiment 4 was designed to properly address the two possible explanations suggested above. In this experiment, we extended the range of colors but kept the same restrictions for the response system. So, observers could see up to six colors in any given trial but the colors could be randomly taken out from the set of seven colors, providing much more particular combinations (see Figure 5, solid line). To explain this manipulation, consider the 6-color condition which is most critical for the experiment. There is only one way to take out six colors of six but there are seven ways to take out six colors of seven. It is easy to store and consistently use a single "full set" template (as was the case in Experiments 1–3) but it is less useful (if not impossible) to store and use seven templates. If the hypothesis of the "full set" template is correct, then using the 7-color set with six response categories would eliminate or at least reduce the reversal pattern found in Experiments 1–3. On the other hand, if the reversal pattern can be explained by the mere "ceiling effect" then our manipulation will keep it intact as the categorical system of responses is the same as before.

Methods

Participants. Fifteen undergraduate students of the Higher School of Economics (nine female, age range between 17 and 24 years, M = 17.4, SD = .63) participated in the experiment for extra credit in their general psychology lab classes or as volunteers. All participants were unaware of the goals of the experiment. All reported having normal or corrected to normal visual acuity, normal color vision and no neurological problems. None had participated in Experiments 1–3.

Apparatus and stimuli. Apparatus and stimuli were basically identical with those used in Experiment 1. The only addition was made to the stimulus options; namely, magenta color (RGB (255, 255, 0); CIE XYZ (59.29, 28.48, 96.98)) was used along with the six colors from Experiments 1–3. That caused the increment in the number of possible color combinations as Figure 5 depicts (dotted line).

Procedure and design. In order to uniformly distribute all possible combinations of seven colors across presentations, we exposed our participants to 35 trials per condition instead of 30. Therefore, the entire experimental design included six Numbers of Subsets × three Set Sizes (6, 12, and 36 dots) × 35 trials = 630 trials per observer. Five rest breaks were made, one after every 105 trials. The rest of the procedural details were the same as in Experiment 1.

Results and Discussion

The results of Experiment 4 are summarized in Figure 6. The methods used to compute the error magnitude and the RT, as well the statistical procedures, were the same as in Experiment 1.

The effect of the Number of Subsets on the error magnitude was significant (F(5, 70) = 85.70, p < .001, η^2_p = .86). The difference between the 1- and 2-color conditions was non-significant. All other pairwise differences between the numbers of subsets were significant

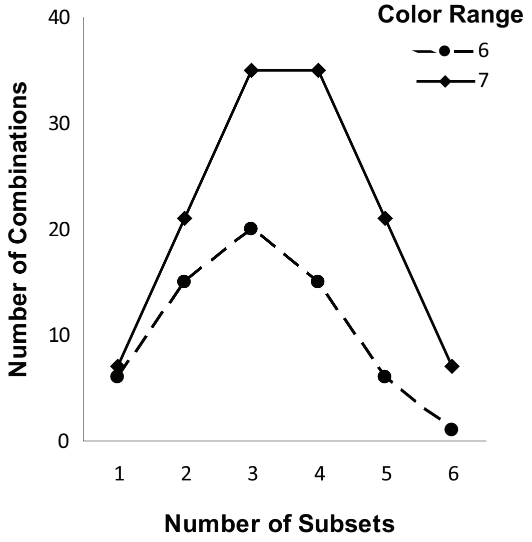

Figure 5. The number of possible color combinations as a function of the number of presented color subsets and the total range of colors. In the six-color range (as used in Experiments 1–3, dotted line) there is only one possible combination that presumably can be stored as a single “full set” memory template (given that the full set includes six colors). The seven-color range (as used in Experiment 4, solid line) generates seven “full set” templates that are harder to store and use for enumeration of large numbers of subsets.

(*p*'s < .001, Bonferroni corrected), including the difference between the 5- and 6-color conditions. Therefore, the error magnitude was monotonically increasing after the 2-color boundary, and no stabilization was observed at the terminal points (see Figure 6a). The effect of the Set Size was also significant ($F(2, 28) = 9.40$, $p = .001$, $\eta^2_p = .40$). It was shown by the advantage of 36-item sets over 6- and 12-item conditions (*p*'s < .001, Bonferroni corrected, see Figure 6c). The effect of the Number of Subsets × Set Size on the error magnitude was significant ($F(10, 140) = 7.48$, $p < .001$, $\eta^2_p = .35$). Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 70) = 54.53$, $p < .001$, $\eta^2_p = .80$; set size = 12, $F(5, 70) = 87.29$, $p < .001$, $\eta^2_p = .86$; set size = 36, $F(5, 70) = 46.48$, $p < .001$, $\eta^2_p = .77$). In all set sizes, there was no difference between the 1- and 2-color conditions. All of the other comparisons of neighboring pairs regarding the number of colors were significant within each set size (*p*'s < .05, Bonferroni corrected).

The effect of the Number of Subsets on the RT was significant ($F(5, 70) = 48.87$, $p < .001$, $\eta^2_p = .76$). All between-neighbor pairwise differences were significant (*p*'s < .01, Bonferroni corrected), except for the 5- and 6-color conditions. As can be seen in Figure 6b, the reversal RT vs. Number of Subsets function, similar to that found in Experiment 1, starts at the 4-color condition. The effect of the Set Size was also significant ($F(2, 28) = 27.53$, $p < .001$, $\eta^2_p = .66$), demonstrating the advantage of the 12- and 36-items sets over the 6-items sets (*p*'s < .001, Bonferroni corrected, see Figure 6c). The effect of the Number of Subsets × Set Size on the RT was significant ($F(10, 146) = 6.59$, $p < .001$, $\eta^2_p = .31$). This effect is predominantly demonstrated by the increasing larger set advantage as a function of the number of subsets. Within each set size, the effect of the Number of Subsets was significant (set size = 6, $F(5, 72) = 60.00$, $p < .001$, $\eta^2_p = .81$; set size = 12, $F(5, 72) = 28.95$, $p < .001$, $\eta^2_p = .67$; set size = 36, $F(5, 72) = 31.74$, $p < .001$, $\eta^2_p = .69$).

These results show that the additional member in the range of possible subset-constituting colors in Experiment 4 had a substantial effect on enumeration accuracy at terminal points, as compared to the previous experiments. Critically, the growth in the error magnitude was maintained between the 5- and 6-subset conditions, while all of the previous experiments showed no such growth. This result is inconsistent with the mere “ceiling effect” caused by the restriction of response categories. Rather, it is consistent with the prediction derived from the hypothesis of the “full set” template in working memory. On the other hand, our RT data replicated the reversal pattern from the previous experiments, and this result is consistent with the “ceiling effect” rather than the “full set” template hypothesis. We conclude, therefore, that stabilization of the error magnitude and the reversal of the RT at terminal points are likely to reflect two different mechanisms. On the one hand, the observers enumerate the large numbers of subsets with more or less accuracy depending on the utility of a template. On the other hand, they appear to make terminal responses faster regardless of the accuracy that can be due to the “ceiling effect”.

Except the effect of the additional color on the error magnitude, all of the other results replicated those observed earlier. Again, we found that no more than two subsets can be enumerated as accurately as one subset. The break in the RT functions was also found at the boundary condition of two subsets. This is provided by the substantial difference between the slopes at the 1–2 and 2–3 regions (138 ms/subset and 391 ms/subset, respectively, which resulted in a ratio of about 2.8). Consistent replication of these two basic results in all experiments indicates the robustness of the pattern and supports our estimate of the boundary condition of subset subitizing. Together with previous data from other researchers (Halberda et al., 2006; Poltoratski & Xu, 2013), our results provide converging evidence that no more than two spatially overlapping subsets can be represented at one time by the human visual system. Finally, in Experiment 4, we also replicated the advantage of large sets over small ones previously found in Experiments 1 and 2. This replication indicates the robustness of this pattern under brief presentation, which was a common condition for those experiments.

General Discussion

Subset Representation within and beyond the Subitizing Range

Applying the standard criteria for distinguishing between subitizing and the counting of individual objects (Trick & Pylyshyn, 1993, 1994), we discovered that similar processes are likely to operate in our subset enumeration task. Specifically, we found a region of almost error-free performance that was accompanied by a rather flat slope of the RT function, which can be recognized as subset subitizing. The boundary condition of this subset subitizing — no more than two — was highly consistent across experiments.

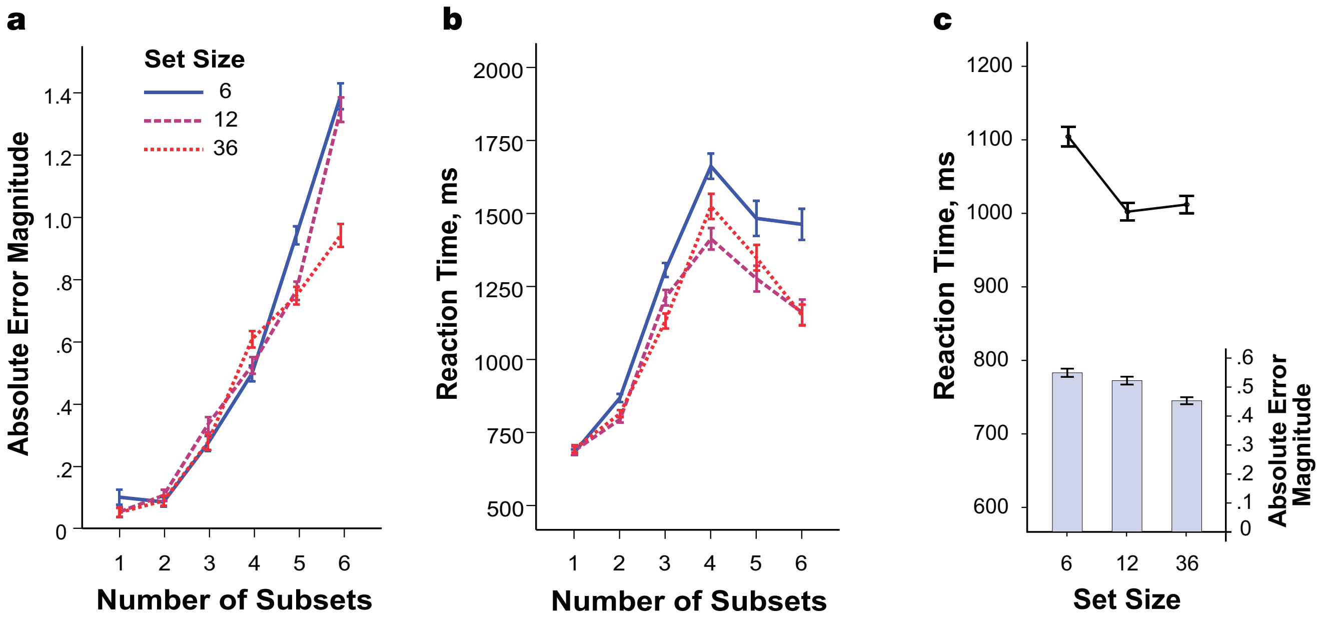

Figure 6. The results of Experiment 4: (a)–(b) the effect of Number of Subsets and Set Size on the error magnitude and the RT and (c) the effect of Set Size on the error magnitude and the RT. Error bars denote ± 1 *S.E.M.*

It is important to note that our estimate is also consistent with that reported by other authors who investigated the limit of parallel object enumeration (Halberda et al., 2006; Poltoratski & Xu, 2013; Watson et al., 2005). Taken together, the results from different paradigms provide converging evidence in favor of a two-unit capacity of the parallel representation of spatially overlapping subsets.

Immediately after the boundary condition of subset subitizing, a substantial break in performance was observed. A very important finding is that both the error magnitude and the RT changed systematically, not by chance, with the number of subsets. We conclude, therefore, that the observers indeed discriminated between different numbers of subsets beyond the subitizing range, despite the failure of representing those subsets in parallel.

A more detailed analysis of the error and RT patterns sheds light on the processes providing the representation of subsets beyond the boundary condition of subitizing. Our data show that observers were able to rely on a set of enumeration strategies such as rapid but approximate estimation and slower but more accurate counting (Chong & Evans, 2011). However, in our case it is hardly possible to say that observers used either of these pure strategies. We conclude this because both the error magnitude and the RT increased quite concordantly in all experiments, while each of the pure strategies presumes that either the error magnitude or the RT, but never both, grows with the number of stimuli. Instead, it appears that some flexible tradeoff strategy was used in our experiments, with a predominant component determined by the experimental conditions. This flexible tradeoff is clearly illustrated by the finding that the slopes of the error and the RT functions tend to change in mutually opposite directions depending on the viewing duration (Experiments 1 and 2 vs. Experiment 3, see Figures 5d and 5e). In the brief presentation condition (Experiments 1, 2, and 4), slow and thorough inspection is naturally less available, so the observers had to judge the number of subsets quite intuitively and approximately. That resulted in the shallower RT but the steeper error function, indicating the greatest contribution of the estimation strategy to subset enumeration. In contrast, in the long viewing condition (Experiment 3), observers had enough time to serially inspect all of the subsets (or even individual items). This, in turn, yielded the steeper RT but the shallower error function which can be ascribed to the greater contribution of the counting strategy.

There is another important implication of the finding that both estimation and counting strategies are involved in subset enumeration. This finding indicates a critical role of attentional selection in subset representation, and this role appears to be greater than in representing individual objects. Chong and Evans (2011) claim that the serial attentional selection of individual items is needed only when an exact number is required, and that can be accomplished by counting. In contrast, when an exact number is not necessary or unavailable (e.g., due to brief presentation or crowding; Valsecchi, Toscani, & Gegenfurtner, 2013), an immediate and approximate estimation can be made with a broadly distributed attentional window that spreads over all items at once rather than selecting them one by one. Our results demonstrate that the serial pattern of enumeration is kept (at least for three and four subsets which are above the subitizing range and far from reaching the "ceiling" response category), even when the duration of presentation is not enough for counting subsets properly. It appears, therefore, that, unlike individual objects, spatially overlapping subsets *require some degree of serial attentional selection* to be consciously represented regardless of a predominant strategy of building that representation.

The Role of Subset Numerosity

We manipulated the set size as a within-subject factor in all experiments in order to probe how a subset representation is extracted from the individual members of that subset. We found a rather enduring advantage of large sets over small ones in almost all experimental conditions except for the "high" range (five and six subsets) in Experiment 3. Experiment 2 showed that this advantage cannot be explained by the difference in the spatial arrangement of items between large and small sets and by the sampling strategy based on this arrangement. We conclude, therefore, that the large set advantage was provided by numerosity itself.

If numerosity improves both speed and accuracy of subset enumeration, the implication is that the visual system is likely to process all items representing a subset in parallel. However, a simple parallel process cannot explain the advantage of large sets, as it implies the independent character of processing all items and predicts no cost and no advantage of the set size. It appears that a more complex, cumulative process underlies building the subset representation from individual items. At least two possible mechanisms may explain the cumulative character of this process. First, a greater number of items per subset can aid the reliability of the holistic representation of a corresponding subset. In other words, the more items represent a subset in the visual field, the more readily we perceive those items as a solid though disseminated group and, hence, easily enumerate them as a single unit. A similar view of the role of numerosity in ensemble representation was advocated by Robitaille and Harris (2011) in the domain of mean perception. The other mechanism is based on the rule of statistical power, which says that a critical value of a statistical test sufficient to confirm the H1 hypothesis (which states the dissimilarity between distributions) decreases with the total number of observations. Continuing the statistical approach to ensemble representation (Alvarez, 2011; Ariely, 2001; Chong & Treisman, 2003), it is reasonable to suppose that visual discrimination between spatially overlapping ensembles can somehow follow the rules of statistical decision. In other words, it may be easier for the visual system to distinguish between differently colored subsets when greater samples of items represent those subsets. Elsewhere, we discussed a similar mechanism of numerosity effects in visual search (Utochkin, 2013). Certainly, both of these mechanisms need thorough testing in future research.

The "Full Set" Memory Template

A robust pattern was found in our experiments at terminal subset numbers, indicating the violation of monotonous growth of the error and RT functions. It can be partially ascribed to the "ceiling" effect of enumeration caused by the finite categorical scale of possible responses (Mandler & Shebo, 1982). However, as Experiment 4 shows, this effect can be also explained by the use of a template representing the whole variety of possible subsets for the given set. This template appears to be useful for enumerating large numbers of spatially overlapping subsets, reducing the error of enumeration where applicable. A detailed explanation of how this "full set" template might work is presented in the preamble for Experiment 4 and depicted in Figure 5. Here, we are going to emphasize the role that such a template can play in subset representation and, more generally, in gist perception. In our opinion, a template of this sort can be an efficient tool for representing familiar scenes, ensembles, or textures. Instead of serial enumeration of each subset one by one in a complex ensemble, we can simply rely on a global impression of the "full" set, the "something lacking" set, or the "something redundant" set. Therefore, a template of this sort in the memory could be an important component of visual expertise requiring rapid decisions about complex ensembles or textures. Note, however, that our results allow only rather preliminary conclusions about the "full set" memory template and its possible functions. Further experiments are needed to properly test our speculations.

Conclusions

In the present study, we addressed the issue of the representation of spatially overlapping subsets in complex visual ensembles. We used a subset enumeration task that allowed us to probe the available representations of subsets and the time course of their formation. We found some similarity between subset enumeration and object enumeration. In particular, we discovered that subsets can be represented in two different ways depending on the number of those subsets. One mode of this representation — fast and almost error-free subitizing — works for no more than two subsets at a time. This estimate provides converging evidence for the previously established boundary of parallel extraction of summary statistics (Halberda et al., 2006; Poltoratski & Xu, 2013; Watson et al., 2005). Beyond this boundary, subsets are represented via slower and more error-prone estimation or counting. Although both of these strategies are less ideal than subitizing in terms of speed and accuracy, their outcome correlates with the actual number of subsets, thus indicating that overlapping subsets are being discriminated well enough beyond the limit of parallel representation. Other results show that subset representation beyond the subtizing boundary appears to be subject to rather complex strategic modulation, appealing to different condition-dependent attentional modes (such as distributed vs. focused attention, Chong & Evans, 2011) or memory templates. In contrast, within the subitizing range, subset enumeration performance was almost insensitive to conditional manipulations supporting the notion of highly parallel and effortless processing.

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экспериментальные сообщения

Зрительная оценка количества в подмножествах, перемешанных в пространстве

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Аннотация. Наблюдатели способны к эффективной зрительной оценке сводных статистик (например, среднего значения какого-либо признака или количества) из подмножеств объектов, перемешанных в пространстве. Однако эта способность ограничена — одновременно могут быть извлечены статистики всего около двух подмножеств, что исходно может быть вызвано ограниченным объемом параллельной репрезентации этих подмножеств. Мы провели четыре эксперимента, в которых наблюдателям предъявлялись наборы точек, окрашенных в разные цвета (от одного до шести цветов в наборе); задача состояла в определении количества показанных цветов. Измерялись скорость и точность ответов. Следуя стандартным критериям, используемым для интерпретации данных в задачах определения количества объектов, мы выделили два режима репрезентации подмножеств: а) параллельная, легкая и стратегически-независимая репрезентация не более двух подмножеств и б) последовательная репрезентация, модулируемая стратегиями внимания и шаблоном рабочей памяти. Также было обнаружено преимущество в точности и скорости в ответах на большие подмножества по сравнению с маленькими, демонстрирующее, что репрезентация подмножества объектов с общим признаком формируется на основе статистического накопления информации об отдельных объектах.

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