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Ensemble Coding Of Semantic Information: Are Numerical Averages Generated In Parallel?

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ENSEMBLE CODING OF SEMANTIC INFORMATION: ARE NUMERICAL AVERAGES GENERATED IN PARALLEL?

Kassandra R. Lee

54 Pages

Previous research has shown evidence for the activation of ensemble coding mechanisms at multiple levels of processing complexity (Ariely, 2001; Haberman & Whitney, 2009). Here we investigated the use of ensemble mechanisms for semantic information, as well as the role of serial and parallel processing and automaticity in generating semantic ensemble representations. Twenty-seven undergraduate students completed tasks in which they reported the average value of an entire digit display or only a subset of digits, or searched for individual digits within the display. Results show that participants could average sets of numbers following only a short presentation, and that reaction times did not increase across increasing display sizes, consistent with parallel processing. Furthermore, participants were able to attend to a full set of digits, but accurately report the average of a specific subset without knowing which subset (defined by color) was relevant ahead of time. Additional research is necessary to further clarify the role of automaticity in ensemble tasks using semantic information and to sufficiently control for low-level, perceptual features of the displays.

KEYWORDS: Ensemble Coding, Visual Crowding, Semantic Information

ENSEMBLE CODING OF SEMANTIC INFORMATION: ARE NUMERICAL
AVERAGES GENERATED IN PARALLEL?

KASSANDRA R. LEE

A Thesis Submitted in Partial
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for the Degree of

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2016

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ENSEMBLE CODING OF SEMANTIC INFORMATION: ARE NUMERICAL
AVERAGES GENERATED IN PARALLEL?

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K. R. L.

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CHAPTER I

INTRODUCTION TO ENSEMBLE CODING

As we move through our environment, we constantly perceive information that our sensory systems must selectively sort and process. During an everyday activity such as walking through a crowded street, there is an abundance of noisy visual information to be processed. We see bright billboards, street signs, and faces, both familiar and unfamiliar. For some of these stimuli, it is important to be able to gather specific information, but for others, it may be more important to extract the gist, or summary information, about a group of stimuli. Haberman and Whitney (2009) expressed this idea by describing how we can perceive a field of grass without processing every blade in the field. In fact, it seems that one function of our visual system is to extract useful information from groups of similar stimuli all at once, creating an efficient, or rapid and useful representation of our environment (Ariely, 2001; Chong & Treisman, 2003; Haberman & Whitney, 2007; Parkes, Lund, Angelucci, Solomon, & Morgan, 2001).

Generating such summary representations is sometimes referred to as ensemble coding, a process that may reflect simultaneous parallel processing of multiple elements as opposed to serially processing individual objects (Alvarez, 2011; Ariely, 2001). Returning to the example of the field, we understand that there are many blades of grass, and if we choose, we can visually distinguish and examine individual blades of grass.

However, processing a field in this way is highly inefficient and not realistic in many real-world situations. Instead, it appears that our visual system is able to process some information from all of the blades in parallel, creating a holistic representation of the field, while sacrificing more detailed information about specific blades (Haberman & Whitney, 2009).

In a review, Alvarez (2011) emphasizes the importance of ensemble coding by asking us to consider the visual information that we gather from objects outside the focus of our attention and/or in our peripheral vision. As observers, we are aware that such objects are lacking individual detail to the extent that we feel we cannot gather much useful information from any one of them. One related deficit, deemed ‘visual crowding’, describes the situation in which objects in our peripheral visual field are more difficult to perceive in detail because they are surrounded by other objects. Visual crowding has been shown to occur due to interference between low-level features of stimuli, such as the orientation of angled lines (Parkes et al., 2001), as well as higher level interference attributes of stimuli, such as the gender of faces (Farzin, Rivera, & Whitney, 2010; Louie, Bressler, & Whitney, 2007; Whitney & Levi, 2011). Ensemble coding, or summary-statistical representation, allows us to combine information about these similar objects outside of the central vision and recoup a precise measure from the group or set. It has been shown that generating this average information leads to sacrifices in obtaining individual details about specific items in a scene (Ariely, 2001; Haberman & Whitney, 2009), but in turn, provides an efficient representation of the whole scene.

Ensemble coding has been demonstrated for various types of low-level feature information, such as the orientation of simple lines or spatial location (Alvarez & Oliva, 2008; Alvarez & Oliva, 2009; Dakin & Watt, 1997; Parkes et al., 2001). For example, participants are able to select from a group of striped patches which patch contains stripes of a different angle, or orientation (Dakin & Watt, 1997), and it is also reported that participants are able to identify average orientation in conditions of reduced attention (Alvarez & Oliva, 2009). Additionally, Alvarez and Oliva (2008) demonstrated that participants can gather summary statistical information regarding object location despite being asked to focus on a distractor task. Participants were able to accurately identify an average central point of circles after they disappeared from the screen with a level of accuracy that suggested that they were pooling information from all (rather than a small subset) of the circles shown during the distractor task.

The visual system has also been shown to form summary statistical representations of features such as the average size and variability in size of a group of objects (e.g., Ariely, 2001; Chong & Treisman, 2003; Oriet & Corbett, 2008). Importantly, Ariely (2001) showed that although participants were able to obtain highly precise mean information from circle sets, as well as information about the size variability, they performed relatively poorly when asked to identify specific size information about any one circle in the set. This finding shows that the ability to identify mean information is independent of in-depth processing of information from individual stimuli in the set, and further exemplifies the idea that we do not need to gather detailed information about specific blades of grass in order to form a useful representation of the entire field. Additionally, there is evidence for ensemble coding of other low-level

features such as direction and speed of motion of groups of stimuli (Watamaniuk, Sekuler, and Williams, 1989; Williams and Sekuler, 1984). From orientation, shape, and spatial location to movement direction, it has been shown that we can gather different types of average information about a variety of low-level features from relatively simple visual stimuli.

Ensemble Coding of Higher-Level Stimuli

In daily life, even though we naturally must process basic, low-level features of visual stimuli such as line orientation, our ability to process more complex aspects of stimuli, such as the identity of objects and faces, is critical to success. In fact, faces in particular are thought to be processed in a way that is distinct from other classes of objects. It is thought that upright faces are processed in a holistic manner, taking into account the ‘global’ configuration of features. But when faces are inverted, we no longer engage holistic processing; instead, we become reliant on the low-level characteristics of the individual features (basic contours, brightness, etc.) themselves rather than the configuration of the whole (Farah, Wilson, Drain, & Tanaka, 1998; Tanaka & Farah, 1993; Valentine, 1988; Yin, 1969). This shows that upright facial processing is unique, either due to a special mechanism dedicated to face processing, or as some have proposed, the high degree of expertise that we develop related to facial recognition and processing (Gauthier & Tarr, 1997).

Haberman and Whitney (2007) demonstrated that summary statistical representations are generated not only for low-level features of simple stimuli but also for higher level attributes of complex stimuli such as faces. The authors morphed faces

displaying varying emotions and of different genders to produce an array of faces expressing emotions ranging from happy to sad and neutral to disgusted, and with gender ranging from male to female. Participants were able to indicate whether a test face expressed more of one emotion or the other compared to the mean of a group of the morphed faces shown for only 2 seconds, despite being unable to report emotions from individual faces in the set. The same pattern was observed for gender. Thus, the extraction of summary information extends to emotions as well as other high-level properties of faces such as gender. Haberman and Whitney (2009) further demonstrated that observers have the ability to flexibly and rapidly (within a 500 ms stimulus presentation) estimate the average emotional expression of a group of faces even when the task instructions were unrelated to identifying the mean emotion, suggesting that they implicitly represented the average expression of the face sets.

Myczek and Simons (2008) argued that participants might create ensemble representations by gathering information only from a subset while ignoring the full set. To rule out that possibility, Haberman and Whitney (2010) again used a paradigm that included groups of face stimuli showing similar emotions. However, two of the faces displayed emotions different from the rest, making those faces identifiable outliers. Results showed that participants computed the appropriate summary statistical representation for the majority of the faces, and appeared to discount the outliers. This is evidence that participants had to gather information from the full set of stimuli in order to identify which faces were the outliers before discounting them. This study showed that observers were able to gather information from a subset when necessary, but still also gathered information from the full set.

Beyond facial expression and gender, Sweeny and Whitney (2014) found evidence that we can extract mean eye gaze-direction from a crowd of faces. Because eye-gaze is identified as a high-level cooperation of head and pupil rotation information, this finding provides additional support that ensemble coding occurs at levels of visual processing beyond low-level feature information, as demonstrated by previous research (e.g., De Souza, Eifuki, Tamura, Nishijo, & Ono, 2005; Perrett, et al., 1985). Taken together, these previous studies have shown that not only can summary information be gathered from a visual scene, but that this is done implicitly, rapidly, efficiently, and at different levels of processing complexity.

Ensemble Coding of Semantic Information

In addition to possessing various low-level and more complex visual properties, many stimuli in the real world are also associated with semantic information. Alphanumeric characters such as letters and digits are ubiquitous in our daily experience, and contain not only characteristic low-level perceptual features such as their shape, but also serve as symbols with specific meanings. Because these characters contain information representing such different levels of processing, they provide a useful tool for investigating how higher level semantic information interacts with low-level attributes to shape visual perception. Sobel, Puri, and Hogan (2014) discuss whether visual perception is unaffected by higher-level cognition, an idea backed by supporters such as Pylyshyn (1999) and Firestone and Scholl (2015). Sobel and colleagues challenge this idea by providing evidence that semantic meaning can influence performance during a visual search task. This leads to the question, do the mechanisms that support ensemble

coding in the visual domain also operate for semantic information? Sobel and colleagues (2014) reported that when controlling for perceptual differences between stimuli, visual search for digits was faster when the targets could be grouped based on numerical value, suggesting that semantic information associated with digits influences visual search independently of perceptual factors. Do semantic meanings influence ensemble representations? Van Opstal, de Lange, and Dehaene (2011) showed that ensemble coding may also occur at a semantic level by demonstrating that participants could rapidly average and sum groups of Arabic numbers (the numbers were displayed for less than 800 ms). Further research has demonstrated that participants were able to extract numeric meaning from familiar digits more quickly than from either familiar letters or shapes in a classification task (Corbett, Oriet, & Rensink, 2006). These findings are important because they provide evidence that we are able to extract summary statistical information at a level even beyond the domain of high-level visual processing.

Potential Contributions of Parallel vs. Serial Processing to Ensemble Representations

The studies described above demonstrate that the extraction of summary information occurs very quickly. For example, participants were highly accurate when judging the average size of a display of objects even when the display was only presented for only 500 ms (Ariely, 2001). In this same study, it was found that participants' performance was unaffected as the number of objects in the display increased. This finding may be indicative of participants' ability to assess different elements of the objects simultaneously, or in a parallel manner (Egeth, 1966). For example, in visual

search tasks, when the target letters possesses very different features from the distractors (e.g. an X vs. Os), reaction times (RTs) increase relatively little with additional distractor items, consistent with the idea that observers process salient, low-level visual attributes of the items in parallel. On the other hand, when targets contain similar or overlapping features with the distractors such as a red *T* among green *T*s and red *L*s, the visual search task is completed by serially inspecting each item until the target is found (Duncan & Humphreys, 1989; Treisman & Gelade, 1980). Because RTs were relatively unaffected by the number of circles in the display in Ariely's (2001) study, participants may have been processing these simple objects in a parallel fashion.

Chong and Treisman (2005) also found that the number of objects in a stimulus array had no effect on participants' accuracy of mean size discrimination, and found further support for the idea of parallel mean extraction by using a cueing paradigm to determine whether participants could extract the mean size of subsets of circle stimuli. Participants were provided with a color cue either before or after they viewed an array. Regardless of when participants saw the color cue, their task was to determine the average size of a specific subset of circles (specified by color). There was no difference in performance between the pre-cued and post-cued conditions, indicating that in the post-cued condition, participants were able to gather information from both subsets at the same time just as accurately as when they knew which subset to attend to ahead of time (pre-cued). This finding suggests that participants extracted information from both subsets of circles in parallel to generate a representation of the average (Chong & Treisman, 2005). Other research by Alvarez and Oliva (2008) also supported this

conclusion by showing that participants could accurately generate summary representations of object locations even without directly attending to the objects.

Townsend (1990) discussed that although parallel and serial processing may both lead to ensemble representations (e.g., Van Opstal et al., 2011), being able to distinguish the contribution of each will provide insights into the mental operations supporting ensemble tasks. As reported by Van Opstal et al., (2011), one might expect to see an increase in participants' RTs when they are extracting an average from a greater number of objects if they are processing according to a serial model, but not a parallel model. If participants are processing all objects at once (in parallel) then they should be able to do this quickly for all objects, without a change in RT, and regardless of the number of objects. For serial processing however, participants would need to individually assess each additional object to gather information. Because Van Opstal and colleagues observed increasing RTs with increasing display size during the Arabic numerals averaging task, they suggested that there could be a serial processing component involved in ensemble numerical averaging. This claim, however, can be called to question after further investigation of earlier research.

Townsend (1990) and Egeth (1966) reported that although researchers often assume that parallel processing implies RT consistency across display sizes, this is not necessarily the case. Egeth (1966) found that parallel processing can lead to an increase in average RTs that occur due to the addition of more stimuli. This idea is supported even in Townsend's (1990) unlimited-capacity parallel processing model which continuously increases in the number of items being presented simultaneously. The idea is that there is

a physiological limit on how quickly an individual item can be processed, but not on how slowly. Therefore, as more items are added to a set, the chances of including an item with a long outlier time increase, which then increase the overall reaction time. Stated more simply, because the overall RT is only as fast as the slowest item processing time, displaying more items would increase the chance of having a slower overall RT. Because of this, Egeth and Townsend reported that it is natural for processing times to differ across trials even in a parallel processing scenario, predicting that the RT for an array of items may increase based on the array size. This finding could explain the increase in RTs observed in Van Opstal and colleagues (2011) while still lending the numerical ensemble task to a parallel processing model.

Parallel and Serial Processing for Numerals

Van Opstal et al. (2011) studied ensemble representations of Arabic digits because they were interested in whether the semantic components of prime displays affected participants' perception of a digit array even when they were not consciously aware of the primes. One component of this research involved assessing participants' RTs for the digit arrays in order to determine whether they were processing summary statistical information in a parallel or serial manner. Addition of a group of digits was identified as a serial process, such that participants accomplished the goal by identifying and adding each number to the next, one-by-one. Digit averaging, on the other hand, was identified as more of a parallel process in which participants concurrently assess the weight of all numbers to identify an average value. Van Opstal and colleagues concluded that participants accurately performed ensemble coding of higher-level, semantic

attributes in a parallel fashion, consistent with previous work investigating low-level stimuli (Alvarez & Oliva, 2008; Ariely, 2001; Chong & Treisman, 2005). However, a closer look at their results reveals variability in RTs across display sizes in the averaging condition, such that the question still remains whether the extraction of average numerical value does in fact involve rapid parallel processing, and if so, does ensemble coding at the semantic level occur automatically across the entire display or only for relevant subsets of items?

Automaticity of Ensemble Coding of Numerical Value

Chong and Treisman (2005) explored automaticity of processing of low-level information by studying how participants gather summary statistical information from subsets of circles. With their cueing paradigm, Chong and Treisman found no statistical differences between pre-cued and post-cued trials, indicating that participants were able to identify the mean sizes of both colors of circles as accurately as the mean of only one subset. In other words, despite being uninformed about which color would be relevant to their final decision when they were presented with the array, participants performed the averaging task just as well as when they were pre-cued. This finding was present even when participants viewed the circle display for 200 ms, suggesting a rapid and automatic parallel extraction of the mean circle size. Other research has explored automaticity of processing at the level of semantic information.

Naparstek and Henik (2010) investigated whether the automaticity of numerical value and numerosity processing is task specific. Participants took part in either a comparative judgement task or a parity judgement task. For the comparative judgment

task, participants were asked to indicate whether the numerical value or numerosity, of the stimuli was smaller or larger than five. In this task all of the numerals were congruent (i.e. participants saw all 5's or all 7's) and were presented among distractor items. For the parity judgment task, participants were asked to indicate whether the numerical value or numerosity of the stimuli was even or odd. Again, all of the numbers presented in any one trial were the same. For both the comparative judgement task and the parity judgement task there were congruent (numerical value and numerosity were the same) and incongruent (numerical value and numerosity were different) trials. By comparing RTs, Naparstek and Henik found that only in the comparative judgment task were participants automatically processing the numerical value of digit stimuli in the congruent trials. So even though participants' responses were based on one digit and not the average of many, Naparstek and Henik found that the comparative judgement task led to automatic processing of numerical value during a congruity task.

Current Research

The current research aims to further investigate the nature of ensemble representations at the semantic level. There is compelling evidence that ensemble coding of low- and high-level visual attributes occurs rapidly, in parallel, and automatically (Ariely, 2001; Chong & Treisman, 2005; Van Opstal et al., 2011); however, less is known about the mechanisms involved in extracting summary information at the semantic level. Despite their claim of parallel processing of the mean value of a digit display, the differences in RTs across display sizes in Van Opstal and colleagues' (2011) study may reflect a serial processing contribution to the numerical averaging task. The

current study will involve a more rigorous attempt to dissociate serial and parallel contributions to ensemble coding of numerical value in a task similar to that used by Van Opstal and colleagues. Arabic digits are convenient stimuli for this purpose because they have exact means and have been successfully used in previous research investigating ensemble representations (Van Opstal et al., 2011; Corbett et al., 2006). Participants' RTs across increasing numbers of stimuli in the display will be compared to RT patterns generated from serial and parallel visual search tasks performed by the same participants, so that conclusions can be drawn regarding the type of processing occurring in the ensemble coding task.

Furthermore, the extent to which the formation of summary statistical representations of semantic information occurs automatically across all items or only subsets of items is still unclear. The pre-cue and post-cue paradigm used by Chong and Treisman (2005) to investigate automaticity of averaging circle size will be used here to determine whether the meanings associated with all items in a display automatically contribute to an ensemble representation at the semantic level. If the averages of subsets of digits are processed at the same level of efficiency regardless of pre-cued or post-cued conditions, this would suggest that the processing of ensemble information at the semantic level proceeds automatically for subsets of stimuli as shown for low-level visual attributes by Chong and Treisman (2005). Based on previous research that used similar tasks (i.e., asking about numerical value and having participants complete a comparative judgement task), it is further expected that support will be found for automatic processing (See above: Naparstek & Henik, 2010).

The current experiment proposes several hypotheses to address the questions regarding semantic ensemble processing as outlined above: 1a) the numerical averaging task will result in differences in RTs as more digits are included in the task. Specifically, it is likely that participants will have slightly longer RTs (perform more slowly) when there are more digits to process. (1b) The differences in RTs for the ensemble task are predicted to be small and to ultimately look more similar to RT patterns generated by the parallel search than the serial search task. We will also examine accuracy for these tasks in order to rule out or identify any speed-accuracy trade-offs. It is possible that participants will perform better in the search tasks as compared to the ensemble task. 2a) Participants will show no difference in accuracy between the pre-cued and 5 digit array single color subset conditions in the whole display task, indicating that they will be able to efficiently select a colored subset of numbers to average when compared to a full set of same-colored numbers. We would also expect to see equal accuracy between the pre-cue and 10 digit arrays in the whole display task; this would provide further evidence that participants are gathering average information from a subset with an efficiency that is comparable to gathering information from a large, full set. Finally, (2b) participants will show no difference in averaging ability for the pre-cued and post-cued conditions, indicating no advantage for participants when they are pre-cued compared to when they are not, meaning that the segregation of the two groups based on perceptual features and subsequent extraction of ensemble semantic information occurs in the absence of attending to one or the other.

Hypothesis (1a) will characterize the RT patterns across display sizes for gathering summary statistical averages for Arabic digits, while hypothesis (1b) will

directly compare RT patterns in the ensemble coding task to parallel and serial visual search RT patterns in order to support the claim that the ensemble task occurs using parallel processing. Further hypotheses will investigate the idea that we can average subsets of numbers (2a) even when we are not able to identify which subset may be relevant ahead of time (2b). Hypothesis (2b) will additionally address the idea of rapid, automatic generation of semantic ensemble representations from perceptually segregated subsets.

The current study aims to determine whether high-level semantic information contributes to ensemble representations of visual stimuli (specifically Arabic digits) in a similar manner as both low-level and other higher level information. This is important because processing of numeric meaning occurs at a higher level of processing beyond that of visual surface perception, (i.e., Arabic numerals do not physically match the values that they represent) (Van Opstal et al., 2011), and the processing of this information is relevant to perceptual tasks in our daily lives.

CHAPTER II

METHOD

Participants

For the current study, we predicted a medium effect size ($f=.5$) based on Cohen's guidelines (Cohen, 1988). A preliminary power analysis was conducted using G*Power 3.1 software (Faul, Erdfelder, Lang, & Buchner, 2007) and the following criteria: $f = .5$, $\alpha = .05$, $\beta = .95$, yielding an estimated minimum sample size of 10 participants for each set of tasks in this study.

Undergraduate students from a large public university in the Midwestern U.S. were recruited via an online recruitment system. Participants were split into two groups that completed different tasks (tasks for each group explained in Procedures). Of the 19 participants, one participant was excluded due to slow RTs (RT plus or minus 2.5 SDs from the mean) in the ensemble task, one for slow RTs in the search tasks, and one for low accuracy in the search tasks. Thus, a total of three datasets were excluded across the three tasks to allow for within-subjects comparisons across tasks. The remaining 16 participants were included in data analyses (13 female, M age = 20.06, $SD = 0.77$). There were originally 20 participants in the whole display and pre-/post-cue tasks group. Of those 20, four were excluded for low accuracy (<60%) on the pre-cue task, one for low accuracy on the post-cue condition, and one for low accuracy in both cue conditions.

Three additional participants were excluded for slow RTs (plus-or-minus 2.5 *SDs* from the mean; no RT exceeded 1565 ms).¹ There were a total of 11 participants included in the analyses (8 female, *M* age = 20.45, *SD* = 1.04). In total, data from 27 participants were included in the final analyses. Inclusion criteria required that students have normal or corrected-to-normal vision. Students received class credit in exchange for their participation. All experimental procedures were approved by the university's Institutional Review Board.

Stimuli and Displays

Visual Search Tasks

Stimuli consisted of arrays of digits ranging from 1- 9 that were presented in white text against a black background. Participants were asked to search for the number greater than or less than five, and to report on which side of the display the number was located by using the keyboard. The 'z' key was pressed for left side of the display, and the '/' was pressed for right. The parallel processing visual search task or the pop-out visual search looked similar, except the target digit was presented in a different color from the distractors (see *Figure 1* for examples).

¹ The relatively large total number of participants excluded due to poor accuracy for the pre- and post-cue tasks was not expected and may reflect greater cognitive demands than required by the circle size task in Chong and Treisman (2005). However, 11 participants were included in the current analyses, exceeding the required minimum sample size of 10 as indicated by the power analysis.

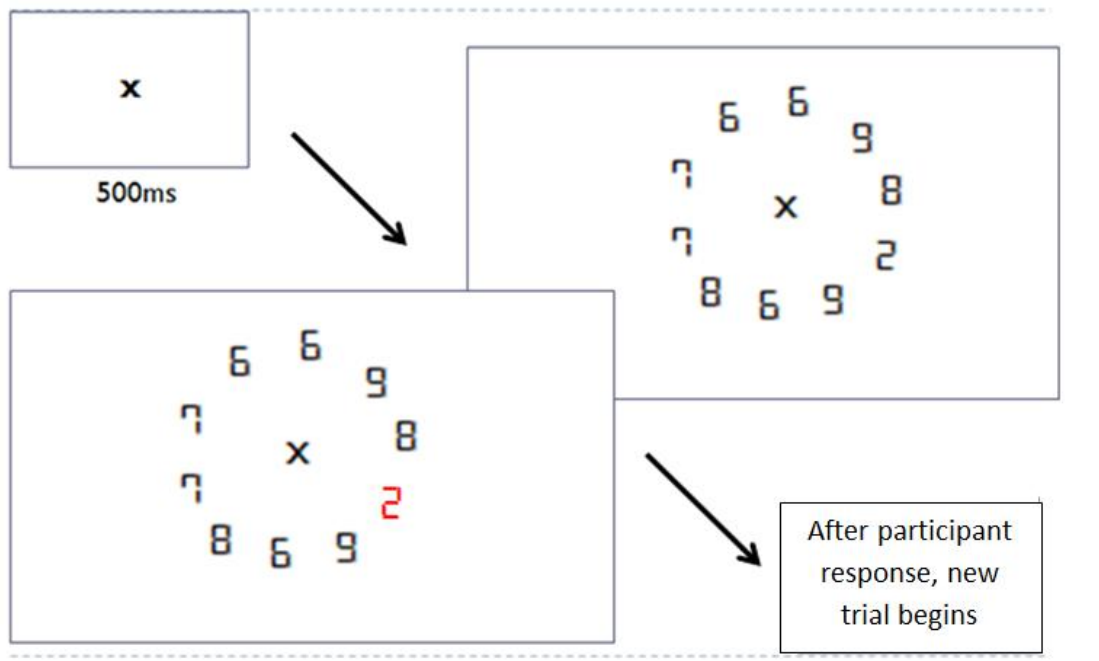


Figure 1. Serial Search and Parallel Search Tasks. A 500 ms fixation screen was followed by a digit display that remained on the screen until participants responded by pressing ‘z’ or ‘/’ to indicate the location of the target (left or right). In this example, participants looked for a number less than 5. In the serial search task, the target did not contain a salient unique feature (upper right), whereas in the parallel search task, targets were presented in red and thus “popped out” (lower left).

Ensemble, Whole Display, Pre-Cue, and Post-Cue Tasks

For the *ensemble task*, trials began with a screen displaying a fixation cross (500 ms) followed by a digit display, which remained on the screen until the participant responded. Participants were instructed to estimate whether the average of the digits was less than or greater than five. Displays consisted of a fixation point at the screen’s center surrounded by five, seven, or ten digits generated to match the displays used for the

search tasks (see *Figure 2* for examples). Participants responded using the ‘z’ key to indicate “less than 5” and the ‘/’ key for “greater than 5”. A second averaging task, the *whole digit task*, was identical to the ensemble task, except the digits exactly matched those used for the pre-/post-cue displays, and were presented for 1500 ms. This task was used to compare performance for a whole display to the subsets in the pre- and post-cue tasks.

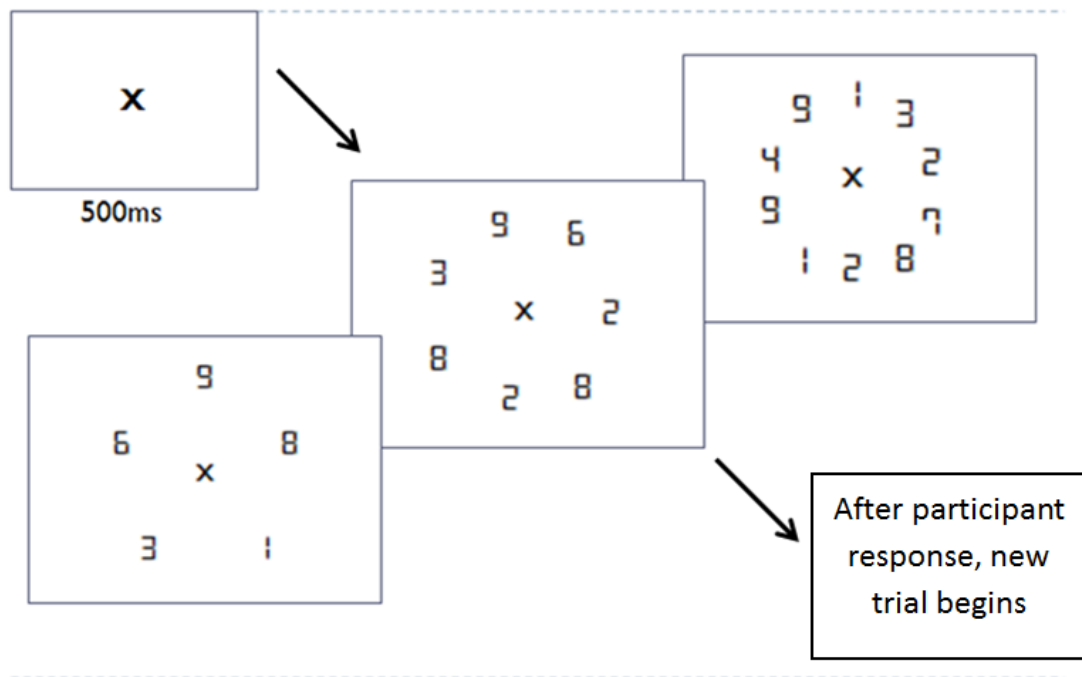


Figure 2. Ensemble Task Display. Participants viewed a fixation screen for 500 ms before viewing a digit display of 5, 7, or 10 digits. This display remained on the screen until participants made a response indicating whether the average was less than or greater than 5, but participants were prompted to respond as quickly as possible.

For the pre-/post-cue ensemble task, the digit displays (1500 ms) were colored red and green, with half of the digits corresponding to each color. Depending on the condition, a cue was shown before (pre-) or after (post-) the digit displays for 250 ms to inform participants which subset of digits they would be averaging (see *Figure 3* and *Figure 4* for examples). Again, participants responded using the ‘z’ key for ‘less than’ responses, and the ‘/’ key for ‘greater than’.

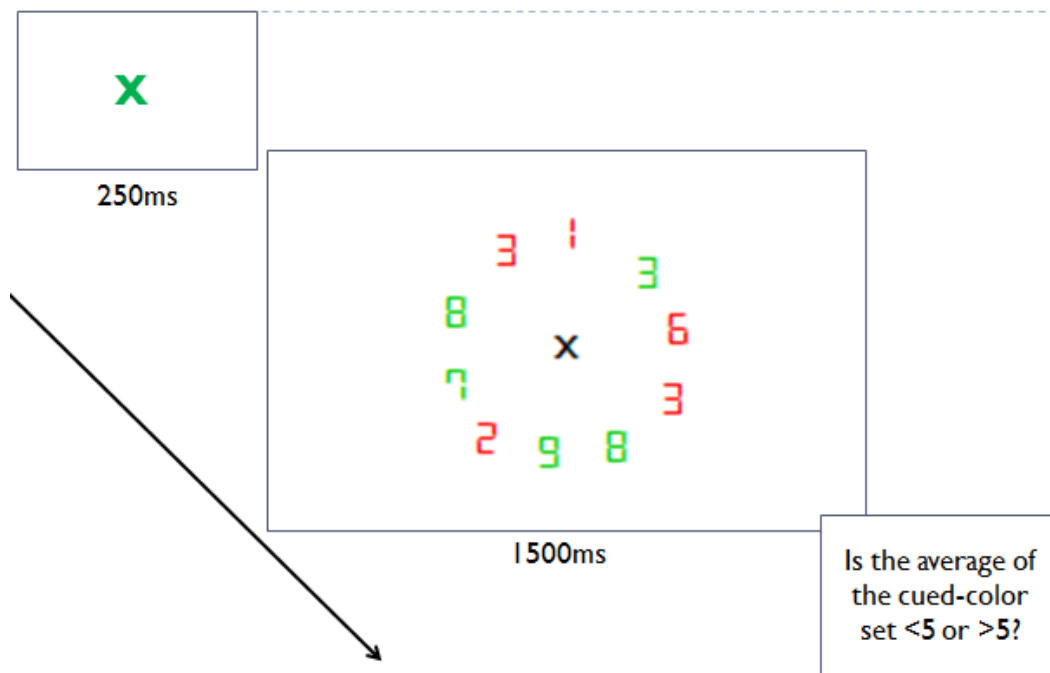


Figure 3. Pre-Cue Task Display. Participants saw the first screen containing the relevant color cue for 250 ms before viewing the digit display for 1500 ms. The final screen was a response screen in which participants reported whether the average of the digits that matched the color with which they were cued was less than 5 or greater than 5.

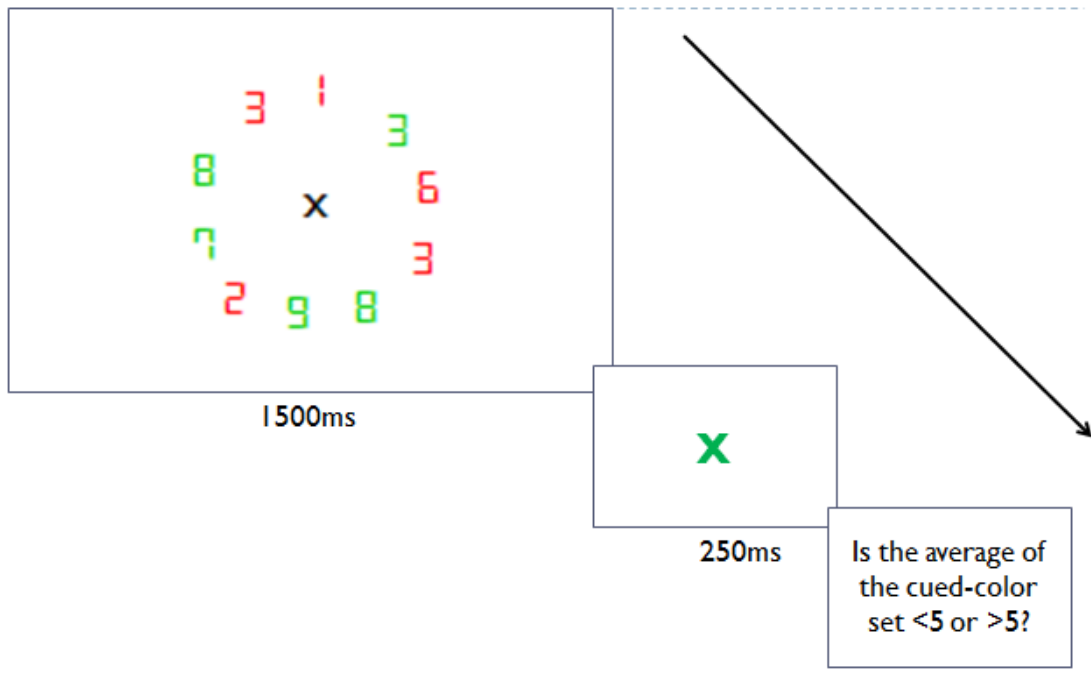


Figure 4. Post-Cue Task Display. Participants saw digit display screen for 1500 ms before viewing the color cue. The final screen was a response screen where participants reported whether the average of the digits that matched the color with which they were cued with was less than 5 or greater than 5.

Measures

Accuracy

In the ensemble tasks, participants determined the numeric average of the target digit display in a comparative judgment manner by reporting whether the average was less than 5 or greater than 5. In the search tasks, participants reported on which side of the display a particular number was located. Accuracy of participants' reported averages and digit locations were recorded.

Reaction Time

Participants' reaction times in response to the target digit display (when reporting in the comparative judgement task) were recorded for the ensemble task, the whole display task, and the search tasks. For the pre-/post-cue task, RT was not of primary interest because participants were color-cued at different points in the stimulus display.

Procedure

Half of the participants completed the search tasks and the ensemble task, while the other half completed the pre/post ensemble task and the whole display task. Participants who completed the first set of experiments completed 240 trials (40 for each display size for each of the two types of visual searches) of a visual search task that included both "pop-out", or parallel, search displays and displays requiring serial search through the items. Participants' RTs and accuracy were recorded for these tasks. For the ensemble coding task, participants completed 168 trials (56 for each display size) that began with a screen displaying a centered fixation cross for 500 ms, followed by a target digit display for 1500 ms. The target display consisted of a fixation point randomly surrounded by five, seven, or ten Arabic digits that matched the displays used in the search tasks. The number five was excluded from the list of possible digits so as to not interfere with participants' ability to determine the average of the digits. This process also required that the randomization procedure exclude a combination of digits whose exact average is five. Following the digit presentation, participants viewed a screen asking them to report whether the average of the digits presented was less than or greater than

five. Participants responded on a keyboard, pressing ‘z’ for a less than response, and ‘/’ for a greater than response.

For the pre-/post-cue ensemble task, participants randomly received 75 colored pre-cued and post-cued trials for a total of 150 trials. On this task, only 10 digit displays were used. For the pre-cued trials, participants first viewed a screen with a fixation point colored either green or red (250 ms). The color of the fixation point cued participants to the color of the subset of digits in the upcoming display to which they should attend. The digit display screen was presented for 1500 ms and contained ten digits (five green digits and five red digits), followed by a screen that instructed participants to respond, using a key press, whether the subset of digits presented in their cued color averaged to less than or greater than five. For the post-cued trials, the fixation screen was immediately followed by the digit display screen (1500 ms) and then a post-cue screen (250 ms), which indicated whether the participant should report the average for the red or green subset. Participants then viewed the response screen as in the pre-cued trials. Along with the pre-/post-cue task, participants also completed the whole display task, identical to the ensemble task in Session 1, except the digit displays were generated so that digits used in the 5 and 10-item displays exactly matched the pre- and post-cue displays.

Data Analysis

Reaction times were compared across digit display sizes (5, 7, and 10) for both of the visual search tasks and ensemble task (hyp. 1a). A 3 (*Task*: parallel search/serial search/averaging) x 2 (*Target Type*: < 5/> 5) x 3 (*Display Size*: 5/7/10 items) ANOVA was conducted on RTs with the number of digits in the display as a factor to assess

whether there was an effect of number of targets on participants' RTs for both the visual search and ensemble coding tasks. In addition, RTs across different display sizes were compared for visual search tasks and the ensemble task (hyp. 1b.). The appropriate follow-up tests were conducted following the ANOVA. A 4 (*Condition*: Pre-/Post-/Ensemble 5 Items/Ensemble 10 Items) x 2 (*Target Type*: < 5/> 5) ANOVA was conducted to compare participants' accuracy on the pre- and post-cue digit ensemble tasks. Paired samples T-tests were used to assess differences in accuracy between the pre-cue and whole display 5 and 10 conditions (hyp. 2a), as well as between the pre- and post-cued conditions (hyp. 2b). Statistical analyses were conducted in SPSS, version 20 (IBM, 2011).

CHAPTER III

RESULTS

In this study, we wanted to compare how reaction times (RTs) change as a function of display size across a numerical ensemble task, a serial search task, and a parallel search task. The goal was to determine whether generating ensemble representations at the semantic level occurs by extracting information from multiple items in parallel, as has been described for lower level visual attributes (Alvarez & Oliva, 2008; Ariely, 2001; Dakin & Watt, 1997; Parkes et al., 2001). RT patterns indicative of parallel processing are commonly seen in visual search tasks in which the target contains a unique, salient feature, such as in the parallel search task utilized here. Alternatively, ensembles based on high-level, semantic information such as numerical value could instead require serial processing of each item, and thus RTs would markedly increase with display size as they do in more difficult visual search tasks that require detailed examination of individual items (Duncan & Humphreys, 1989; Treisman & Gelade, 1980). If the numerical ensemble task relies on a parallel processing mechanism as has been shown for low-level feature ensemble representations, RT patterns for the ensemble task should resemble the RT patterns generated by the parallel search task, with much smaller increases in RT with increasing display size than for the serial search task.

In addition, we wanted to see if subjects performed just as well when they were post-cued to a specific subset of digits within a display as when they were pre-cued.

Chong and Treisman (2005) demonstrated that participants performed equally well when estimating the average size of subsets of colored circles across both a pre-cued condition, in which participants were cued to attend to a specific subset before its presentation, and a post-cued condition, in which they were cued only after its presentation. That participants were able to report average circle size even when they were uninformed about which set to attend to during a 200 ms presentation suggests that we are able to rapidly and automatically extract ensemble information based on low-level visual information. Here, we hypothesized and tested whether the same holds true for higher level, semantic information.

We addressed these two ideas with a separate set of analyses for each, as described below.

Serial vs. Parallel Processing

A 3 (*Task*: Ensemble/Serial Search/Parallel Search) x 2 (*Target Type*: < 5/>5) x 3 (*Display Size*: 5/ 7/ 10 items) repeated measures ANOVA was conducted on RTs. There was a significant main effect of Task, $F(2, 30) = 92.60, p < .001$, such that overall, RTs for the ensemble task were longer ($M = 804.32, SD = 160.97$) than RTs for the serial search task ($M = 708.08, SD = 117.10$), which in turn were longer than for the parallel search task ($M = 398.74, SD = 33.07$) (see *Figure 8*). A significant main effect of Target Type, $F(1, 15) = 17.18, p < .005$, was a result of faster RTs in the greater-than-5 compared to the less-than-5 condition for the ensemble (> 5: $M = 766.98, SD = 140.71$; < 5: $M = 841.66, SD = 181.22$) and serial tasks (> 5: $M = 680.58, SD = 105.47$; < 5: $M = 735.59, SD = 128.72$). There was also a main effect of Display Size, $F(2, 30) = 11.59, p <$

.001, such that as display size increased, so did RTs (5 items: $M = 621.11$, $SD = 101.69$; 7 items: $M = 634.74$, $SD = 98.48$; 10 items: $M = 655.30$, $SD = 110.97$).

These main effects were qualified by a significant Task x Target Type x Display Size interaction, $F(4, 60) = 15.230$, $p < .001$. We examined this three-way interaction by conducting a 2 (Target Type) x 3 (Display Size) repeated measures ANOVA for each task type followed by simple effects analyses and pairwise comparisons when appropriate. Results of these follow-up analyses are broken up by task, and follow a description of the overall results for accuracy, below.

A 3 (Task: Ensemble/Serial Search/Parallel Search) x 2 (Target Type: < 5/>5) x 3 (Display Size: 5/ 7/ 10 items) repeated measures ANOVA was also conducted on accuracy. There was a significant main effect of Task, $F(2, 30) = 17.92$, $p < .001$, such that overall performance was worse in the ensemble task ($M = .90$, $SD = .08$) compared to the serial search ($M = 0.97$, $SD = .03$) and parallel search ($M = .98$, $SD = .03$) tasks. There was also a main effect of Target Type, $F(1, 15) = 6.610$, $p < .05$, such that performance was higher in the greater-than-5 condition for both the ensemble task ($M = .92$, $SD = 0.06$) and the serial search task ($M = 0.97$, $SD = 0.03$) compared to the less-than-5 condition (ensemble, $M = 0.88$, $SD = 0.10$; serial, $M = 0.97$, $SD = 0.14$). There was no main effect of Display Size, $F(2, 30) = 1.86$, $p = .17$.

These main effects were qualified by a significant Task x Target Type x Display Size interactions, $F(4, 60) = 9.27$, $p < .001$. In order to understand this three-way interaction, we conducted a 2 (Target Type) x 3 (Display Size) repeated measures ANOVA for each task type followed by simple effects analyses and pairwise

comparisons, just as for RTs. These results are reported in the sections below, after RT follow-ups.

Serial Search Task

For serial search there was a significant main effect of Target Type, $F(1, 15) = 8.98, p < .01$, such that subjects had overall faster RTs for greater-than-5 targets ($M = 680.58, SD = 105.47$) compared to less-than-5 targets ($M = 735.59, SD = 128.72$). There was also a significant effect of Display Size, $F(2, 30) = 70.19, p < .001$ such that as display size increased, RTs also increased (5 items: $M = 636.37, SD = 98.73$; 7 items: $M = 701.57, SD = 107.29$; 10 items: $M = 786.31, SD = 145.27$). There was no interaction between these variables (see *Figure 5*). There were no main effects or interactions regarding accuracy for the serial search task.

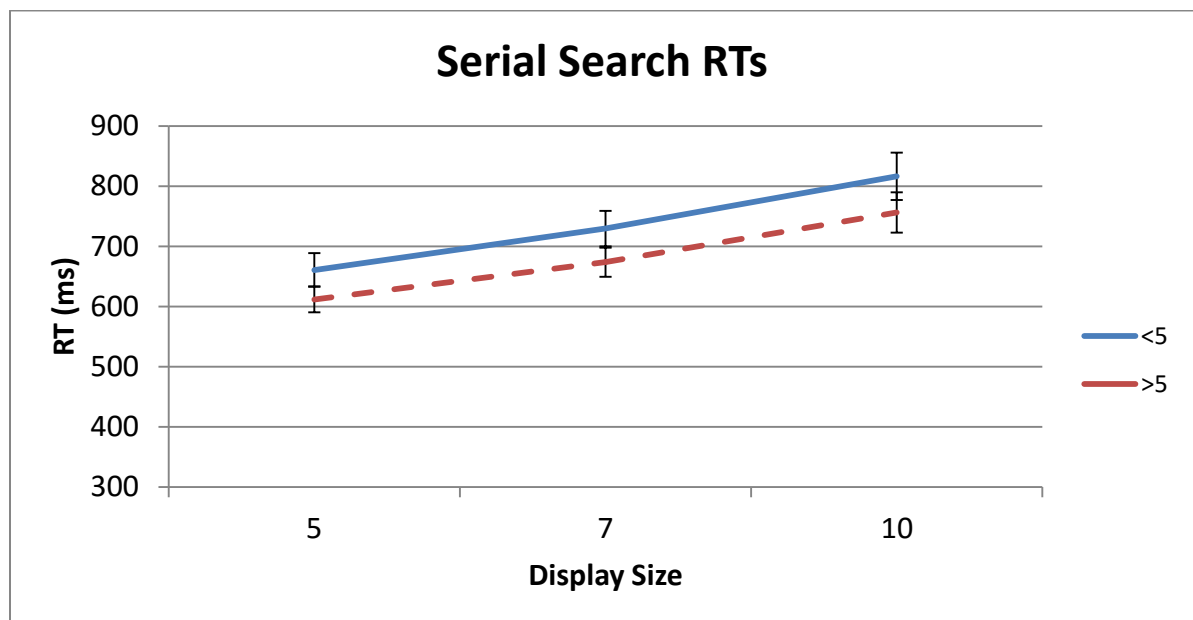


Figure 5. Serial Search RTs. Average RTs on serial search task graphed by display size and less-than-5/ greater-than-5 search targets. The less-than-5 target displays are

presented with a solid blue line, and are overall slightly slower than the greater-than-5 targets. The graph depicts the main effect of display size, such that RTs increased with increasing display size, $F(2, 30) = 70.19, p < .001$. Error bars represent standard error of the mean.

Parallel Search Task

For the parallel search task there was no main effect target type, but there was a marginal main effect of display size, $F(2, 30) = 3.772, p = .05$ such that as displays size increased, RTs also increased slightly, as predicted (5 items: $M = 396.40, SD = 33.27$; 7 items: $M = 398.75, SD = 32.36$; 10 items: $M = 401.08, SD = 33.57$). There was no interaction between these variables (see *Figure 6*).

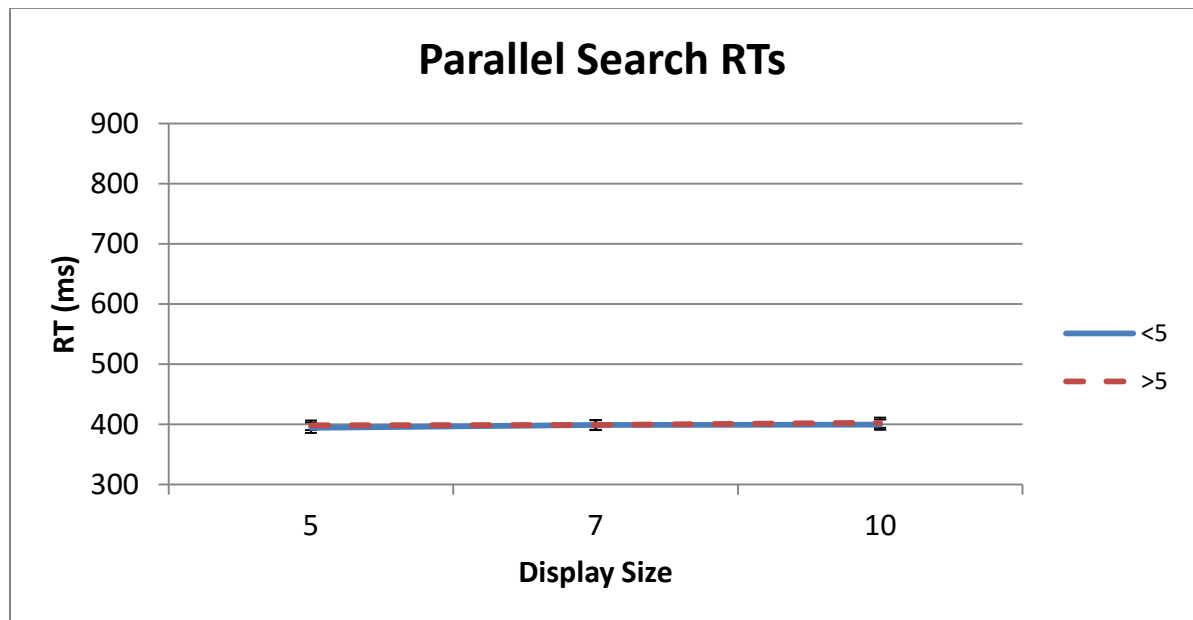


Figure 6. Parallel Search RTs. Average RTs on parallel search task graphed by display size and less-than-5/ greater-than-5 search targets. Less-than-5 targets are graphed with a solid blue line. The graphs shows the marginal effect of display size, such that as display

size increased, RTs also slightly increased, $F(2, 30) = 3.772, p = .05$. Error bars represent standard error of the mean.

A 2 (*Task*: serial v. parallel search) x 3 (*Display Size*) ANOVA was conducted to compare the increases in RTs for both tasks, collapsed across target type. There was a main effect of Task, $F(1, 31) = 220.308, p < .001$, such that the overall RTs for the serial search ($M = 708.08, SD = 119.13$) were slower than for the parallel search ($M = 398.74, SD = 32.58$). There was also a main effect of Display Size, $F(2, 62) = 98.045, p = .000$, due to an overall increase in RTs with increasing display size (5 items: $M = 516.38, SD = 66.91$; 7 items: $M = 550.16, SD = 70.82$; 10 items: $M = 593.69, SD = 89.84$) (see *Figure 8*). There was also a significant interaction between Task and Display Size, $F(2, 62) = 73.314, p < .001$, which was further investigated using one-way ANOVAS.

A main effect of Display Size was observed for the serial search task, $F(2, 62) = 87.980, p < .001$, but not for the parallel search task, $F(2, 62) = 2.120, p = .129$, indicating that the large increase in RTs across display size in the serial, compared to parallel, task is driving the significant interaction between task and display size. There were no main effects or interactions regarding subject accuracy for the parallel search task.

Ensemble Task

For the ensemble task, there was a main effect of Target Type, $F(1, 15) = 12.161, p < .01$ due to faster RTs for the greater-than-5 condition ($M = 766.98, SD = 140.71$) than the less-than-5 condition ($M = 841.66, SD = 181.23$). A significant main effect of Display Size, $F(2, 30) = 5.401, p < .05$ revealed that larger display sizes yielded faster RTs (5: M

= 830.57, $SD = 173.05$; 7: $M = 803.89$, $SD = 155.77$; 10: $M = 778.50$, $SD = 154.08$).

Since there was also significant interaction between Target Type and Display Size, $F(2, 30) = 21.134$, $p < .001$, we conducted two one-way ANOVAs to assess the simple effect of display size for each target type.

There was a simple main effect of Display Size for the greater-than-5 condition, $F(2, 30) = 23.343$, $p < .001$, but not for less-than-5 condition. For trials in which the average of the display was greater than 5, RTs decreased with increasing display size (5 items: $M = 849.05$, $SD = 172.32$; 7 items: $M = 752.79$, $SD = 117.2756$; 10 items: $M = 699.10$, $SD = 132.53$).

Follow-up paired-samples t-tests were conducted to compare RTs across display sizes for the greater-than-5 condition. There was a significant difference shown between all pairs of the display sizes, (all $ps < .01$) indicating significantly shorter RTs as display size increased (see *Figure 7*).

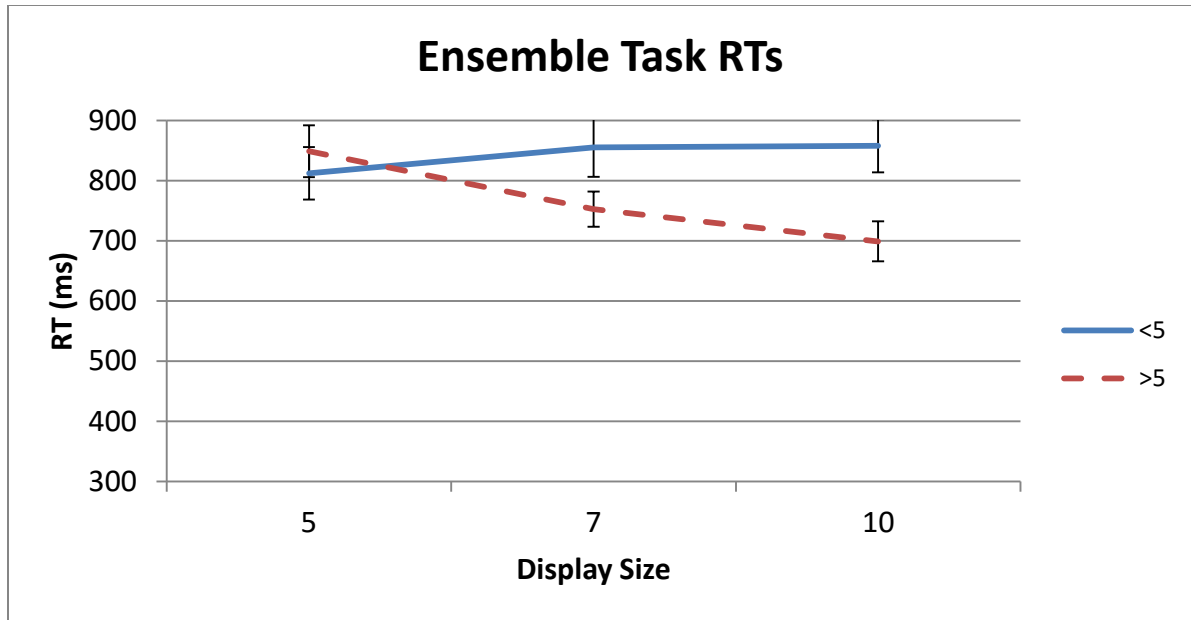


Figure 7. Ensemble Task RTs. Average RTs on ensemble coding task graphed by display size and less-than-5/ greater-than-5 search targets. The less-than-5 targets are graphed with a solid blue line, showing overall slower RTs compared to the greater-than-5 targets for the 7 and 10 digit displays. The graph also shows an effect of Display Size in the greater-than-5 condition such that RTs decreased with increasing display size. Error bars represent standard error of the mean.

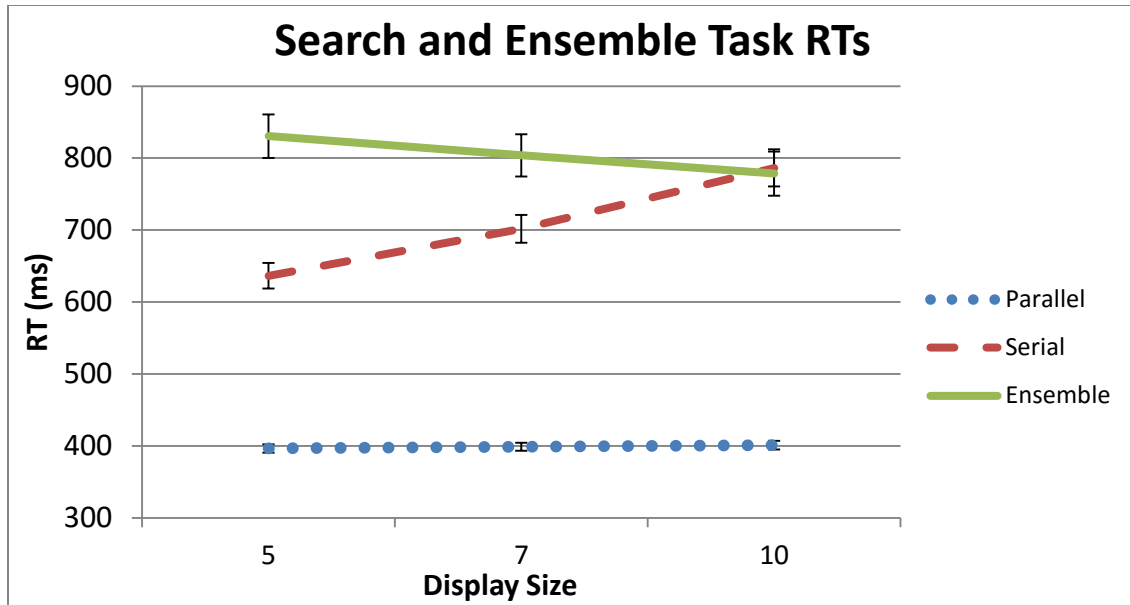


Figure 8. Search and Ensemble Task RTs. Average RTs collapsed across less-than-5 and greater-than-5 conditions for the search tasks and ensemble coding task, graphed by display size. The graph shows the relatively small change in RTs for the parallel and ensemble tasks, while the search task led to a more drastic increase in RTs with increasing display size. For both the serial and parallel searches, RTs increased with increasing display size, but for the ensemble task, RTs decreased with increasing display size. Error bars represent standard error of the mean.

Regarding accuracy for the ensemble task, there was a significant main effect of Target Type, $F(1, 15) = 7.194, p < .05$, since participants performed better in the greater-than-5 condition ($M = 0.92, SD = 0.06$) compared to the less-than-5 condition ($M = 0.88, SD = 0.10$). There was also a significant main effect of Display Size, $F(2, 30) = 7.958, p < .01$, such that accuracy increased with increasing display size (5 items: $M = 0.89, SD = 0.09$; 7 items: $M = 0.91, SD = 0.080$; 10 items: $M = 0.91, SD = 0.07$). There was also a

significant interaction between Target Type and Display Size, $F(2, 30) = 9.310, p < .005$. One-way ANOVAs were conducted to further assess the interaction.

The simple main effect of Display Size in the greater-than-5 condition was significant, $F(2, 30) = 20.430, p < .001$, showing an increase in accuracy with increasing display size in the greater-than-5 condition (5 items: $M = 0.87, SD = 0.09$; 7 items: $M = 0.94, SD = 0.04$; 10 items: $M = 0.96, SD = 0.04$). The simple main effect of the less-than-5 condition was non-significant.

Follow-up pairwise comparisons were conducted to compare accuracy across display sizes for the greater-than-5 condition. There were no significant differences between the 7 and 10 item displays, but significant differences between the 5 and 7 item displays as well as the 5 and 10 item displays (both $ps < .005$), indicating that the differences between the 5 item and the two larger item displays is driving the interaction between target type and display size, ultimately leading to increased accuracy with increasing display size in the greater-than-5 condition (see *Figure 9*).

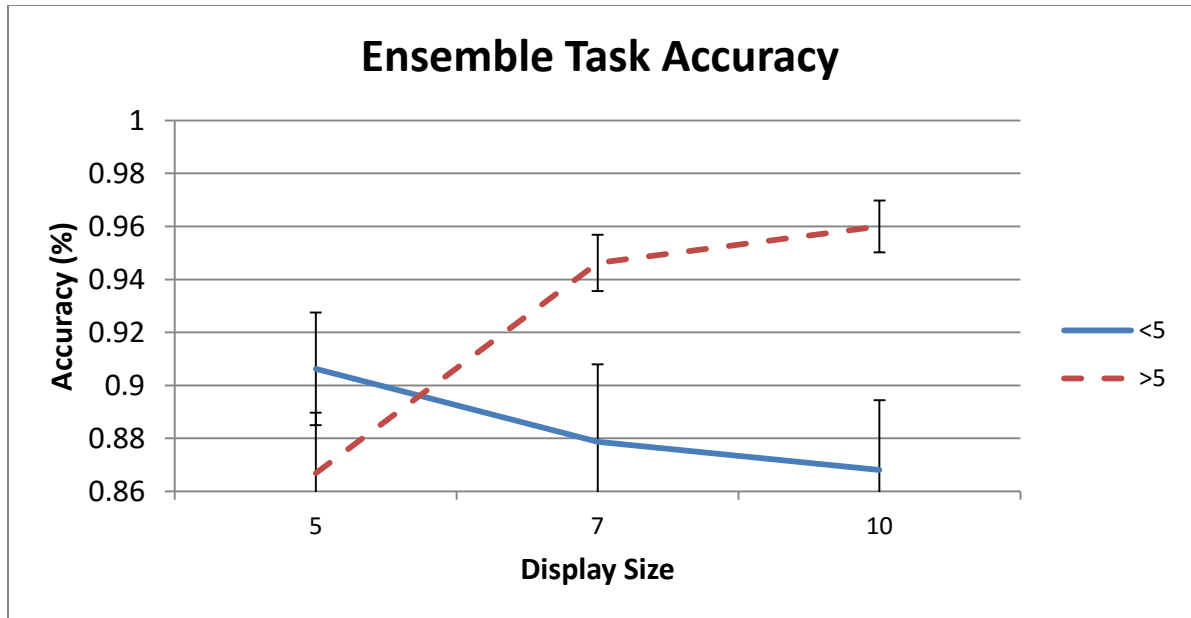


Figure 9. Ensemble Task Accuracy. Average accuracy on ensemble coding task graphed by display size and less-than-5/ greater-than-5 search targets. The dashed red line represents the greater-than-5, in which accuracy for the 7 and 10 digit displays was higher compared to the less than 5 condition. A significant main effect of Display Size was driven by increasing accuracy with larger display sizes in the greater-than-5. Error bars represent standard error of the mean.

Whole Display Task and Pre-/Post-Cue Tasks

A paired-samples t-test was conducted to compare RTs for the 5 and 10 item whole display conditions. Again, for this task, participants were averaging digits that matched those used in the pre-/post-cue task. Since these digits were of a uniform color, participants were averaging the whole display. There was a significant difference in RTs for the two conditions, $t(10) = 2.380, p < .05$, such that RTs were faster for the 10 item condition ($M = 872.35, SD = 109.66$) than the 5 item condition ($M = 947.36, SD =$

178.03). This result is consistent with our finding of faster RTs for larger displays in the ensemble task described above.

Although RT data was collected for the pre-/post-cue tasks, it was not analyzed for the purpose of this study due to the forced differences in response times between tasks. Specifically, unlike for the pre-cue task, in the post-cue task, participants were unable to respond immediately following the stimulus display because they had to wait until they were shown the post-cue. Thus, it would not be appropriate to compare RTs across the pre- and post-cue tasks.

A 4 (*Condition: Pre-/Post-/Whole 5 Items/Whole 10 Items*) x 2 (*Target Type: < 5/> 5*) repeated measures ANOVA was conducted to compare subjects' accuracy on the pre- and post-cued digit ensemble tasks. This analysis design was selected because the whole-display condition was treated as a separate task since there was no 5 item display for the pre-/post-cue condition. With this analysis, we were able to compare all of the tasks by target type. There was a significant main effect of Condition, $F(3, 30) = 8.606, p < .001$, due to overall higher accuracy for the whole-digit task ($M = 0.96, SD = 0.03$) than for the pre/post tasks ($M = 0.90, SD = 0.05$) regardless of target type. There was no main effect of Target Type, and there was no significant interaction. Collapsing across target type, there was no significant difference in accuracy between the pre- ($M = 0.91, SD = 0.03$) and post-cue ($M = 0.90, SD = 0.05$) conditions, $t(10) = .537, p = .60$, or the 5 item and 10 item conditions of the whole display task, $t(10) = .1.307, p = .220$ (see *Figure 10*).

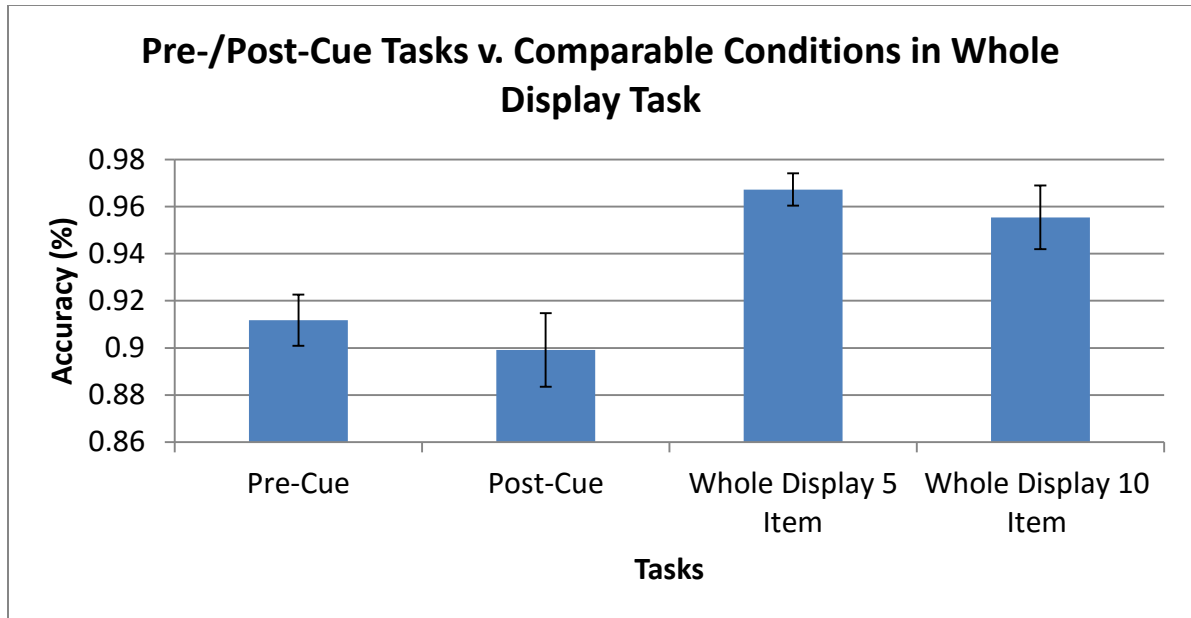


Figure 10. Pre-/Post-Cue Tasks v. Comparable Conditions in Whole Display Task.

Average accuracy for the pre-cue task, the post-cue task, and the 5 and 10 item conditions in the whole-display task. The accuracy for the whole-display task conditions was higher than for the pre-/post-cue tasks, $F(3, 30) = 8.606, p < .001$. There were no significant differences in accuracy between the 5 and 10 item whole-display conditions or between the pre-/post-cue tasks. Error bars represent standard error of the mean.

Summary of Results

The results of our analyses reveal that the serial and parallel search tasks yielded expected RT patterns, with the serial task leading to an increase in RTs with increasing display size. In the parallel search task, increasing the display size also led to an increase in RTs, although this effect was much less dramatic and only marginally significant, consistent with typical findings of only small, if any, RT increases in parallel search tasks (also known as “feature” or “pop-out” search tasks).

The critical analysis for our study showed that RTs for the numerical ensemble task were significantly longer than for both the serial and parallel search tasks, but ultimately generated patterns most similar to those observed for the parallel search task.

Accuracy was higher overall for the whole-digit display task compared to the pre- and post-cue tasks, regardless of target type. The comparison of primary interest was between the pre- and post-cued conditions, for which we found no significant differences in accuracy. Within the whole-digit displays, there were no significant differences in accuracy between the 5 and 10 item displays.

CHAPTER IV

DISCUSSION

Interpretation and Relevance of Results

The current research aimed to assess the role of parallel processing in ensemble coding of semantic information, as well as determine whether the ability to gather low-level ensemble information from subsets of stimuli automatically (i.e., without prior cues as to which set will be relevant) holds for semantic-level information as it does for low-level stimulus attributes (Chong and Treisman, 2005). Previous research has demonstrated ensemble coding for low-level visual information (e.g., Alvarez & Oliva, 2008; Parkes et al., 2001; Ariely, 2001), as well as for more complex stimuli such as faces (e.g., Haberman & Whitney, 2007). The current study is unique in that we believe it provides evidence of an ability to gather numerical averages of groups of digits, and that this ensemble coding mechanism extends to even higher level, semantic information. Furthermore, we observed RT patterns that indicate the use of parallel processing during such tasks, and accuracy patterns that show participants' ability to average subsets of digits without being aware of which subsets are relevant ahead of time.

Serial vs. Parallel Processing in Numerical Ensembles

When identical types of digit displays were presented in an ensemble coding task, a serial visual search task, and a parallel visual search task (in which the target was presented in a salient color), RTs for the ensemble task were slower than for both search

tasks. This overall difference in RTs across the three tasks is discussed below. However, the key finding with respect to whether ensemble representations at the semantic level are generated via serial or parallel mechanisms is that unlike in the search tasks, for ensemble estimation, RTs reduced overall as display size increased. This reduction was driven by the large target (greater-than-5) condition; in contrast, RTs in the less-than-5 condition remained consistent across display sizes. This overall decrease in RTs with increasing display size was counter to hypothesis (1a) in which we predicted a small increase as is often seen in parallel search tasks (Egeth, 1966; Treisman & Gelade, 1980). Nonetheless, the ensemble task generated a pattern more similar to the parallel than the serial search, supporting hypothesis (1b) that extracting ensemble information at the semantic level occurs in parallel across the display.

This decrease in RTs (and increase in accuracy) with increasing display size in the ensemble task may align with the results of Sweeny and Whitney's (2014) research on perceiving the average direction of eye gaze. In their study, participants were able to accurately gather ensemble gaze direction from sets of faces, and in fact, participants reported more accurate eye gaze estimates for larger subsets of face stimuli. Sweeny and Whitney suggest that when more information is available to contribute to the ensemble representation, estimates will be more accurate (Sweeny & Whitney, 2014). Along these lines, the increase in display size for the current study could have led to faster RTs and more accurate estimates (at least in the greater-than 5 condition) because larger displays provide more items from which to gather information when estimating the average value of the digits.

Alternatively, we cannot rule out that the faster RTs for larger displays sizes observed in the greater-than-5 condition in the ensemble task could also potentially be explained by low-level differences between the less-than-5 and greater-than-5 conditions. In the greater-than-5 condition, the digit displays tended to have more lines constituting the digit than in the less-than-5 condition, which may have provided a cue to the correct response based on the overall luminance of the display. What is not clear is why for the less-than-5 condition, accuracy remained consistent, as did RTs. For this condition, display sizes likely contained more of the number “1”, which may have been salient due to their unique shape comprised of a singular line. It may be that “1”s were not as salient as the brightness cues, or even that the “7”s included in the greater than 5 displays balanced it out because they also contained a prominent singular line. These displays also contained more digits to gather information from, but this did not seem to be useful in the less-than-5 condition as it was for the greater-than-5 condition. It is interesting that in the serial search task, participants also displayed faster RTs in the greater-than-5 compared to the less-than-5 condition. It is possible that larger displays may have biased participants towards a “greater-than-5” response.

To return to the findings of overall differences in RTs and accuracy across the three tasks, RTs were slower and accuracy was lower for the ensemble task compared to both of the search tasks. This difference between the ensemble and search tasks can potentially be explained by differences in task demands. In the parallel search task, participants’ attention was likely immediately drawn to the “pop-out” digit, generating the fastest RTs. In the serial search task, participants responded immediately after searching for a digit less-than-5 or greater-than-5, whereas for the ensemble task,

participants were asked to estimate the average, a process which may involve inherently greater uncertainty. Note that whereas RTs for both the serial search and the parallel search increased across display sizes, in the parallel search task, RTs increased by less than 10 ms from the smallest to largest display size, compared to a 150 ms increase for the serial search task. This pattern was predicted based on Egeth (1966) who found small increases in RTs as display sizes increased even in parallel tasks. Our data also confirm slower RTs for the serial search compared to the parallel search. This is expected because the salient target in the parallel search captures participants' attention, whereas in the serial search participants would have to scan each item in the display until finding the target (Duncan & Humphreys, 1989; Treisman & Gelade, 1980). Overall, RT patterns on the ensemble task more closely resembled those observed in the parallel search task, demonstrating that participants did not need to examine each digit individually in order to incorporate it into a representation of the average, but rather were able to extract information from items across the entire display in parallel.

Automaticity of Averaging Numerical Subsets

As discussed above, comparing a semantic ensemble task to visual search tasks suggests that we can gather semantic information from multiple items in a display simultaneously. We also wanted to investigate the ability to generate ensemble representations of subsets within a display. To do this we presented participants with color cues either before or after a display that informed them about which colored subset of digits to respond to. In a similar task, but with circle sets, Chong and Treisman (2005) reported no difference in the ability of participants to report average size after being

either pre-cued or post-cued to the relevant subset. Thus, participants were able to extract the average circle size of the subsets even when they were not aware of which subset of circles they should attend to. Findings of this study may also suggest that the ability to gather semantic information occurs quickly for subsets of stimuli, indicating a potential automatic component that allows for attention to a full set, yet report information for only a subset. A whole-digit display task was used in the current study to compare performance on averaging the whole vs. subsets.

Comparing the whole digit display task to the pre- and post-cue task revealed overall higher accuracy for the whole display task. This goes against our prediction of no difference between the 5 item display in the whole display task and the pre-cued condition (hypothesis 2a), and also shows that compared to the 10 item display, participants are less accurate for the subset task, indicating the possibility that they are not gathering the average strictly from the subset of interest, but rather are attempting to incorporate information from digits in the other subset. Although this difference could indicate that participants were not extracting an ensemble average from the pre- and post-cued displays in a similar manner to the whole-display task, the difference could also be due to an additional working memory component involved in the pre-/post-cue tasks. For the whole-display task, participants immediately reported the average, whereas in the pre- and post-cue tasks, participants had to either remember the cued color while viewing the stimulus display (pre-cued), or maintain information about the stimulus display while viewing the cue color (post-cue). These additional requirements could have led to decreased accuracy in the pre-/post-cue tasks. The decreased performance due to a heavier cognitive load is in accordance with the cognitive load theory, originally

explained by Sweller (1988) as problem-solving ineffectiveness due to the division of cognitive processes among two different tasks. Because holding the color cue in memory and estimating the average are different tasks, they could contribute to a greater conflict between cognitive resources during task completion for the pre-/post-cued tasks.

Despite lower accuracy in the pre- and post-cue tasks as compared to the whole display task, accuracy was not different between the pre- and post-cue tasks. Consistent with hypothesis (2b), participants were able to average subsets of digits as accurately when they had to attend to the full set to gather information (post-cue task) as when they knew ahead of time to which subset they should attend (pre-cue task). This result suggests a degree of automaticity in extracting ensemble semantic information from perceptually defined subsets, as shown by Chong and Treisman (2003) for circle size.

Conclusions, Limitations, and Future Research

The current study provides novel insights into the ways that our visual system uses ensemble coding. Results suggest that we gather ensemble information from semantic stimuli using a parallel processing mechanism, and that we can also gather this information from subsets of digits in a display. However, there are several limitations of the study that may impact the interpretation of the findings and will be important to address in future research.

One major limitation of the study is the potential negative influence of low-level cues on performance on the ensemble coding tasks. For ensemble coding as well as visual crowding phenomena, it has been shown that low-level features contribute substantially to perception of a cluttered display (Ariely, 2001; Chung, Levi, & Legge, 2001; Parkes,

Lund, Angelucci, Solomon, & Morgan, 2001; Pelli et al., 2004). In the current study, although we were interested in the contribution of semantic information to perception of the average of digit displays, it is nonetheless possible that participants used low-level features such as overall luminance to make decisions about the average numerical value of displays. This limits our ability to draw strong conclusions regarding the role of semantic information in ensemble coding based on the results of the present study. To help control for low-level confounds, future research could replicate the current task using two-digit numbers so as to better account for brightness and other low-level differences. With two-digit numbers there is more opportunity to match less-than-5 and greater-than-5 displays with regard to the number of lines (more lines in the tens place could be balanced by fewer in the ones place), allowing screen luminance to be matched across conditions and minimizing the possibility that participants could rely on brightness to make their judgments. Using double-digit numbers would also work to control for other perceptual features, such as salient line orientation of the “1” or “7” digits in this experiment.

Another limitation of the current study was the need to exclude the data from a greater number of participants from the pre-/post-cue tasks as compared to the whole-display task due to chance-level accuracy or by nature of being an outlier for RTs. Since we were conducting repeated-measures analyses, we also had to remove data from these participants from the whole-display task, even though their performance on that task may have been sufficient for analysis. This means that performance on the whole-display task could have been different than what our analyses allowed with the remaining participants. Furthermore, exclusion of several datasets reflecting poor performance from the pre- and

post-tasks resulted in an average performance that could be viewed as artificially inflated. However, the accuracy of the excluded participants was within the range that could be considered chance performance (< 60% correct), whereas the remaining participants on average scored well above chance (> 90% correct). In addition, the greater number of participants excluded for low accuracy were actually from the pre-cue condition, meaning that the post-cue performance could not have been inflated by removing low-accuracy cases. This further supports the idea that there was no advantage in the pre-cue condition. In fact, the lower accuracy in this condition could potentially represent a disadvantage for being pre-cued. This unexpected accuracy difference among excluded participants could be due to the pre-cue task requiring participants to hold the cued color in mind while gathering the ensemble, or some other unexpected difficulty within the task. The differences in excluded participant accuracy were not due to pre-cue/post-cue presentation order because about half of those who were excluded from the pre-cued analyses received this condition before the post-cue condition, while the other half received it after. Nonetheless, a greater number of participants would help to parse out differences if they exist between the pre- and post-cue conditions.

Future research could also assess the role of automaticity in ensemble perception of semantic information in more detail. In the current study, the cues were always congruent. Thus, we cannot assess whether participants automatically extracted information from a subset of the display when not attending to that subset. Here, participants were aware of the need to attend to the whole set, rather than attending entirely to the wrong set of digits. By incorporating the use of congruent and incongruent pre-cues, researchers could investigate whether participants automatically, without

attention, gather information from one subset, despite being cued to the other subset. If they were cued incongruently, then they would attend to the set opposite to the one that they were later asked to report. If they still report the average with high accuracy, this would mean that participants are able to extract the average of an ignored subset while actively attending to a different subset.

The current study calls for methodological follow-ups in order to further assess our ability to gather ensemble information from semantic stimuli, as well as to obtain additional evidence addressing the potential automaticity of this process. Nonetheless, the current research provides useful information that can pave the way for future research aimed at revealing the strategies employed by our perceptual systems in order to make sense of our cluttered environment. Here, we have provided preliminary evidence that builds on the work of Van Opstal and colleagues (2011) and Chong and Treisman (2005) to show that we can rapidly gather useful semantic information about multiple items in parallel and use that information to make ensemble judgments about the group or subsets within the group. The novelty of this current study is grounded in the uniqueness of semantic stimuli in that they have both low-level perceptual features as well as high-level semantic meaning. This means that our investigation of these stimuli (in terms of ensemble coding) has provided additional evidence for our ability to rapidly gather information about groups of numbers that are processed at a level beyond that of only low-level perception (Ariely, 2001; Alvarez & Oliva, 2008; Alvarez & Oliva, 2009; Dakin & Watt, 1997; Parkes et al., 2001). We have also identified potential directions for future work that will allow for better understanding of the mechanisms that underlie this ability.

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