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Dynamics of Perceptual Organization in Complex Visual Search: The Identification of Self Organized Criticality with Respect to Visual Grouping Principles

Attila Jozsef Farkas

University of Southern Mississippi

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DYNAMICS OF PERCEPTUAL ORGANIZATION IN COMPLEX VISUAL SEARCH: THE IDENTIFICATION OF SELF ORGANIZED CRITICALITY WITH RESPECT TO VISUAL GROUPING PRINCIPLES

by

Attila Jozsef Farkas

Abstract of a Dissertation
Submitted to the Graduate School
of The University of Southern Mississippi
in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy

August 2013

ABSTRACT

DYNAMICS OF PERCEPTUAL ORGANIZATION IN COMPLEX VISUAL SEARCH: THE IDENTIFICATION OF SELF ORGANIZED CRITICALITY WITH RESPECT TO VISUAL GROUPING PRINCIPLES

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The current project applies modern quantitative theories of visual perception to examine the effect of the Gestalt Law of proximity on visual cognition. Gestalt Laws are spontaneous dynamic processes (Brunswik & Kamiya, 1953; Wertheimer, 1938) that underlie the principles of perceptual organization. These principles serve as mental short-cuts, heuristic *rule-of-thumb* strategies that shorten decision-making time and allow continuous, efficient processing and flow of information (Hertwig & Todd, 2002). The proximity heuristic refers to the observation that objects near each other in the visual field tend to be grouped together by the perceptual system (Smith-Gratto & Fisher, 1999). Proximity can be directly quantified as the distance between adjacent objects (inter-object distances) in a visual array. Recent studies on eye movements have revealed the interactive nature of self organizing dynamic processes in visual cognition (Aks, Zelinsky, & Sprott, 2002; Stephen, & Mirman, 2010). Research by Aks and colleagues (2002) recorded eye-movements during a complex visual search task in which participants searched for a target among distracters. Their key finding was that visual search patterns are not randomly distributed, and that a simple form of temporal memory exists across the sequence of eye movements. The objective of the present research was to identify how the law of proximity impacts visual search behavior as reflected in eye movement patterns. We discovered that 1) eye movements are fractal; 2) more fractality will result in decreased reaction time during visual search, and 3) fractality facilitates the improvement of reaction times over blocks of trials. Results were interpreted in view of theories of cognitive resource allocation and perceptual efficiency. The current research could inspire potential innovations in computer vision, user interface design and visual cognition.

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A Dissertation
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Approved:

Alen Hajnal
____
Director

Sheree Watson
____

Tammy Greer
____

David J. Echevarria
____

John Harsh
____

Susan A. Siltanen
____
Dean of the Graduate School

August 2013

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CHAPTER I

INTRODUCTION

Finding your friend at a ball game in a crowd of people, spotting your favorite candy bar in your local supermarket's candy aisle are everyday examples of visual search tasks performed routinely. Traditionally, visual search has been investigated using typical cognitive psychology measures such as reaction time and hit rate. In recent years there has been much interest in the analysis of eye movements as prime indicators of cognitive processes involved in visual cognition. What do eye movement patterns reveal about visual perception and cognition? How can researchers make sense of the seemingly chaotic dynamics of eye movements during visual search? Our present investigation is an attempt to contribute to this growing body of research by analyzing eye movement patterns during the emergent processes of perceptual organization.

The Gestalt movement started by Max Wertheimer in 1912 has made great strides in the study of perceptual organization. Gestalt psychologists of the early twentieth century had developed a set of laws to describe the perceptual organization of visual stimuli. The Gestalt movement was not just a new theory, but also a revolution developed in direct response to the traditional theories of perception at that time (Rock & Palmer, 1990). The true legacy of this revolution lies within the integration of Gestalt concepts into today's modern theories of perception (Palmer, 1990).

The present project focuses specifically on the law of proximity, which states that objects or visual items that are near each other tend to be grouped together (Smith-Gratto & Fisher, 1999). Proximity as a grouping principle has been incorporated into the latest research on object recognition algorithms (Kim, Yoon, & Kweon, 2008), ecological statistics (Martin, Fowlkes, Tal, & Malik, 2001) and computer vision (Sarkar & Boyer, 1993). Kim et al.'s study on object recognition found that the accuracy of object identification can be increased by including algorithms that resemble Gestalt rules such as information about the relative closeness of items used in defining related contours. Earlier quantitative studies suggested that the perceptual system is particularly responsive to proximity cues (Uttal, Bunnel, & Corwin, 1970).

Quantification of Gestalt laws can be better understood if we consider that the human visual system organizes figural unity based on many characteristics (e.g. color, orientation, motion) of the perceived stimuli (Brunswik & Kamiya, 1953). These characteristics guide the integration and segregation of visual input into separate areas of distinctive objects. The emergent segmentation of the perceived visual world can be described by mathematical equations to define the relations of visual elements using relative distance, level of brightness or orientation of edges. These variables form the foundation of contextual information that is used by the visual system to calculate which elements are parts of the same object and which are not (Elder & Goldberg, 2002). According to the Gestalt laws, visual items can be considered as sets where each set contains elements that contribute to the perception of similar spatial direction (the law of common fate), nearness (the law of proximity), and many other spatial patterns. By using a collection of sets that represent distinct parts of the visual world, the perceptual system arranges all parts (Elder & Goldberg, 2002) to generate a perceptual experience of the whole visual field. This percept is qualitatively different than the mere collection of its individual sets, indicating that perception is more than the simple aggregate of visual stimuli. Elder and Goldberg (2002) demonstrated that it was possible to quantify contour organization. Their basic aim was to determine the statistical utility of Gestalt grouping mechanisms on natural images. The investigation discovered that among the three classical Gestalt rules of grouping (good continuation, proximity and similarity), proximity had the greatest inferential power for grouping contours together (Elder & Goldberg, 2002). Another significant property of the law of proximity is that it can be directly measured. Modifying the distance between arrays of dots is how Wertheimer represented the rule of nearness (Wertheimer, 1938). If we think in terms of a lattice of black dots on a white background and the distances between rows a, b, c, and d the distance between rows can be defined by a single variable. If distance *l*, between rows a, b, c, and d, and distance *o*, between columns 1, 2, 3, and 4 are equal, then the set of dots should not be organized into vertical or horizontal arrays (see Figure 1).

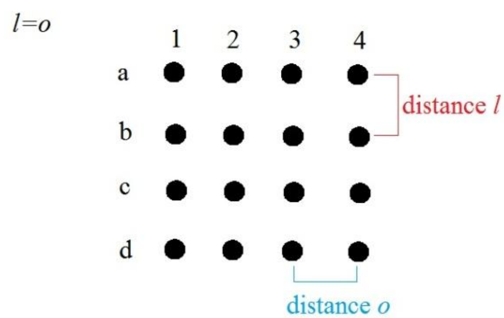

Figure 1. Equally spaced dot lattice (*l*=*o*): distance *l*, between rows a, b, c, and d, and distance *o*, between columns 1, 2, 3 and 4 are equal.

Based on equal interdot distances the chance that the perception of a dot lattice will become spontaneously organized into rows should not be greater than the chance of seeing columns. However, if a constant value is added to *l* (as illustrated in Figure 2), the vertical distance will be increased between rows a, b, c, and d and the emergent law of proximity will organize dots into horizontal arrays, resulting in the perception of distinct rows (Hochberg & Silverstein, 1956).

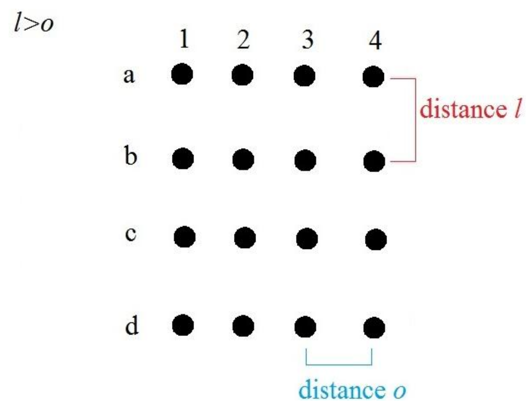

Figure 2. Horizontally organized dot lattice (*l*>*o*): by adding a constant value to *l*, the vertical distance increased between rows a, b, c, and d and the emergent law of proximity will organize dots into horizontal arrays.

In summary, if equal distance among the dots is not preserved, the probability of perceptual outcomes (the visual experience of rows or columns) will change based on the nature of the manipulation (Kubovy & Wagemans, 1995). A paper by Elder and Goldberg (2002) identified Oyama (1961) to be the first to engage in the precise quantification of the law of proximity. He suggested a mathematical relationship called the power law to describe the emergence of different perceptual outcomes as a function of interdot distances. Power law phenomena have been observed in many experiments investigating human performance in various cognitive tasks (Aks et al., 2002; Anderson & Schooler, 1991; Lemoine, Torre, & Delignieres, 2006; Oyama, 1961; Ritter & Schooler, 2001). Power law can be used as the quantitative description of improvement with practice over time, where the grade of improvement seems to follow the same pattern across different tasks (Ritter & Schooler, 2001). According to this pattern the standard deviation from the mean of performance or reaction times will decrease, as well as the skew of the distribution over time. The power law explains that practice always improves performance regardless of the task, but the most dramatic changes will occur early and then slowly decrease with some fluctuation over time (Ritter & Schooler, 2001). In relation to the perceptual organization of dots, Oyama (1961) has found that the variability of the two possible visual experiences of seeing rows or columns has followed a power law as a function of relative item spacing.

Oyama's idea was recently reformulated in an experiment that measured grouping strength and used an exponential model to express the effects of dot spacing on perception (Kubovy, Holcombe & Wagenmans, 1998). Kubovy et al., (1998) tested sixteen different configurations (e.g. hexagonal, rectangular, and square structures) of dot lattices. The data analysis showed that the probability of dot lattices grouped into vertical lines by observers followed an exponential function of relative interdot distances on the *y* axis. Results also revealed that perceptual organization is unaffected by the spatial configuration of dot lattices and the emergence of the law of proximity seems to be only sensitive to changes in the equality of adjacent dot spacing (Kubovy et al., 1998; Kubovy & Wagemans, 1995).

Based on the extensive literature on Gestalt grouping laws (Brunswik & Kamiya, 1953; Elder & Goldberg, 2002; Hochberg & Silverstein, 1956; Kubovy et al., 1998; Oyama, 1961; Wertheimer, 1938), the law of nearness appears to play a crucial role in computer and human visual processing because it is quantifiable, flexible, and possibly the most fundamental of all Gestalt rules (Kubovy & Holcombe, 1998)[1]. The wide range of vision and visualization research that has employed the law of nearness as a variable has also advanced the basic science of how the visual system's operation reflects the law of proximity.

How does vision science describe the mechanisms of the law of nearness? Where we look is what we see, or more precisely, focal visual information is determined by the gaze orientation of our eyes. The eyes serve as the gate to visual processing as their movements create the trajectory of how we scan our visual environment. If we consider that the law of proximity was used to enhance object recognition algorithms (Kim et al., 2008), modeling contour grouping (Elder & Goldberg, 2002) and user interface design (Chang, Dooley, & Tuovinen, 2002) it becomes conceivable that this law is an essential part of visual perception for both humans, and computers. Previously mentioned studies (Aks, 2005; Kubovy et al., 1998; Kubovy & Wagemans, 1995) have described how organization of visual elements produces perceptual grouping. However, it is currently not known how proximity cues guide visual attention to form the related perceptual experience.

Visual search can be expressed as a non-random quantifiable pattern (Aks, 2005; Bridgeman, Van der Heijden, & Velichkovsky, 1994; Stephen & Mirman, 2010). It is considered an interaction-dominant self organized process (Aks et al., 2002; Stephen & Mirman, 2010). As such, exploring how proximity cues are revealed by this structured

[1] The law of spatial proximity is applicable in many areas, such as interface design for visual education purposes. The proximity principle was successfully applied in organizing visual instructions for nursing students' wound management (Chang et al., 2002). The proximity law was also applied to spatially arrange multiple screens for displaying related information (Chang & Nesbitt, 2006).

search pattern could serve as additional data for understanding the dynamics of visual cognition. In the field of computer vision, object recognition algorithms could be further enhanced by a search mechanism specified for accommodating proximity cues. The efficiency and ergonomics of user interfaces and multiple displays applied in aviation control could be improved by combining data from eye movements and probability distributions of perceptual organization in relation to proximity information. The idea is to present stimuli at a location where the perceptual system would automatically drive our attention with the highest probability.

To establish a common conceptual framework for the previously mentioned applications the relationship between changes in gaze locations and variations of perceptual experience has to be substantiated as a function of manipulated proximity cues. During a typical visual search experiment participants inspect a display and then localize a target item presented among a field of distracter items. Targets can differ from distracter items in a range of features, such as orientation or color. Differences between distracters and target determine the complexity of the task and the type of search used. For example, it is easier to find a target if it has a unique color among a field of distracters that are achromatic, whereas, if the target has the same color and only differs in orientation the task becomes harder.

Different types of search tasks also differ in their efficiency. In a simple feature search task items are defined by the presence of a single feature such as color or orientation. Reaction times required to find the target will increase as the number of items escalate. On the contrary, if the target item sufficiently stands out visually from its neighbors, the number of distracter items present does not seem to affect the search meaningfully. It was also found that the visual system is able to process color or orientation of all items at the same time (Wolfe & Horowitz, 2004). This type of parallel visual search is supported by stimulus properties that are easily observable like size, orientation, color, and motion (Treisman & Gelade, 1980; Wolfe & Horowitz, 2004). The ease of search attributed to parallel processing can be perturbed by using visual search tasks that operate with targets and distracters that contain the same basic features. Defining basic features as vertical and horizontal bars, the visual appearance of the letter *L* is not much different from the appearance of the letter *T*. Both target and distracter items are composed of the same basic features, vertical and horizontal bars. During a visual search observers need to pay attention to all of the individual items in order to be able to distinguish the arrangement of basic features. This search requires scanning all items, adding about 20-30 ms processing time per unit to successfully localize a target (Friedman-Hill & Wolfe, 1995). This type of unit-by-unit scan is described as a serial self-terminating search (Donders, 1969; Sternberg, 1966; Wolfe, Cave, & Franzel, 1989) where the additional processing time is spent examining stimuli one after another (serially) until the target is found or all items have been scanned (Julesz & Bergen, 1983). This type of serial search has proven to be slow and ineffective. Even if we consider that an observer can localize the target by chance right after the onset of the stimuli, typically about half of the items would have been scanned before the target is identified. If the target is not present observers will scan each individual item (Friedman-Hill & Wolfe, 1995). According to Treisman's feature integration theory (Treisman & Gelade, 1980) conscious attention is required in order to complete the integration of features. For example, in the case of *T*s and *L*s observers may be able to simultaneously process basic features, such as horizontal and vertical lines, but in order to define how these features are spatially related to one another participants must actively direct attention to each individual item. According to a review of computational models of visual attention, eye movements and attention jointly create the spatial pattern that controls foveal visual attention (Itti & Koch, 2001). If we treat the perceived visual scene as a map, then attention breaks down this map into smaller areas, like squares in an atlas. These areas represent portions of the whole map and contain only local information that can, due to its relatively small size (or limited detail), be rapidly analyzed. Computationally, the process of attention decreases the workload by segmenting the visual map into smaller information packages (Itti & Koch, 2001). By moving from one area to another, attention gathers information about the whole visual map. Data that describes the dynamics of visual attention can be employed in many applications such as computer vision, automatic target detection, human computer interaction (Jacob & Karn, 2003) and navigation (Itti & Koch, 2001).

The aim of this project is to investigate how we integrate visual information from successive fixations in the presence of proximity cues. How can we describe the nature of the trajectory formed by fixations over time? According to Aks (2005) the pattern produced by visual search is the key to understanding the mechanism that drives search behavior. Let us consider everyday search and selection problems. Selecting items or targets involves organizing our perceptions into objects based on the Gestalt rules (Wertheimer, 1938) and then integrating the specific features with the help of attention (Treisman & Gelade, 1980). Search itself can be described with a set of measurements on speed, accuracy, and performance. What is the nature of the mechanism that makes the search effective, precise, and rapid? At the level of neural functioning the inhibition-of-return mechanism constrains the pattern of effective scanning trajectories. The brain is involved in a tagging procedure of sorts that marks visited items to inhibit the return of the eyes to the same location (Posner & Cohen, 1984). After viewing and noting the position of the item, memory of the item's location is formed. In order to avoid redundancy and inefficiency attention is subsequently oriented towards other areas of the visual field. The memory for the location of visited items does not seem to be permanent as reexamination of items does occur in all search tasks (Horowitz & Wolfe, 1998). The complete absence of memory may be reflected in the randomness of eye movements (Aks, 2005). The existence of a special type of memory that guides eye movements was discussed in several studies that explored visual search (Horowitz & Wolfe, 1998; Irwin, 1992; Jonides, Irwin, & Yantis, 1982). Research by Aks (2005) presented a novel view on the nature of memory that guides scanning behavior. According to Aks, previous studies, such as Horowitz and Wolfe (1998), have failed to detect the existence of memory across saccades because the measurement was not focused on the direct analysis of eye movement patterns. The key finding in Aks' study was that visual search is not random and contingencies do exist across fixations. These contingencies refer to a special type of memory which can be described by a power law function. Interestingly, an earlier finding by Oyama (1961) already indicated that the interval of perceiving horizontal versus vertical perceptual organization can be modeled as a power law[2] of the

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[2] Power law distributions occur in many scientific measurements and reflect dynamics in complex natural and artificial systems. Data that exhibit power law patterns have been found in many perceptual and cognitive processes such as self-paced tapping (Lemoine et al., 2006) and the slope of the forgetting curve (Anderson & Schooler, 1991).

ratio of interdot spacing (ratio of distances on x and y axes). Research by Aks and colleagues has found the same pattern occurring in visual cognition (Aks et al., 2002). The study of Aks and colleagues in 2002 recorded the duration and x, y coordinates of successive eye fixations while participants performed a visual search task where the goal was to find a target *T* among distracters (randomly rotated *Ts).* Results showed similar trends for *x* and *y* eye positions. Locations of fixations (measured in pixel units) created clear clusters in the center and at the boundaries of the screen. Using the Iterated Function systems test (IFS), which can reliably detect divergence from randomness in data (Jeffrey, 1992); it was revealed that emerging fractal[3] structures are present in eye movements. Self-similar patterns in eye movements are markers of an efficient memory guided search (Aks, 2005; Aks et al., 2002).

An efficient information process is not only fast, but also uses minimal resources. To achieve the above mentioned goals a system could apply a simple set of rules that are iterated during the search and complex processes will emerge from the interaction of these rules (Aks, 2005). If these rules emerge in a repetitive way while guiding the search itself, then the pattern created by fixation points should not consist of independent locations in the search field. If we think in terms of commands that are repeated over time, then the points that are defined by these commands at a point in time should not be independent from one another. Thus, they can be characterized by some form of temporal correlation. Dynamics of human behavior are known to produce variability

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[3] One of many significant properties of fractals is that the smaller components can be comprehended as a reduction or a minimized copy of larger parts that make up the whole structure (Liebovitch & Scheurle, 2000).

(noise) that can be characterized by temporal self similarity (Farrell, Wagenmakers, & Ratcliff, 2006). *1/f* noise is considered to be appropriate for modeling dynamically changing systems, and it is often used to demonstrate the correlation of past events with present behavior (Keshner, 1982). The occurrence of pink noise in visual cognition tasks indicates that long term correlations exist between data points, which also reflect the existence of memory guided search. Based on an extended analysis using models of complex systems and statistical procedures it was concluded that the movement trajectory of the eyes reflects self organized search patterns that require a number of complex processes while minimizing computational load (Aks, 2005). Stephen and Mirman (2010) revealed the interactive nature of visual cognition and provided further evidence of non random self organizing dynamics of eye movements. By using complex analyses of eye-movements we can detect the emergent structure of processes that are broadly distributed among subsystems serving visual search.

Oyama (1961) discovered that perception is biased toward vertical organization. Aks and colleagues indicated that differences across vertical eye positions are gradually increased over time. Can the bias toward vertical organization be related to the gradual increase of gaze location distances on the y axis over time? If the answer is yes, then we can conclude that the Gestalt law of proximity is biased by the inherent properties of visual search behavior. This could also mean that the experienced outcome (vertical versus horizontal organization) exhibits power laws in relation to changes in inter-item distance and reflects the gradual increase of vertical distances inherent in successive gaze locations of the search behavior. Another intriguing finding is that Euclidean distances measured between successive fixation coordinates over time showed signs of *1/f* pink noise (Aks et al., 2002). We may reason that if the law of proximity influences the memory that guides visual search over time the dichotomy of perceptual outcomes (perceived rows or columns) may also interact with the *1/f* noise of successive gaze locations and reaction times.

It has already been documented that eye movements will naturally follow paths derived from the presented visual space (Chang et al., 2002). Taking an example from visual screen design: functional groups of visual instructions for wound care are closely arranged together to create a guide for visual attention. Closely coupled visual elements provide an easy comprehension of associated groups. Screen design that applied the proximity gestalt law has been proven superior as compared to homogenous displays (Chang et al., 2002). When the proximity law exerts its influence as a function of inter-item spacing the search field will be perceived as organized into columns or rows of items.

Efficiency of Visual Search

To perform an efficient visual search, both humans (Estes & Taylor, 1966) and computer programs (Sivic & Zisserman, 2006) are required to encode a given visual field. Efficiency in this setting is a measure of speed and accuracy (Julesz & Bergen, 1983; Wolfe, 1998). If we consider speed and the area that needs to be scanned efficiency also means doing the same (scan the same amount of elements) or more in equal or less amount of time. Consequently if an efficient scan pattern exists, it should be reflected by a relationship between the fractal measurement of gaze locations and a decrease in reaction time. Our current thinking is that more fractal eye movements should be associated with more efficient visual searches resulting in faster reaction times in visual search tasks.

The logic of our empirical test was organized around four hypotheses. Hypothesis 1 states that Euclidian distances of successive gaze locations are not random during typical visual search tasks. Visual search is a complex behavior that requires the coordination of both higher and lower level (e.g.: visual memory and basic feature perception) visual processes (Horowitz & Wolfe, 1998; Irwin, 1992; Jonides et al., 1982). Besides visual cognition, it has been shown that fractally configured neural networks increase the speed of the given computations e.g. image compression (Jiang, 1999).

Hypothesis 2 claims that fractal fluctuations of eye movements may improve the efficiency of visual search. Specifically, based on the results of recent investigations (Stephen & Anastas, 2011; Stephen, Mirman, Magnuson, & Dixon, 2009) the measured magnitude of fractal fluctuations is expected to be associated with a decrease in reaction time on a given trial.

Hypothesis 3 posits that vertical perceptual organization based on the Gestalt law of proximity will result in faster and more efficient visual search than horizontal organization. This assumption is based on the findings of Oyama (1961) and Aks (2005). While experimenting with the organization of dot lattices it has been revealed that emergence of perceptual outcomes is biased toward vertical organization (Oyama, 1961). Aks and colleagues (2002) indicated that differences across vertical eye positions are gradually increased over time. Due to the nature of the bias toward vertical organization (both in perception and in fixation location distances) a preference toward a vertically organized visual field is expected. This preference is hypothesized to emerge as a decrease in reaction times while scanning a vertically organized visual field.

Hypothesis 4 expresses a prediction that scanning patterns may reflect gender differences. The expectation is that males will typically find targets faster whereas females will use a distinctive strategy to scan the visual field. Gender related divergences in scanning behavior should be reflected by the distinctive relationship between fractal measurements and reaction time. There is a large body of literature on gender differences in relation to various spatial cognitive and perceptual abilities. Specifically, gender differences have been discovered in relation to a variety of spatial skills. An example has been provided by a research on playing videogames that demonstrated the existence of gender difference in the distribution of spatial attention. It has also been argued that with training these differences can be reduced (Feng, Spence, & Pratt, 2007). Research on spatial orientation found that males are more likely to utilize spatial cues while navigating whereas females show greater tendency to orient themselves by landmarks (Halpern & LaMay, 2000). Besides navigation skills, it has been revealed that males tend to outperform females in mental rotation tasks (De Lisi & Cammarano, 1996; Kimura, 1992; Parsons et al., 2004; Terlecki & Newcombe, 2005).

The aforementioned four hypotheses were tested in a single experiment that employed a typical visual search task.

CHAPTER II

METHOD

Six male and six female graduate students between the ages of 20 and 30 from the University of Southern Mississippi participated in the study. Participants did not have any vision deficits, and had normal or corrected-to-normal eyesight. Subjects were recruited using a snowball sampling method among psychology graduate students at USM. All procedures were approved by the Institutional Review Board that ensures ethical principles of treatment of human subjects follow federal guidelines.

Materials and Apparatus

Participants were using a chin rest to minimize head movements and seated approximately 50cm away from an ACER LCD monitor with a size of 1570×1250 in pixels and a default refresh rate of 60Hz. Monocular data was sampled with a Basler 210Hz Mono 648×488 Gigabit Camera with a sampling rate of 200Hz. The live video signal of the eyeball was recorded in real-time and post-processed with a custom made MATLAB eye tracking software.

Stimuli and Measurements

The display for the visual search task, demonstrated in Figure 3, consists of eighty-one white T shapes presented on a black background to ensure maximum contrast (Aks, 2005).

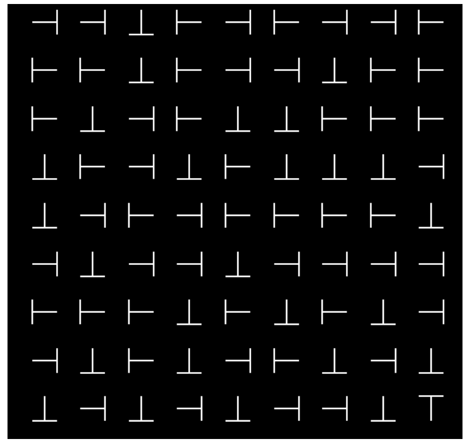

Figure 3. A screenshot of the experimental display. The stimuli matrix consists of eighty-one white T shapes including the target. The task is to find the target, an upward T which in the current case is located at the lower right corner.

The target item differs in orientation by 90° from distracters (Aks, 2005). Items were presented in a 9x9 matrix where all locations have an equal chance to contain the target. Depending on constraints of the actual condition inter-item distances (horizontal or vertical) gradually increased. The participant's task was to search the screen and press a space bar on a keyboard when the target was located. Elapsed time until successful target localization was recorded electronically. Data from eye movements was collected as a series of x and y coordinates of consecutive pupil locations, and was used to map the trajectory of eye movements.

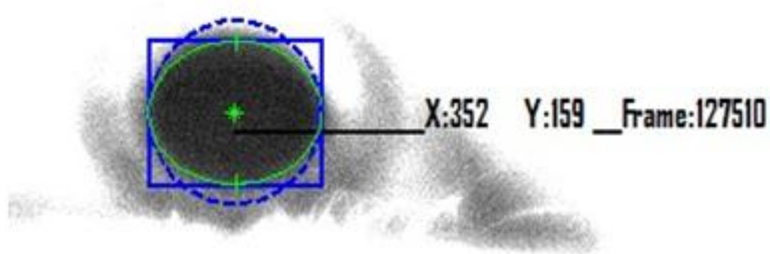

Figure 4. A screenshot of the video camera feed illustrating the current position of the tracked eye. The numbers indicate calculated coordinates of the pupil's position during a typical experimental trial. The rectangle shows a bounding box around the cluster of pixels representing the pupil. The circle with dashed lines indicates the full size of the

pupil based on its vertical perimeter. The full line ellipsoid indicates the actual size of the pupil that is visible to the camera. The star at the middle indicates the center of the pupil calculated by the program.

The resulting trajectories for different orientation conditions were compared. Data from the vertical and horizontal trajectory time series was subject to further analysis to trace signs of long term correlation across data points over time. The time range of a typical experimental session was between 45 minutes and 1 hour.

Design and Procedure

Participants started the experiment either in a vertical or horizontal orientation condition (based on how inter-item spacing was gradually changed over trials). The first experimental session consisted of 620 stimulus presentations. Each participant was introduced to a homogenous visual field (equally spaced items) in the first 260 trials (Block 1), followed by a transition period of 100 trials (Block 2), and ending with another 260 trials of either horizontally or vertically arranged items (Block 3). To avoid the possibility of a confounding trial order effect, the presentation sequence was counterbalanced so that half of the participants were introduced to the horizontal condition during the first session, and the other half received the vertical condition first. As a consequence, the whole experiment consisted of two sessions, on separate days. The inter item distances gradually changed from trial to trial during the transition period (Block 2) which was concluded by reaching the maximum horizontal or vertical distance between items. After the transition period, participants continued to perform the search task with the horizontally/vertically organized visual field for another 260 trials (Block 3). Trial-by-trial incremental change of inter-item distance was linear. The incremental manipulation technique is based on previous explorations of perceptual and action boundaries that describe affordances (Coello, Bartolo, Amiri, Devanne, Houdayer, & Derambure, 2008; Cornus, Montagne, & Laurent, 1999). The study by Cornus and colleagues on the perception of stepping-across affordance revealed that taking action (stepping across an obstacle) followed a logistic curve as a function of distance of the obstacle from the participant. Coello et al. (2008) have found the same pattern in visual perception of what is reachable. The second session did not include the homogenous trials, therefore consisting of only 360 trials (100 transition trials, and 260 nonhomogenous trials).

The recording equipment was calibrated for each subject to ensure accuracy of eye positions in relation to location of stimuli (Figure 5). The calibration procedure was conducted in a single one minute session where participants had to fixate on a white cross that continuously changed position with 1 second pauses.

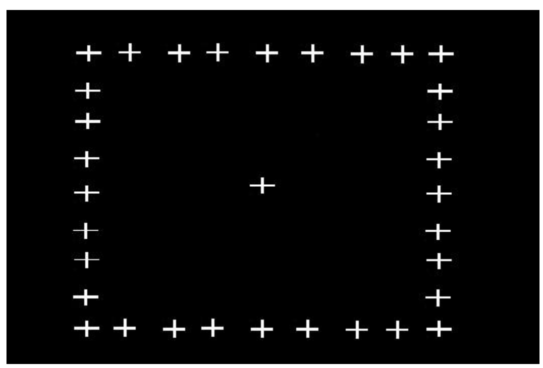

Figure 5. The presentation and locations of calibration stimuli were defined by the borders and the center of the screen. The central cross is the initial fixation location.

Eye movements that were recorded during the calibration session served to establish a reference coordinate system to match x, y eye position data with x and y location data of the presented stimuli.

Data Analysis

In a previous investigation in which researchers collected eye movement data in two dimensions (x, y) Detrended Fluctuation Analysis (DFA; Peng et al., 1994; Peng, Havlin, Stanley, & Goldberger, 1995) was used to test fractality of fluctuations in gaze orientation (Stephen & Anastas, 2011). In this experiment the authors estimated the scaling exponents H of the collected angular-change time series of six participants by utilizing the DFA method. In the pioneering research by Aks in 2005 they used only one participant's data to reveal fractal dynamics of visual search. The present investigation collected data from 12 participants. Based on the number of participants >1 the current analysis will differ in the analysis procedure that Aks used in 2005 and utilize the DFA method presented in the work of Stephen and Anastas (2011). The analysis will follow two main steps: 1) testing data for the presence of colored noise, 2) checking for possible predictors of changes in reaction time series in relation to the organization of the visual field. Following the work of Aks et al., (2002) and Aks (2005) the analysis is intended to replicate prior results by searching for signs of *1/f* noise within the Euclidian distance distribution of consecutive samples of gaze locations over time. In order to detect 1/f noise in the data a detrending method should be applied. Detrending is required due to the non-stationary nature of the collected data. An example of non-stationary time series would be collecting data on the distribution of body fat over centuries. The analysis of the collected data should consider the changes in nutrition over time. The term stationary signifies a time series whose statistical properties remain constant over time, whereas in non-stationary series statistics vary over time (Huang et al., 1998). The Detrended Fluctuation Analysis (DFA) is also known as a modified root-mean-square (rms) method applied to analyze data characterized as random walk. According to previous researches, the sequence of absolute eye positions resembles a random walk (Aks et al., 2002; Aks, 2005) thus suitable for DFA. Based on the summary of Xu et al., (2005) the procedure of applying DFA method starts with acquiring a signal *u(i)*. *N* stands for the length of the signal and *i* can be defined as the sample number, $i=1,\ldots,N$. The first stage is the integration of *u(i)* which can be defined by the following equation, *y(i)*

$$\mathrm{y(i)} = \sum_{j=1}^{i} (u(j) - \bar{u}), \tag{1}$$

where $\bar{u}$ can be expressed as

$$\bar{u} = \frac{1}{N} \sum_{j=i}^{N} u(i) \tag{2}$$

After integration of *u(i)* in equation 3 y(i) is divided into bins of equal *n* elements. A local trend in each bin is then represented by a polynomial function $y_n(i)$ that fits *y(i)* in every single bin. In the following step y(i) is further detrended by subtracting the local trend y_n(i) in each bin of length n as follows:

$$\mathrm{Y_n(i) = y(i) - y_n(i)} \tag{3}$$

thus providing us with the residual (Y_n(i)) of the local polynomial fit. In our present contribution we chose a linear regression fit, as it is consistent with past research on the fractality of eye movements. In the final step for each bin the root-mean-square fluctuation for the detrended signal is calculated:

$$F(n) = \sqrt{\frac{1}{N}\sum_{j=i}^{N}\left[Y_n(i)\right]^2} \qquad (4)$$

This calculation is then iterated for various bin lengths (n) to acquire the fluctuation function, $F_{(n)}$ over a broad range of scales (Xu et.al., 2005). A power-law relationship can be established between the rms fluctuation function $F_{(n)}$ and the scale n:

$$F(n) \sim n^{\alpha} \qquad (5)$$

Due to the scale invariant nature of power-laws $F_{(n)}$ is the scaling function and α is the scaling exponent. The value of α is the indicator of the extent of the correlation in the signal. The value of α ranges from 0 to 1 where 0.5 indicates an uncorrelated time series (random or white noise), $\alpha > 0.5$ indicates that the signal exhibits positive log term correlations (persistence) and $\alpha < 0.5$ shows that the signal shows negative long term correlations (antipersistence).

In the present investigation this method was used to test the time series of eye location coordinates. Time series collected from *x* and *y* coordinates of consecutive gaze locations were treated as independent vectors during the analysis. Differences between data points were calculated as x_n-x_{n+1} horizontally and as y_n-y_{n+1} vertically. Frame by frame eye gaze displacements were expressed as $(\Delta x^2 + \Delta y^2)^{½}$, where Δx and Δy indicate displacements (Euclidian distances). The time series of the Euclidean distance between neighboring samples was submitted to fractal analysis using the DFA method. The aim was to detect statistical correlations between data points over time (Aks et al., 2002). The analysis strategy followed the dynamical approach used in the study of Aks (2005), and utilized a direct numerical examination of data collected from consecutive gaze locations.

Multilevel modeling

The multilevel modeling method was used to explore variables that best describe variances in reaction times. The reason to diverge from standard statistical tests (e.g., ANOVA) in the current analysis is that ordinary least-squares (OLS) regressions are based on the assumption of homogeneous variance across participants and experimental conditions over time. Due to the likely significant magnitude difference of individual variances in scan paths and reaction times across subjects we used a multiple linear regression technique (Multilvevel Modeling, MLM, sometimes also called Growth Curve Modeling) to explain results. MLM is a statistical procedure that uses a maximum-likelihood (ML) estimation well suited to estimating effects of time-varying predictors and fitting random effects to account for individual differences across subjects (Singer & Willett, 2003). MLM has proven to be an effective way to handle changes over time which may result in heteroscedasticity (Maerten-Rivera, 2010; Singer & Willett, 2003).

In the present analysis the MLM method was used to test the effects of a time-varying predictor (the trial-by-trial Hurst exponents of Euclidian distances between consecutive gaze locations) on the length of reaction times. The MLM method has been successfully applied in previous experiments engaged in analyzing complex perceptual responses such as information sharing between anatomically distinctive systems and fractal fluctuations of gaze orientation during visual search (Mirman, Dixon, & Magnuson, 2008; Stephen & Hajnal 2011; Stephen & Anastas, 2011).

CHAPTER III

RESULTS

To test Hypothesis 1, we computed and analyzed the Hurst exponents on Euclidian distances of gaze locations. The one sample t-test confirmed that the average Hurst exponent is 0.589, which is significantly larger than 0.5 (corresponding to random white noise), $t(7555) = 62.5$, $p < .0001$. An H value significantly greater than 0.5 corresponds to 1/f (pink) noise (Xu, et.al., 2005) which is an indicator of the presence of long term auto correlations (Aks et al., 2002; Stephen & Mirman, 2010).

The multiple linear regression model we used included reaction time (RT) as a dependent variable, whereas Block, Orientation, Gender and Hurst were used as predictors (fixed effects). Block, Orientation and Gender were dummy coded categorical variables, and Hurst was a continuous variable. Due to the incompleteness of the design we omitted the first block (homogenous trials) from all but one analysis. The model looked like this:

$$RT \sim Block \times Orientation \times Gender \times Hurst.$$

Due to heavy positive skew, reaction time was transformed by taking the natural logarithm of individual values. The coefficient values and significance levels of the significant interactions are listed in Table 1. No main effects were statistically significant.

Table 1

Significant interactions measured on the Euclidian distances of consecutive gaze locations.

Predictor	*B*	*SE*	*p*
	Support for Hypothesis 2:		
Block × Hurst	-1.464	0.719	< .043
	Support for Hypothesis 4:		
Block × Gender	-1.473	0.590	< .013
Gender × Hurst	-6.597	2.806	< .019
Block × Gender × Hurst	2.708	1.016	< .008

Note. *B* is the regression coefficient, *SE* is the standard error, and *p* is the significance level (criterion is $p<0.05$).

Support for Hypothesis 2 was provided by a significant Block x Hurst interaction. Table 1 shows interaction effects returned from the model (interaction of trial block and Hurst exponents measured on the Euclidian distances between *x*, *y* coordinates of consecutive gaze locations (H_{xy}); $B = -1.464$, $SE=.719$, $p < .043$). Data indicates that as the Hurst exponent increases, reaction time decreases, and this decrease is steeper (see Figure 6) in the last blocks (Block 3, vertical and horizontal combined).

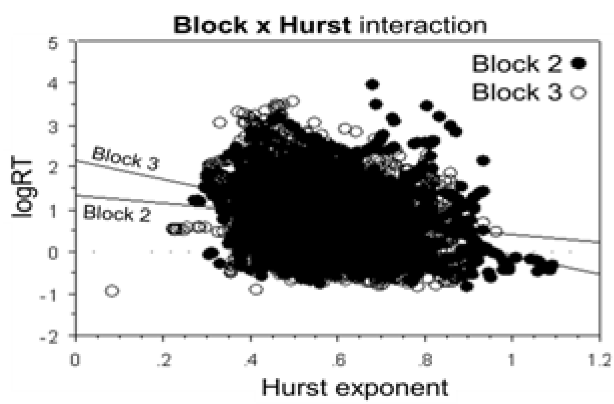

Figure 6. Interaction between the magnitude of the Hurst exponent and Blocks of trials.

All the remaining significant interactions support Hypothesis 4. Table 1 shows a significant Block × Gender interaction (B = -1.473, SE =.590, p < .013). Results in Figure 7 indicate that males were faster, and did not change across blocks of trials, whereas females became slower in Block 3.

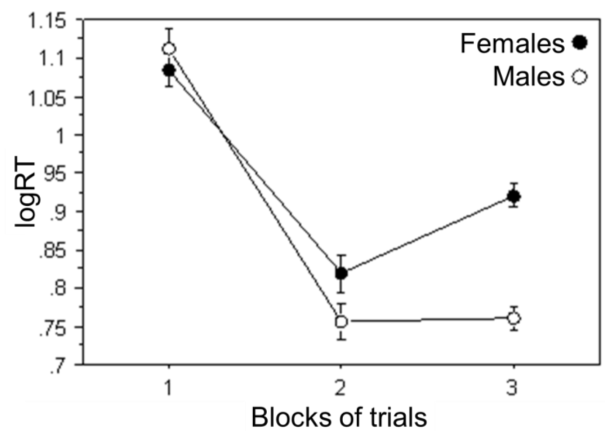

Figure 7. Gender Differences revealed by reaction time series obtained in Block 2 and Block3. The first block of trials is included for illustration purposes only, and was not incorporated into the statistical analysis.

The interaction between gender and the magnitude of fractal fluctuations measured on the time series of x, y fixation location distances was also significant. The outcome suggests that there is a significant difference between the scan pattern produced by males and females as the Hurst exponent changes from low to high values (B = -6.597, SE =. 2.806, p < .019). As the Hurst exponent increases, reaction time decreases, and this decrease is larger for females. This finding also supports Hypothesis 4 (see Figure 8).

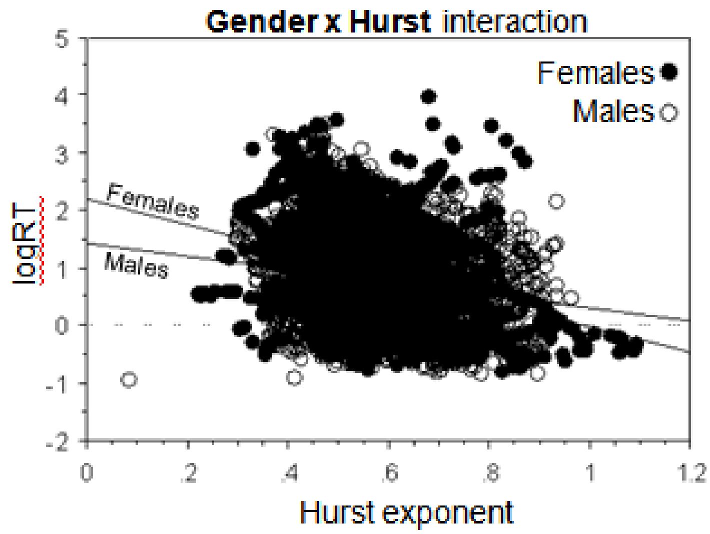

Figure 8. The interaction of gender and the Hurst exponent.

The Significant Block × Gender × Hurst interaction indicates that not only does increased fractality benefit female performance more than males, but it does so the most in Block 3. Increase in H will go along with the steepest relative decline in reaction time within Block 3 for females (B = 2.708, SE = 1.016, p < .008).

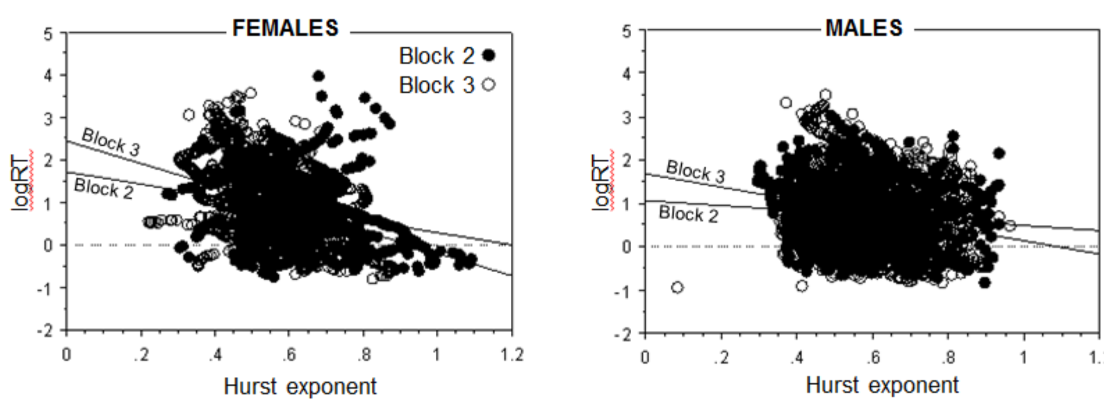

Figure 9. Support for Hypothesis 4 is provided by a three-way interaction of Gender x Block x Hurst: as the Hurst exponent increases, reaction time decreases, and this decrease is faster for females as we compare Block 2 to Block 3.

No support has been found for Hypothesis 3. Even though the Gestalt principle of proximity influences perceptual reorganization, there is no difference between perception of horizontal rows and vertical columns. The regression model we used has not returned any significant effects or interactions related to Orientation (vertical versus horizontal) of the visual display.

Possible indicators of efficient visual search may include 1) decrease in reaction time (observed in significant interactions just reported); 2) decrease in number of fixations (not analyzed in present contribution); 3) increase in fractality of visual search (observed and reported in present contribution; and 4) decrease in fixation durations. In fact, Block 3 fixations turned out to be shorter than in Block 2, $F(1, 10) = 25.8$, $p < .005$, as measured by a within-subjects analysis of variance (ANOVA). The results of fixation duration are presented in Figure 10.

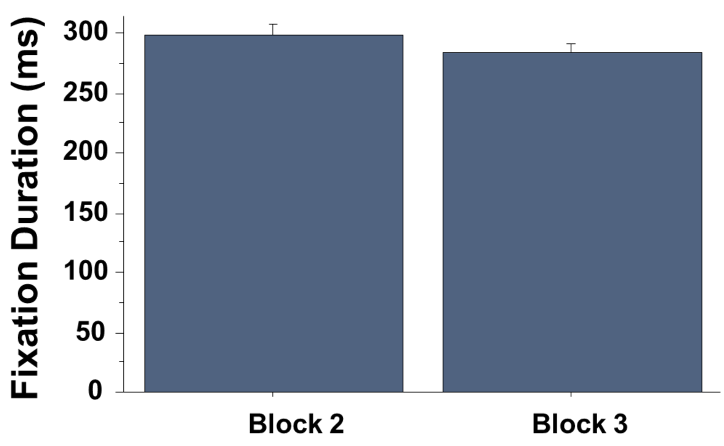

Figure 10. Fixation durations are shorter in Block 3 (nonhomogenous trials) compared to Block 2 (transition trials).

CHAPTER IV

DISCUSSION

The aim of the present research was to identify how Gestalt principles of perceptual organization impact visual search behavior as reflected in eye movement patterns. The law of spatial proximity appears to play a crucial role in both human and computer vision, and it may possibly be the most fundamental of all Gestalt rules (Kubovy et al., 1998). Based on the extensive literature on Gestalt grouping laws (Brunswik & Kamiya, 1953; Elder & Goldberg, 2002; Hochberg & Silverstein, 1956; Kubovy et al.,1998; Oyama, 1961; Wertheimer, 1938), the law of nearness was found to be easily quantifiable, flexible, and a reliable indicator of how the visual system organizes our perceptual experiences. At a basic level, the emergence of all our visual experiences starts with ocular movements that execute the scanning of the visual array. Recent studies have revealed that eye movements are not random, and visual scan patterns are reflecting the self organizing dynamic processes of visual cognition (Aks et al., 2002; Stephen & Mirman, 2010). The interaction dominant dynamics of visual processes have been indicated by the fractal fluctuations in the time series of consecutive eye position distances (Aks, 2005; Stephen & Anastas, 2011). In our current investigation results indicated an interaction between the fractal nature of scanning patterns and the emergence of perceptual experiences in relation to the law of nearness.

The first Hypothesis, that eye movements are fractal in nature was based on the results of previous investigations (Aks, 2005; Stephen & Anastas, 2011). Current analysis shows that the Euclidian distances of successive gaze locations are characterized by fluctuations in the fractal range. The outcome also points out that the results are possible to replicate, and the novel analysis (DFA of Euclidian distances between fixation positions) is a reliable detector of fractal fluctuations in eye movement data. These fluctuation patterns produced by the shifting of visual attention reflect the interaction dominated nature of visual cognition (Stephen & Mirman, 2010). Due to the presence of fractal dynamics, in Hypothesis 2 we expected to find an interaction between the magnitude of fractal fluctuations and the effectiveness of scanning behavior. This assumption was based on a recent study where results indicated that the extent of fractality in eye gaze orientation has an impact on reaction time (Stephen & Anastas, 2011). The analysis of eye movements and reaction time series shows that the fractality of distances of consecutive fixation locations influences the effectiveness of visual search. Results indicate that the visual system modifies the parameters of scanning behavior as the organization of the visual field changes from homogenous to non-homogenous. A possible explanation is that the emergence of different perceptual outcomes (perceiving rows or columns) is a function of inter-dot distances (Oyama, 1961). For example, as the inter-item distance increases or decreases, our perception shifts accordingly by perceiving the visual array as rows or columns. It is possible that scanning behavior is also sensitive to changes in the visual array. The above assumption can be backed up by a recent theory that describes visual cognition as a dynamic interaction dominated system (Stephen & Mirman, 2010).

According to Stephen and Mirman (2010), visual cognition is a result of many interacting agents (both high and low level visual functions such as feature processing and visual memory) that organize themselves into a complex structure. When interaction is the dominating method of communication among distinctive functions, then the organization of functions is context dependent. In the current investigation the context is provided by the organization of the visual field (homogenous, nonhomogenous). Conversely, a context independent process would be reflected by the independent variance of reaction times and the scaling exponents H in relation to changes in the visual field. According to a proposed framework by Kay (1988), functions in a complex system are not encapsulated which means that elements within the system arrange themselves in relation to the actual strains of context. Stephen and Mirman (2010) explained this framework as a system where constituent parts (parts responsible for specific cognitive functions) could run alongside or disconnect to accommodate the changing conditions. Perceptual outcomes can be considered as an output of this system just as the resultant scanning behavior. Taking into account that in an interaction dominated system functions are not encapsulated and may bind together to suit current circumstances, based on the results it is reasonable to assume a connection between a given perceptual outcome and an ongoing scanning behavior. Consequently, data that describes the changing properties of the output over time possibly carries information about how the system accommodates its functions in relation to the actual input. As our data signals significant differences in scanning behavior (output) in relation to the organization of the visual field (input) a possible connection between perception and scanning can be established. Results indicate that as different perceptual outcomes emerge the visual system responds to it by modifying the scanning pattern. This pattern can be thought of as an algorithm that describes how to construct the trajectory of visual information processing. The trajectory itself represents a map that contains the x and y coordinates of eye movements in relation to the observed visual array. Our data shows that if the visual array changes the algorithm of constructing the trajectory will change as well. This algorithm refers to the rules of how distances between successive fixations are governed. As it has been discussed in the introduction section, Aks in 2005, referred to this governing function as an iteration of a simple set of rules over time that produces temporal dependency among data points. Our data shows changes in these rules in relation to the organization of the visual field which is in line with recent findings (Aks et al., 2002; Aks, 2005) and theories of interaction dominated systems (Kay, 1988; Stephen & Mirman, 2010). Data analysis performed in the current paper has confirmed the occurrence of pink noise in eye tracking data, as a signature of such an interaction dominated complex system.

In terms of perceptual efficiency and cognitive resource management we can conclude that the trajectory of eye movements reflects a self organized search pattern that requires a whole host of complex processes while minimizing computational load (Aks, 2005). In summary, a self organized system carries the capacity to change its operational rules in order to dynamically adapt to changes in circumstances. By fitting the rules (rules to plan and generate the scanning path) to actual demands, the visual system is inherently capable of minimizing computational loads while maximizing efficiency. Due to the unique properties of a complex system this type of resource management can be captured in the data produced by eye movements. Traditional investigations of visual search attributed changes in reaction time to activation of higher level functions such as the visuospatial sketch pad in visual working memory (Aks, 2005; Stephen & Anastas, 2011). Resource management in this case refers to the reallocation of available computational power among higher level visual processes. The advantage of fractal measurements of gaze trajectory is that it can be directly measured in relation to reaction time. By analyzing the structure of eye movements, resource management can be directly measured as a function of efficient distribution of fixation locations and time. Measuring higher level visual functions such as the visuospatial sketch pad, would require more complex equipment (e.g.: positron emission tomography) for detecting online changes in relation to variations in reaction time (Cupini et al., 1996). However, even sophisticated brain imaging measurements have not completely mapped out the exact mechanisms that govern activation of high level cognitive functions. In addition, these imaging techniques have not provided us with the exact details of the algorithms or computations that may underlie such efficient resource allocation over extended periods of time. Behavioral data from recent research (Stephen & Anastas, 2011) and from present research indicates that ocular movements can serve as a reliable measure of a special type of resource reallocation manifested by the management of the spatial distribution of gaze locations. Results suggest that fluctuations in consecutive gaze location distances may support efficiency of how visual cognition engages in active exploration of the visual world.

Regarding differences in fractal fluctuations in relation to the organization of the visual field, the current analysis did not find support for Hypothesis 3. The expectation was that vertical perceptual organization will result in faster and more efficient visual search than horizontal organization. This assumption was based on the discovery of the extended bias toward vertical organization both in perception by Oyama (1961) and in eye position distances by Aks (2005). While our participants anecdotally reported that the vertically organized visual field was easier to scan, statistical analysis has not identified any significant change in search efficiency in relation to vertical organization.

This might be due to the nature of the analysis. Current investigation used the DFA method to define the magnitude of the Hurst exponent which was then used as a trial by trial predictor of changes in reaction time. The analysis only focused on the distances between gaze locations and disregarded other aspects of oculomotor behavior such as the number of fixations. While trial by trial Hurst exponents have proven to be a useful predictor of changes in reaction times, it is possible that the properties of the scanning path are not sensitive to changes in the visual field. At this point, the verbal reports of participants need to be considered. It is possible that the perceived ease of scan was not a result of fractal fluctuations; rather it is a byproduct of the number of fixations. It can be speculated that scanning a vertically organized visual field requires less fixations compared to a horizontal organization. In this case the number of fixations that were required to find the target would be a better indicator of differences between vertical and horizontal organizations. Support for this assumption may reside in a previous finding by Aks (2005). Her extended analysis of eye movement data indicated that distances of fixation positions tend to increase on the vertical axes. If we consider fixations as resting locations over the course of an eye’s trajectory, the fewer stops we make the more distance we can cover between pauses. During scanning it means that we can cover a given area of space (e.g., the size of the display) with fewer fixations. This speculation points toward a future investigation that involves the analysis of the number of fixations produced in relation to the organization of the visual field.

Gender Differences in Visual Search

Regarding gender differences in visual scan, the overall pattern of results was in agreement with predictions from Hypothesis 4. While male participants tended to be faster, and did not change across blocks of trials; females became slower in Block 3. Data also indicates that the presence of fractal fluctuations in gaze patterns has a distinctive effect on genders. Male participants seem to perform the same way regardless of the magnitude of the Hurst exponent whereas females tend to benefit from the presence of stronger correlations between Euclidian distances of consecutive fixations. This effect is best revealed by the changes in reaction times from Block 2 (transition period) to Block 3 (nonhomogeous, vertical or horizontal organization). While females were slower in Block 3 compared to Block 2, data also shows a significant decrease in reaction time in relation to the increase in magnitude of the Hurt exponent (Hypothesis 2) across Blocks and Gender, as noted in the significant Gender x Block x Hurst interaction.

The success of information selection lies within the interaction dynamics of the selection method and the organization of the visual field. The knowledge of gender differences in visual search allows us to more appropriately design and organize visual fields for the different genders which may have applications for manufacturing personalized user interface designs, such as computer screens. Different types of visual searches are dependent on the nature of the required underlying cognitive process (Treisman & Gelade, 1980; Wolfe & Horowitz, 2004). Current research applies a search task that qualifies as a difficult conjunction search where the target has a unique orientation (i.e., upward T). When distracters differ from the target in orientation, visual searches become inefficient (Wolfe, 1998). In addition, the present investigation manipulated the spatial configuration of the visual array. However, due to the nature of the search task the collected data mirrors distinctive cognitive processes, such as mental rotation, spatial orientation and search strategy. Accuracy and reaction time of finding the target reflects a decision making process that requires mental rotation due to the orientation of various items. Furthermore, scanning behavior requires the use of spatiotemporal coordination. As a result, the search task requires simultaneous handling of several visually dependent cognitive processes. Different strategies of efficient resource management among genders during the execution of these processes may point toward an evolutionary basis of said behavior. It has been suggested that these gender differences evolved as a result of divisions in labor types (Joseph, 2000). For example, in traditional ancient societies men were typically hunters and women gatherers, thus it is possible that different visual search demands were imposed on ancient men and women. Other research on gender differences has revealed that females typically outperformed males at tasks requiring rapid identification and matching of items (Kimura, 1992). These skills can easily be related to gathering and distinguishing edible fruits from other plants (Joseph, 2000). The visual search task utilized in present research requires spatial rotation skills. Accordingly, it is likely that the emerging gender differences can be accounted for in part by the nature of the task.

Current results indicated that male participants require less time to complete the task in both transition (Block 2) and non-homogenous trials (Block 3). These differences in reaction time might be related to the type of search pattern performed by females and males. Data shows that while reaction times of male participants were less affected by the strength of temporal correlations in eye movement data, stronger correlations tend to benefit females. This benefit means that the higher score of the Hurst exponent comes with a lower reaction time (Hypothesis 2). A Hurst exponent value within the range $0.5 < H < 1$ signals long-term positive autocorrelation in the data. This is what Aks (2005) referred to as the indicator of the existence of a special type of long term memory in the data. It means that a high value in the series of data points will most likely be followed by another high value and it indicates that the values that will occur in the future will also be likely high. In terms of eye movement data a high value represents a greater Euclidian distance measured between consecutive gaze locations. The stronger correlation between the measured distances predicts a decreased reaction time on a given trial. This suggests that the increase of fractal fluctuations in gaze locations promotes a more efficient spatial exploration of the visual field. The greater value of the scaling exponent predicts a shorter amount of time that it takes to find the target. While males tended to be faster than females, their reaction times seemed to be less correlated with the value of H. On the other hand, female reaction time series appeared to be sensitive to changes in the strength of long-term positive autocorrelation. Gender differences in this case can be understood as a distinctive scanning pattern. As such, the divergence in scanning behavior is manifested in relation to the given task.

Limitations of Current Study

A limitation of the present investigation is that it was conducted using participants that come from Western, Educated, Industrialized, Rich and Democratic societies (WEIRD, Henrich et al., 2010). The results are usually generalized to all of the human population regardless of culture or environmental distinctiveness. A growing number of articles propose that there are significant cultural and individual differences in the instantiation of the same fundamental cognitive processes (Henrich et al., 2010; Ji, Zhang, & Guo, 2008). It is important to note that our results may differ in cultures that use a different alphabet or different reading directions. People who have participated in this study were quite familiar with a T shape thus possibly have advantages in finding it among distracters that are T shapes of different orientation. On the other hand, people who do not encounter T shapes as frequently probably would process the task by using a different search strategy. The everyday practice of reading may have a strong influence on scanning vertical or horizontal visual arrays. As the direction of reading can be dependent on the given culture, it is possible that it also influences scanning behavior. This points toward a cross cultural assessment of visual search patterns. Another limitation is related to the analysis method. The collected time series were subjected to the DFA method to reveal the extent of fractal fluctuations. While the presented analysis applied the detrending method to reveal the fine tuned fractal structure of the collected data, there are other more complex measurements to explore the extent of fractal fluctuations. For example, in addition to the DFA method Stephen and Anastas (2011) used ARFIMA modeling which is an elaboration of ARIMA (autoregressive moving average) modeling. The discussion of the above mentioned methods is beyond the scope of the current project. However, it is important to highlight that due to the complexity of these methods, by leaving them out from the analysis the interpretation of results is restricted by the boundaries of the DFA method.

Conclusion

In the current research the conversation between the pattern drawn by the shifting of focal visual attention and the organization of the visual field has been discussed. The presence of 1/f behavior indicates temporal dependency of data points, in this case the spatial allocation of visual attention over time. Results showed that the increase in this temporal dependency among Euclidian distances of gaze locations facilitates perceptual efficiency by reducing scanning time to find a target. Fractal fluctuations seem to promote a faster exploration of the visual environment by organizing spatial allocations of fixation coordinates. Without the proper distribution of fixation locations scanning would become random and finding a target would be independent from successive gaze locations. In addition, reaction times most likely would increase as a result of the chance level searching pattern. While predicting the behavior of a complex system is difficult due to the strong mutual dependency of variables, the human visual system has a unique property that can serve as a reliable indicator of changes in the system. This indicator is the emergence of changes in eye movement patterns in relation to the visual input. Analyzing eye gaze positions and the resultant visual experience in relation to the structural changes of the visual display could provide an insight into the interaction dynamics of visual information acquisition. Such insight can lead to the possibility of presenting visual information at a future location to where the environment would automatically drive our focus of visual attention, as the designer of the environment originally intended.

Current findings can open up a new avenue to understanding the relationship between the organization of the visual field and the pattern produced by the shifting of focal visual attention. The results could serve as a guide for engineering graphical interfaces that are capable of accommodating the most effective visual scanning patterns related to given areas. The identification of an emergent pattern produced by an interaction dominated system in relation to controlled changes in the input could further contribute to the field of complex systems. An innovative component of the presented approach is to use fractal measures such as the Hurst exponent (H) as a trial-by-trial predictor of changes in reaction times and locations of information acquisition. Beyond applying new methods in visual display design it is also an intriguing possibility to use fractal dynamics of eye movements in biometrics. Based on the revealed gender differences in scan patterns, the applied analysis can be used to distinguish male and female eye movement patterns.

The way we interpret our visible environment shapes our concept of the world and essentially our description of reality. The presented research intended to quantify the first step towards this description.

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