THE INTERACTION BETWEEN ENSEMBLE AND ITEM REPRESENTATIONS

IN A TEMPORALLY EXTENDED CONTEXT

UMAY ŞEN

BOĞAZİÇİ UNIVERSITY

2018

THE INTERACTION BETWEEN ENSEMBLE AND ITEM REPRESENTATIONS IN A TEMPORALLY EXTENDED CONTEXT

Thesis submitted to the

Institute for Graduate Studies in Social Sciences

in partial fulfillment of the requirements for the degree of

Master of Arts

in

Psychological Sciences

by

Umay Şen

Boğaziçi University

July 2018

The Interaction Between Ensemble and Item Representations in a

Temporally Extended Context

The thesis of Umay Şen

has been approved by:

Prof. Ayşecan Boduroğlu
(Thesis Advisor) _______________

Assist. Prof. Esra Mungan _______________

Assist. Prof. Ahu Gökçe
(External Member) _______________

July 2018

DECLARATION OF ORIGINALITY

I, Umay Şen, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

Signature...

Date ....20.07.2018.....................

ABSTRACT

The Interaction Between Ensemble and Item Representations

in a Temporally Extended Context

To date, research demonstrated that visual perceptual judgments are susceptible to information which is accumulated in the recent past. However, it is not well known how localization of a particular item of a set is affected by the information coming from previous trials within an experimental session. The present research investigated how accumulated information during an experimental session impacted spatial item representations. In the present study, participants reported the location of an item in one of two types of perceptual sets. While one group of trials was of randomly generated sets, the other trials consisted of spatial configurations that belonged to perceptual families. We specifically tested whether localization in the latter group of trials would be more accurate. Also, previous research had demonstrated that individuals high in working memory were more likely to utilize spatial configuration information in visual change detection tasks. Thus, in the current set of experiments, we explored whether there were individual differences in working memory capacity impacted how efficiently viewers utilized perceptual set information in spatial localization. Results demonstrated that people were more able to accurately localize items in perceptual set trials compared to random configuration trials; however, this effect was observed only for some perceptual sets and not all suggesting that perceptual characteristics of sets may be critical. We also found that visual working memory capacity did not selectively predict localization errors in perceptual set and random configuration conditions.

ÖZET

Özet ve Nesne Temsillerinin Genişletilmiş Zaman Bağlamındaki İlişkisi

Araştırmalar göstermektedir ki algısal yargılar kendilerinden önce gelen denemelerdeki özet bilgilerden etkilenmektedir. Öte yandan, setlere ait nesnelerin yer bilgisi temsillerinin (görsel-uzamsal bilgi) kendinden önce gelen sahnelerden nasıl etkilendiği henüz detaylıca araştırılmamıştır. Bu çalışmanın amacı görsel uzamsal bilginin temsilinin kendinden önce gelen sahneler boyunca biriken özet bilgiden nasıl etkilendiğini araştırmaktır. Deneylerde katılımcılar bir görsel uyaran seti ile karşılaşmıştır ve kendilerinden bu uyaran setindeki bir nesnenin yeri sorulmuştur. Deneydeki setlerden bazıları aynı algısal aileye ait uzamsal konfigürasyonlardan oluşurken (prototip aileleri), diğerleri ise rastgele konumlandırılmış nesnelerden oluşmaktadır. Beklentimiz rastgele konumlandırılmış setlerde, nesne yerinin tespitinin daha hatalı olacağı yönündedir. Ayrıca, görsel uzamsal çalışma belleği kapasitesindeki farklılıkların uzamsal konfigürasyon bilgisini görsel fark deneylerinde kararları etkilediği gösterildiğinden, bu çalışmada da çalışma belleği kapasitesinin aynı aileye ait uzamsal bilginin nesne yeri tespiti için kolaylaştırıcı olabileceği düşünülmüştür. Sonuçlar göstermektedir ki nesneler prototip ailelerinin üyeleri olduklarında daha güçlü temsil edilebilmektedirler; ancak, bu etki prototip ailelerinin çeşitli algısal özelliklerine bağlıdır. Görsel uzamsal bellek kapasitesi geniş olan bireylerin hem prototip ailelerinin üyelerinin yerlerini hem de rastgele konumlandırılmış nesnelerin yerlerini daha iyi temsil ettiği gözlemlenmiştir.

ACKNOWLEDGEMENTS

Many people have made various contributions to the completion of this thesis. I would like, first, to thank to my supervisor, Ayşecan Boduroğlu, for your patience, support and encouragement to work out my inner passion and to offer a methodology that fit with my convictions. You have planted the seeds what will make me a competent researcher and I will always be grateful for that.

Secondly, I wish to acknowledge my committee members, with real appreciation for their role in my work. I wish to thank Ahu Gökçe for providing insightful comments and valuable ideas as a member of my thesis committee. I want to thank Esra Mungan, for your sharing of knowledge and interest, beyond that, for your innate understanding and enthusiasm that you have passed on me.

I would like to give special thanks to Reşit Canbeyli, for providing me the courage to pursuit my excitement and curiosity while I was taking my first steps in this journey. To all members of the Department of Psychology, I feel very lucky to have done my masters within such a wonderful and inspiring community.

Thanks to my sister, Pınar Çiğdem Babayiğit and my very special friends who have also contributed in ways too numerous to mention- emotionally, intellectually, practically: Elif Canseza Kaplan, Erdem Ozan Meral, Dorukhan Açıl. I would like to acknowledge my dear friend Berkant Kepez who used his excellent computing skills to help me for generating the stimuli.

Finally, I want to extend my biggest thanks to the guardians of my sanity. Thanks to Çağatay for each word, each laugh and for your consistent encouragement and support throughout this journey. The thought of caring and love that I received from you at the moments of feeling exhausted and discouraged has been the resource which kept me moving towards the completion of this task. Last but not least, I would like to thank my family, people helping shape me into someone that I am proud to be. This thesis is dedicated to you with greatest love and gratitude.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

How we perceive and represent a stimulus depends on various variables, with context being one of the most important determinants (see Albright & Stoner, 2002 for a review). Although it is difficult to provide a comprehensive definition of what constitutes context, it could be described as what co-occurs with a target stimulus either simultaneously or within a temporally extended period. There are many illustrations of contextual effects on perceptual processes. For instance, the famous Ebbinghaus illusion reveals how the size of the central circle is perceived as different based on the size of the other circles surrounding it. The same central circle is perceived as larger when it is surrounded by smaller than larger circles. This illusion demonstrates how the relationship between simultaneously presented items in a visual display affect the response towards the item belonging to a set. On the other hand, there could be a relationship between members of the set that is formed within a temporally extended period. For instance, while listening a melody in a particular key, even non-musician adults heard the change in the melody which had an out of key note since they were able to represent the musical context (Trainor & Trehub, 1992). Similarly, during speech perception the phonemes were perceived faster when they were embedded in words than non-words (Rubin, Turvey & Gelder, 1976). Thus, the context as (either being) a meaningful word or a non-sense word affected the perception of the auditory information. A similar phenomenon is likely to exist for visual as well as auditory inputs (see Diehl, Lotto & Holt, 2004 for a review). The aim of the present thesis is to investigate how visuospatial judgments are affected by the temporal context which is formed within an experimental session.

There is considerable empirical evidence to indicate that the visual system is efficient in representing both immediately available and also temporally extended contexts. For instance, it is known that viewers can effectively extract the configural relationship between items (Boduroglu & Shah, 2009; Jiang, Olson & Chun, 2000). In a similar vein, viewers can use spatial configuration information to increase the resolution of target location representations (Mutlutürk & Boduroglu, 2014). This ability to process immediately available context facilitates perception.

The visual system can also effectively extract relationships that are not immediately present. For instance, observers could utilize the configural background information in visual search tasks resulting in decrease in reaction time for identifying targets when the background configuration was the same across trials (Chun & Jiang, 1998). Similarly, viewers can represent the spatial configuration formed by sequentially presented locations (Boduroglu & Shah, 2014) and can learn the statistical regularities of sequential patterns presented (Fiser & Aslin, 2002; Turk-Browne, Jungé & Scholl, 2005). Also, viewers can accurately extract the summary representation of sequentially presented (Corbett & Oriet, 2011; Hubert-Wallander & Boynton, 2015) and dynamic items (Albrecht & Scholl, 2010) and of sets presented across time (Oriet & Hozempa, 2016; Whiting & Oriet, 2011). Whiting and Oriet (2011) asserted that observers' mean judgments of sets were biased towards the cumulative mean information from previous sets even when the previously shown stimulus is masked and not perceived accurately. Similarly, Oriet and Hozempa (2016) demonstrated that central tendency characteristics of sets, such as the cumulative mean of all sets in an experimental session, could be extracted in an incidental manner. Both studies indicate that observers represent the temporally extended context by summarizing all the studied sets in an experimental session. However, it is not known whether the available temporally extended context summary impacts the perceptual averaging process/outcome in a particular trial. The major aim of the present study is to explore how summary representations and the dynamic representation of their temporally extended context interact in an experimental session.

The summary information of a set of items could be extracted effortlessly even when item information is not represented in high precision (Ariely, 2001; Chong & Treisman, 2003). Viewers can summarize size (Ariely, 2001), orientation (Attarha & Moore, 2015), brightness (Bauer, 2009), color (Maule & Franklin, 2015) of lines and circles and also average the facial emotion and identity of groups of faces (Haberman & Whitney, 2007; 2009). It is believed that these summary representations are represented along with some, if- not-all, item information. For instance, Brady, Konkle and Alvarez (2011) argued that item level information is encoded along with the summary information and they are represented interactively in a hierarchy. For instance, at retrieval, the mean size of an item could be biased towards the mean size of same color sub-group (Brady & Alvarez, 2011). Similarly, spatial working memory studies have shown that ensemble and item information are not represented in an independent fashion; memory for visual and spatial features of items are impacted by the configural information that these items belonged to (Jiang et al., 2000; Mutlutürk & Boduroglu, 2014). A similar interaction between the ensemble and its temporally extended context may also exist. This possibility is likely given recent evidence showing that the accumulating average is represented in long term memory (Oriet & Hozempa, 2016;

Whiting & Oriet, 2011). This may lead to a dynamic interaction between the continuously updated average and the ensemble representation. The goal of this thesis is to investigate this dynamic interaction between the accumulating information over past trials and items belonged to the ensembles.

CHAPTER 2

LITERATURE REVIEW

To date, there are only a few studies that have directly investigated how summary information is represented across time. Some of these studies have directly questioned this effect when the items were presented sequentially (Corbett & Oriet, 2011; Haberman, Harp & Whitney, 2009; Hubert-Wallender & Boynton, 2012) and few have explored this issue when items were presented in dynamic motion (Albrecht & Scholl, 2010). It has also been demonstrated that observers are also able to extract a summary representation of all presented sets within an experimental session (Oriet & Hozempa, 2016; Whiting & Oriet, 2011).

Hubert-Wallender and Boynton (2012) presented participants with perceptual sets consisting of ten sequentially presented circles, each for 150 ms. Then, they asked viewers to indicate the mean size of the whole sequence of items. In this task, the most recent items contributed more heavily to the mean judgments, indicating a recency effect. A similar recency effect was observed in a study in which observers indicated the spatial frequency of studied Gabor patches (Huang & Sekuler, 2010). Two Gabor patches were presented consecutively to the observers in a single trial. They were asked to reproduce the spatial frequency of the target Gabor patch indicated with a post-cue. The results demonstrated that after stimulus onset, the reproduced target Gabor was biased towards the non-target item regardless of being presented before or after the target Gabor suggesting that the reproduced spatial frequency of items was also biased towards the cumulative summary of all Gabor patches in previously shown trials. Thus, the influence of both short and long-term memory on perception could be observed in lower level visual processes.

When the temporal context is extended to the whole experimental session, some general characteristics of the sets like their mean and the variability information could gain greater importance. Whiting and Oriet (2011) asked participants to choose the mean size of the previously shown set which was presented for different durations (0, 50, 100, 1000 ms) in a two forced-choice paradigm. When the stimulus was shown for less than 200ms, participants were more likely to choose the test item which was the size of the cumulative mean of all previous trials. Poor visibility of the stimulus led participants' judgments to be biased more towards the cumulative mean.

Huttenlocher and colleagues also demonstrated that the perceptual judgments about items were affected by the characteristics of the distribution an item belonged to (Duffy, Huttenlocher, Hedges & Crawford, 2010; Huttenlocher et al., 2000). Participants were asked to reproduce the size of a previously shown item while distribution characteristics of the stimuli were manipulated. The reproduced size was biased towards the running mean of all items in the session, especially when it was difficult to judge whether the presented item belonged to the distribution or not. When the sizes of all presented items had the same presentation frequency, it was difficult to use the cumulative mean as a predictor of the upcoming stimuli. On the other hand, when the items were selected from a normal distribution, the size of the reproduced items was biased towards cumulative mean of the highly frequent items. Therefore, viewers were representing both the cumulative mean of the previously shown items and also the characteristics of the distributions that these items belonged to. In some cases, this information could create a bias in the immediate perceptual judgments. In some other cases, the temporally extended spatial context was shown to enhance performance in visual search tasks. For instance, observers became much better in a given task when background item configurations were the same across the trials (Chun & Jiang, 1998). In this experiment, the experimental session was divided into different epochs in order to understand the perceptual learning process. As experimental session was investigated epoch by epoch, it was shown that participants got better in visual search task as experimental session proceeded. Similarly, Corbett and Melcher (2014) demonstrated that when mean size of Gabor patches in the background was constant over trials, the observers spent less time to find the target Gabor in a visual search paradigm.

The visual system is also efficient in implicitly learning the summary information of all sets presented in an experimental session. Oriet and Hozempa (2016) asked observers to indicate how many circles were in the presented set or whether there were same-color circles in a given trial. Critically, at the end of the experiment, participants also specified the mean size of all previously studied circles. They were very accurate in estimating the mean size of the circles even when this estimation was task irrelevant suggesting that viewers were continuously summarizing the displays as they engaged in other critical tasks. It is possible that also in a spatial task, the visual system may continuously update the spatial summary (i.e. the centroid) of all previously shown displays.

The current study investigates how information coming from the recent past effects perceptual judgments in the spatial domain. More specifically, to what extent are spatial representations effected by the information accumulated during an experimental session. Mutlutürk and Boduroglu (2014) demonstrated that the spatial resolution of individual item representations was facilitated by the presence of the studied configural context during retrieval. They argued that the preserved configural context between encoding and retrieval allowed people to utilize the centroid information while estimating individual item locations, further reducing error (also see Boduroglu & Shah, 2014 for sequential displays). We also know that spatial configuration information may be efficiently summarized as centroid (Alvarez & Oliva, 2008; Mutlutürk & Boduroglu, under review). However, we still do not know how multiple spatial configurations presented across time are represented and how the item and ensemble representations are affected by this temporally extended context. To date, the effect of the cumulative mean information from past trials on perceptual judgments has been investigated in terms of mean size of items (Whiting & Oriet, 2011), mean spatial frequency of Gabor patches (Huang & Sekuler, 2010) and memory of faces (Poirier, Heussen, Aldrovandi, Daniel, Tasnim & Hampton, 2017). The present study is an attempt to extend these effects into the spatial domain. Specifically, the current set of experiments investigated whether people could learn and utilize perceptual category information in item localization. Participants were asked to report the locations of particular items from sets that are either members of particular perceptual families or systematically unrelated to all other sets (called "random" here onwards). Posner & Keele (1968) demonstrated that people implicitly learn the prototype of displays after viewing slight spatial distortions of it. Furthermore, they demonstrated that people confidently report that they have studied the prototype even though the actual prototype was never presented to them. In the present study, we predicted that the spatial configurations belonging to a perceptual family (referred to as "prototype" here onwards) could be learned across trials and that information could facilitate item representation. As in item localization tasks where we have shown the benefit of preserved spatial configurations on item localization

(Mutlutürk & Boduroglu, 2014), we expected that for prototype families, the shared properties between members of the family may be implicitly learned and this may help narrow the possibilities during target location retrieval, reducing localization error. We also expected that this learning process could take place in the form of gradual decrease in localization error, as the experimental session proceeds.

A secondary goal of the present study was to understand whether there are individual differences in how well prototype configurations are learned across trials and how effectively this information is utilized to increase item precision. While previous research on summary representations have not looked into this issue, work on spatial configuration representations had shown that there are individual differences in how efficiently people utilize spatial configuration information. Boduroglu & Shah (2009) demonstrated that high ability participants whose false alarm rate in visual change detection task was lower than median false alarm rate of the sample were able to utilize configural congruency between study and test displays while low ability participants who had more false alarms than average median false alarm score were not able to utilize configural congruency to foster visual change detection performance. Therefore, in Experiment 2, we predicted that there may be individual differences in how well the prototype information is learned and utilized during item localization. To determine ability differences, we chose to use both a visual working memory task and measures of processing speed. We chose to use a visual change detection task as in Boduroglu & Shah (2009), since performance on this task is one of the most reliable measures estimating the visual working memory capacity (Fukuda, Vogel, Mayr & Awh; Luck & Vogel, 1997) and executive functions (Miyake, Friedman, Rettinger, Shah & Hegarty, 2001). To rule out the possibility finding a correlation between two measures are driven solely due to motivational factors, we also included verbal and visuospatial speed of processing measures. Speed of processing measures, such as pattern matching and number matching, are good indicators of short term memory capacity but not working memory (Conway, Cowan, Bunting, Therriault & Minkoff, 2002). Since ability differences are typically driven by differences in working memory as opposed to differences in short-term memory capacity, we expected the spatial localization task performance to be correlated with working memory but not speed of processing measures.

CHAPTER 3

EXPERIMENT 1A

3.1 Participants

Twenty-nine students (18 female; mean age = 20.45 ± 1.34) from Boğaziçi University participated the study in exchange for course credit. All had normal or corrected to normal vision.

3.2 Materials

Each trial began with the presentation of a fixation cross for 500 ms. Participants were required to look at the fixation cross as long as it was visible. After the fixation, the display, that consisted of 7 same size and different colored squares was presented on the screen for 500 ms. Each square had sides of 0.8 cm subtending 0.8°. The squares were blue, cyan, red, yellow, pink, green and purple and they were presented on a grey background. After stimulus offset, participants heard the name of the color of the target via headphones. The speech sound was simultaneous with the onset of the blank, grey screen. The participants responded by clicking the location of the target item on the blank screen which was visible up until the response (see Figure 1).

In each trial, locations of the squares were generated within a 12° x 12° square region (see Figure 1). The boundary of this region was identified by taking the center of the screen as the center of the grid. The items were never located on the peripheral region of the screen because of the lower representational resolution of the item locations in the peripheral region.

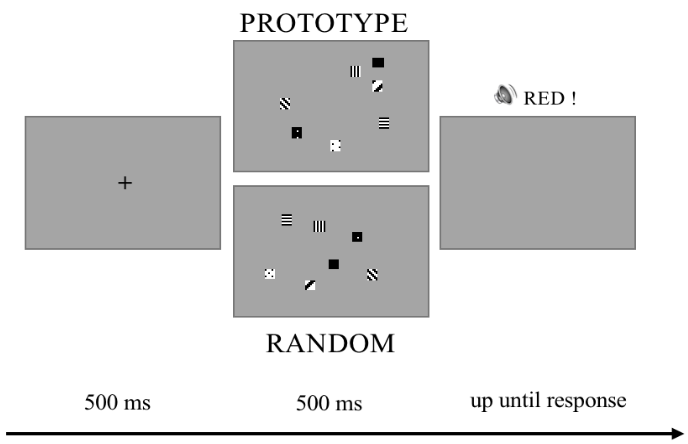

Figure 1. The trial sequence

There were two types of trials: prototype and random. In the prototype trials, we presented participants the vertices of members of Attneave shape families (Attneave & Arnolt, 1956)[1]. We generated 7 sided Attneave figures by running a Matlab program designed for this purpose (Collin & McMullen, 2002). For each family set, there was a prototype member and its variations. For each prototype family, the locations of the vertices of the variations consisted the location of to-be-displayed colors. In the displays, we only showed the vertices not the sides. There were 60 variations of each family. The prototype was never showed to the participant. We generated 3 separate prototype families (see Figure 2). The members of each shape family had .80 family resemblance rating which was the recommended value as it was indicated in the Matlab program in order for the shapes to have some degree of subjective similarity (Collin & McMullen, 2002). In order to create prototype variations, the program shifts the vertices of the prototype shapes while creating each member of the family. The number of vertices to be shifted was set for three families to the value of ‘6’ which was the default value.

[1] Attneave shapes are hard-to-name polygons.

There were three different methods to implement for choosing which vertices to shift. Each method was implemented for each family to generate shape families. The random method which was choosing arbitrarily a new set of points to shift each time was implemented for Family A. The sequential method which was incrementally moving through all the points in the shape by shifting one vertex at a time was implemented for Family B. The constant method which was shifting the same points each time was implemented for Family C. The other parameters such as length limit of sides and angle limit of the vertices were set as they had been suggested by the program. They were same for all three family types.

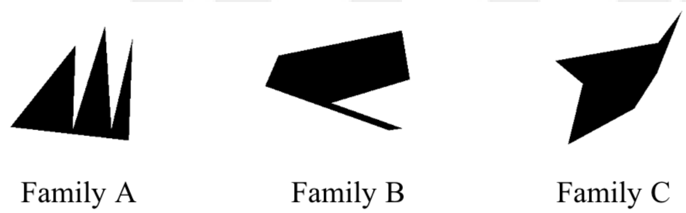

Figure 2. Attneave figures generated as prototype of different perceptual families

For the random trials, we used the same coordinates that were used in the spatial localization task in Mutlutürk & Boduroglu (2014). Mutlutürk & Boduroglu pseudo-randomly generated locations of 7 items, for each display with the constraints that the items were never located in the central foveal region (3°x 3°).

After we generated a set of locations for both conditions, we calculated the inter-item distance between items in each display and excluded any set where any one of the inter-item distances were at least 30 pixels (1.5°) to ensure that items were spatially distinguishable.

Overall, participants completed a total 360 trials, distributed evenly across the two conditions in three blocks. The prototype trials and random trials in a block were presented in a mixed order since learning of a category could take place even in the presence of intervening non-category members during the learning phase (Turk-Brown et al., 2005). In each block, for the prototype trials, we presented participants with members of separate prototype families (Family A, B, C) and the order of these families were kept the same. There were 13 training trials in the beginning of the task in order to familiarize the participants with the task requirements.

3.3 Apparatus

A computer with an Intel Core 2 Duo processor, an ATI Radeon X300/X550/X1050 Series graphics card, and a 17-in. CRT Philips 107S6 monitor was used to present stimuli. The screen resolution was set to 640 x 480, with refresh rate of 75 Hz (Refresh duration = 13.33 ms). The experiment was programmed in E-Prime (Psychology Tools, Inc.). Participants viewed the computer screen from 57 cm, where 1 cm corresponds to 1°.

3.4 Procedure

The study took place in a well-lit room. Participants completed a spatial localization task in which they first studied a display and afterwards, subsequent to an auditory cue, retrieved a target location. After completing the computer-based task, the participants were asked to fill the demographic form. At the end of the experiment, they were thanked and debriefed. The whole procedure took approximately 45 minutes.

3.5 Results and discussion

The Euclidian distance between the target and response coordinates was determined as the dependent variable indicating the spatial resolution, in other words localization error. The trials in which the error was higher than the outlier threshold (determined as any value two standard deviations of the sample mean) were eliminated from the data. We excluded the data of three participants whose responses fell outside the outlier boundary on more than 25% of the trials.

Kolmogorov-Smirnov test of normality demonstrated that the normality assumption was violated in both conditions (ps < .05). Therefore, to normalize the data, we log transformed the data as recommended by Osborne (2008a)[2]. In order to assess whether learning of different prototypes had an impact on localization errors, we conducted a 2(Condition: Prototype vs. Random) x3 (Block/Family Type: Family A, Family B, Family C) within subject ANOVA. The results demonstrated that there was a main effect of condition, $F(1, 25) = 4.50$, $MSE = .002$, $p < .05$, $\eta_p^2 = .15$. Participants made less localization error in the prototype ($M = 48.13$, $SD = 13.11$) than in the random condition ($M = 49.65$, $SD = 12.23$). There was also main effect of Block Type, $F(2, 50) = 6.69$, $MSE = .003$, $p < .001$, $\eta_p^2 = .21$. Participants made more localization error in 3rd Block (Family C) ($M = 51.38$, $SD = 12.91$) than the 1st Block (Family A) ($M = 46.76$, $SD = 11.83$) and 2nd Block ($M = 48.54$, $SD = 13.28$), $p < .05$. The increased error in the 3rd Block may have suggested a fatigue effect. There was no interaction between Condition and Block Type, $F(2, 50) = 1.58$, $MSE = .002$, $p = .21$, $\eta_p^2 = .06$ (see Figure 3; error bars in the figures correspond to ± 1 SEM from that point) . Even though the interaction was not significant, inspection of the data in Figure 3 suggested that the prototype- random difference may not be equally strong in all family types. Therefore, we carried out some post-hoc comparisons for each block and these analyses revealed that the strongest difference between prototype and random conditions was in the second, Family B block (prototype ($M = 46.78$, $SD = 13.60$) and random conditions

[2] Descriptive statistics such as mean and standard deviation values were presented with their non-transformed values in text and graphs.

(*M* = 50.31, *SD* = 12.96) in *t*(25)= -2.66, *p*= .01. The error difference was not significant for Family A block (prototype (*M* = 46.59, *SD* = 12.36) and random conditions (*M* = 46.92, *SD* = 11.29) in *t*(25)= -. 232, *p*= .82) and Family C block (prototype (*M* = 51.02, *SD* = 13.37) and random conditions (*M* = 51.75, *SD* = 12.45) in *t*(25)= - .543, *p*= .59).

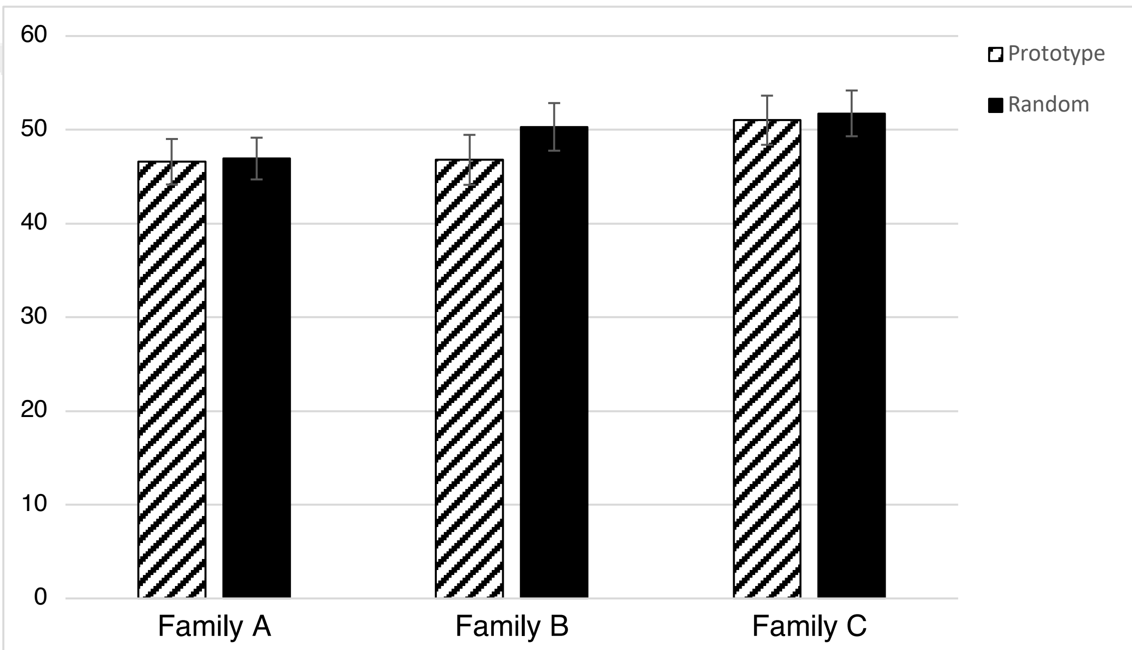

Figure 3. Mean errors as a function of block/family type in Experiment 1A

The distance between the items presented in different conditions and blocks may have had an impact on learning of configural congruencies and family members, since proximity is an important Gestalt principle for perceiving the items to be grouped together (Quinlan & Wilton, 1998). In order to understand this, we calculated the inter item distance of the seven locations for each trial. A comparison of the average inter-item distances via a 2(Condition: Prototype vs. Random) x 3(Block/Family Type: Family A, Family B, Family C) ANOVA revealed that there was neither a main effect of

Condition ($F(1, 118) = .02$, $MSE = 363.02$, $p > .10$, $\eta_p^2 < .001$) nor a main effect of Family/Block Type ($F(2, 236) = .13$, $MSE = 127.40$, $p > .10$, $\eta^2 < .001$). The Condition and Family/Block Type interaction was not significant, either ($F(2, 236) = 1.24$, $MSE = 127.396$, $p > .10$, $\eta^2 < .001$). Thus, the differences between prototype and random conditions across different blocks/family types may not be simply due to differences in inter-item distances across different conditions.

Experiment 1A demonstrated that the observers could use prototype information to increase the precision of item resolution. Also, we found that the error rate was lowest in the second block for both the prototype and random trials. Since we had not counterbalanced the different prototype members across different blocks, these findings may have unfortunately been tainted by training and fatigue effects. The post-hoc analyses comparing prototype-random differences for different families also revealed that there seemed to be family-specific perceptual properties that may facilitate the implicit learning of family memberships and the utilization of such information in item localization.

CHAPTER 4

EXPERIMENT 1B

We carried out Experiment 1B with two particular goals in mind. First, we wanted to determine whether increased exposure to family members could lead to an increase in the utilization of prototype information resulting in better resolution for item locations. To ensure this, we doubled the number of trials with the same 60 members of Family B and C, hoping it would facilitate, possibly implicitly, the learning of family members (for effects of increased exposure on perceptual learning see Chun & Jiang, 1998). Secondly, we also manipulated prototype family as a between-subject manner such that participants were exposed to members of a single prototype family. We specifically exposed participants to either Family B trials (where we observed the largest prototype-random difference) or to Family C sets. Even though the localization error was largest for Family C trials in Experiment 1A and there was no reliable difference between the two conditions, the confound in our earlier design did not allow us to rule out whether a potential difference may have been washed out by an even stronger fatigue effect.

4.1 Participants

Fifty-two students (30 female; mean age = 22.02 ± 1.92) from Boğaziçi University participated the study in exchange for course credit (26 for each family type). All of them had normal or corrected to normal vision.

4.2 Materials and procedure

In Experiment 2, everything was the same as Experiment 1 except that we doubled the trials by presenting each prototype trial twice and used only Family B & C displays for prototype trials. The prototype and random trials were presented in a mixed order, different for each participant. The experimental session was divided into three epochs; each epoch consisted of eighty trials, evenly distributed across random and prototype.

4.3 Results and discussion

Unlike in Experiment 1A, the normality assumption was not violated (Kolmogorov Smirnov test of normality, *p*s > .05). We separately analyzed errors for the group that received the Family B and Family C sets. For the Family B group, 2(Condition: Prototype vs. Random) x3 (Epoch: 1st, 2nd and 3rd Epoch) within subject ANOVA revealed a marginal main effect of condition $F(1, 25) = 3.88$, $MSE = 30.11$, $p = .06$, $\eta_p^2 = .13$. Participants made less localization error in prototype condition (M = 41.05, SD = 8.76) than the random condition (M = 42.09, SD = 7.68). There was no main effect of Epoch, ($F(2, 50) = .25$, $MSE = 30.79$, $p > .10$, $\eta_p^2 < .05$) and the Condition by Epoch interaction did not reach significance ($F(2, 50) = 1.37$, $MSE = 20.06$, $p = .56$, $\eta_p^2 < .05$). For the Family C group, the same analyses revealed a slightly different pattern. There was no main effect of condition, $F(1, 25) = .86$, $MSE = 27.42$, $p = .36$, $\eta_p^2 < .05$. However, there was a main effect of Epoch, $F(2, 50) = 3.88$, $MSE = 34.86$, $p < .05$, $\eta_p^2 = .12$, driven by the greater errors in the last epoch ($M_{3rd} = 46.82$, $SD_{3rd} = 11.76$) compared to the earlier two epochs ($M_{1st} = 43.80$, $SD_{1st} = 10.42$; $M_{2nd} = 45.65$, SD_{2nd} = 10.38). There was no interaction between two conditions, $F(2, 50) = .77$, $MSE = 29.23$, $p > .10$, $\eta^2 < .05$).

Since the data for the two families did not yield consistent results, we further explored whether there were any particular individual differences that were overlooked in the group level analyses. For each group, we identified the top 25% and bottom 25% participants based on the error in the prototype condition. Specifically, we were curious whether both the top and bottom performers in the Family B group showed the prototype-random difference similarly. A comparison of prototype-random difference across the two groups, with 2(Group: Top vs. Bottom)x 2(Condition: Prototype vs. Random) ANOVA revealed an expected main effect of condition ($F(1, 12) = 5.64$, $MSE = .001$, $p < .05$, $\eta_p^2 = .32$) and main effect of group ($F(1, 12) = 73.86$, $MSE = .187$, $p < .001$, $\eta^2 = .86$.). There was a significant interaction between Group and Condition, $F(1, 12) = 9.59$, $MSE = .009$, $p < .05$, $\eta_p^2 = .44$. As can be seen in Figure 4, this interaction was driven by the fact that there was a prototype ($M = 31.88$, $SD = 1.43$) and random ($M = 37.29$, $SD = 5.49$) difference for the top performers, $t(6)= - 3.085$, $p < .05$. However, prototype ($M = 50.67$, $SD = 5.15$) and random ($M = 49.56$, $SD = 3.04$) difference was not significant for the bottom performers, $t(6)= .756$, $p > .10$. A similar comparison of the top and bottom 25% of performers in the Family C group also revealed the significant Group and Condition interaction ($F(1, 12) = 11.39$, $MSE = .004$, $p < .05$, $\eta^2 = .49$). This interaction was driven by marginal error difference between prototype ($M = 34.75$, $SD = 4.27$) and random ($M = 36.71$, $SD = 5.30$) difference for top performers, $t(6)= -2.197$, $p= .07$. Surprisingly, bottom performers made more error in prototype ($M = 59.33$, $SD = 4.67$) than random ($M = 56.02$, $SD = 7.03$) condition which could be seen as another determinant of this interaction, $t(6)= 2.411$, $p= .05$.

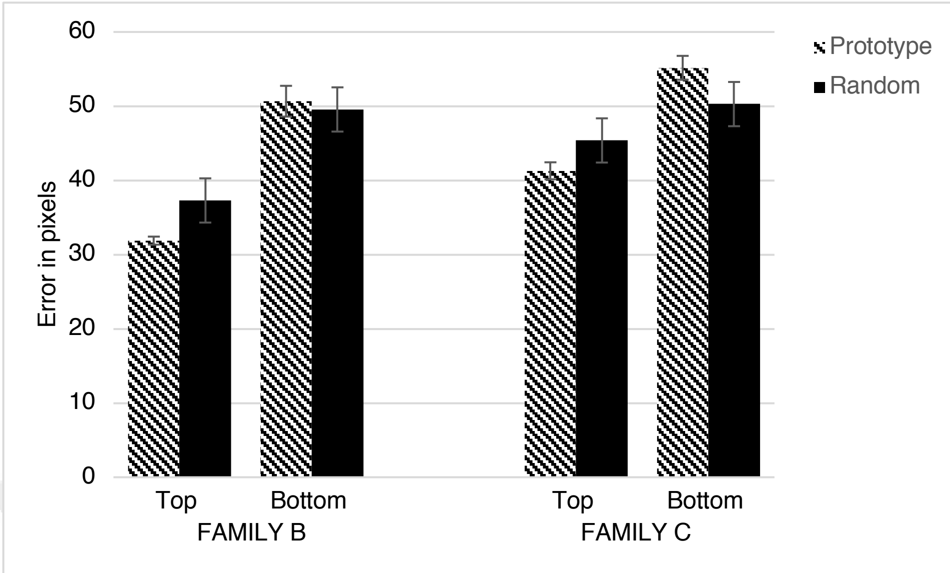

Figure 4. The performance of top and bottom performers on spatial localization task (Experiment 1B) for Family B and Family C

Experiment 1B demonstrated that the prototype information, most likely implicitly learned throughout the session, increased spatial representation resolution. However, this effect was pronounced for Family B trials, and increasing exposure to Family C members did not lead to increased utilization of prototype information in spatial localization in all viewers. Interestingly, post-hoc analyses revealed that in both Family B and Family C groups, the top performers' data actually yielded a prototype advantage. This finding of an individual difference in learning and utilizing spatial configuration information is not unique to this study. Earlier work from our lab had shown that top performers were able to utilize spatial configuration information to assist in visual change detection tasks. The prototype trials in the currently used spatial localization task, require participants to learn (implicitly) spatial configuration information unique to families, from information presented in a temporally extended context. Thus, it seems as if individual differences as well as prototype family qualities contribute to the learning and utilization of temporally extended spatial context. Surprisingly, bottom performers in Family C group made more errors in prototype than the random condition contrary to the findings in Family B group. The characteristics of the bottom performers' behavior remain unclear to which degree they could utilize the prototype information whereas it is important to highlight that they did not perform in a total random fashion[3].

[3] To determine whether the bottom 25% of the participants were randomly localizing target objects, we simulated the data of a random observer who independently picked a location within the region where objects appeared. Comparison of the random observer data (M= 133.34) with the participant data revealed that even the poor performers (M= 56.85, SD=5.97) were not responding in a totally randomly manner, $t(51)= 76.09$, $p < .001$.

CHAPTER 6

EXPERIMENT 2A

In Experiment 2A, we wanted to further understand the prototype advantage partly observed in the earlier experiments, replicate those findings and determine the basis for the individual differences observed using independent measurements of visual working memory capacity. We also wanted to determine whether the particular qualities of the random trials utilized in Experiments 1A and 1B might have confounded some of the results because the constraints used to generate the random displays (e.g. ensuring the centroids of the random display were not within a central region) might have unknowingly decreased similarity across random displays since each random trial used different part of the visual display (see Figure 5). If that was the case, then the random trials may have created a visual pop-out effect, reducing the prototype-random difference. Therefore, in Experiment 2A, we generated a new set of random locations.

6.1 Participants

Sixty Boğaziçi University students (44 female; mean age = 20.58 ± 1.43) participated the study in exchange for the course credit. All of them had normal or corrected to normal vision.

6.2 Materials

In Experiment 2A, everything was the same as Experiment 1B except that we only used Family B members and a new set of random locations. In each random trial, locations of the squares were generated within the same 12 x 12 ° square region without any constraints by using the total area within the grid. Seven random locations were generated for each trial by using ‘rand’ function in Matlab. We also included a visual change detection task and processing speed measures described in detail under the individual differences heading.

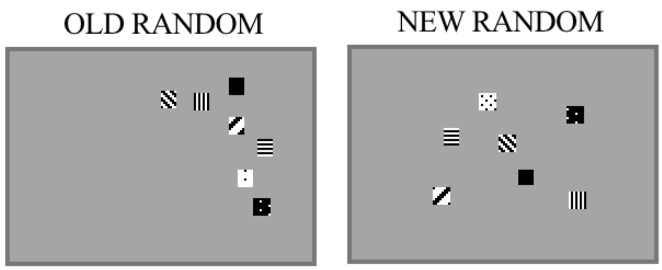

Figure 5. Old and new random sets

6.3 Individual differences measures

We used the color change detection task used by Buschkuehl and colleagues (2017)[4]. In the color change detection paradigm, participants are presented with a study set and after a brief delay, they are presented with a probe item. Participants have to decide whether this probe item is the same color as the one studied in the same location earlier. In this version of the task we used, a trial began with a fixation cross presented for 1000 ms. Following fixation, a set consisting of 2, 4, 6, 8 or 10 items were presented for 250 ms. Then, a mask consisting of striped squares located in the same positions were presented for 700 ms. After 100 ms blank screen, the probe item was presented. Participants were asked to press “A” key or “L” key, if the color was the same or different colors, respectively. There were equal number of trials for each set size. Participants completed 150 trials and trials were presented in a mixed order. For each participant, we determined the capacity index, Cowan’s *k*.

[4] We would like to thank Buschkuehl and colleagues for providing us the program of the change detection task that was used in Experiment 2.

Participants also completed two separate, one verbal and the other visuospatial, speed of processing tasks. Both of these tasks were paper-pencil measures, and everything was presented visually to participants. In the Number Matching task (verbal), the participants had to decide whether two numbers were the same or not in a given trial. The numbers consisted of 3, 6 or 9 digits. There were three different parts, on three differences pages. Each part had 64 trials. The difficulty level increased in each part as the number of digits per number increased. Participants had 45 seconds to complete each part. They were asked complete each level as quickly as possible with the highest accuracy. The Pattern Matching task was very similar to the Number Matching Task. In this task, participants are presented with 2-D patterns and asked to match the target shape with the identical one from among four alternatives. There were two parts in this task at the same difficulty level. For each part, there were 30 trials. Each participant had 30 seconds per section. The score for each task was calculated by subtracting the wrong answers from the total number of correct answers.

6.4 Procedure

Participants first completed the experimental spatial localization task. Then, they completed the visual change detection task, Number Matching and Pattern Matching tasks in fixed order. After filling the demographic form, the participants were thanked and debriefed.

6.5 Results and discussion

For the spatial localization task, the error was calculated as in the previous experiments. Unlike in Experiment 1A, the normality assumption was not violated (Kolmogorov Smirnov test of normality, *p*s > .05).

Our comparison of the error in the prototype and random condition revealed that participants made less localization error in the prototype (*M* = 39.90, *SD* = 6.88) than in the random condition (*M* = 41.98, *SD* = 6.78), $t(58)= -4.074$, $p < .001$, replicating earlier findings with a new set of random display locations.

To determine whether there is a relationship between one's ability to utilize prototype information in spatial localization and visual working memory capacity, we carried out a correlation analysis between each participant's prototype-random localization error difference and change detection task scores (Cowan's *k*). The Cowan's *k* scores ranged from 2 to 10 (*M* = 4.15, *SD* = 2.04)[5]. We identified three visual working memory (VWM) capacity groups which were high, medium and low capacity groups based on the Cowan's *k* scores. The groups were formed in accordance with the condition that each group had a similar sample size. High capacity participants' scores ranged from 6 to10 (*N*= 16); medium capacity participants had the score of 4 (*N*= 27) and low capacity participants had the score of 2 (*N*= 17). 3(VWM Capacity: High, Medium, Low) x 2(Condition: Prototype vs. Random) mixed design ANOVA was carried out in order to understand whether there were any differences between these groups in terms of learning of prototype configurations. There was a main effect of condition ($F(1, 57) = 14.70$, $MSE = 7.26$, $p < .001$, $\eta^2 = .21$) as indicated earlier. There was also main effect of VWM capacity ($F(2, 57) = 5.54$, $MSE = 74.69$, $p < .05$, $\eta_p^2 = .16$) with least error for high capacity participants (*M* = 36.65, *SD* = 6.84) compared to medium capacity (*M* = 42.93, *SD* = 5.67) and low capacity participants (*M* = 41.80, *SD* = 7.14). There was no interaction between Condition and VWM

[5] Kolmogorov Smirnov test of normality indicated that the distribution was not normal ($p< .00$). There was no outlier in the sample detected by the SPSS.

capacity, $F(2, 57) = .898$, $MSE = 7.26$, $p > .10$, $\eta_p^2 < .05$. We carried out some post-hoc comparisons for each working memory capacity condition and these analyses revealed that the difference between prototype and random conditions was not significant in the high capacity participants (prototype ($M = 36.12$, $SD = 6.18$) and random conditions ($M = 37.18$, $SD = 7.49$) in $t(15)= - .912$, $p = .38$). The error difference was significant for medium capacity (prototype ($M = 41.61$, $SD = 6.21$) and random conditions ($M = 44.27$, $SD = 5.13$) in $t(26)= - 4.579$, $p < .01$) and low capacity participants (prototype ($M = 40.75$, $SD = 7.49$) and random ($M = 42.85$, $SD = 6.45$) in $t(16)= - 2.108$, $p= .05$). High capacity participants performed equally well in prototype and random conditions. On the other hand, medium and low capacity participants were the ones who could utilize the prototype information. It could be speculated that the high capacity participants may have utilized the prototype information, whereas they were also performed equally well in the random condition resulting in the decrease in the error difference between prototype and random conditions.

There was a significant negative correlation between the visual working memory scores and the localization error in both prototype condition, $r(58) = -.30$, $p < .05$ and random condition, $r(58) = -.38$, $p < .001$ (see Figure 6). This suggests that as observers' visual working memory capacity increased, they made less errors in the spatial localization task. Two correlations were compared in order to understand whether the latter is stronger than the former since stronger correlation between random errors and visual working capacity may have resulted in a different explanation (Hittner, May & Silver, 2003). In that case, the high capacity participants may have performed better in random condition because it is more difficult to perform than prototype condition. Their visual working memory capacity may have facilitated their performance more in random sets than the prototype sets. However, the correlation between visual working memory capacity (VWM) and the amount of error in random condition was not stronger than the correlation between VWM and prototype scores (Z= 1.22, p= .22), eliminating prior suggestions regarding the relationship between task difficulty and visual working memory capacity.

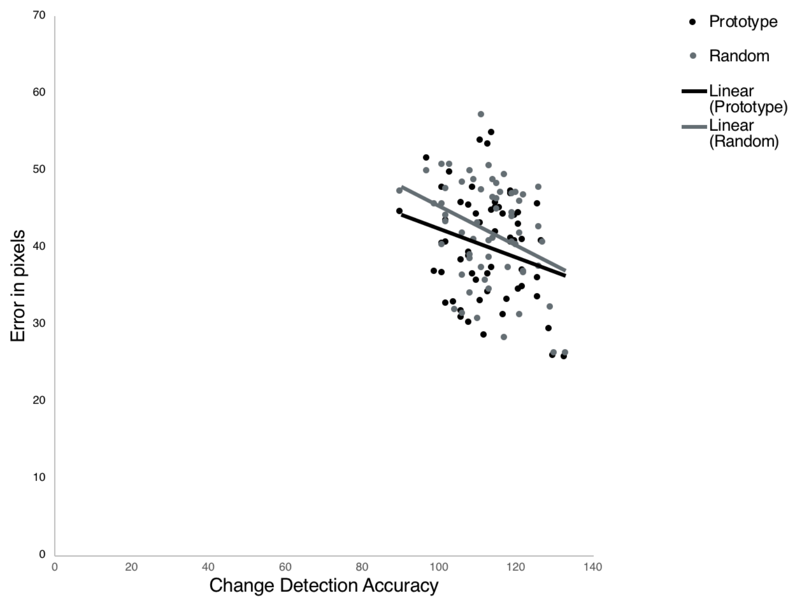

Figure 6. The correlation between visual working memory capacity and prototype/random errors in Experiment 2A

6.5.1 Pattern matching task

Another correlation analysis was conducted to determine whether processing speed had any relationship to localization error. There was a significant negative correlation between pattern matching task and the localization errors in the prototype condition, $r(58) = -.28$, $p < .05$ (see Figure 5). The participants who had higher processing capacity of visual patterns were also the ones who made less error in the prototype condition. The correlation between localization errors in random condition and pattern matching performance was marginally significant, $r(58) = -.23$, $p = .07$.

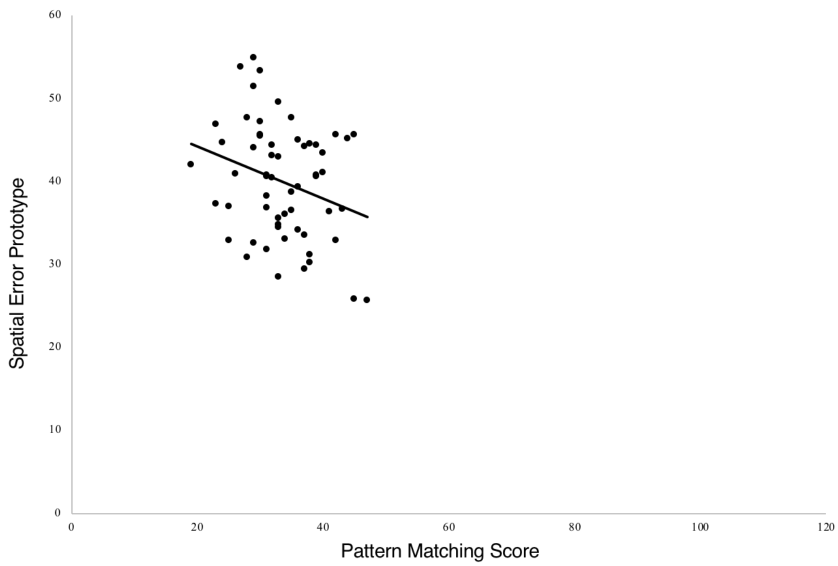

Figure 7. The relationship between localization errors in prototype condition and capacity for processing visual patterns in Experiment 2A

6.5.2 Number matching task

Localization error in prototype trials was not related to number matching performance, $r(58) = -.14$, $p > .10$. Similarly, errors in the random condition were not correlated with number matching scores, $r(58) = -.07$, $p > .10$.

In Experiment 2A, we replicated the prototype and random error difference for Family B, with a new set of random displays. We also found that visual working memory capacity was linked to spatial localization performance; spatial localization error both for prototype and random conditions was also significantly correlated with perceptual speed performance in the visuospatial domain.

In Experiment 2A, we also changed the locations of objects in the random trials. Eliminating the random confound resulted in stronger error difference between prototype and random trials in Experiment 2A than Experiment 1. Sharing the same visual field for both conditions may have contributed to the increase in the amount of error difference between prototype and random trials by increasing the amount of error in random conditions.

Individual differences in visual working memory and short-term memory capacity may play a crucial role in the performance for spatial localization task. However, this relationship between visual working memory capacity and the facilitation of the prototype information may not be solely attributed to the individual differences in utilizing configural congruency.

Individual differences in processing speed of visual patterns could determine the facilitation of the prototype information. In contrast, number matching task scores did not have a relationship with spatial localization task. This overall pattern may be linked to the visuospatial nature of the spatial localization task and the role of domain-specific abilities in perceptual learning and utilization of spatial configural patterns.

CHAPTER 7

EXPERIMENT 2B

In Experiment 2B, we wanted to test whether a prototype facilitation effect would be detected once the new set of random locations are used in comparison to Family A and Family C sets.

6.1 Participants

Fifty undergraduate students (27 for Family A and 23 for Family C) were recruited for the experiment in exchange for the course credit (29 female; mean age = 21.32 ± 1.76). All of them had normal or corrected to normal vision. One of the participants was excluded from the data since more than thirty five percent of his/her errors was determined as outlier (above mean plus two standard deviations of the sample errors).

6.2 Materials

Everything was identical to Experiment 2A except for the following changes. Two different prototype families (Family A & C) that were created for Experiment 1 by using the identical Matlab program designed for generating Attneave shapes (Collin & McMullen, 2002) were used in Experiment 2A. The members of the shape families had .80 similarity rating as in the Experiment 1& 2A. The trials were presented in a mixed order.

6.2 Results and discussion

The analysis of the data was similar to Experiment 1 & 2A. Kolmogorov Smirnov test of normality demonstrated that one of the Prototype families (Family A) violated the normality assumption (for all conditions, *p*s $< .01$). In order to normalize the data for Family A, the scores were log transformed. Taking the spatial resolution scores as the dependent variable, we compared prototype and random scores of the participants for each family. The results revealed that there was not a significant difference between prototype (M = 45.09, SD = 10.15) and random conditions (M = 44.41, SD = 10.42) for Family A, $t(26)$= 1.006, p= .32. Similarly, prototype (M = 45.46, SD = 8.24) and random (M = 44.94, SD = 8.67) difference was not significant for Family C, $t(21)$= .553, p= .58. Thus, the configural information did not facilitate the spatial item resolution both for Family B and Family C.

In the Experiment 2B data, we identified the top 25% and bottom 25% participants based on the error in the prototype condition as in Experiment 1B. We conducted 2(Condition: Prototype vs Random) x 2(Performer Type: Top Performer vs Bottom Performer) mixed design ANOVA in order to understand whether top or bottom participant groups performed differently in spatial localization task for Family A trials. There was no main effect of condition ($F(1, 12) = .08$, $MSE = 6.425$, p= .78, $\eta_p^2 = .01$), whereas there was a main effect of performer type, $F(1, 12) = 3.68$, $MSE = 147.51$, $p < .001$, $\eta_p^2 = .66$. The interaction between condition and performer type was not significant, ($F(1, 12) = .28$, $MSE = 6.425$, p= .61, $\eta_p^2 = .02$.

We carried out 2(Performer Type: Top Performer vs Bottom Performer) x 2(Condition: Prototype vs Random) mixed design ANOVA in order to understand whether top or bottom participant groups performed differently also for Family C trials. There was no main effect of condition, ($F(1,12) = .42$, $MSE = 5.942$, p= .53, $\eta_p^2 = .03$).There was a main effect of performer type, $F(1, 12) = 23.57$, $MSE = 70.84$, $p < .001$, $\eta_p^2 = .66$. The interaction between condition and performer type was marginally significant, $F(1, 12) = 4.16$, $MSE = 5.942$, $p = .06$, $\eta_p^2 = .26$ (see Figure 7). We also carried out some post-hoc comparisons for each performer type and these analyses showed that the difference between prototype and random conditions was not significant in the top performers (prototype (*M* = 37.42, *SD* = 6.50) and random conditions (*M* = 39.89, *SD* = 8.20) in *t*(6)= - 1.946, *p*= .10). The error difference was not significant for bottom performers (prototype (*M* = 54.74, *SD* = 3.75) and random conditions (*M* = 53.42, *SD* = 5.46)) in *t*(6)= . 96, *p*= .37).

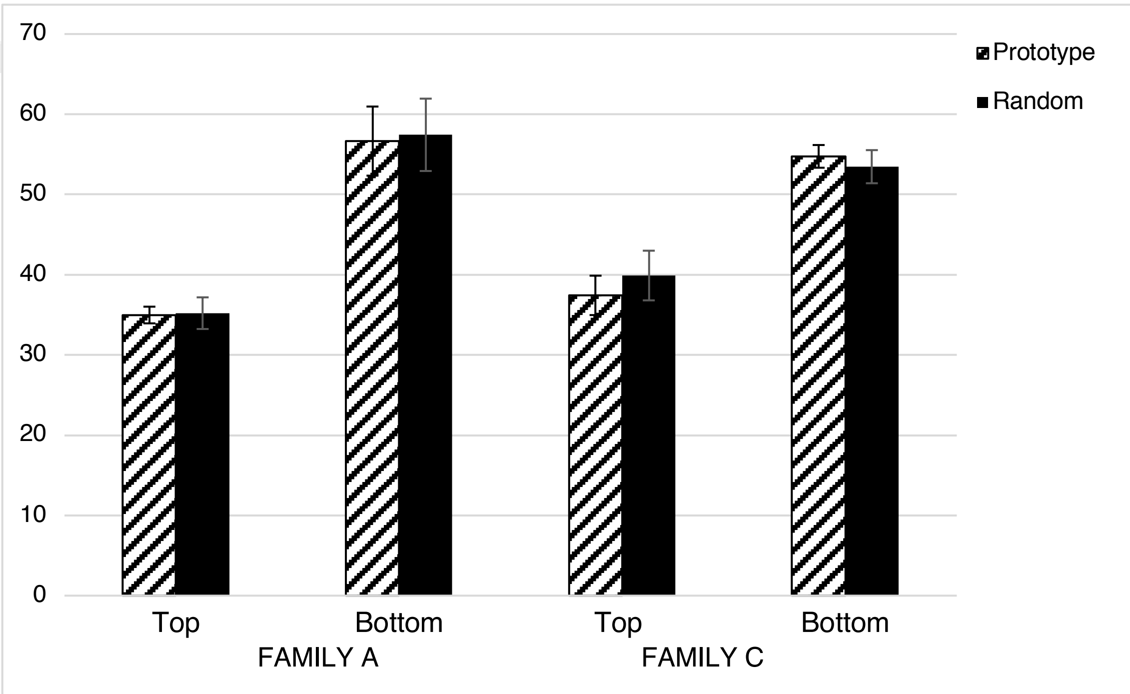

Figure 8. The performance of top and bottom performance on the spatial localization task in Experiment 2B

The results of Experiment 2B revealed that the participants did not utilize prototype information in order to increase the item resolution for both Family A and Family C. These findings may indicate that learning and utilizing the prototype information may not be easily generalized to the other perceptual families since there could be prototype characteristics that impact the likelihood of the prototype facilitation observed during the spatial localization task.

In Experiment 2B, the performance difference between prototype and random trials across different participants types was not replicated for Family A. Marginal significance of interaction effect between condition and performer type may indicate that there could be individual differences regarding utilization of the prototype information for Family C.

CHAPTER 8

GENERAL DISCUSSION

Findings of the reported experiments demonstrated that shared properties of configurations belonging to perceptual families could be learned and utilized when they are presented throughout experimental session whereas this may be subject to prototype characteristics. The findings which are presented in this study are consistent with the literature indicating that the observers could learn background item configurations (Chun & Jiang, 1998) and regularities of visual patterns (Turk-Browne et al., 2005). The effects of the regularities on item representations were studied in terms of processing of verbal stimuli through chunking (Cowan, 2010). The observers were more inclined to chunk semantically related stimuli than unrelated stimuli. This is one of the examples indicating the effects of redundancy resulting from the interaction between items and the whole that the items belonged to on verbal representations. Another line of the study indicated that regularities in terms of probabilistic co-occurrence of color pairs resulted in the higher visual capacity for items (Brady, Konkle & Alvarez, 2009). The current study elaborated the findings of the literature by investigating the effect of the regularities of configurations which are learned throughout an experimental session on the spatial resolution of items belonging to these configurations. This is an important finding in the understanding of to what extent the immediate perceptual judgments are affected by the regularities within the spatial configurations formed across time.

One of the possible explanations regarding the effect of learned configurations on item precision may be that participants decreased the target location possibilities by narrowing down the target field throughout experimental session due to the learning of the configural information. Another possibility could be that the centroid information of configurations belonging to the perceptual family may facilitate the spatial representation of the items since they fall into approximately same location on the screen across trials. Previous research showed that availability of the configural cues facilitates the spatial resolution of the items when the partial configuration is presented during retrieval since the partial configuration information facilitates the centroid representation (Mutlutürk & Boduroglu, 2014). Similarly, the centroid representation formed across trials may facilitate the item precision. One limitation of this interpretation could be that the centroid information has never been asked the participants in this experimental design.

Experiment 1 and 2 showed that particular configural properties could contribute to learning and utilizing the prototype information. In the present study, the metrical proximity of the items in the sets did not contribute to the distinctive qualities of the configurations belonged to different prototype families. Another important determinant which contribute to different characteristics of the prototype families could be seen as different methods that implemented by generating Attneave shapes. However, it is difficult to explain how these methods led one prototype family to be more useful or available during retrieval. Future work could focus on the investigation of the nature of these characteristics and how they impact learning and utilizing configural information across time.

In Experiment 1B, it was demonstrated that participants who made fewer errors in the prototype trials were the ones who could utilize the congruencies between prototype trials. However, the current experiments did not directly address the question of whether visual working memory capacity predicted the learning of the shared characteristics of the configurations, since the performance in visual change detection task predicted both the performance in localization of the random items and items belonging to the perceptual families. On the other hand, it could be concluded that visual working memory is a good predictor of the performance in the localization of the target items.

One of the interesting findings in this study regarding the individual differences is that individuals' processing speed capacity for visual patterns predicted the performance in utilization of the learned configurations. This finding may indicate that there could be some domain specific characteristics of the processing speed tasks since this effect was not evident for the other processing speed measure which is the number matching task. Research demonstrated that number processing requires a distinct mechanism highly dependent upon semantic representations (Dehaene, Piazza, Pinel & Cohen, 2003). On the other hand, pattern matching task does not require any semantic processing capacity since the patterns that were used in the task are novel and difficult to name kind of shapes requiring visual processing capacity. These qualitative differences related to different cognitive mechanisms may explain the different contributions of processing speed capacity in learning and utilizing the configural information. Future research could also identify the nature of these different tasks and their contribution to the other cognitive capacities.

REFERENCES

Albrecht, A. R., & Scholl, B. J. (2010). Perceptually averaging in a continuous visual world: Extracting statistical summary representations over time. *Psychological Science*, *21*(4), 560-567.

Albright, T. D., & Stoner, G. R. (2002). Contextual influences on visual processing. *Annual Review of Neuroscience*, *25*(1), 339-379.

Alvarez, G. A., & Oliva, A. (2008). The representation of simple ensemble visual features outside the focus of attention. *Psychological Science, 19(4)*, 392-398.

Ariely, D. (2001). Seeing sets: Representation by statistical properties. *Psychological Science*, *12*(2), 157-162.

Attarha, M., & Moore, C. M. (2015). The capacity limitations of orientation summary statistics. *Attention, Perception, & Psychophysics*, *77*(4), 1116-1131.

Attneave, F., & Arnoult, M. D. (1956). The quantitative study of shape and pattern perception. *Psychological Bulletin*, *53*(6), 452-471.

Bauer, B. (2009). Does Stevens's power law for brightness extend to perceptual brightness averaging?. *The Psychological Record*, *59*(2), 171-186.

Boduroglu, A., & Shah, P. (2009). Effects of spatial configurations on visual change detection: An account of bias changes. *Memory & Cognition*, *37*(8), 1120-1131.

Boduroglu, A., & Shah, P. (2014). Configural representations in spatial working memory. *Visual Cognition*, *22*(1), 102-124.

Borsky, S., Tuller, B., & Shapiro, L. P. (1998). "How to milk a coat:" The effects of semantic and acoustic information on phoneme categorization. *The Journal of the Acoustical Society of America*, *103*(5), 2670-2676.

Brady, T. F., & Alvarez, G. A. (2011). Hierarchical encoding in visual working memory: Ensemble statistics bias memory for individual items. *Psychological Science*, *22*(3), 384-392.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2009). Compression in visual working memory: Using statistical regularities to form more efficient memory representations. *Journal of Experimental Psychology: General*, *138*(4), 487-512.

Brady, T. F., Konkle, T., & Alvarez, G. A. (2011). A review of visual memory capacity: Beyond individual items and toward structured representations. *Journal of Vision*, *11*(5), 1-34.

Buschkuehl, M., Jaeggi, S. M., Mueller, S. T., Shah, P., & Jonides, J. (2017). Training change detection leads to substantial task-specific improvement. *Journal of Cognitive Enhancement*, 1-15.

Chong, S. C., & Treisman, A. (2003). Representation of statistical properties. *Vision Research*, *43*(4), 393-404.

Chong, S. C., & Treisman, A. (2005). Attentional spread in the statistical processing of visual displays. *Attention, Perception, & Psychophysics*, *67*(1), 1-13.

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. *Cognitive Psychology*, *36*(1), 28-71.

Collin, C. A., & McMullen, P. A. (2002). Using Matlab to generate families of similar Attneave shapes. *Behavior Research Methods, Instruments, & Computers, 34*(1), 55-68.

Conway, A. R., Cowan, N., Bunting, M. F., Therriault, D. J., & Minkoff, S. R. (2002). A latent variable analysis of working memory capacity, short-term memory capacity, processing speed, and general fluid intelligence. *Intelligence*, *30*(2), 163-183.

Corbett, J. E., & Melcher, D. (2014). Stable statistical representations facilitate visual search. *Journal of Experimental Psychology: Human Perception and Performance, 40(5)*, 1915.

Corbett, J. E., & Oriet, C. (2011). The whole is indeed more than the sum of its parts: Perceptual averaging in the absence of individual item representation. *Acta Psychologica*, *138*(2), 289-301.

Cowan, N. (2010). The magical mystery four: How is working memory capacity limited, and why?. *Current Directions in Psychological Science*, *19*(1), 51-57.

Dehaene, S., Piazza, M., Pinel, P., & Cohen, L. (2003). Three parietal circuits for number processing. *Cognitive Neuropsychology*, *20*(3-6), 487-506.

Diehl, R. L., Lotto, A. J., & Holt, L. L. (2004). Speech perception. *Annual Review of Psychology*, *55*, 149-179.

Duffy, S., Huttenlocher, J., Hedges, L. V., & Crawford, L. E. (2010). Category effects on stimulus estimation: Shifting and skewed frequency distributions. *Psychonomic Bulletin & Review*, *17*(2), 224-230.

Fiser, J., & Aslin, R. N. (2002). Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(3), 458-467.

Fukuda, K., Vogel, E., Mayr, U., & Awh, E. (2010). Quantity, not quality: The relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review, 17(5),* 673-679.

Haberman, J., & Whitney, D. (2007). Rapid extraction of mean emotion and gender from sets of faces. *Current Biology*, *17*(17), 751-753.

Haberman, J., & Whitney, D. (2009). Seeing the mean: ensemble coding for sets of faces. *Journal of Experimental Psychology: Human Perception and Performance*, *35*(3), 718.

Haberman, J., Harp, T., & Whitney, D. (2009). Averaging facial expression over time. *Journal of Vision*, *9*(11), 1-13.

Hittner, J. B., May, K., & Silver, N. C. (2003). A Monte Carlo evaluation of tests for comparing dependent correlations. *The Journal of General Psychology*, *130*(2), 149-168.

Huang, J., & Sekuler, R. (2010). Distortions in recall from visual memory: Two classes of attractors at work. *Journal of Vision*, *10*(2), 1-27.

Hubert-Wallander, B., & Boynton, G. M. (2015). Not all summary statistics are made equal: Evidence from extracting summaries across time. *Journal of Vision*, *15*(4), 1-12.

Huttenlocher, J., Hedges, L. V., & Vevea, J. L. (2000). Why do categories affect stimulus judgment?. *Journal of Experimental Psychology: General*, *129*(2), 220-241.

Jiang, Y., Olson, I. R., & Chun, M. M. (2000). Organization of visual short-term memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(3), 683-702.

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279-281.

Maule, J., & Franklin, A. (2015). Effects of ensemble complexity and perceptual similarity on rapid averaging of hue. *Journal of Vision*, *15*(4), 1-18.

Miyake, A., Friedman, N. P., Rettinger, D. A., Shah, P., & Hegarty, M. (2001). How are visuospatial working memory, executive functioning, and spatial abilities related? A latent-variable analysis. *Journal of Experimental Psychology: General, 130(4)*, 621-640.

Mutlutürk, A., & Boduroglu, A. (2013). *Spatial summary representations of visual displays.* Manuscript submitted for publication.

Mutlutürk , A., & Boduroglu, A. (2014). Effects of spatial configurations on the resolution of spatial working memory. *Attention, Perception & Psychophysics*, *76*(8), 2276-2285.

Oriet, C., & Hozempa, K. (2016). Incidental statistical summary representation over time. *Journal of Vision*, *16*(3), 1-14.

Osborne, J. W. (2008). Best practices in data transformation: The overlooked effect of minimum values. *Best Practices in Quantitative Methods. Thousand Oaks, CA: Sage Publishing*.

Poirier, M., Heussen, D., Aldrovandi, S., Daniel, L., Tasnim, S., & Hampton, J. A. (2017). Reconstructing the recent visual past: Hierarchical knowledge-based effects in visual working memory. *Psychonomic Bulletin & Review, 24(6),* 1-11.

Posner, M. I., & Keele, S. W. (1968). On the genesis of abstract ideas. *Journal of Experimental Psychology*, *77*(3), 353-363.

Quinlan, P. T., & Wilton, R. N. (1998). Grouping by proximity or similarity? Competition between the Gestalt principles in vision. *Perception*, *27*(4), 417-430.

Rubin, P., Turvey, M. T., & Van Gelder, P. (1976). Initial phonemes are detected faster in spoken words than in spoken non-words. *Perception & Psychophysics*, *19*(5), 394-398.

Trainor, L. J., & Trehub, S. E. (1992). A comparison of infants' and adults' sensitivity to western musical structure. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(2), 394-402.

Turk-Browne, N. B., Jungé, J. A., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General*, *134*(4), 552-564.

Whiting, B. F., & Oriet, C. (2011). Rapid averaging? Not so fast! *Psychonomic Bulletin & Review*, *18*(3), 484-489.