TASK DIFFICULTY AND EXPERTISE MEDIATE THE EFFECTS OF ROVING ON PERCEPTUAL PERFORMANCE

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE

OF BILKENT UNIVERSITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

MASTER OF SCIENCE

IN

NEUROSCIENCE

By

Gizay Ceylan

January 2019

TASK DIFFICULTY AND EXPERTISE MEDIATE THE EFFECTS OF ROVING ON PERCEPTUAL PERFORMANCE

By Gizay Ceylan

January 2019

We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

Hüseyin Boyacı(Advisor)

Burcu Ayşen Ürgen

Aslı Kılıç Özhan

Approved for the Graduate School of Engineering and Science:

Ezhan Karaşan
Director of the Graduate School

ABSTRACT

TASK DIFFICULTY AND EXPERTISE MEDIATE THE EFFECTS OF ROVING ON PERCEPTUAL PERFORMANCE

Gizay Ceylan
M.S. in Neuroscience
Advisor: Hüseyin Boyacı
January 2019

Experience-dependent improvement of perception, known as perceptual learning, is possible in the absence of feedback, but feedback enables faster progress as demonstrated by both unsupervised and supervised learning mechanisms. Perceptual learning models have shown that mixing these two learning mechanisms may potentially cause synaptic drift and disruption of learning. Models predict this disruption in simultaneously learning two tasks with differing difficulty levels, but not for tasks of equal difficulty. The roving, randomly intermingling of two different tasks, has thus sometimes been found to disrupt learning, but not always. Interestingly, the deleterious effect of roving may occur not only during learning but also even after a task has been learned. In this study, we examine roving's effects based on task difficulty as a function of expertise level. Subjects were trained with a vertical line bisection task, where they were asked to decide if the central line was offset to the left or right outer lines. Following training, the trained stimulus was roved with a narrower untrained bisection stimulus; half of the subjects were exposed to the roved stimuli, which were equated for difficulty using an adaptive staircase method, while other half were exposed to stimuli made to differ in difficulty levels using different staircase procedures for each. We demonstrated that performances improved with training. Moreover, roving deteriorated performance for the trained task under mixed difficulty conditions but not under matched difficulty conditions. Training participants over multiple days further revealed that roving's deleterious effects decreased with increasing expertise levels.

Keywords: Perceptual Learning, Roving, Task Difficulty, Expertise.

ÖZET

ROVİNGİN ALGISAL PERFORMANS ÜZERİNDEKİ ETKİLERİNE GÖREV ZORLUĞU VE UZMANLIK DAHİL OLUR

Gizay Ceylan
Nörobilim, Yüksek Lisans
Tez Danışmanı: Hüseyin Boyacı
Ocak 2019

Algısal öğrenme olarak bilinen, algının deneyime bağlı olarak gelişmesi, geribildirimin yokluğunda mümkündür; ancak geribildirim, gözetimsiz ve gözetimli öğrenme mekanizmaların da belirttiği gibi, öğrenme sürecinin daha hızlı ilerlemesini sağlar. Algısal öğrenme modelleri bu iki öğrenme mekanizmasının karıştırılmasının, potansiyel olarak sinaptik sapmaya ve öğrenme bozukluğuna neden olabileceğini göstermiştir. Modeller öğrenmedeki bu bozulmayı, aynı anda öğrenilen iki görevin farklı zorluk seviyelerinde olduğu durumlarda öngörmekte, eşit zorluk seviyelerinde olduğu durumlardaysa öngörmemektedir. İki farklı görevi rastgele karıştırmak olarak adlandırılan roving, bu nedenle her zaman olmasa da, öğrenmeyi olumsuz etkiler. İlginç bir şekilde, rovingin bu olumsuz etkisi sadece öğrenme sırasında değil, öğrenme gerçekleştikten sonra da meydana gelebilir. Bu çalışmada, rovingin görev zorluklarına dayalı etkilerini uzmanlık seviyelerine göre inceledik. Katılımcılar, dikey çizgi-bölme görevi ile eğitildiler. Bu görevde katılımcılardan, merkez çizginin sol veya sağ dış çizgilere yakın olma durumuna karar vermeleri istendi. Eğitimin ardından, pratik edilmiş uyaran ile pratik edilmemiş daha dar bir uyaran karıştırıldı; katılımcıların yarısı uyabilen merdiven metodu kullanılarak zorluk seviyeleri eşleştirilmiş uyaranlarla rovinge maruz kalırken, diğer yarısı her biri için farklı merdiven prosedürleri kullanarak zorluk seviyeleri farklılaştırılmış uyaranlarla gerçekleştirilen rovinge maruz bırakıldı. Bunun sonucunda, performansların pratikle geliştiğini gösterdik. Ayrıca rovingin, öğrenilmiş görevdeki performansları, karışık zorluk koşulları altında düşürürken, eşlenmiş zorluk koşulları altında düşürmediğini; bununla birlikte, katılımcıların bir günden fazla eğitilmesi durumunda rovingin öğrenilmiş görev üzerindeki zararlı etkilerinin artan uzmanlık seviyesiyle azaldığını gözlemledik.

Anahtar sözcükler: Algısal Öğrenme, Roving, Görev Zorluğu, Uzmanlık.

Acknowledgement

First and foremost, I would like to present my deepest gratitude to my advisor and one of my dearest friends, Dr. Aaron Michael Clarke, for all his contributions to my life. His constant support on me, the broad knowledge and the encouragement for *cracking the brain code* he gave me, the opportunities he provided to me, the recipe of his famous Canadian oatmeal raisin cookie and the rest of everything he shared with me; undoubtedly, will always be priceless to me.

I am genuinely thankful for my official advisor, Assoc. Prof. Hüseyin Boyacı, for his trust in me, and for all understanding and guidance with great kindness, he offered to me. I am also grateful to other members of the jury, Asst. Prof. Burcu Ayşen Ürgen and Asst. Prof. Aslı Kılıç for agreeing to read the manuscript, to participate in defense of this thesis and for their precious contributions.

With infinite gratitude, love and respect, I would like to thank *million times* for my mom, Gülten, and dad, Ünal, both who have offered unconditional love, great support, and continuous care. My mom has given me the sense of responsibility and my dad has taught me how to be a strong person. I feel privileged to have them and to know that they are always there for me.

With my whole hearth, I would like to thank Yiğit for everything we built up together, and specifically for his generous help while writing this thesis. Bilkent has been our home where we have grown up together and supported each other to become who we are now. I know we have already *transcended* each other.

I also wish to thank my *secret power*, Luna - the cat, for helping me to survive in the toughest times.

Last but not least, I would like to express my sincere gratitude to every Bilkenter who has transformed this university into a home with a fairytale-like garden where we all *live long and prosper*.

I dedicate this work to Aaron who was the friend with the warmest hearth, the child with the longest laugh, the vision scientist with the broadest horizon and, of course, the best cookie maker, I have seen, ever.

You will always be remembered...

Contents

1 Introduction **1**

1.1 Perceptual Learning 2

1.2 Specificity of Perceptual Learning 4

1.3 Factors Affecting Perceptual Learning 7

1.4 Roving 8

1.4.1 Task Difficulty and Roving 11

1.4.2 Expertise and Roving 13

1.5 The Present Study 14

2 Methods **18**

2.1 Participants 18

2.2 Apparatus 19

2.3 Stimuli 19

2.4 Procedure 20

2.4.1 Pre-training Phase 21

2.4.2 Training Phase 21

2.4.3 Post-training Phase 22

2.4.4 Roving Phase 22

2.4.5 Offsets 23

2.5 Psychophysics 23

2.5.1 Method of Constant Stimuli 24

2.5.2 Staircase Procedure 26

2.5.3 Psychometric Function 28

2.5.4 Psychometric Function Implementation 28

2.6 Sensitivity 29

3 Results **31**

3.1 Statistical Results on The Task Difficulty 31

3.2 Statistical Results on The Amount of Training 34

3.3 Statistical Results on the Task Sensitivity 43

4 Discussion **46**

5 Future Directions **51**

6 Conclusion **52**

A Descriptive Statistics **61**

B Consent Form **65**

C Onay Formu **68**

List of Figures

1.1 Vertical line-bisection stimuli 9

1.2 Vernier stimuli 14

1.3 The illustration of stimuli that interfere with learning when roved together 15

2.1 Vertical line-bisection stimuli 20

2.2 The experimental procedure 21

2.3 The illustration of a roving phase 22

2.4 The representation of threshold detection 25

2.5 Adaptive staircase procedures 27

2.6 The representation of threshold detection at roving phase 29

3.1 The effect of task difficulty 32

3.2 The effect of amount of training on performance changing across pre- and post-training phases 35

3.3 The effect of amount of training on performance changing under matched difficulty condition 38

3.4 The effect of amount of training on performance changing under mixed difficulty condition 39

3.5 The effect of amount of training on wide bisection task under matched difficulty condition 40

3.6 The effect of amount of training on wide bisection task under mixed difficulty condition 41

3.7 Interactions between the amount of training day and task difficulty 42

3.8 The training group's effect on task sensitivity 44

3.9 The training day's effect on task sensitivity 45

3.10 Interactions between the training group and the training day . . . 45

4.1 The representation of human visual field 48

List of Tables

2.1 The number of successful subjects 19

A.1 Descriptive statistics for roving phase under matched and mixed difficulty conditions 61

A.2 Descriptive statistics for performance changing between pre-training and post-training phases 62

A.3 Descriptive statistics for performance changing between post-training and roving phases 63

A.4 Descriptive statistics for performance comparison between post-training and roving phases 64

Chapter 1

Introduction

> "I have engaged in what seems to be a historical excursus not for the sake of giving historical information but in order to indicate the origin of the distinction between empirical knowledge and practice, on the one hand, and rational knowledge and pure activity on the other; between knowledge and practice, that are admittedly of social origin and intent on insight and activity, were supposed to have NO social and practical bearings. This origin is itself social-cultural. Such is the irony of the situation."
>
> John Dewey – *"Common Sense and Scientific Inquiry [1]"*

Learning is one of the most important functions of the brain. While learning in the educational literature was traditionally theoretical and lacking in empirical grounding [1], in the scientific literature empirical learning studies have led to much more nuanced theories, starting as early as Pavlov [2].

As a classical experiment, Pavlov showed that a dog conditioned to expect food in response to a bell, will eventually salivate in response to the bell alone [2]. Later studies of this type of learning, now called "reinforcement learning" led to the famous Rescorla-Wagner model [3], which predicted several important properties of reinforcement learning, and that was later adopted by the machine learning community in the development of Q-learning and $Sarsa(\lambda)$ models (see

[4] for a review), which are now widely used in robotics applications. The key idea of these models is that learning progresses via punishment and reward to optimize actions such that punishment is minimized and reward is maximized.

In 1949, Donald Hebb codified a new type of learning – learning by association, where pairs of stimuli could be learned simply by their frequent association, even if neither of them were rewarding or aversive [5]. This type of learning, now called "Hebbian learning" represents the first instance of a class of learning models called "unsupervised" learners. The key here is that no supervisor rewards or punishes behaviours, and that learning progresses by making associations. On a neural level, this type of learning has been described by the adage: "neurons that fire together wire together, while neurons that don't fire in sync lose their link". Models that implement this learning rule have enjoyed great success in the machine learning literature with the development of Boltzmann machines, and Hopfield networks (see [6] for a review). These two forms of learning may be combined, such that learning progresses in the absence of feedback, but more slowly than when feedback is provided. Perceptual learning is an example of a phenomenon that is guided by both forms of learning.

1.1 Perceptual Learning

Theories about the optimal way to learn have abounded for centuries, however, it's only relatively recently that empirical evidence has been brought to bear on the topic. In order to truly understand what is being learned and what affects learning, it is important to use well-defined learning problems with controllable parameters. Perceptual learning offers such a paradigm. Perceptual learning (PL) is the process of adjusting one's neural responses to incoming sensory input in order to better facilitate detection and discrimination of those inputs. It has also been defined as a form of implicit memory as well as an improvement in sensory discrimination with an extended practice [7]. In visual perceptual learning, for example, performance on even the simplest tasks may be improved with practice.

Only extensive training, however, is not always enough to produce robust learning; attention and reinforcement may be needed as well [8]. Sensory systems can learn to classify upcoming signals to process important ones more efficiently when attention is directed only to important signals. Learning is driven with this mechanism of attention in which neuronal population is arranged according to the signal level [9, 10]. Therefore, the role of attention in perceptual learning should not be underestimated. Likewise, reinforcement is another cornerstone in perceptual learning. Reinforcement can be a reward for desired behaviors to promote them further or a punishment for undesired behaviors to discourage them from happening. Even, desired behaviors can still be encouraged by a reward which is received unawarely [8]. Reinforcement can be provided as feedback in perceptual learning studies. Herzog and Fahle [11] also emphasize the importance of feedback in their perceptual learning model suggesting that feedback does not only help perceptual learning to occur but also accelerates it to progress.

PL can be observed in every sensory modality with all kinds of sensory information such as tactile, auditory or olfactory. For instance, Atienza, Cantero, and Dominguez-Marin [12] have shown that people can become an expert on the detection and discrimination of two complex acoustic patterns with practice. Wine experts who can even detect which half of the bottle is being tested can be given as another example. Additionally, using Brill alphabet is another well-known example of expertise in processing tactile sensory information. The current study, however, focuses only on the visual aspects of perceptual learning. Thus, unless otherwise is stated, PL corresponds to visual perceptual learning.

Besides the fact that training can improve particular visual skills, if these skills can transfer is one of the most challenging questions in PL studies. Indeed, PL can be highly specific to the stimuli which are previously practiced. Therefore, transfer of learning may not be observed very often, but this does not mean that it is impossible.

1.2 Specificity of Perceptual Learning

Specificity of PL refers to the situation in which performances can be improved only for the trained task. One of the best reasons describes the specificity as the activation of different cortical regions or as the involvement of separate processes due to practicing perceptual tasks under different conditions. Previous studies have shown that PL is highly specific. The orientation [13] and the size of the stimulus [14], the position of visual field [15], the direction of motion [16] and the novelty of the eye [17] are the features known to contribute to the specificity of the perceptual learning.

However, learning specificity is still controversial as even the findings from previous studies conducted with very similar perceptual tasks can contradict [17, 18, 19]. For example, Schoups et al. [18] investigated transferability of learning for a particular stimulus position and orientation as well as the monocularity of the learning mechanism using psychophysical orientation discrimination task. Their results were as follows; even a mere displacement of stimulus position caused a decrease in performance, suggesting early localization in the visual processing. After changing the stimulus orientation performance diminished even under the level of inexperienced subjects. Nevertheless, complete or almost complete learning transfer occurred between trained and untrained eye, meaning that improvement was not restricted to monocular cells in the orientation discrimination task. These results support an earlier finding suggesting a sensory level practice effect of orientation discrimination rather than a decision level process attributing attention or accommodation [20].

On the other hand, Karni and Sagi [17] found a strong monocularity as well as positional and orientational specificity in the texture discrimination task. Their results suggest that training with texture discrimination task induces local plasticity which occurs in early visual processing, particularly at the level of orientation-gradient sensitive cells which are responsive to input from one retina in the primary visual cortex. Another contradictory finding by Ahissar and Hochstein [14] shows that inter-ocular transfer of learning between trained and untrained eyes

is possible. The results are surprising considering the task used by Ahissar and Hochstein was very similar to the texture discrimination task which was previously employed by Karni and Sagi [17].

Although the PL is highly specific to the trained task, sometimes learning can transfer from the trained task to a novel task. The next question would be whether there are particular rules to determine the transferability of PL. Recent studies show that some conditions are needed for the transfer of learning to take place. The task difficulty [19], the similarity of stimuli [21] and attention [15, 22, 23] are some of the popular examples of the conditions affecting the transfer of learning.

It has previously been shown that there is a close relationship between the degree of specificity and the difficulty of the training conditions. On the one hand, increase in task difficulty results in increased specificity of practice effect [19]. Ahissar and Hochstein [24] proposed a theory, named as reverse hierarchy theory (RHT), which suggests that PL occurs as a result of a top-down guided increase in usability of task-relevant information from higher to the lower level. According to the theory, learning starts at a higher level but back-propagates to lower level to enhance task-relevant and eliminate task-irrelevant information.

Neurons located in the primary visual cortex, V1, are selective for orientation and retinal position. Therefore, changing position or orientation after training on a perceptual task using stimuli whose orientation and retinal position are fixed can activate a non-overlapping population of neurons at V1, so improvement may not transfer new stimulus condition which results in reduced performance compared to the initial condition and re-learning process may be required. But if the learning occurs at higher-level initially, then a transfer of learning would be possible to new position and orientation. RHT does not claim that there are no bottom-up modifications, rather it does claim that performing a perceptual task leads to weight re-tuning which is reverse to bottom-up information processing and so plasticity is dominated by top-down processes. Ahissar and Hochstein [19] used the simple feature detection paradigm to show that increasing task difficulty also increase task specificity which stemmed from activation of different

learning processes. The idea was that training on difficult orientation discrimination modifies population of neurons which are finely tuned to orientation, while fine orientation separability is not required during modification processes in easy conditions. In that study, it is also important to note that task difficulty depended on position or orientation, and specificity increased with increasing task difficulty bidirectionally; which means, orientational difficulty induced positional specificity or vice versa [19].

On the other hand, transfer of learning can be observed not only as the increased performance but also as the accelerated learning rate on the untrained task [25]. Liu and Weinshall [25] also studied the generalization of the learned skills, in other words, transferability of PL. They have claimed PL to be transferable between easy and difficult tasks which were involved in different learning processes at different visual cortical areas. Their experimental results from motion direction task showed that the learned skill transferred across motion directions since training an easy condition led to immediate improvement in other directions. This result was in line with the previous findings which defend the transferability of PL from easy to difficult tasks due to decreased specificity [19, 26]. Also interestingly, they found that the learning rate for the novel task dramatically increased after training with the difficult task. Liu and Weinshall have further considered it to be equivalent to learning transfer. Following this interesting finding, they have broadened the meaning of generalization beyond its traditional explanation. According to them, "generalization is the rule, rather than an exception" [25].

Another factor which promotes the transfer of learning is the shared characteristics of stimuli. For example, learning can transfer from vertical line-bisection task to horizontal line-bisection task and vertical dot-bisection task; however, transferring to the vertical dot bisection task would be stronger compared to horizontal line bisection task [21]. According to Parkosadze et al. [21], transfer of learning to dot stimuli occurs because the spatial location of dot stimuli is already contained in the trained line stimuli. Therefore, the reason might be that the dot bisection stimuli cause the firing of a group of neurons which were already activated frequently during training with the line bisection stimuli. Also, since

the transfer from vertical to horizontal stimuli is weak, orientation is a strong property which promotes specificity rather than transfer.

1.3 Factors Affecting Perceptual Learning

Feedback is one of the most effective factors known to facilitate learning. In the absence of feedback, perceptual learning is still possible but slower [11]. Additionally, different types of feedback might have a different level of influence on perceptual learning. To better understand the role of feedback during learning, Herzog and Fahle [11] conducted a study where they compared improvement through training in vernier acuity task under complete feedback, no feedback, block feedback, partial feedback, and uncorrelated feedback conditions. In their study, complete feedback was provided after each trial. Block feedback was given as a percentage of correct responses after each block. Partial feedback was supplied not after every trial but half of the trials. Uncorrelated, in other words, manipulated feedback was given unrelated to responses. Their results showed that rather than manipulated (uncorrelated) and no feedback conditions, correct feedback conditions such as complete, partial and block feedback can facilitate learning. Also, an increase in overall performance and a decrease in individual difference can be observed through correct feedback conditions. However, while performance under the block and complete feedback conditions do not change, performance under partial and no feedback conditions can improve slower and more individual differences can be observed.

Moreover, Schoups et al. [18] indicates that fatigue and consolidation phase has essential roles in the learning process. They have suggested that fatigue deteriorates performance during the training. They tested performances between each training session in which they provided the different resting duration. According to their results, even giving six hours break between the training sessions (morning to afternoon) was not enough to overcome fatigue. On the other hand, they showed that the highest performance difference between training sessions found between different days, which suggests that the latent phase such as a night sleep

is necessary for consolidation of improvement [18].

Furthermore, "roving", randomly interleaving two or more perceptual tasks is another factor affecting perceptual performance. In PL studies, usually, one stimulus is presented during training to improve performance, particularly for that stimulus. The main reason is the belief that performance improvement cannot be observed if more than one stimulus is presented randomly because roving interrupts encoding of stimulus information. When only one stimulus is presented, performance increase quickly and strongly [27, 28], but no short-term improvement occurs when more than one stimulus presented [29, 28, 30]. Kuai et al. [29] suggested that since there is no short-term learning, there cannot be long-term learning under roving conditions due to disturbance of continuous interaction between top-down and bottom-up information. Recently, however, many studies have proven that this is not entirely true. For instance, Parkosadze et al. [21] contradict this idea by claiming that extensive training makes perceptual learning possible even under roving conditions although there was no short-term performance improvement. Due to extensive training, one might think that roving condition is accommodated. However, according to performance comparison before and after training, this improvement was not caused by accommodation to roving paradigm because performances presented under roving and non-roving conditions were comparable [21].

1.4 Roving

As previously discussed, performance on even the simplest tasks may be improved with practice in visual perceptual learning. If a subject is presented with two parallel vertical lines with a third line placed between them (Figure 1.1) and asked to decide whether the middle line is closer to the left or right line, performance initially starts off fairly good, but improves remarkably with practice. With successive correct answers, the middle line can approach to the center of two outer-lines so that the task can be more challenging. Nonetheless, subjects can still accurately discriminate between the two cases.

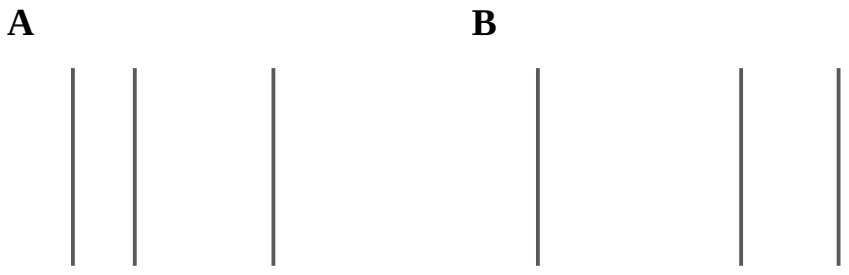


Figure 1.1: Vertical line-bisection stimuli. The task is to indicate whether the middle line is closer to the left outer-line. (A) is a left-aligned narrow bisection stimulus and (B) is a right-aligned wide bisection stimulus.

This kind of performance improvement with practice holds not only for simple bisection tasks, as shown in Figure 1.1, but also for several other visual discrimination tasks [31, 19, 16, 32, 33, 34]. Interestingly, however, perceptual learning may be disrupted if the task to be learned is randomly intermingled with a secondary task that is similar, but somewhat different from the original task. Returning to the bisection example, Parkosadze et al. [21] showed that if the bisection stimulus with a $30'$ outer-line separation is randomly intermixed on a trial-by-trial basis with a bisection stimulus having a $20'$ outer-line separation, then both tasks become so much more difficult to learn that it takes an order of magnitude more trials to reach the same level of performance as in the single-stimulus alone condition.

Moreover, roving not only inhibits learning, but it also inhibits performance even if a discrimination task has already been learned. Clarke et al. [35] showed that even though the $30'$ stimulus was learned to a high level, performance still drops when roved with the $20'$ stimulus. A control experiment with even more training blocks revealed that if testing with a single stimulus resumes after roving,

then performance recovers to pre-roving levels. The average post-roving performance was not significantly different from the pre-roving performance, indicating that roving hinders performance, but does not undo learning.

Although roving's negative impact on both learning and post-learning is a known fact, it is still unclear if randomly intermixing any two stimuli together will impair learning. According to Clarke et al. [35], the stimuli must be somewhat similar to interfere with each other. In their study, two non-interfering stimuli were roved together (a vertical and a horizontal line-bisection stimulus), and the result was that performance for the learned task was not affected by roving. Following the roving period, however, there was a significant drop in performance for the learned stimulus, even when tested in isolation (i.e., without roving).

Another elaborated study was conducted by Tartaglia et al. [36] to address in which conditions roving deteriorates the performance. First, they roved a bisection stimulus and a vernier stimulus to see how task similarity affects roving performance. Since the important parts of both stimuli spatially overlap, roving performance did not decrease rather improved. Second, a vertically aligned bisection stimulus and 45° rotated version of that stimulus were roved. Even though the task was same, performance improved during roving as stimuli were different. This results indicated that if stimuli are sufficiently different, roving does not impair learning due to non-overlapped neuron population. Third, they showed that roving does not facilitate learning when two vertically aligned bisection tasks with different lengths were intermixed. Though, they noted that they expected improvement at least for the shorter stimulus due to frequently activated overlapped neuron populations of both stimuli as the shorter stimulus was contained in longer stimulus. In the end, Tartaglia et al. [36] have suggested that roving interferes with learning, but this interference occurs as a result of the overlapping neuron population which is based on similar stimulus types and tasks but not on similar spatial locations.

1.4.1 Task Difficulty and Roving

Task difficulty is one of the major factors affecting PL. In addition to its role on the transfer of learning between perceptual tasks as discussed previously, task difficulty has a critical part on performance when the multiple tasks interleaved randomly so-called roving. Task difficulty and roving's cross effect on perceptual performance has not been investigated directly. Nevertheless, there are studies by which we can deduce and presume possible outcomes of this cross effect on PL.

Roving has sometimes been found to disrupt learning by many studies [28, 35, 21, 36], but not always [36, 37, 38]. The main difference between the two results was difficulty levels of roved tasks. For example, Otto et al. [28] revealed that randomly interleaving two bisection tasks with different outer-line distances (i.e., $20'$ and $10'$) impeded learning because the narrow stimulus was relatively easier than wide stimulus. Clarke et al. [35] also confirmed their result by showing that when the task difficulties of roved stimuli differ in difficulty levels (i.e., roughly 55% and 85% accuracy thresholds) performance diminished. In fact, not only roving performance but also post-roving performance was deteriorated due to differing task difficulty levels. Moreover, Tartaglia et al. [36] found that in case of training under a roving condition with manipulated stimulus presentation duration (i.e., 150 ms and 500 ms), performance does not improve, although intermixed stimuli were very same. Here, stimuli which were presented for a longer period can be assumed to be easier compared to rest of the stimuli [19].

On the other hand, Tartaglia et al. [36] showed that performance did not decrease rather enhanced when 45° and 315° rotated line-bisection tasks were randomly interleaved. As two orthogonal bisection tasks had the same properties (i.e., stimulus size and outer-line distance), task difficulties were assumed to be equal. Likewise, Yotsumoto, Chang, Watanabe, and Sasaki [37] used a texture discrimination task (TDT) to investigate if training under roving condition disrupts TDT learning, and found no disruption by roving. In their experiment, the task was to indicate the target letter (i.e., T or L) and the orientation of the

target array (i.e., horizontal or vertical). Though, they randomly interleaved the orientation of the target letter and of background lines, but not the orientation of the target array. Since the task was to determine the orientation of the target array but not the orientation of the target letter or background lines, task difficulties of all stimulus combinations remained the same.

Through computational modeling studies, Herzog et al. [39] have suggested that simultaneous learning of two tasks with differing difficulty levels impairs learning. They defined roving's deleterious effect on learning as a surprising outcome if we consider how successful the supervised and the unsupervised neural network models are even under roving condition. Therefore, Herzog et al. [39] have claimed that human perceptual learning is neither supervised nor unsupervised, but it is reward-based. According to reward-based model, the average reward has to be estimated. However, estimation is not possible with more than one stimulus types which come with different rewards. For the very reason, Frémaux, Sprekeler, and Gerstner [40] have presented us to "unsupervised bias" term to explain why reward-based learning model suffers from roving. Either supervised or unsupervised learning is possible, but mixing these mechanisms (reward-based) may potentially lead to synaptic drift and disruption of learning due to unsupervised bias. To diminish disruption and to assist learning, this unsupervised bias must be reduced as much as possible. In this case, an internal *critic* would play a role as a neuromodulator in the nervous system. The critic can modulate estimated rewards for each task and diminish unsupervised bias. According to Herzog et al. [39], without the critic model cannot predict learning in any roving condition. However, as previously mentioned, roving does not always hinder learning (i.e., interleaving vertical and horizontal line-bisection tasks, see [35]). Therefore, the critic is necessary for reward-based learning models to explain roving's role in PL in a better way. On the other hand, the critic cannot assign estimated rewards to two different tasks whose difficulties are different. Herzog et al. [39] have also proposed that the critic can learn to assign reward properly for adjusted difficulty levels or with an increased amount of training.

1.4.2 Expertise and Roving

Studies investigating perceptual performance as a function of the level of expertise are abounding in literature, yet studies that tried to address directly how different level of expertise would affect roving performance in what way seems limited.

As Frémaux, Sprekeler, and Gerstner [40] claimed with their learning model, the internal critic, which is similar to a neuromodulator such as dopamine [41] in the nervous system, can diminish unsupervised bias by assigning expected rewards for each stimulus during simultaneously learning of two tasks. In a case where two tasks differ in difficulty levels, the model cannot predict learning because the critic is unable to assign expected rewards. Nevertheless, as Herzog et al. [39] have previously proposed, with an increasing amount of training, the critic would become able to assign the rewards for each task so that learning would take place.

Parallel with Herzog et al.'s proposal [39], Parkosadze et al. [21] suggested that extensive training, even under a roving condition, made perceptual learning possible. They examined the effect of roving on a bisection task where they roved two bisection stimuli with two outer-line distance (i.e., $20'$ and $30'$). Different from the other studies, subjects were trained extensively under roving condition (i.e., 150 training blocks; 18000 trials in 10 training sessions). Similarly, Clarke et al. [35] detected a decreasing trend on roving-induced performance deficiency under an increased amount of training condition. This trend indicates that performances under a higher amount of training condition dropped less compared to performances under a lower amount of training condition (three days and two days, respectively). This observation was not the focus of Clarke et al. [35]; thus, this effect has not been pursued in more detail with rigorous experiments designed specifically to test this phenomenon. The significance of this effect would be that it would show roving's diminishing impact on the performance the more a person becomes an expert at a task. If this is true, then it would mean that roving does indeed impair performance, but this impairment can be diminished if a person becomes good enough at one of the tasks.

1.5 The Present Study

Perceptual learning involves improving performance on tasks that require detection or discrimination of sensory stimuli [19, 16, 33, 11, 42, 34, 43, 36]. Figure 1.2, for example, illustrates two stimuli often employed in perceptual learning experiments.

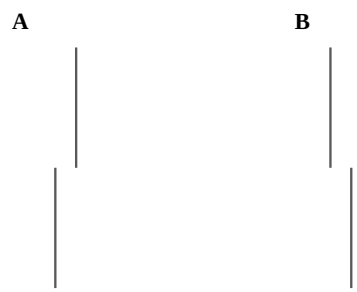


Figure 1.2: Vernier stimuli. Here the task is to indicate whether the bottom line is to the left (A), or right (B) of the top line.

In these tasks, performance improves with practice [11]. That is, with practice the bottom line can be progressively more aligned with the top line, and subjects can still correctly indicate the offset direction of the bottom line at better than chance levels.

Perceptual learning does not always proceed unhindered. Even with feedback, if two similar, but slightly different tasks are randomly intermingled on a trial-by-trial basis then learning may be severely reduced [31, 21] (see Figure 1.3).

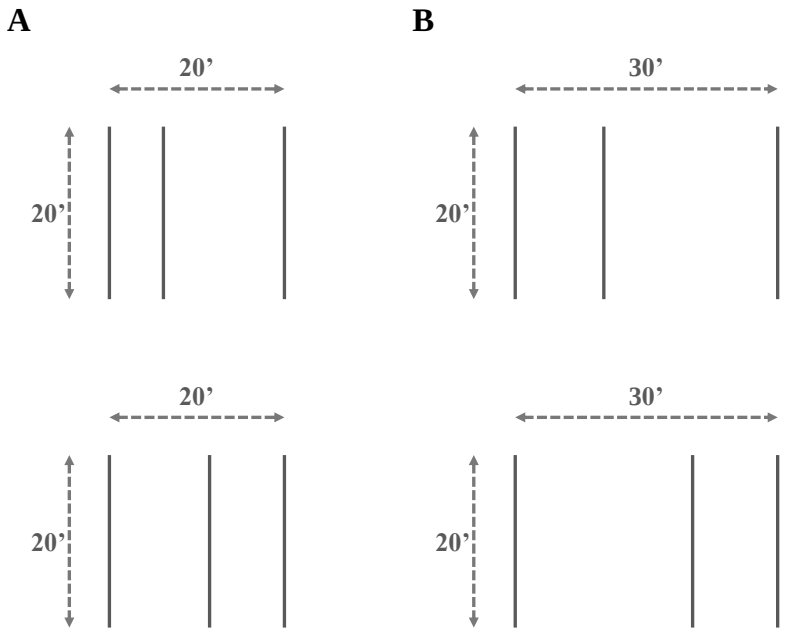


Figure 1.3: The illustration of stimuli that interfere with learning when roved together. In (A) two outer lines define a reference frame. The task is to indicate whether the central line is closer to the left or right of the reference frame. Here the top panel indicates a left-offset and the bottom panel indicates a right-offset central line. In (B) the distance between outer lines is decreased relative to (A) ($20'$ as opposed to $30'$), but otherwise the stimuli and task are the same. Randomly interleaving these two learning tasks on a trial-by-trial basis (i.e., roving) greatly slows learning [21].

Whether or not roving two stimuli impairs learning depends on the stimuli used. For example, roving the two stimuli illustrated as (A) and (B) in Figure 1.3 does impair learning [31, 28, 21], but roving the Vernier stimulus of Figure 1.2 with the bisection stimulus of Figure 1.3 does not [36]. In general, several studies have found stimuli that impair learning [31, 30, 28, 21, 36, 44], and some other studies have found stimuli that do not impair learning [29, 36] when roved together.

A key insight into why some stimuli interfere with each other, while others do not was further studied by Frémaux, Sprekeler, and Gerstner [40]. Through computational modeling studies, they were able to show that one consequence of combining both supervised with unsupervised learning rules is that mixing two learning tasks with differing difficulty levels impairs learning. This would explain why the two tasks presented in Figure 1.3 as (A) and (B) cause learning interference, since the task shown in Figure 1.3 (B) is much harder than the task in Figure 1.3 (A).

Another key finding in the roving literature is that roving not only hinders learning, but it also hinders performance for a task that has already been learned [35]. For example, if the task in Figure 1.3 (A) is trained to proficiency, then roving it with the task in Figure 1.3 (B) still causes a performance deficit. As previously mentioned, this performance deficit seems to depend on the level of proficiency reached for the trained task – the more highly trained a subject is on a task, the less their performance seems to suffer from roving. This observation still requires rigorous empirical validation and represents an important gap to be filled in the literature.

Moreover, in light of the findings from Frémaux, Sprekeler, and Gerstner [40], it would seem important to control for task difficulty on the roved tasks. It is possible that the reduced performance deficits arise because the $30'$ task's difficulty level approaches that of the $20'$ task with extended training. It is also possible, however, that the performance deficit reduction happens because once the $30'$ task is trained to perfection, it no longer requires significant cognitive resources, and the $20'$ task may be performed as if the $30'$ task was not present. Controlling for task difficulty level will allow these two possibilities to be discriminated. Therefore, in our study, we trained subjects on a bisection stimulus and then we roved trained stimulus with a slightly different version of that stimulus. The cognitive resources theory would be supported if performance with the trained bisection stimulus was unaffected by how difficult the untrained task is made to be. Conversely, the task difficulty theory would be supported if performance is comparable when task difficulty was equal, but performance is impaired when task difficulty levels were different.

In this study, we tested if the task difficulty and the amount of training affect roving-induced performance deficits or not. Either way, the results have important inferences for learning models and to understand the contributions of cognitive resources to learning.

Chapter 2

Methods

2.1 Participants

156 university students aged between 18-35 years old participated in the experiment. All participants were provided with the written consent form and told they were free to quit the experiment if they please. At the beginning of this study, we planned to recruit participants for 1, 2, 3, 4, and 5 days. Later, however, we decided to change participation duration as 1, 3 and 5 days. Therefore, data from 6 participants, who were selected to participate for 2 or 4 days and already completed the experiment, were discarded. 13 participants decided to withdraw from the study and left the experiment early. 17 participants failed to follow the instructions and their data were excluded. The total number of successful subjects was 120. All subjects had a normal or corrected-to-normal vision as assessed by the Freiburg Visual Acuity Test [45]. The detailed subject-condition information is provided with Table 2.1 below. This study was approved by Bilkent University Ethics Committee.

		Day Condition		
		1 - Day	**3 - Day**	**5 - Day**
Difficulty Condition	**Matched Difficulty**	$N = 18$	$N = 20$	$N = 22$
	Mixed Difficulty	$N = 18$	$N = 20$	$N = 22$

Table 2.1: The number of successful subjects. The table shows the number of subjects according to the amount of training day and the level of task difficulty.

2.2 Apparatus

The experiment run in a darkened room. A Dell XPS 8700 with an Intel Core i7-4790 processor and an NVIDIA GeForce GTX 745 4GB DDR3 graphics card was used during the experiment. Stimuli were presented on a Dell 22 – S2240L 54.6 cm monitor. A head-rest and a chin-rest which were placed 230 cm away from monitor were used to minimize head movements and to make sure all subjects were exposed to stimuli with the same visual angle. The feedback was provided via Logitech speakers. Subject responses were collected via a Logitech wireless gamepad. The experiment was designed with MATLAB R2016b using Psychtoolbox 3.0.

2.3 Stimuli

In the experiment, a simple bisection task with three vertical lines which horizontally aligned was conducted. We used two different bisection stimuli. The lengths of both stimuli were the same as $2.2'$. They only differed in their widths as $4.9°$ and $7.3°$ (see Figure 2.1). The maximum luminance of the stimulus was 262.6 cd/m^2. Stimuli presented in the middle of the screen one by one in each trial with a self-paced manner.

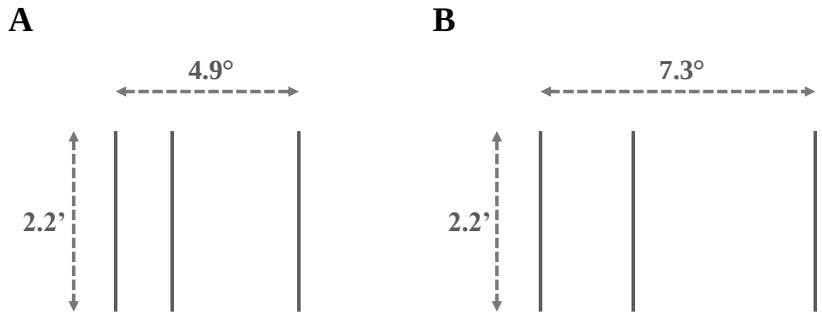


Figure 2.1: Vertical line-bisection stimuli. (A) is the representation of narrow stimulus and (B) is the representation of wide stimulus used in the experiment. In this case, both central lines of (A) and (B) are offset to the left outer-line.

2.4 Procedure

Prior to the experiment, the Freiburg visual acuity test (FrACT) was applied by participants and only participants who were successful at the test (getting score $\geq$ 1 out of 2) were allowed to perform the original experiment. After signing written content forms, the whole procedure was explained to the subjects by the experimenter one more time. All subjects were asked to complete the simpler and shorter version of the experiment before starting the original experiment to make sure all instructions were understood. All successful subjects completed four main phases in the order as the pre-training phase, the training phase, the post-training phase, and the roving phase (see Figure 2.2). Subjects were asked to decide if the middle line is closer to the right or the left outer line. Subjects were not required to respond in a limited time and response times were not collected. We provided them with auditory feedback after each response according to whether the answers were correct or incorrect. After the experiment was completed, all subjects were debriefed orally by the experimenter.

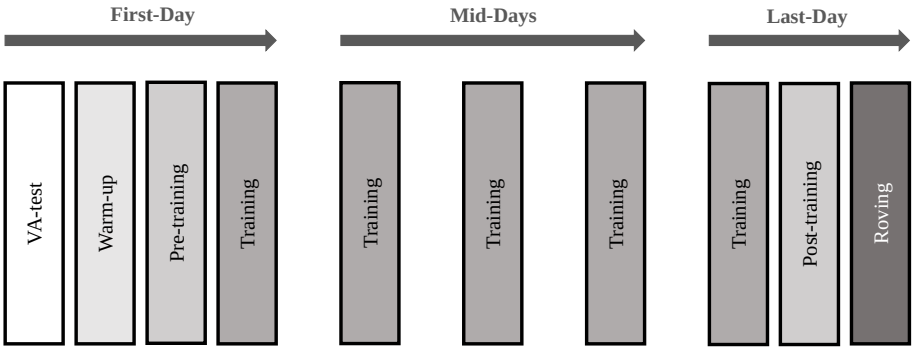


Figure 2.2: The experimental procedure. The figure illustrates phases taken throughout the experiment.

2.4.1 Pre-training Phase

In this phase, subjects' thresholds concerning both narrow and wide bisection stimuli were measured. Pre-training phase consisted of four blocks of 120 trials of each. We used a narrow bisection task during the first two blocks and a wide bisection task during the next two blocks.

2.4.2 Training Phase

Training phase consisted of 20 blocks of 80 trials each. Subjects were exposed to only wide bisection stimuli. The purpose of the training phase was to train subjects on only wide bisection task with a fixed offset size. Therefore, subjects who completed 20 blocks were allowed to give at least 30 minutes break before proceeding to the post-training phase. However, subjects who are in multiple day conditions were asked to stop the training and come the next day to complete another 20 blocks until the last block of the experiment was completed.

2.4.3 Post-training Phase

All procedure of the pre-training phase was repeated in this phase. The main purpose of repeating the same procedure was to compare pre and post-training performances after the subjects had a different level of expertise on wide bisection task.

2.4.4 Roving Phase

We used both narrow and wide bisection stimuli during the roving phase. In this phase, subjects completed four blocks of 120 trials each. In each roving blocks, the same number of narrow and wide bisection stimuli presented randomly in each trial one by one (see Figure 2.3 for an illustration of roving phase during two trials).

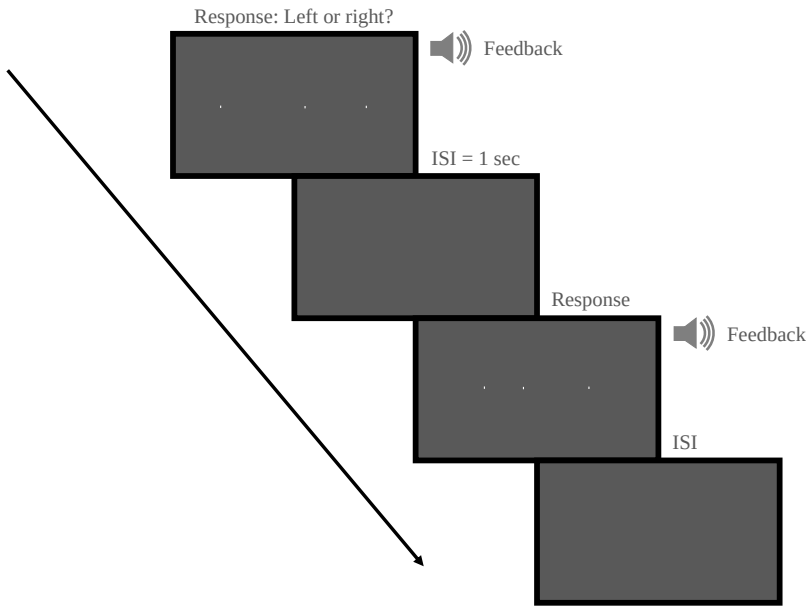


Figure 2.3: The illustration of the roving phase. The figure shows presentations of wide and narrow stimuli during roving phase, respectively. In this case, correct responses would be left and right, respectively. Inter stimulus interval (ISI), the temporal interval between stimulus presentations, was 1 *sec*. Speaker icons represent the auditory feedbacks given right after subject's response.

2.4.5 Offsets

We used fixed offsets in all phases except the roving phase. Our offsets were 1, 3, 5, 12 or 20 pixels (approximately $0.37'$, $1.11'$, $1.85'$, $4.44'$, $7.4'$, respectively). Therefore, the middle lines of the stimuli moved 1, 3, 5, 12 or 20 pixels away from the middle of the screen to left or right direction during pre-training and post-training phases for both narrow and wide tasks. Furthermore, once the subject's threshold of the wide task was detected, we used this threshold value as a fixed offset size during the training phase. For example, if the subject's threshold of wide bisection task was detected as 5-pixel at the pre-training phase, then the middle lines of wide stimuli shifted 5 pixels to left or right direction randomly during the training phase. Lastly, in the roving phase, offsets were determined by the staircase procedures depended on the subject's current performance. Thus, we did not control the number of the different offsets directly. In all phases, the numbers of left and right offset directions were kept equal.

2.5 Psychophysics

Psychophysics is a field of methodology concerned with studying the quantitative relations between the physical stimuli and the perception of the stimuli.

Psychophysical studies test subjects' ability to detect and discern the stimuli as well as the magnitude of the difference between perceived stimuli. In psychophysics, the threshold is defined as the minimum amount that can be perceived. The method of limits, the method of constant stimuli, and the method of adjustment are the classical psychophysical methods [46]. Each method provide with a threshold; however, they differ in sensitivity and efficiency under different experimental conditions. In addition to these classical psychophysical methods, there are adaptive psychophysical methods [47] such as staircase procedures, Bayesian and maximum-likelihood procedures and magnitude estimation for testing perception in stimulus detection and differentiation.

In this study, we benefited from the method of constant stimuli and staircase procedures for stimulus presentation and threshold detection.

2.5.1 Method of Constant Stimuli

Method of constant stimuli (MCS) is a psychophysical method developed by Gustav Fechner for studying sensory thresholds. In MCS, stimuli which happen to be above or below the threshold are presented in a random order. This is the main difference between MCS and method of limits where stimuli presented sequentially in a fixed order. MCS reduces habituation and expectation errors because random stimulus presentation prevents making predictions about the next stimulus since the presentation does not depend on the characteristics of the stimulus such as intensity or difficulty. In MCS, all stimuli in which different level should be presented with an equal number of times. Therefore, using this psychophysical method might be sometimes or in some case quite time-consuming. In MCS, the threshold to be picked generally is 50% meaning that the stimulus with 50% hit and 50% miss ratio is the threshold. However, a different percentage can be used as well (i.e., 75% hit and 25% miss ratio).

We preferred to use MCS to detect subject thresholds for narrow and wide bisection tasks during pre and post-training phases. We determined 5 fixed offset sizes as 1, 3, 5, 12 and 20 pixels, which means that the middle line was positioned away from the center of the screen randomly toward left or right with a determined pixel-size in each trial. The outer lines were always kept stable and the stimuli never moved in vertical direction. Stimulus with 1-pixel offset size was thought to be more difficult than the stimulus with 20-pixel offset size since detection of offset gets easier if the middle line is closer to the outer lines. We picked 75% as a threshold meaning that the stimulus that is detected 75% of the time and not detected 25% of the time was considered to be the threshold. However, since we did not use sequential offset sizes with same paces between offset size (1 to 3 or 12 to 20) we chose to fit a sigmoidal line to MCS data where we detect a hypothetical stimulus offset as a threshold at 75% accuracy rate (see Figure 2.4).

We applied two blocks with narrow stimuli and two blocks with wide stimuli before and after training phase. Threshold values detected after each block were averaged to get one single value as a threshold. This method was applied to both pre and post-training performance. The threshold, which was detected at pre-training phase for wide bisection task, was also used as a fixed offset during training phase.

The fixed offset, $Offset_{wide}$, which was used in training phase can be calculated via:

$$Offset_{wide} = \frac{(T_{pre1} + T_{pre2})}{2} \tag{2.1}$$

where T_{pre1} and T_{pre2} are thresholds detected at pre-training phase for wide-bisection stimulus.

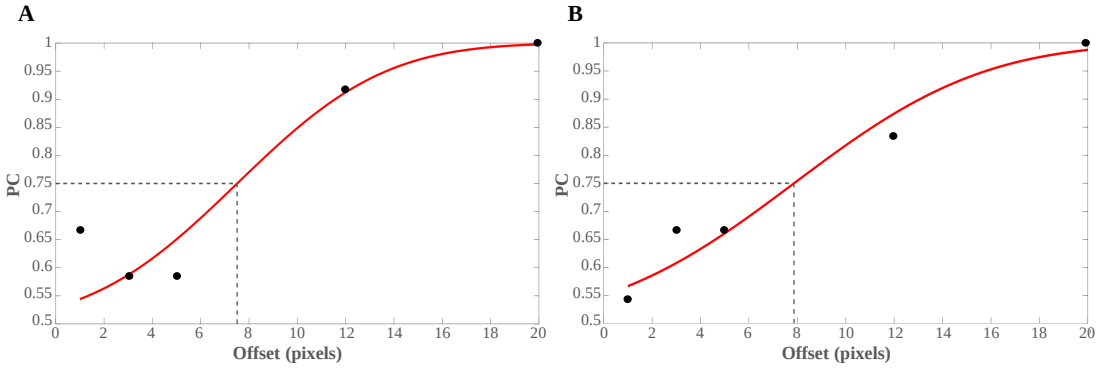


Figure 2.4: The representation of threshold detection. (A) and (B) show the performances of a subject who completed the first and second blocks with wide bisection stimuli in pre-training phase, respectively. Performance was measured as percentage of correct responses.

2.5.2 Staircase Procedure

Staircase procedure is another psychophysical method to study sensory threshold. This method can sometimes be mentioned as an up-down method as well. In this method, the level of stimulus characteristics (e.g., intensity, size, contrast and orientation) changes on a trial by trial basis according to the subject's response.

Many variations of the staircase procedure are used by psychophysicists. For example, García-Pérez [48] preferred to use a fixed step size for his simulation studies while Robbins and Monro [49] and later Chung [50] suggested reducing step size to converge data around targeted stimulus level; or Gelfand [51] chose to average the transition points (or reversals) whereas Kollmeier, Gilkey, and Sieben [52] fitted a psychometric function to staircase data to get thresholds; also Verghese and Stone [53] 3Up1Down staircase in their speed discrimination task and Wattam-Bell [54] preferred 2Up1down procedure to use in motion discrimination task instead. There is no single rule best to apply on staircase procedures; however, it is crucial to choose optimal criteria considering given conditions.

We used two different adaptive staircase procedures as 1Up1Down and 1Up3Down. We only applied these procedures during the roving phase. Therefore, stimulus presentation was based on subjects' current performance during roving phase. We applied 1Up1Down procedure to both narrow and wide stimuli presentations in matched difficulty level condition. However, we used 1Up1Down and 1Up3Down procedures to present narrow and wide stimuli, respectively, in the mixed difficulty level conditions. The main reason for using two different procedures was to further manipulate difficulty levels.

The 1Up1Down procedure progress faster compared to 1Up3Down procedure, so we expected that interleaving narrow and wide stimuli using different staircase procedures would alter difficulties of both tasks. All subjects started to roving phase with the offset size 23-pixel for both stimulus types. As can be seen in Figure 2.5, offset size reached to 0-pixel (most difficult) quickly with 1Up1Down staircase method while offset size stayed around 10-pixel (relatively easier) with 1Up3Down staircase method. To avoid the confounding effect due to applying

different staircase procedures, we used the fixed initial offset size and provided a high number of trials during the roving phase. By this means, all subjects started to the roving phase at the same difficulty level, and their performances were able to progress throughout the roving phase. For instance, the subject whose performance during the first roving block illustrated in Figure 2.5 could be able to reach the 0-pixel offset size at the end of the last roving block. Therefore, 1Up3Down procedure did not prevent subjects to perform their actual performance rather it slowed down the progress, which ended up with exposing narrow and wide stimuli with different difficulty levels as we purposed.

We used reducing step size in both staircase procedures. In the 1Up1Down procedure, offset sizes increased or decreased two levels (2 pixels) after given wrong or correct response, respectively, until reaching offset size 10-pixel and then sizes changed only one level (1 pixel). In the 1Up3Down procedure, offset size increased two levels right after given wrong response and decreased two levels after three correct responses until reaching offset size 10-pixel, then step sizes altered one level.

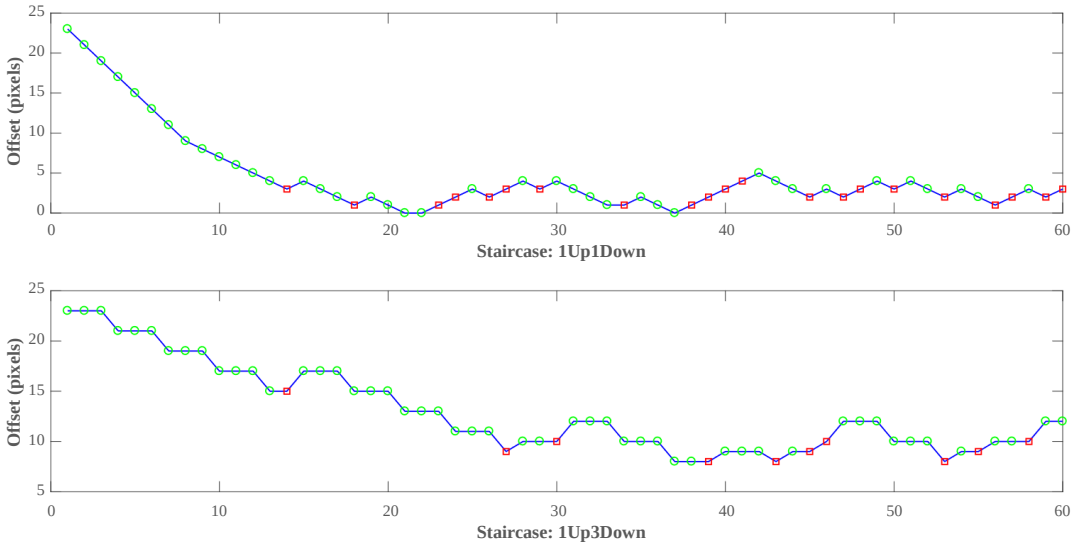


Figure 2.5: Adaptive staircase procedures. Top and bottom panels, respectively, represent 1Up1Down and 1Up3Down staircase procedures applied to one of the subjects during roving phase. Green circles and red squares denote correct and wrong answers, respectively. For simplicity, only first block is presented here.

2.5.3 Psychometric Function

The psychometric function is an inferential model used in psychophysics, especially in detection and discrimination tasks. A psychometric function indicates the relationship between the physical stimulus and perception; more specifically, the underlying percentage of a correct response and the stimulus intensity or difficulty. For example in a bisection task, if the offset number is high (i.e., 100-pixel),which means the middle line is very close to one of two outer lines, the subject would always be able to detect the offset correctly, but if the middle line is very close to the exact center of two outer lines (i.e., 1-pixel), detection of offset is the hardest, therefore, the probability of correct responses would be at chance level. In between 50% and 100% where the offset is detected correctly above-chance level but not always (i.e., 75%), is usually taken as the threshold.

We used a psychometric function to fit a curve to subjects' data obtained by the method of constant stimuli [55] and two adaptive staircase procedures [56]. Thresholds were detected as 75% correct response at pre-training, post-training, and roving phases.

2.5.4 Psychometric Function Implementation

In this study, we used a modified version of the error function as a psychometric function (see Eq. 2.2). $f_{psy} \in [0.5, 1]$ takes three inputs, a for the mean of sigmoid-like trend, b for tuning shallowness mapping on a vector x.

$$y = f_{psy}(\{a, b\}, x) = 0.25 \left[\frac{2}{\sqrt{\pi}} \int_0^{a(x+b)} e^{-t^2} dt \right] + 0.75 \tag{2.2}$$

To fit f_{psy} to offset data of each subject, we used nonlinear programming solver $fminsearch$ function of MATLAB to minimize the cross-entropy loss between offset data and f_{psy}, by adjusting fitting parameters $\{a, b\}$.

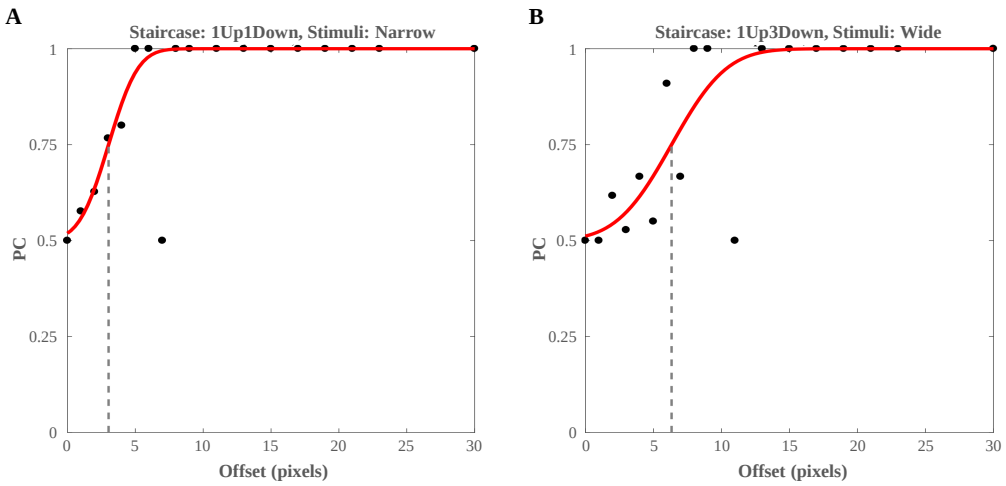


Figure 2.6: The representation of threshold detection at roving phase. (A) and (B) show the thresholds of a subject for narrow and wide stimuli, respectively. Performance was measured as percentage of correct responses.

2.6 Sensitivity

Sensitivity, symbolized by d', is a measure used in signal detection theory to distinguish the means of the signal and the noise distributions which are compared with the standard deviations of the signal and noise distributions [57]. Perception studies often use signal detection theory to measure subjects' ability to discriminate signal from noise while making a decision. For instance, Makovski, Watson, Koutstaal, and Jiang [58] measured subjects' visual working memory performance based on sensitivity through yes-no and two-alternative forced-choice (2AFC) color tasks, and found that memory sensitivity was much higher in yes-no color task compared to 2AFC color task. In the yes-no task, subjects were asked to decide if the color presenting at a current time was previously shown or not. In the 2AFC task, subjects were presented with two colors and asked to decide which one was the color previously shown.

In our study, sensitivity was the measure to show how successful the subject was at detecting the offset of the bisection stimuli during the training phase.

As previously stated, during training phase we used a fixed offset size for wide stimuli, which we determined as subject's threshold at pre-training phase. Thus, each subject was trained on the same offset-size, repeatedly, which were generated based on individual thresholds (where the proportion of correct responses was 75%). For example, if the threshold of a subject was 10 pixels, then the middle-line placed to 10 pixels away from the mid-point in the left or right direction. In order to avoid decisional bias, the numbers of presentations of left and right offsets were kept equal. At the end of the training, we expected to observe the increase in task sensitivity and therefore, the decrease in threshold with training.

For unbiased performance cases, sensitivity index (d') can be evaluated via:

$$d' = \sqrt{2}Z(p(c)_{max,2AFC}), \tag{2.3}$$

where $Z(p), p \in [0, 1]$ is the inverse of the cumulative distribution function (ICDF) of the Gaussian distribution, and $p(c)_{max,2AFC}$ is the maximum proportion correct in two alternative forced choice experiments, calculated by $hits/total\_trials$.

In order to calculate $Z(p)$, we used, $erfcinv()$ function, such that

$$Z(p) = -\sqrt{2}erfcinv(2p), \tag{2.4}$$

where $erfcinv()$ is the inverse complementary error function, $erfcinv(erfc(x)) = x$, and the complementary error function is defined as

$$erfc(x) = 1 - erf(x) = \frac{2}{\sqrt{\pi}} \int_x^\infty e^{-t^2} dt. \tag{2.5}$$

Chapter 3

Results

3.1 Statistical Results on The Task Difficulty

In order to investigate the effect of task difficulty on perceptual performance we compared the subject thresholds on matched and mixed task difficulty levels. Since the task difficulty was manipulated in only roving phase we tested results on this phase. First, all roving performances were included to observe the task difficulty effect in general; in this way, we were able to understand if the effect was similar on both narrow and wide bisection task. Later, we tested the task difficulty effect in only wide bisection task to eliminate any cause due to absence of training with narrow bisection task as the subjects were trained only with wide bisection task.

Levene's test showed that the homogeneity of variance assumption was not violated ($p > .05$). Therefore, we conducted a 2 x 2 mixed factorial design and used a mixed ANOVA. The within-subjects factor was the stimulus size with two levels (narrow or wide), and the between-subjects factor was the task difficulty with two levels (matched or mixed). The detailed descriptive of statistics can be seen in Table A.1. According to Box's M test of equality of covariance matrice and Mauchly's test of sphericity, homogeneity and sphericity

assumptions were not violated (both $p > .05$). Test of within-subjects effects revealed that there was a significant main effect of stimulus size on performance ($F(1, 118) = 110.63$, $MSE = 3.57$, $p < .001$, $\eta^2_{partial} = .48$), meaning that roving performances were different in narrow bisection task compared to wide bisection task. Also, there was a significant interaction between stimulus size and task difficulty ($F(1, 118) = 144.15$, $MSE = 3.57$, $p < .001$, $\eta^2_{partial} = .26$), which can be explained as that matched or mixed task difficulty affected performance on narrow and wide bisection task under roving condition differently. Moreover, test of between-subjects effects showed that the task difficulty had a significant main effect on performance ($F(1, 118) = 9.48$, $MSE = 11.25$, $p = .003$, $\eta^2_{partial} = .07$), so influence of matched and mixed task difficulty on roving performance were statistically different.

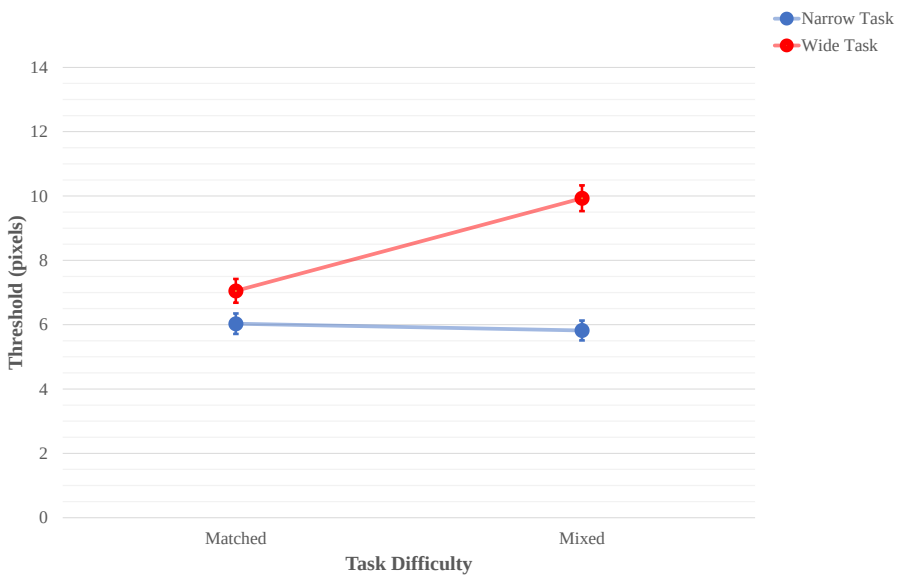


Figure 3.1: The effect of task difficulty. The figure compares performance at roving phase performed with narrow and wide bisection stimuli under matched and mixed task difficulty conditions. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

As previously mentioned, we additionally tested the effect of task difficulty on only wide bisection task performance under roving condition to eliminate training's possible impact on results; therefore, a one-way ANOVA was conducted. The significant main effect of task difficulty was found, again, on roving performance ($F(1, 118) = 28.12$, $MSE = 8.87$, $p < .001$, $\eta^2_{partial} = .19$), meaning that mixed task difficulty influenced performance on wide bisection task under roving condition different than on narrow bisection task. As can be seen on Figure 3.1, mean of the thresholds for wide bisection task in mixed difficulty condition higher compared to matched difficulty condition, meaning that mixing task difficulty reduced roving performance for wide bisection task.

According to Shapiro-Wilk test results, our variables were not normally distributed. Therefore, we used Wilcoxon signed-rank test which is alternative to paired sample t-test for the pairwise comparison. The significant difference was found between following pairwise comparison; pre- and post-training performance with narrow ($Z = -3.27$, $p = .001$) or wide stimulus size ($Z = -4.25$, $p < .001$); pre- and roving performance with narrow ($Z = -4.38$, $p < .001$) or wide stimulus size ($Z = -6.28$, $p < .001$) in matched difficulty condition, pre- and roving performance with narrow ($Z = -4.53$, $p < .001$) or wide stimulus size ($Z = -2.24$, $p = .025$) in mixed difficulty condition; post-training and roving performance with narrow ($Z = -4.04$, $p < .001$) or wide stimulus size ($Z = -5.62$, $p < .001$) in matched difficulty condition, post-training and roving performance with narrow ($Z = -2.59$, $p = .01$) but not with wide stimulus size in mixed difficulty condition; pre-training performance with narrow and wide stimulus size ($Z = -8.49$, $p < .001$), post-training performance with narrow and wide stimulus size ($Z = -8.05$, $p < .001$), roving performance with narrow and wide stimulus size ($Z = -7.22$, $p < .001$).

3.2 Statistical Results on The Amount of Training

In addition to the fact that training improves perceptual performance, we wanted to test if facilitating effect of training occur under roving condition. First, we tested the amount of training's impact on performance changing between pre- and post-training phases in general. Thus, performance changing on narrow bisection task was included in the statistical test, even though subjects were never trained by narrow stimulus. The primary reason for collecting subjects' thresholds for narrow bisection task was to see if transfer of learning is possible from a difficult task to easier task. Second, performance changing was tested only on wide bisection task to eliminate the stimulus size's impact on results. Third, we wanted to see the role of amount of training on performance at roving phase. Thus, roving results were tested on narrow and wide bisection tasks together across training groups, then only performance on wide bisection task. Last, training effect was tested on roving performance separated by matched or mixed task difficulty. Again, we did not exclude narrow bisection task's thresholds first, but later we tested roving performance in wide bisection task alone.

Levene's test showed that the homogeneity of variance assumption was not violated ($p > .05$). Therefore, again, we conducted a 2 x 3 mixed factorial design and used a mixed ANOVA to test performance changing (post-training - pre-training). The within-subjects factor was the stimulus size with two levels (narrow or wide), and the between-subjects factor was the number of training days with three levels (1-day, 3-day or 5-day). The detailed descriptive of statistics can be seen in Table A.2. According to Box's M test of equality of covariance matrice and Mauchly's test of sphericity, homogeneity and sphericity assumptions were not violated (both $p > .05$). Test of within-subjects effects revealed that there was no significant main effect of stimulus size on performance changing, meaning that performance difference between pre- and post-training phase was not influenced by narrow and wide bisection task differently. Also, the interaction between the stimulus size and the number of training days was not significant.

It is worth noting that these results showing no main effect of the stimulus size on performance changing between pre- and post-training phase might be a clue for learning transfer between narrow and wide bisection tasks. Test of between-subjects effects showed that the number of training days had a significant main effect on performance changing ($F(1, 117) = 5.01$, $MSE = 12.18$, $p = .008$, $\eta^2_{partial} = .08$). To understand the interaction, we conducted Tukey HSD post-hoc pairwise comparisons since our group sizes were different ((1-day, $N = 36$), (3-day, $N = 40$), (5-day, $N = 44$)), and normality or homogeneity assumption was met. Only significant interaction was found between 1-day and 5-day training performance changing ($MD = .174$, $p = .006$). As can be seen in Figure 3.2, thresholds reduced significantly in 5-day condition compared to 1-day condition, meaning that performance improved with increasing amount of training. No other comparisons reached significance.

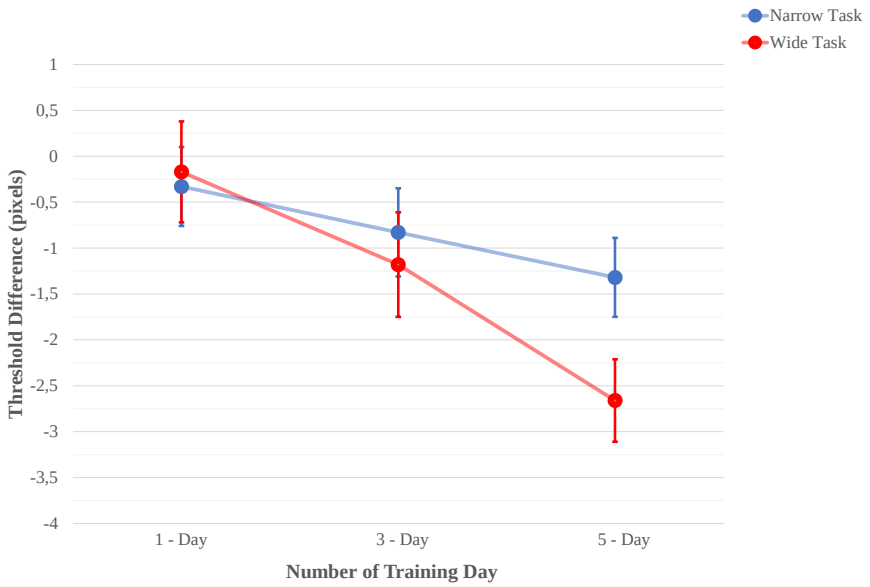


Figure 3.2: The effect of amount of training on performance changing across pre- and post-training phases. The figure compares performance changing between pre- and post-training phases performed with narrow and wide bisection stimuli. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

Additionally, performance changing was tested on only wide bisection task. A one-way ANOVA results revealed that there was a significant main effect of the amount of training on performance changing ($F(2, 117) = 5.90$, $MSE = 10.72$, $p = .004$, $\eta^2_{partial} = 0.09$). Tukey HSD post-hoc pairwise comparisons revealed that only, again, significant interaction was found between 1-day and 5-day training performance changing in wide bisection task ($MD = 2.49$, $p = .003$).

In order to observe the role of amount of training at roving phase, a two-way mixed ANOVA was conducted. The within-subjects factor was the stimulus size with two levels (narrow or wide), and the between-subjects factor was the number of training days with three levels (1-day, 3-day or 5-day). According to Box's M test of equality of covariance matrice and Mauchly's test of sphericity, homogeneity and sphericity assumptions were not violated (both $p > .05$). Test of within-subjects effects revealed that there was a significant main effect of stimulus size on roving performance ($F(1, 117) = 86.32$, $MSE = 4.70$, $p < .001$, $\eta^2_{partial} = .43$), but there was no significant interaction between the size of stimulus and the amount of training days, which can be interpreted as that roving performances were different for narrow and wide bisection tasks, but this was not changed by amount of training. The results from test of between-subjects effects showed that the amount of training had no significant main effect on roving performance. Test results of a one-way ANOVA which was conducted to observe training effect on only wide bisection task under roving condition also showed that the amount of training was not a significant main effect. We thought that the reason for that there was no significant main effect of the amount of training was found might be pooling all roving performance without considering the effect of task difficulty. Thus, following tests were conducted to eliminate task difficulty's confounding impact on results.

Furthermore, performances changing (post-training - roving) in narrow or wide bisection task was tested. Levene's test showed that the homogeneity of variance assumption was not violated ($p > .05$). Therefore, we conducted a 2 x 3 x 2 mixed factorial design and used a mixed ANOVA. The within-subjects factor was the stimulus size with two levels (narrow or wide), and the between-subjects

factors were the number of training days with three levels (1-day, 3-day or 5-day), and the task difficulty with two levels (matched or mixed). The detailed descriptive of statistics can be found in Table A.3. According to Box's M test of equality of covariance matrice and Mauchly's test of sphericity, homogeneity and sphericity assumptions were not violated (both $p > .05$). Test of within-subjects effects revealed that there was no significant main effect of the stimulus size and no significant interaction between the stimulus size and the amount of training on performance changing; but there was a significant interaction between the stimulus size and the task difficulty ($F(1, 114) = 14.79$, $MSE = 5.29$, $p < .001$, $\eta^2_{partial} = .115$). Test of between-subjects effects showed that task difficulty had a significant main effect on performance changing ($F(1, 114) = 30.02$, $MSE = 7.37$, $p < .001$, $\eta^2_{partial} = .21$) while the amount of training did not ($F(2, 114) = 2.96$, $MSE = 5.29$, $p = .056$, $\eta^2_{partial} = .049$). Since Box's M test's result was close to violation of normality ($p = .06$), and there was a clear difference between performance changing across different training-day condition in Figure 3.3 and Figure 3.4, we suspected that an existence of the outlier(s). Therefore, we conducted a Shapiro-Wilk test of normality. Test results showed that the performance changing in narrow bisection task was non-normally distributed, with *skewness* of .852 ($SE = .39$) and *kurtosis* of 3.05 ($SE = 0.77$) and one outlier variable was detected and eliminated later on. After elimination of the outlier, according to Shapiro-Wilk test results, performance changing in narrow bisection task was normally distributed, with *skewness* of $-.208$ ($SE = .40$) and *kurtosis* of .69 ($SE = 0.79$). A three-way mixed ANOVA with the same mixed factorial design was conducted after the outlier was eliminated. Box's M test of equality of covariance matrice showed increased homogeneity ($p = .19$), and Mauchly's test of sphericity revealed no violation of sphericity assumptions ($p > .05$). In accordance with the new test of within-subjects effects, there was, again, no significant main effect of the stimulus size on performance changing and no significant interaction between the stimulus size and the amount of training, but there was a significant interaction between the stimulus size and the task difficulty on performance changing ($F(1, 113) = 16.08$, $MSE = 5.22$, $p < .001$, $\eta^2_{partial} = .13$). However, the new tests of between-subjects effects showed that the amount of training had a significant main effect on performance changing

($F(2, 113) = 3.37$, $MSE = 6.76$, $p = .038$, $\eta^2_{partial} = .06$) as well as the task difficulty had ($F(1, 113) = 28.55$, $MSE = 6.76$, $p < .001$, $\eta^2_{partial} = .20$). Multiple comparison with Tukey HSD indicated that the only significant interaction was found between 3-day and 5-day conditions ($MD = 1.02$, $p = .03$).

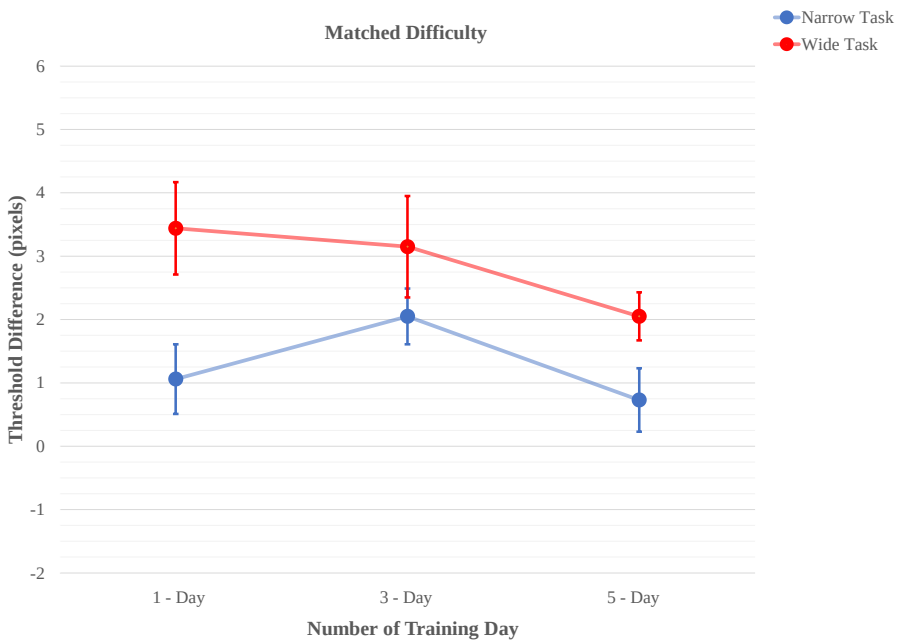


Figure 3.3: The effect of amount of training on performance changing under matched difficulty condition. The figure compares performance changing between post-training and roving phases performed with narrow and wide bisection stimuli under matched difficulty condition. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

Figure 3.4: The effect of amount of training on performance changing under mixed difficulty condition. The figure compares performance changing between post-training and roving phases performed with narrow and wide bisection stimuli under mixed difficulty condition. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

Finally, a three-way mixed ANOVA was conducted to compare post-training and roving performance for only wide bisection task. The within-subjects factor was the phase with two levels (post-training or roving), and the between-subjects factors were the number of training days with three levels (1-day, 3-day or 5-day), and the task difficulty with two levels (matched or mixed). The detailed descriptive of statistics can be found in Table A.4. According to Box's M test of equality of covariance matrice and Mauchly's test of sphericity, homogeneity and sphericity assumptions were not violated (both $p > .05$). The results from the tests of within-subjects were as follow; phase had a significant main effect on performance ($F(1, 114) = 27.76$, $MSE = 3.88$, $p < .001$, $\eta^2_{partial} = .20$) and interaction between the phase and the task difficulty was significant ($F(1, 114) = 36.26$, $MSE = 3.88$, $p < .001$, $\eta^2_{partial} = .24$), but the phase and the amount of training had no significant interaction. The tests of between-subjects effects showed that there was a significant main effect of the amount of training ($F(2, 114) = 6.13$,

$MSE = 12.04$, $p = .003$, $\eta^2_{partial} = .10$) as well as of the task difficulty on performance ($F(1, 114) = 9.92$, $MSE = 12.04$, $p = .002$, $\eta^2_{partial} = .08$). Multiple comparison with Tukey HSD indicated that the only significant interaction was found between 1-day and 5-day conditions ($MD = 1.91$, $p = .002$). According to ANOVA results, roving performances were significantly different from post-training performance for the wide bisection task. As Figure 3.5 and Figure 3.6 illustrate below, this difference was obvious in matched difficulty condition compared to mixed difficulty condition. Also, the increasing amount of training reduced thresholds so improved both post-training and roving performances. Improvement by training was more apparent between 1-day and 5-day conditions as expected.

The detailed interactions between the amount of training day and task difficulty were illustrated in Figure 3.7.

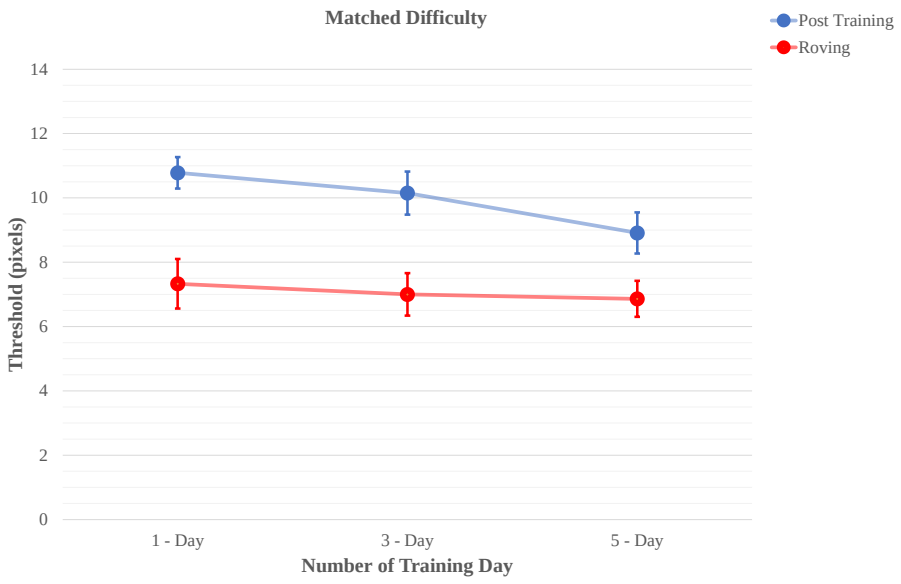


Figure 3.5: The effect of amount of training on wide bisection task under matched difficulty condition. The figure compares post-training and roving performances considering only wide bisection stimuli under matched difficulty condition. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

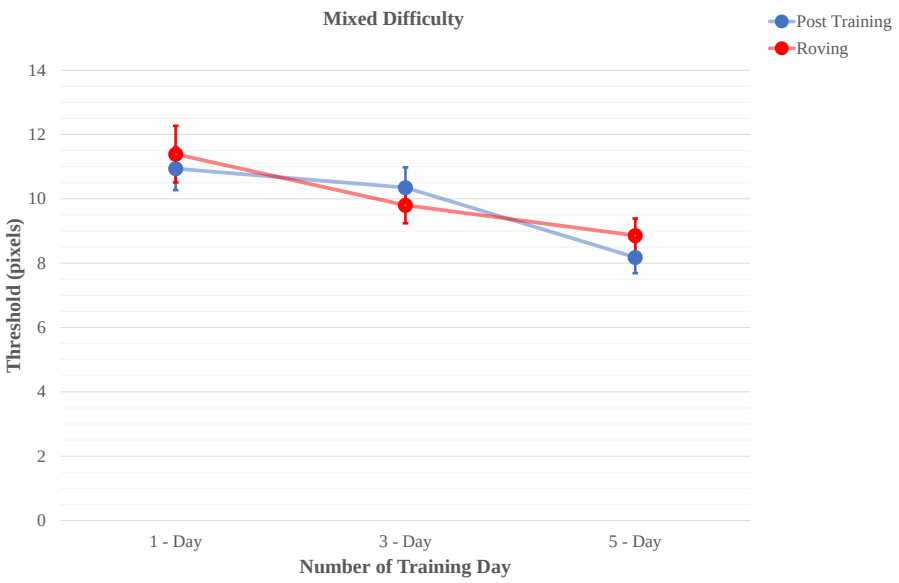


Figure 3.6: The effect of amount of training on wide bisection task under mixed difficulty condition. The figure compares post-training and roving performances considering only wide bisection stimuli under mixed difficulty condition. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

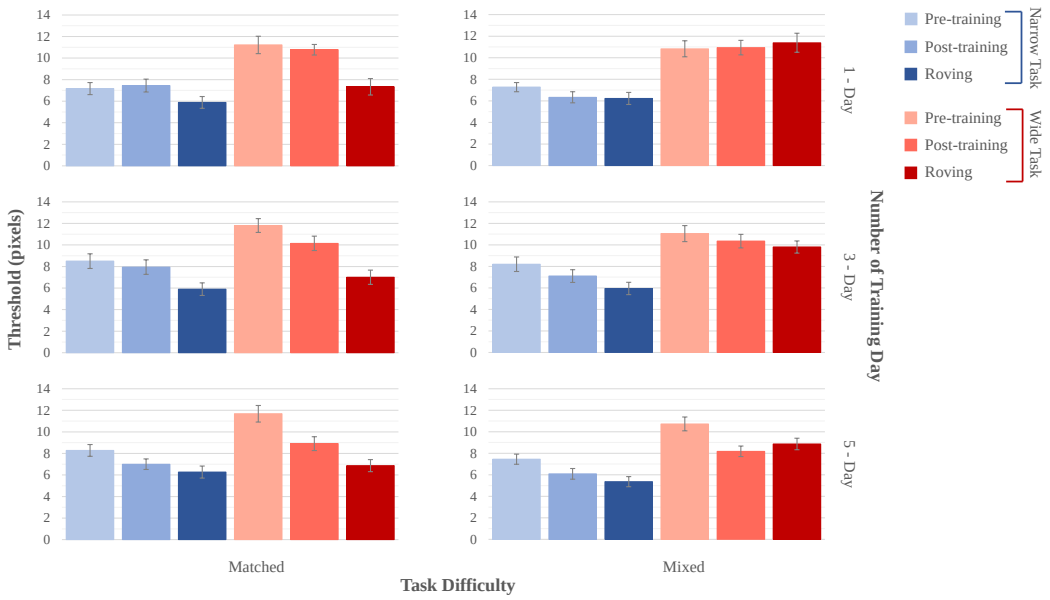


Figure 3.7: Interactions between the amount of training day and task difficulty. The figure also shows average thresholds for pre-training, post-training and roving phase with narrow or wide bisection stimuli. The lower threshold stands for better performance. Error bars plot ± 1 SEM.

3.3 Statistical Results on the Task Sensitivity

As previously stated in Methods section, subjects' thresholds were not collected as percentage of correct responses; instead, task sensitivity was measured during the training phase.

A one-way ANOVA was conducted to see the amount of training's impact on task sensitivity which was measured via d'. The dependent variable was task sensitivity, and the independent variable was the training group with three levels (1-day, 3-day or 5-day). According to test results, the training group had a significant main effect on task sensitivity ($F(2, 177) = 16.55$, $MSE = .02$, $p < .001$, $\eta^2_{partial} = .16$), meaning that the task sensitivity changed with different amount of training. Furthermore, based on Levene's test of homogeneity of variances, homogeneity assumption was violated. Considering violation of homogeneity and unequal sample sizes, The Games-Howell post-hoc test was conducted as it does not assume equal variances and sample sizes. Post-hoc test revealed that all possible pairwise comparisons were significant, so task sensitivity changed across all groups ($p = .013$ for 1-day and 3-day comparison, and $p < .001$ for the rest). As Figure 3.8 shows that subjects' sensitivities in groups where the amount of training was higher were also elevated.

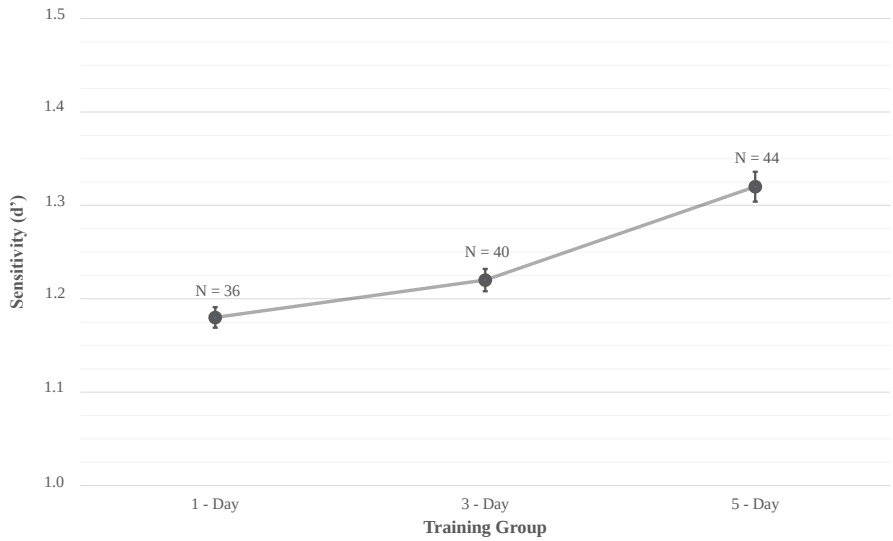


Figure 3.8: The training group's effect on task sensitivity. The figure compares sensitivity means across 1-day, 3-day and 5-day training groups. The higher d' value stands for better detection. Error bars plot ± 1 SEM.

In addition to group-wise comparison, we wanted to analyze results with a day-wise comparison. Therefore, we conducted again a one-way ANOVA. The dependent variable was, again, task sensitivity and the independent variable was the training day with five levels (first-day, second-day, third-day, fourth-day or fifth-day). A significant main effect of the training day was found ($F(4, 175) = 44.59$, $MSE = .01$, $p < .001$, $\eta^2_{partial} = .51$), so subjects' task sensitivity changed across all training days. Since Levene's test results found no violation of homogeneity of variances, Tukey HSD post-hoc was used for pairwise comparisons. Except for between second-day and third-day as well as fourth-day and fifth-day, all possible pairwise comparisons were significant ($p = .003$ for third-day and fourth-day comparison, and $p < .001$ for the rest). In accordance with Figure 3.9, almost a linear increasing of task sensitivity was observed throughout each day.

The detailed interactions between the training group and the training day were illustrated in Figure 3.10.

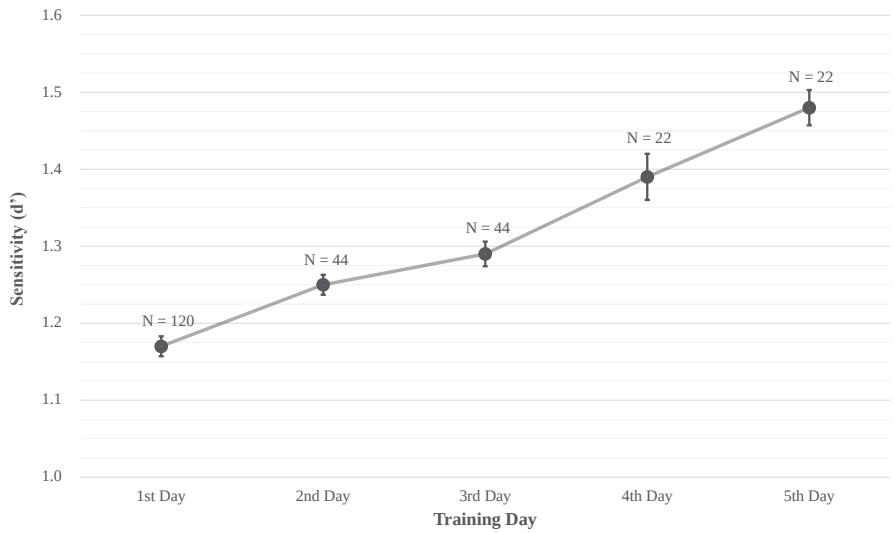


Figure 3.9: The training day's effect on task sensitivity. The figure compares sensitivity means across first-, second-, third-, fourth- and fifth-day. The higher *d'* value stands for better detection. Error bars plot ± 1 SEM.

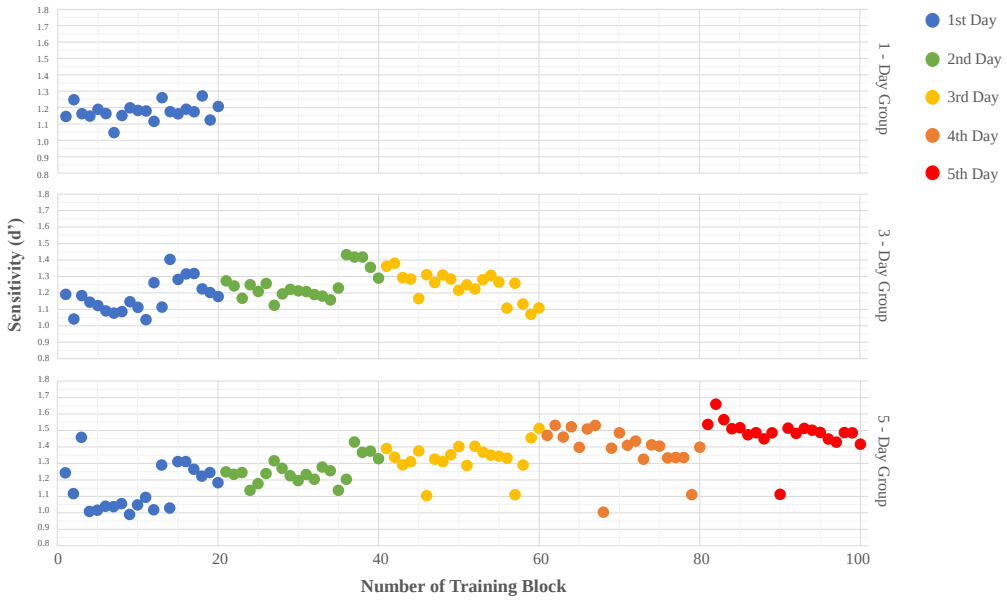


Figure 3.10: Interactions between the training group and the training day. The figure shows average task sensitivity across training groups as well as training day. Higher *d'* value stands for better detection.

Chapter 4

Discussion

In the current study, we aimed to examine the effect of task difficulty and level of expertise on a learned perceptual task under roving condition. Studies investigated the inhibiting effect of the roving or facilitating effect of the training on perceptual tasks are abundant in the literature. Different from past studies, we build a bridge between these two phenomena in our research. Here, we tested following hypotheses; first, differing task difficulty levels contribute to performance impairments in roving. Second, the increasing level of expertise reduces the deleterious effect of roving.

First, we found that performances improved as usual in perceptual learning studies. Second, subjects' performances were better at the narrow task in general. Third, training with only wide stimuli helped to improve performance on the untrained task with narrow stimuli. Fourth, stimuli with equated difficulty levels did not impair performances; in fact, they facilitated performances for both narrow and wide stimuli. Fifth, performances decreased significantly as a result of interleaving narrow and wide bisection stimuli by different staircase procedures. Last, the increasing amount of training reduced roving's deleterious effect on the learned task.

In visual perceptual learning studies, various stimulus types such as Gabor

patches [59], vernier [11], dot-bisection [21], line-bisection [60], Chevron [61], oblique lines [19] and curvatures [62] as spatial discrimination tasks can be used to investigate the role of training on perceptual performance. In our study, subjects performed the bisection discrimination task where they tried to decide the offset of a central line (left or right) in a bisection stimulus. In parallel with all those past studies, we showed that perceptual learning is possible with a sufficient amount of training on a vertical line-bisection task. Also, our results revealed that narrow stimulus was easier in offset detection compared to wide stimulus. As illustrated in Figure 4.1 below, our both narrow and wide stimuli fall within the parafoveal visual area (outer line distances were 4.9° and 7.3°, respectively). As the spacing between the two lines increases, the task gets harder. This could be simply explained by the structure of the visual system. The density of cone photoreceptors decreases dramatically outside of the fovea, which is called eccentricity [63]. Therefore, increasing eccentricity with distance from foveal region results in lower visual acuity due to the reduced density of cone photoreceptors. Alongside the eye physiology, attention might be another factor affecting performance on visual tasks. For example, Staugaard, Petersen, and Vangkilde [64] suggested a decrease in attentional capacity with increasing stimulus eccentricity. Also, Carrasco, Evert, Chang, and Katz [65] found that reaction times and error rates increase with the eccentricity of a visual target in an orientation discrimination task. Hence, the lower eccentricity might be a reason to observe better performance on the narrow task rather than the wide task.

Furthermore, perceptual learning is highly specific to the trained task [66, 67, 68, 32, 69, 70] and specificity of perceptual learning increases with training [71]. Though, generalization or, in other words, the transfer of learning is not impossible. However, the direction of learning transfer could be from easier task to difficult task [19] so how did learning transfer from more difficult task (wide-bisection) to easier task (narrow-bisection) in our study? According to reverse hierarchy theory, learning starts at higher levels and backpropagates to lower levels to optimize information as reverse to bottom-up sensory processing, so plasticity is dominated by top-down processes. If learning occurs at lower level areas such as V1 where neurons are selective for orientation and position, exposing

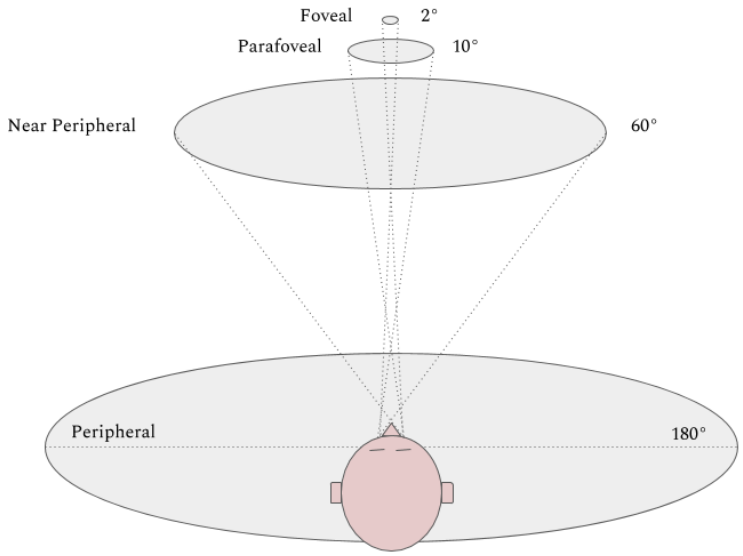


Figure 4.1: The representation of human visual field. The figure illustrates visual field based on approximate eccentricities.

untrained stimuli with a different orientation would activate a non-overlapping population of neurons, which in return reduces performance on novel task [24]. In our case, we believe that transfer happened from wide to narrow stimuli by means of an overlapping neuron population; in other words, the narrower stimulus was already contained in the wider one. Similarly, Parkosadze et al. [21] reported that learning transferred from trained vertical line-bisection task to untrained vertical dot-bisection task as a result of overlapping neuron population but not to untrained horizontal line-bisection task due to a recently activated non-overlapping neuron population. Thus, in order to make more accurate inferences on transferability of learning, it may be more feasible to take into consideration of the size of overlapping neuron populations of two tasks in addition to the difficulties of these tasks.

Moreover, interestingly, we observed a drastic performance improvement on both narrow and wide bisection task during the roving condition when the same staircase procedure applied to two tasks. The first reason could simply be attention regain. Performing the same task repeatedly for a long while might be

ended with attention decrement whereas mixing two tasks could promote attention. However, past studies showed, in fact, that switching between two tasks increases cost in cognitive processes [72], which might reduce performance on both tasks [73, 74, 75]. Second reason could be the contribution of the overlapping population of neurons which was activated by both narrow and wide bisection stimuli for wiring plasticity. In this situation, we would expect to observe performance improvement when we roved two stimuli by different staircase procedures as well; but, instead, roving performance deteriorated or did not change. Another reason could be that applying matched task difficulties (via the same staircase procedures) on similar tasks with overlapped neural populations created another training effect so improved performance for both tasks as suggested by Tartaglia, Aberg, and Herzog [36] as well.

Previously many studies found no effect of roving on post-learning performance [36, 37, 38] seemingly conflict with our results. In our opinion, the reason for this confliction is that they all used adjusted task difficulty for each stimulus type, resulted in similar performance levels for the roved tasks. Frémaux, Sprekeler, and Gerstner [40] and Herzog et al. [39] recently revealed in their modeling studies that reward cannot be assigned individually to two similar stimulus types by the *critic* of reinforcement learning models. This phenomenon is called "unsupervised bias" in the literature [40]. Frémaux, Sprekeler, and Gerstner's [40] learning model predicts the synaptic *drift* and disruption of learning if simultaneously learning two tasks differ in difficulty levels due to unsupervised bias; however, the model does not predict disruption of learning for equated difficulty levels. According to Aberg and Herzog [76], roving occurs as a result of competition between stimulus types for resources in long-term potentiation (LTP). Additionally, as demonstrated in Ahissar and Hochstein's [24] the reverse hierarchy theory (RHT), neurons are highly specific to stimuli in low-level visual areas; therefore, these neurons compete for creating plasticity with higher-level areas. Those criticisms on competing for plasticity [76, 24] are parallel with Frémaux, Sprekeler, and Gerstner's [40] unsupervised bias argument. Thus, unsupervised bias could explain why roving sometimes deteriorates learning [21, 36], but not always [36]. Our mathematical analysis also confirmed the unsupervised bias argument by

showing that roving disrupted performance only under mixed difficulty condition where the task difficulty manipulated in narrow and wide bisection tasks but not under matched difficulty condition with equated levels of task difficulty of both narrow and wide bisection tasks. In modeling point of view, equal task difficulty levels do not require individually assigned reward for each task by the critic, so the model predicts no disruption of learning.

Clarke et al. [35] previously found no facilitative effect of increased training on roving performance. In the current study, on the other hand, we hypothesized and confirmed that the deleterious effect of roving due to differing task difficulty levels decrease with training. Different from our study, Clarke et al. [35] trained subjects on bisection stimulus for only three days. Three-day training with 20 blocks for each day might not be enough for robust learning since we also observed no significant performance improvement and so no recovery on roving performance until the fifth day. Besides, even extensive training alone might not be enough to produce robust learning. As Seitz [8] suggested that attention and reinforcement are two other important factors facilitating robust learning. Even though perceptual learning is possible without feedback, it accelerates with feedback [11]. Therefore, subjects who did not receive feedback during training in Clarke et al.'s experiment [35], could possibly fail to develop robust learning which could be acquired either by providing feedback or by prolonged training (i.e., for one or two more days). We provided with constant auditory feedback in each trial for helping learning to progress. Also, we had an extensive training group who performed the experiment on five consecutive days (20 blocks per day). It is worth noting that if the same amount of training (100 blocks) was performed in one day we would not expect the same magnitude of performance improvement as Karni et al. [77] and Sasaki, Nanez, and Watanabe [78] suggested. Thus, in perceptual learning studies requiring extensive training, dividing practice process on separate days is crucial to avoid fatigue and promote attention with overnight consolidation [79].

Chapter 5

Future Directions

Future research is needed to shed light on how performance is affected after roving. Previously, it has been tested to see if roving had an effect on perceptual learning [21, 36] or on performance for learned tasks [35]. In the current study, we built on these results to determine roving's effects on performance for the learned task as a function of the level of expertise. However, the role of expertise on post-roving performance has yet shown. Conducting additional experiments after roving phase with a trained-stimulus alone would be an important step to characterize the post-roving effects on task performance. Also, adding a control group performing roving blocks where the stimulus is randomly interleaved with another version of the same stimulus which is known not to cause learning interference (i.e., horizontal bisection task vs. vertical bisection task) [31] might be a good direction to pursue in examining the post-roving performance.

Moreover, the current study has great potential to open up new avenues of exploration in the field of perceptual learning for modeling studies. For example, our results confirmed Frémaux, Sprekeler, and Gerstner's [40] and Herzog et al.'s [39] learning model presenting unsupervised bias argument; though, the model cannot account for all of our findings, particularly that decrease in roving's negative effects with increasing training. To accurately model our findings, we need a model that takes into account how much training a person has done.

Chapter 6

Conclusion

In the current study, we tested the effects of matched and mixed task difficulty levels on roving performance for a learned task. We wanted to characterize roving's deleterious impact on performance under different levels of expertise and of task difficulty.

Our results are important in terms of being the first study to explore the combined role of task difficulty and expertise on roving performance for the learned perceptual task. Our findings demonstrate that randomly interleaving two perceptual tasks deteriorates performance if two tasks differ in difficulty levels; also, the increasing amount of training reduces the impairment caused by roving. These results have important implications for learning models and for our understanding of the contributions of cognitive resources to learning. Therefore, the current study fills gaps in our knowledge about how perceptual learning works, how it can be augmented and how it can be inhibited by external factors such as roving and expertise.

Bibliography

[1] W. R. Dennes and J. Dewey, "Logic: The Theory of Inquiry," *The Philosophical Review*, 1940.

[2] F. Fearing, I. P. Pavlov, and G. V. Anrep, "Conditioned Reflexes. An Investigation of the Physiological Activity of the Cerebral Cortex," *Journal of the American Institute of Criminal Law and Criminology*, 1929.

[3] R. Rescorla and A. Wagner, "A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement," in *Classical conditioning: current research and theory, Vol. 2*, 1972.

[4] R. S. Sutton and A. G. Barto, "Introduction to Reinforcement Learning," *Learning*, 2005.

[5] D. O. Hebb, F. Attneave, and M. B., "The Organization of Behavior; A Neuropsychological Theory," *The American Journal of Psychology*, 1950.

[6] D. J. C. Mackay, *Information theory, inference and learning algorithms*. New York, NY: Cambridge University Press, 2003.

[7] W. Li, V. Piëch, and C. D. Gilbert, "Perceptual learning and top-down influences in primary visual cortex," *Nature Neuroscience*, 2004.

[8] A. R. Seitz, "Perceptual learning," 2017.

[9] Y. Yotsumoto and T. Watanabe, "Defining a link between perceptual learning and attention," 2008.

[10] M. Ahissar and S. Hochstein, "Attentional control of early perceptual learning," *Proceedings of the National Academy of Sciences*, 1993.

[11] M. H. Herzog and M. Fahle, "The role of feedback in learning a vernier discrimination task," *Vision Research*, 1997.

[12] M. Atienza, J. L. Cantero, and E. Dominguez-Marin, "The time course of neural changes underlying auditory perceptual learning," *Learning and Memory*, 2002.

[13] M. Fahle and S. Edelman, "Long-term learning in vernier acuity: Effects of stimulus orientation, range and of feedback," *Vision Research*, 1993.

[14] M. Ahissar and S. Hochstein, "Learning pop-out detection: Specificities to stimulus characteristics," *Vision Research*, 1996.

[15] L. P. Shiu and H. Pashler, "Improvement in line orientation discrimination is retinally local but dependent on cognitive set," *Perception & Psychophysics*, 1992.

[16] K. Ball and R. Sekuler, "Direction-specific improvement in motion discrimination," *Vision Research*, 1987.

[17] A. Karni and D. Sagi, "Where practice makes perfect in texture discrimination: evidence for primary visual cortex plasticity," *PNAS*, 1991.

[18] A. A. Schoups, R. Vogels, and G. A. Orban, "Human perceptual learning in identifying the oblique orientation: retinotopy, orientation specificity and monocularity.," *The Journal of Physiology*, 1995.

[19] M. Ahissar and S. Hochstein, "Task difficulty and the specificity of perceptual learning," *Nature*, 1997.

[20] R. Vogels and G. A. Orban, "The effect of practice on the oblique effect in line orientation judgments," *Vision Research*, 1985.

[21] K. Parkosadze, T. U. Otto, M. Malania, A. Kezeli, and M. H. Herzog, "Perceptual learning of bisection stimuli under roving: slow and largely specific.," *Journal of vision*, 2008.

[22] M. Fahle and J. P. Harris, "The use of different orientation cues in vernier acuity," *Perception and Psychophysics*, 1998.

[23] M. Ahissar, "Perceptual learning," *Current Directions in Psychological Science*, vol. 8, no. 4, pp. 124 – 128, 1999.

[24] M. Ahissar and S. Hochstein, "The reverse hierarchy theory of visual perceptual learning," 2004.

[25] Z. Liu and D. Weinshall, "Mechanisms of generalization in perceptual learning," *Vision Research*, 2000.

[26] L. Zili, "Learning a visual skill that generalizes," tech. rep., 1995.

[27] M. Fahle and M. Morgan, "No transfer of perceptual learning between similar stimuli in the same retinal position," *Current Biology*, 1996.

[28] T. U. Otto, M. H. Herzog, M. Fahle, and L. Zhaoping, "Perceptual learning with spatial uncertainties," *Vision Research*, 2006.

[29] S. G. Kuai, J. Y. Zhang, S. A. Klein, D. M. Levi, and C. Yu, "The essential role of stimulus temporal patterning in enabling perceptual learning," *Nature Neuroscience*, 2005.

[30] Y. Adini, A. Wilkonsky, R. Haspel, M. Tsodyks, and D. Sagi, "Perceptual learning in contrast discrimination: The effect of contrast uncertainty," *Journal of Vision*, 2004.

[31] K. C. Aberg and M. H. Herzog, "Interleaving bisection stimuli - randomly or in sequence - does not disrupt perceptual learning, it just makes it more difficult," *Vision Research*, 2009.

[32] A. Fiorentini and N. Berardi, "Perceptual learning specific for orientation and spatial frequency," *Nature*, 1980.

[33] J. Gold, P. J. Bennett, and A. B. Sekuler, "Signal but not noise changes with perceptual learning," *Nature*, 1999.

[34] Z. Hussain, A. B. Sekuler, and P. J. Bennett, "Perceptual learning modifies inversion effects for faces and textures," *Vision Research*, 2009.

[35] A. M. Clarke, L. Grzeczkowski, F. W. Mast, I. Gauthier, and M. H. Herzog, "Deleterious effects of roving on learned tasks," *Vision Research*, 2014.

[36] E. M. Tartaglia, K. C. Aberg, and M. H. Herzog, "Perceptual learning and roving: Stimulus types and overlapping neural populations," *Vision Research*, 2009.

[37] Y. Yotsumoto, L. hung Chang, T. Watanabe, and Y. Sasaki, "Interference and feature specificity in visual perceptual learning," *Vision Research*, 2009.

[38] J. Y. Zhang, S. G. Kuai, L. Q. Xiao, S. A. Klein, D. M. Levi, and C. Yu, "Stimulus coding rules for perceptual learning," *PLoS Biology*, 2008.

[39] M. H. Herzog, K. C. Aberg, N. Frémaux, W. Gerstner, and H. Sprekeler, "Perceptual learning, roving and the unsupervised bias," *Vision Research*, 2012.

[40] N. Fremaux, H. Sprekeler, and W. Gerstner, "Functional Requirements for Reward-Modulated Spike-Timing-Dependent Plasticity," *Journal of Neuroscience*, 2010.

[41] W. Schultz, "Dopamine signals for reward value and risk: Basic and recent data," 2010.

[42] Z. Hussain, P. J. Bennett, and A. B. Sekuler, "Versatile perceptual learning of textures after variable exposures," *Vision Research*, 2012.

[43] Z. Hussain, B. S. Webb, A. T. Astle, and P. V. McGraw, "Perceptual Learning Reduces Crowding in Amblyopia and in the Normal Periphery," *Journal of Neuroscience*, 2012.

[44] C. Yu, S. A. Klein, and D. M. Levi, "Perceptual learning in contrast discrimination and the (minimal) role of context," *Journal of Vision*, 2004.

[45] M. Bach, "The Freiburg Visual Acuity Test - Automatic Measurement of Visual Acuity," *Optometry and Vision Science*, 1996.

[46] J. G. Snodgrass, "Psychophysics," *Experimental sensory psychology*, pp. 17 – 67, 1975.

[47] B. Treutwein, "Adaptive psychophysical procedures," 1995.

[48] M. A. García-Pérez, "Forced-choice staircases with fixed step sizes: Asymptotic and small-sample properties," *Vision Research*, 1998.

[49] H. Robbins and S. Monro, "A Stochastic Approximation Method," *IEEE Transactions on Systems, Man and Cybernetics*, 1971.

[50] K. L. Chung, "On a stochastic approximation method," *The Annals of Mathematical Statistics*, vol. 25, pp. 463 – 483, 1954.

[51] S. Gelfand, *Hearing: An Introduction to Psychological and Physiological Acoustics*. 1982.

[52] B. Kollmeier, R. H. Gilkey, and U. K. Sieben, "Adaptive staircase techniques in psychoacoustics: A comparison of human data and a mathematical model," *The Journal of the Acoustical Society of America*, 1988.

[53] P. Verghese and L. S. Stone, "Combining speed information across space," *Vision Research*, 1995.

[54] J. Wattam-Bell, "Visual motion processing in one-month-old infants: Preferential looking experiments," *Vision Research*, 1996.

[55] F. A. Wichmann and N. J. Hill, "The psychometric function: I. Fitting, sampling, and goodness of fit," *Perception and Psychophysics*, 2001.

[56] S. P. McKee, S. A. Klein, and D. Y. Teller, "Statistical properties of forced-choice psychometric functions: Implications of probit analysis," *Perception & Psychophysics*, 1985.

[57] N. A. Macmillan and C. D. Creelman, *Detection Theory: A User's Guide: 2nd edition*. 2004.

[58] T. Makovski, L. M. Watson, W. Koutstaal, and Y. V. Jiang, "Method Matters: Systematic Effects of Testing Procedure on Visual Working Memory

Sensitivity," *Journal of Experimental Psychology: Learning Memory and Cognition*, 2010.

[59] R. W. Li, A. Provost, and D. M. Levi, "Extended perceptual learning results in substantial recovery of positional acuity and visual acuity in juvenile amblyopia," *Investigative Ophthalmology and Visual Science*, 2007.

[60] L. Grzeczkowski, E. M. Tartaglia, F. W. Mast, and M. H. Herzog, "Linking perceptual learning with identical stimuli to imagery perceptual learning," *Journal of Vision*, 2015.

[61] K. C. Aberg, E. M. Tartaglia, and M. H. Herzog, "Perceptual learning with Chevrons requires a minimal number of trials, transfers to untrained directions, but does not require sleep," *Vision Research*, 2009.

[62] M. Fahle, "Specificity of learning curvature, orientation, and vernier discriminations," *Vision Research*, 1997.

[63] H. Song, T. Y. P. Chui, Z. Zhong, A. E. Elsner, and S. A. Burns, "Variation of Cone Photoreceptor Packing Density with Retinal Eccentricity and Age," *Investigative Ophthalmology & Visual Science*, 2011.

[64] C. F. Staugaard, A. Petersen, and S. Vangkilde, "Eccentricity effects in vision and attention," *Neuropsychologia*, 2016.

[65] M. Carrasco, D. L. Evert, I. Chang, and S. M. Katz, "The eccentricity effect: Target eccentricity affects performance on conjunction searches," *Perception & Psychophysics*, 1995.

[66] A. R. Seitz and H. R. Dinse, "A common framework for perceptual learning," 2007.

[67] R. E. Crist, M. K. Kapadia, G. Westheimer, and C. D. Gilbert, "Perceptual Learning of Spatial Localization: Specificity for Orientation, Position, and Context," *Journal of Neurophysiology*, 1997.

[68] T. Watanabe, J. E. Naánñez, S. Koyama, I. Mukai, J. Liederman, and Y. Sasaki, "Greater plasticity in lower-level than higher-level visual motion processing in a passive perceptual learning task," *Nature Neuroscience*, 2002.

[69] A. Schoups, R. Vogels, N. Qian, and G. Orban, "Practising orientation identification improves orientation coding in V1 neurons," *Nature*, 2001.

[70] K. Ball and R. Sekuler, "Adaptive processing of visual motion," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 7, no. 4, p. 780, 1981.

[71] P. E. Jeter, B. A. Dosher, S. H. Liu, and Z. L. Lu, "Specificity of perceptual learning increases with increased training," *Vision Research*, 2010.

[72] S. Monsell, "Task switching," *Trends Cogn Sci*, 2003.

[73] M. J. Morgan, R. M. Ward, and E. Castet, "Visual Search for a Tilted Target: Tests of Spatial Uncertainty Models," *Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology*, 1998.

[74] H. L. Hawkins, S. A. Hillyard, S. J. Luck, M. Mouloua, C. J. Downing, and D. P. Woodward, "Visual Attention Modulates Signal Detectability," *Journal of Experimental Psychology: Human Perception and Performance*, 1990.

[75] Y. Yeshurun and M. Carrasco, "Spatial attention improves performance in spatial resolution tasks," *Vision Research*, 1999.

[76] K. C. Aberg and M. H. Herzog, "About similar characteristics of visual perceptual learning and LTP," *Vision Research*, 2012.

[77] A. Karni, D. Tanne, B. S. Rubenstein, J. J. Askenasy, and D. Sagi, "Dependence on REM sleep of overnight improvement of a perceptual skill," *Science*, 1994.

[78] Y. Sasaki, J. E. Nanez, and T. Watanabe, "Advances in visual perceptual learning and plasticity," 2010.

[79] N. Censor, D. Sagi, and L. G. Cohen, "Common mechanisms of human perceptual and motor learning," 2012.

[80] K. Spang, C. Grimsen, M. H. Herzog, and M. Fahle, "Orientation specificity of learning vernier discriminations," *Vision Research*, 2010.

[81] Z. L. Lu, T. Hua, C. B. Huang, Y. Zhou, and B. A. Dosher, "Visual perceptual learning," *Neurobiology of Learning and Memory*, 2011.

[82] M. H. Herzog, K. R. Ewald, F. Hermens, and M. Fahle, "Reverse feedback induces position and orientation specific changes," *Vision Research*, 2006.

Appendix A

Descriptive Statistics

Descriptive Statistics **Roving**				
	Task Difficulty	Mean	Std. Deviation	N
Narrow Task	Matched	6.03	2.504	60
	Mixed	5.82	2.376	60
	Total	5.93	2.433	120
Wide Task	Matched	7.05	2.890	60
	Mixed	9.93	3.064	60
	Total	8.49	3.300	120

Table A.1: Descriptive statistics for roving phase under matched and mixed difficulty conditions.

Descriptive Statistics **Pre Training vs. Post Training**				
	Number of Training Day	Mean	Std. Deviation	N
Narrow Task	1 - Day	-0.33	2.575	36
	3 - Day	-0.83	3.012	40
	5 - Day	-1.32	2.843	44
	Total	-0.86	2.829	120
Wide Task	1 - Day	-0.17	3.291	36
	3 - Day	-1.18	3.580	40
	5 - Day	-2.66	2.957	44
	Total	-1.42	3.407	120

Table A.2: Descriptive statistics for performance changing between pre-training and post-training phases.

Table A.3: Descriptive statistics for performance changing between post-training and roving phases.

Descriptive Statistics **Post Training vs. Roving**					
	Number of Training Day		Mean	Std. Deviation	N
Narrow Task	1 - Day	Matched	1.06	2.277	17
		Mixed	0.11	2.166	18
		Total	0.57	2.240	35
	3 - Day	Matched	2.05	1.986	20
		Mixed	1.15	2.059	20
		Total	1.60	2.048	40
	5 - Day	Matched	0.73	2.354	22
		Mixed	0.73	1.518	22
		Total	0.73	1.957	44
	Total	Matched	1.27	2.250	59
		Mixed	0.68	1.927	60
		Total	0.97	2.105	119
Wide Task	1 - Day	Matched	3.24	3.052	18
		Mixed	-0.44	3.091	18
		Total	1.34	3.556	36
	3 - Day	Matched	3.15	3.573	20
		Mixed	0.55	2.874	20
		Total	1.85	3.461	40
	5 - Day	Matched	2.05	1.786	22
		Mixed	-0.68	2.102	22
		Total	0.68	2.370	44
	Total	Matched	2.76	2.867	59
		Mixed	-0.20	2.698	60
		Total	1.27	3.145	120

Table A.4: Descriptive statistics for performance comparison between post-training and roving phases.

Descriptive Statistics **Post Training vs. Roving (Wide Task)**					
	Number of Training Day		Mean	Std. Deviation	N
Post Training	1-day	Matched	10.78	2.074	18
		Mixed	10.94	2.859	18
		Total	10.86	2.463	36
	3-day	Matched	10.15	2.978	20
		Mixed	10.35	2.815	20
		Total	10.25	2.862	40
	5-day	Matched	8.91	3.022	22
		Mixed	8.18	2.302	22
		Total	8.55	2.680	44
	Total	Matched	9.88	2.823	60
		Mixed	9.73	2.875	60
		Total	9.81	2.838	120
Roving	1-day	Matched	7.33	3.254	18
		Mixed	11.39	3.744	18
		Total	9.36	4.022	36
	3-day	Matched	7.00	2.956	20
		Mixed	9.80	2.526	20
		Total	8.40	3.062	40
	5-day	Matched	6.86	2.624	22
		Mixed	8.86	2.494	22
		Total	7.86	2.724	44
	Total	Matched	7.05	2.890	60
		Mixed	9.93	3.064	60
		Total	8.49	3.300	120

Appendix B

Consent Form

Bilkent University

Psychology Department

Aaron Clarke, Ph.D.
Office: H344
Phone: +90 (312) 290-8771
Fax: +90 (312) 290-2561

E-Mail: aaron.clarke@bilkent.edu.tr
Web: http://aaron.clarke.bilkent.edu.tr

Informed Consent Form:

Research Study

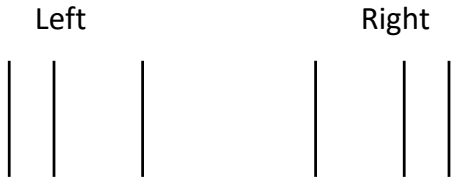
You are invited to participate in a learning study being conducted by Dr. Aaron Clarke, Assistant Professor at Bilkent University.

Purpose of the Study

Learning is one of the most important functions of the brain. Even the way we see the world is learned. By performing certain visual tasks, the brain adjusts its responses to the incoming stimuli in order to perform better on those tasks. Some manipulations can inhibit or enhance this learning, as well as inhibition or enhancing task performance. In this study we aim to study the factors affecting perceptual learning and how they influence performance once the task has been learned.

Explanation of Procedures

You will be presented with images on a computer monitor consisting of two lines with a third line in the middle as in the figure below.



Your task will be to indicate if the stimulus presented is the left- or right-offset bisection stimulus. If it is the left-offset stimulus, press the “X” button otherwise press the “B” button. In one condition the stimuli will be rotated by 90°. In this case, indicate whether the middle line is closer to the top or bottom of the stimulus by pressing either the “Y” or “A” buttons respectively. If you wish to quit the experiment at any time you may press the “BACK” button.

Potential Risks and Discomforts

There are no particular physical risks or discomforts associated with participation in this study. This study poses the same risks as you may experience any time you sit in front of a computer and use the gamepad.

Potential Benefits

Throughout the course of this experiment you will engage in perceptual learning that makes you an expert at line bisection tasks. Furthermore, you participation in this study will help in prove our current understanding of how learning works and what factors affect it. If you like, we can forward the results of this study to you when it has been published.

Assurance of Confidentiality

For this study we will not collect personally identifying information. If you wish to be contacted about the study's results, we will ask for your e-mail address and keep it in a secure location where it cannot be seen by others. Otherwise, information such as your age (which is not unique to you anyway) will be used only for reporting group summary statistics (e.g. age range). You may have access to information collected from you, which will be available upon request, but you may not view the information associated with other individual participants in this study.

Voluntary Participation and Withdrawal from the Study

You participation in this experiment is voluntary. If you decide to participate, you are free to withdraw your consent and discontinue the experiment at any time.

Questions

Please feel free to ask any questions now or at any time during the study. If you have questions about this study, you can contact Dr. Aaron Clarke (+90 312 290-1153, aaron.clarke@bilkent.edu.tr) or you can contact the experimenter.

Consent Statement

You are voluntarily making a decision as to whether or not to participate. Signing this form indicates that you are at least 18 years old and have decided to participate, having read the information provided above. A copy of this consent statement will be e-mailed to you should you request one and provide your e-mail address.

_____

Signature

Appendix C

Onay Formu

Bilkent Üniversitesi

Psikoloji Bölümü

Aaron Clarke, Yrd. Doç. Dr.
Ofis: H344
Telefon: +90 (312) 290-8771
Faks: +90 (312) 290-2561
E-Posta: aaron.clarke@bilkent.edu.tr
Web: http://aaron.clarke.bilkent.edu.tr

Bilgilendirilmiş Rıza Formu:

Araştırma Çalışması

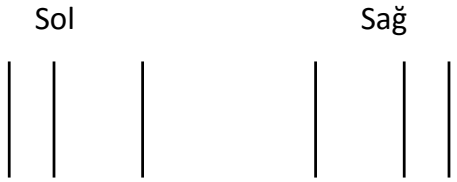
Bilkent Üniversitesi'nde çalışan Yardımcı Doçent Dr. Aaron Clarke tarafından yürütülen doğal görüntü istatistiği ile ilgili bir çalışmaya çağrılmış bulunmaktasınız.

Çalışmanın Amacı

Öğrenme beynin en önemli işlevlerinden biridir. Dünyayı nasıl gördüğümüz bile öğrenilen bir şeydir. Beyin belirli görsel görevleri yaparak gelen uyaranlara verdiği tepkileri düzenler. Burada amaç bu görevler üzerinde daha iyi performans sağlamaktır. Bazı manipülasyonlar görevlerdeki performansları kısıtladığı veya artırdığı gibi öğrenmeyi de inhibe edebilir ya da geliştirebilir. Bu çalışmada algısal öğrenmeyi etkileyen faktörleri ve bu faktörlerin öğrenilmiş olan görevlerdeki performansları nasıl etkilediğini incelemeyi amaçlıyoruz.

Prosedür Açıklaması

Aşağıdaki şekillerde örneklendiği gibi, size bilgisayar ekranından sağ, sol ve orta olmak üzere üç çizgi gösterilecektir.



Burada sizden istenen, ekranda gösterilen uyaranın sol-taraflı mı yoksa sağ-taraflı mı biseksiyon (ikibölümlü) uyaranı olduğunu belirlemek. Bunu yaparken oyuntablası (gamepad) kullanmanız istenecektir. Eğer ortada bulunan çizgi sol taraftaki çizgiye daha yakınsa, bu sol-taraflı biseksiyon uyaranıdır ve soldaki "X" tuşuna basmanız gerekmektedir. Tam tersi eğer orta çizgi sağ taraftaki çizgiye daha yakınsa, bu sağ-taraflı biseksiyon uyaranıdır ve sağdaki "B" tuşuna basmanız gerekmektedir. Deney sırasında uyaranların 90° döndürülmüş durumlarıyla da karşılaşacaksınız. Bu durumda, yukarıdaki "Y" ya da aşağıdaki "A" tuşlarına basarak orta çizginin üst veya alt çizgilerden hangisine yakın olduğunu belirlemeniz istenmektedir. Herhangi bir anda deneyi bırakmak isterseniz geri "BACK" tuşuna basabilirsiniz.

Olası Riskler ve Rahatsızlıklar

Bu çalışmaya katılımınızla oluşacak belirli bir fiziksel risk ve rahatsızlık yoktur. Çalışma yalnızca, herhangi bir zamanda bilgisayar karşısında oturup oyuntablası kullandığınızda oluşabilecek riskleri taşımaktadır. Ayrıca bu çalışmada hiçbir aldatmaca olmayacaktır.

Olası Faydalar

Deney boyunca sizi çizgi biseksiyon görevlerinde uzmanlaştıracak olan algısal öğrenme ile meşgul olacaksınız. Ayrıca bu çalışmaya olan katılımınızla, beynin nasıl çalıştığı ve hangi faktörlerin bunu etkilediği hakkındaki güncel bilgilerimizi geliştirmede yardımcı olacaksınız. Dilerseniz, çalışma yayınlandığında sonuçlarını size de iletebiliriz.

Gizlilik Güvencesi

Bu çalışma için kişisel bilgilerinizi istemeyeceğiz. Eğer çalışmanın sonuçları ile ilgili bilgilendirilmek isterseniz, size e-posta adresinizi soracağız ve bu bilgileri başkaları tarafından görülemeyecek güvenli bir yerde muhafaza edeceğiz. Diğer taraftan, yaş veya cinsiyet gibi bilgiler yalnızca grup özet istatistiklerini (örn. yaş aralığı, cinsiyet oranı) bildirmek için kullanılacaktır. İstekte bulunmanız halinde sizden toplanan bilgilere ulaşma imkânınız vardır. Ama bu çalışmada diğer katılımcılarla bağlantılı olan bilgilere ulaşamayabilirsiniz.

Gönüllü Katılım ve Çalışmadan Çekilme

Deneye katılımınız gönüllü olmaktadır. Katılmaya karar verdikten sonra fikrinizi değiştirirseniz, vazgeçtiğinizi belirterek deneyi istediğiniz zaman bırakabilirsiniz.

Sorular

Şu an ya da deney boyunca dilediğiniz zaman rahatlıkla soru sorabilirsiniz. Eğer çalışma ile ilgili sorularınız olursa Dr. Aaron Clarke (+90 312 290-1153, aaron.clarke@bilkent.edu.tr) ile iletişime geçebilirsiniz.

Rıza Bildirimi

Deneye katılıp katılmama yönünde kendi isteğinizle bir karar alıyorsunuz. Bu formu imzalamanız sizin en az 18 yaşında olduğunuzu ve deneye katılmaya karar verdiğinizi, yukarıda belirtilmiş olan bilgileri okuduğunuzu göstermektedir. Bu rıza formunun bir kopyası, siz e-posta adresinize gönderilmesini istediğiniz ve e-posta adresinizi belirttiğiniz takdirde, tarafınıza gönderilecektir.

_____

İmza