University of Cincinnati

Date: 11/2/2011

I, Ramon D. Castillo Guevara, hereby submit this original work as part of the requirements for the degree of Master of Arts in Psychology.

It is entitled:
Coordination of Local and Global Features: Fractal Patterns in a Categorization Task

Student’s name: Ramon D. Castillo Guevara

This work and its defense approved by:

Committee chair: Adelheid Kloos, PhD
Committee member: John Holden, PhD
Committee member: Guy Van Orden, PhD
Coordination of Local and Global Features: Fractal Patterns in a Categorization Task

A thesis submitted to the
Graduate School
of the University of Cincinnati
in partial fulfillment of the
requirements for the degree of
Master of Arts
in the Department of Psychology
of the College of Arts and Sciences

by

Ramon D. Castillo Guevara

November 2011

Committee Chair: Heidi Kloos, Ph.D.
Abstract

To categorize an object successfully, one needs to attend to both local and global aspects to group it meaningfully. The open question pertains to how the mind coordinates local and global features of a display. Coordination of mental processes can be studied by looking at correlational patterns across many thousands of trials. The coordination among these time scales can be described according to a mathematical constructs called fractals. Even though fractals have been detected in trial series pertaining to motor and cognitive tasks, they have not been evaluated in categorization tasks in which are required attention to local and global features. The goal of this research was to fill this gap.

Two experiments were implemented on undergraduate students in order to obtain a measure of the coordination of local and global aspects during a categorization task. Participants had to decide if two stimuli had the same contour around a string of elements, and if they shared an element. The assumption was that such competition might maximize the degree to which global and local attributes need to be coordinated. Therefore, this coordination might be characterized by fractal exponents, which in turn might be susceptible to constraints in task and participants.

Experiment 1 \((n = 32)\) tested the effect of two of those task constraints; the first being the predictability of the response of a trial from the answer of the previous trial. Depending on condition, trials were presented either in random order or in a predetermined sequence that allowed participants to anticipate the next trial. The idea was that predictability might increase the fractal exponent, while added randomness decreases the fractal exponent. Another factor manipulated pertained to the participants’ skill. Here, it was assumed that a greater familiarity was associated with a greater skill in identifying the stimuli; and that fractal exponents close to \(1/f\) pink noise must appear more clearly with familiar stimuli than novel stimuli.

Experiment 2 \((n = 64)\), was based on a new version of the categorization task. Here, the structure was modified to decrease the competition for attentional resources. In some conditions, participants were asked to make decisions by focusing their attention on elements, while in other conditions they were asked to focus on the global shapes. Thus, it was hypothesized that the fractal exponents obtained in the second experiment should be higher than those obtained in the first experiment.

Reaction times were compared between familiarity of stimuli, the predictability of the next trial, and among types of slides. Also they were submitted to Spectral Analyses to detect fractal organization. The results show that the predictability of the next trial was the most important factor. When trials were administered sequentially, exponents were higher than those obtained with random procedure. Additionally, when decision was centered on global aspects, exponents were higher when decision was centered on local elements and centered on both aspects. Finally, alpha exponents were higher in only one condition—where participants were focused on global shapes and responded to familiar stimuli presented sequentially.
Acknowledgements

I would like to thank Dr. Heidi Kloos for her guidance and support, as well as her helpful critiques on previous versions of the Master's Thesis. I would also like to thank Drs. John Holden and Guy Van Orden, the committee members for this thesis, for their help with identifying relevant ideas and for providing feedback on this project. Dr. Holden also helped with issues pertaining to the fractal analyses. Furthermore, I would like to thank Dustin Faller, Keith Needham, and Shana Vanderburgh for their help with constructing the stimuli. Keith Needham and Shana Vanderburgh also helped with data collection, as well as with providing continuous support. Finally, I would like to thank Anna Haußmann, David Pfeiffer, and Sebastian Wallot for their comments on previous versions of the thesis. The author of this master thesis is sponsored and funded by Fulbright-Laspau, US, Fulbright-Mecesup II Program, Chile, and Universidad de Talca, Chile.
Table of contents

Abstract .......................................................................................................................... ii

I) Introduction ............................................................................................................... 1

1.1) Local and Global Processing .............................................................................. 1

1.2) Coordination across Scales .............................................................................. 4

1.3) Overview of Experiments .................................................................................. 9

II) Experiments .......................................................................................................... 11

2.1) Experiment 1 ....................................................................................................... 11

2.1.1) Method ........................................................................................................... 11

2.1.2) Results and Discussion ................................................................................. 16

2.1.2.1) Proportion of Correct Answers ................................................................. 17

2.1.2.2) Mean and Standard Deviation of Reaction Times ..................................... 18

2.1.2.3) Spectral Analyses ..................................................................................... 20

2.2) Experiment 2 ....................................................................................................... 24

2.2.1) Method ........................................................................................................... 25

2.2.2) Results and Discussion ................................................................................. 26

2.2.2.1) Proportion of Correct Answers ................................................................. 26

2.2.2.2) Mean and Standard Deviation of Reaction Times ..................................... 29

2.2.2.3) Spectral Analyses ..................................................................................... 33

2.2.2.4) Effect associated with the competition for attentional resources ............... 37

III) General Discussion .............................................................................................. 40

IV) References ........................................................................................................... 47
List of tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 1</td>
<td>Processes involved on perceptual organization in hierarchical patterns.</td>
<td>1</td>
</tr>
<tr>
<td>Table 2</td>
<td>Unique string shapes represented schematically as a function of elements types.</td>
<td>12</td>
</tr>
<tr>
<td>Table 3</td>
<td>Number of Times that an element (Letter or Tetragon) appear in a certain position in a string.</td>
<td>14</td>
</tr>
<tr>
<td>Table 4</td>
<td>Sequential structure of sequential-order condition.</td>
<td>15</td>
</tr>
</tbody>
</table>
# List of figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>Spectral graph of l/f scaling.</td>
<td>6</td>
</tr>
<tr>
<td>Figure 2</td>
<td>Example of slides used in Experiments.</td>
<td>13</td>
</tr>
<tr>
<td>Figure 3</td>
<td>Means and standard errors of average of the proportion of correct answers.</td>
<td>17</td>
</tr>
<tr>
<td>Figure 4</td>
<td>Means and standard errors of average of reaction time (sec) for each experimental condition.</td>
<td>19</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Means and standard errors of standard deviation of reaction time for each experimental condition.</td>
<td>20</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Cumulative graphs for four experimental conditions.</td>
<td>21</td>
</tr>
<tr>
<td>Figure 7</td>
<td>Means and standard errors of the average of alpha’s exponents.</td>
<td>23</td>
</tr>
<tr>
<td>Figure 8</td>
<td>Means and standard errors of average of the proportion of correct answers.</td>
<td>27</td>
</tr>
<tr>
<td>Figure 9</td>
<td>Means and standard errors of the average of reaction time.</td>
<td>30</td>
</tr>
<tr>
<td>Figure 10</td>
<td>Means and standard errors of the average of standard deviation of reaction time.</td>
<td>31</td>
</tr>
<tr>
<td>Figure 11</td>
<td>Cumulative graphs for four experimental conditions in which the participant had to make decision focused on elements.</td>
<td>33</td>
</tr>
<tr>
<td>Figure 12</td>
<td>Cumulative graphs for four experimental conditions in which the participant had to make decision focused on shapes.</td>
<td>35</td>
</tr>
<tr>
<td>Figure 13</td>
<td>Means and standard errors of the average of alpha’s exponents.</td>
<td>36</td>
</tr>
<tr>
<td>Figure 14</td>
<td>Means and standard errors of the average of alpha’s exponents for each experimental condition, summarizing data from Experiments 1 and 2.</td>
<td>39</td>
</tr>
</tbody>
</table>
I) Introduction

How does the mind make sense of an ever-changing array of light? This question has a long history, often addressed under the framework of local and global processing (e.g., Kimchi, 1990; Kimchi, 1998; Kimchi, Hadad, Behrmann, & Palmer, 2005; Köhler, 1969; Quinn, Burke & Rush, 1993). Indeed, a scene could be loosely divided into local elements and global patterns. And adaptive functioning needs both: the ability to integrate local elements into higher-order Gestalts, and the ability to segregate higher-order Gestalts into their component parts. In fact, processes of integration most likely must be coordinated fluidly with processes of segregation.

Traditional research in visual processing has shown that in the process of switching from global configurations to local elements and vice versa, are interacting the characteristics of stimuli and the properties of the perceptual system (Kimchi et al., 2005). However, this approach has no clear description of how humans coordinate these aspects in visual search, visual matching, categorization tasks, and so on. The current project is concerned with the question of this coordination. In which the coordination of global and local aspects, are analyzed with conceptual and methodological tools that come from another paradigm. In this alternative theoretical framework are used large time series, in order to identify stable patterns of variability in different time scales, called fractals (Brown & Liebovitch, 2010; Eke, Hermán, Kocsis, & Kozak, 2002; Gilden, 2001).

To demonstrate how coordination between local and global aspects can be explained by the identification of fractal patterns, the introduction is divided into three parts. The first part describes the conceptual elements associated to global and local processing of stimuli. The second part is explaining the concept of fractality and its connection with the coordination between systems operating on different time scales. Finally, the overall structure of experiments is explained, emphasizing the rationale of design and hypotheses underlying each manipulation.

1.1) Local and Global Processing

The findings on perceptual organization of hierarchical patterns have shown differences depending on the nature of the patterns. Studies in this area support the idea that processes of grouping
and segmentation of elements interact with the characteristics of the configurations (see Table 1). In developmental terms, already 5-year-olds are capable of grouping many small elements into a whole, and segmenting relatively few large elements quickly and accurately. This trend is stable in the course of development; even when it can be experimentally modified according to manipulations in size, orientation, or sparsity of number of elements. On the other hand, the segmenting process of many small elements and the grouping of few large elements are achieved gradually in development. Where adults are more efficient than infants and the performance is highly sensitive to the characteristics of elements and the task (Kimchi, 1998; Kimchi et al., 2005).

Table 1

<table>
<thead>
<tr>
<th>Processes involved on perceptual organization in hierarchical patterns.</th>
<th>Elements (quantity and size)</th>
<th>Grouping</th>
<th>Easy</th>
<th>Difficult</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Many, relatively small elements</td>
<td>Few, relatively large elements</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processes</td>
<td>Segmentation-Individuation</td>
<td>Difficult</td>
<td>Easy</td>
<td></td>
</tr>
</tbody>
</table>

Note: The grouping many relatively small elements into a global configuration and the individuation of few large elements are rapid, effortless, and the performance is more accurate; whereas grouping a few relatively large elements and the individuation of many small elements consume time, requires attention and the performance is less accurate.

Traditionally, the emphasis has been on determining how attention to local aspects competes with the perception of global aspects, whether the stimuli pertain to faces, arbitrary items, or entire scenes (Kimchi et al., 2005). Navon’s (1977) well-known task is a good illustration of this emphasis. Stimuli involved small letters arranged spatially in such a way that they form a larger letter. The element letters either matched the Gestalt letter or not. And the task was to name a letter (either the element letter or the Gestalt letter) as fast as possible. The general finding suggests an asymmetry in competition: Perception of Gestalt features appears to interfere more with the perception of elemental features than vice versa.
Consistent with the laws of perception outlined by Gestalt psychology, the organization of whole entities apparently takes priority over the separation into isolated elements (Kimchi, 1998; Köhler, 1969).

While subsequent research has supported the general finding of unidirectional competition between global and local processes, the issue might be more complex (Dukette & Stiles, 1996; 2001). Kimchi and her colleagues, for example, showed that the priority of global processes depends on the specific details of the stimuli used. When items consist of few relative large elements (e.g., four triangles spatially arranged to form a square), the global preference disappears (e.g., Kimchi, 1990; Kimchi et al., 2005). It is only when items consist of many small elements (e.g., twelve triangles spatially arranged to form a square) that global patterns take precedence. This pattern of findings was demonstrated in adults as well as children as young as 5 years of age; and it was replicated in speeded classification tasks, matching tasks, or visual searching task (Burack, Enns, Iarocci, & Randolph, 2000; Enns & Girgus, 1985; Kimchi, 1990). Together, they provide convincing evidence that attention to local elements is coordinated with attention to global patterns.

A more direct indication for a coordinated interaction between local and global processes comes from findings with young infants (Quinn et al., 1993). In a habituation task, infants were first familiarized with geometrical shapes that consisted of elements that formed higher-order Gestalts. While participants dishabituated to changes in the higher order Gestalt, they were surprisingly sensitive to relatively minimal changes in local elements. In fact, perceiving elements was enhanced in the context of an organized whole (see Experiment 4 of Quinn et al, 1993). These findings suggest an intricate interdependence among attention to local and global features, one in which the perception of higher-order Gestalts highlights local elements that—in turn—make up the higher-order Gestalt.

Despite isolated findings on the interplay between local and global processing, the methods commonly employed in this domain do not lend themselves to explicitly measuring coordination. This is because the choice of stimuli is likely to bias the perceptual system to focus either on local elements (e.g., when the elements highly salient) or on global patterns (e.g., when small elements form highly salient patterns). Such methods are ideal to measure possible interferences of hierarchical scales, but they might
miss the adaptive coordination that takes place when scales of hierarchical organizations interact. We therefore turn to a different method, one that can gauge a possible coordination among the many nested levels of order.

1.2) Coordination across Scales

Changes in the mind-body system happen at different rates or scales. The metabolic activity in a motor cell, for example, is a process changing on very fast timescales. And the overt movement of eyes is an example of a process changing on a slower time scale. For adaptive and flexible performance to be possible, no single timescale can dominate coordination. Instead the system has to maintain a balance between competing and cooperating changes in a flexible coupling across the body (Kloos & Van Orden, 2010). Similarly, the focus of attention is likely to change on multiple time scales: For example, paying attention to local elements of a display necessarily needs to change on a fast timescale (to track small changes in shape, texture, or color), while paying attention to more global patterns of a display needs to change on slower timescales. Are these different timescales coordinated?

Coordination of smaller and larger timescales can be studied by looking at long-term correlational patterns across many trials, a mathematical constructs named fractals. Fractals represent self-similar structures with functional and topographical features that are reproduced in miniature on finer and finer scales, and their organization, that assume the form of power law distributions (Brown & Liebovitch, 2010, Eke, et al., 2002; Holden, 2005; Holden, Van Orden & Turvey, 2009). Consistent with this idea, it has been hypothesized that variability in a set of cognitive variables is not fully accounted for by the effect of external stimuli, but also by emergent phenomena characterized as a complex systems. Specifically, it has been proposed that self-organized behaviors have a variability that remains constant among different scaling levels in which the behavior is being expressed. This strong tendency to be coupled has been linked to a system’s coordination among different timescales (Gilden, 2001, Holden, 2005; Kello, & Van Orden, 2009, Kloos & Van Orden, 2010; Van Orden, Holden & Turvey, 2003; for a different view Hausdorff & Peng, 1996; Peng, Havlin, Stanley, & Goldberger, 1995).
Fractals provide a potentially useful way of gauging the coordination among different time scales. The necessary ingredient is a task that produces a sufficiently long trial series. Figure 1 shows such a trial series, one that has over 1,100 data points (top right). To determine the fractal exponent, the trial series is then decomposed into sinusoidal components of different wavelength. Slow changes in the data series are captured by low-frequency high-amplitude sine waves (top left of Fig. 1), and fast changes are captured by high-frequency low amplitude waves (bottom left of Fig. 1). A power spectrum is then constructed, with relative amplitude on the vertical axis, and frequency of change on the horizontal axis (on loglog scales). The amplitude represents the relative size of change, also referred to as power. The slope of the regression line in the spectral plot defines the scaling relation between amplitude and frequency. The estimated exponent ($\alpha$) reflects the degree of long-range correlations across the different time scales (Kloos & Van Orden, 2010).

A multitude of tasks have been tested in large trials and subjected to fractal analyses, and when had been excluded phenomena of priming, responses series show a long-range correlation (e.g., Gilden, 2001; Kello & Van Orden, 2009; Hollis, Kloos & Van Orden, 2009; Van Orden, Holden & Turvey, 2005), including motor tasks (e.g., walking, standing, tapping, tracing, or sensori-motor synchronization), perceptual tasks (e.g., Necker-cube task; visual search), or cognitive tasks (e.g., Word recognition, speeded categorization, speech production, time estimation, and mental rotation). However, there has been little research on the coordination of attention to local and global aspects of stimuli. An exception was an investigation with a visual-search task, where participants had to observe a series of trials in which target objects were either present or absent. Results showed evidence of fractal organization: When the reaction times were plotted for target-absent trials only, a power law distribution emerged (McIlhagga, 2008).
Figure 1. Spectral graph of l/f scaling. One person’s reaction time data (top right), decomposed into sign waves of a particular amplitude and frequency (examples of which are shown on the left). Each sign wave is plotted as a function of its amplitude (power) and frequency, in log-log coordinates, yielding a spectral plot (bottom right). Size of change $S(f)$ is plotted against the frequency ($f$) of changes (on log-log scales). The slope of the regression line between $f$ and $S(f)$ in the spectral plot estimates the scaling relation between size and frequency of change. In this Figure, the size of change $S(f)$ is inversely proportional to its frequency ($f$): $S(f) = 1/f \alpha = f^{-\alpha}$, with scaling exponent $\alpha \approx 0.859$, a value close to $\alpha = 1.0$. The slope of the regression line reflects the scaling exponent $\alpha$.

Fractal exponents have been extracted from analysis of reaction times (and release times) associated to manual-motor-responses and ocular-motor-responses (Kello & Van Orden, 2009; Van Orden, Holden & Turvey, 2005). In these contexts, fractal exponents have been susceptible to task manipulations and the capabilities of subjects. For example, by introducing changes in the inter-stimulus-interval in simple reaction tasks, the slope decreased in magnitude, reflective of added randomness (Holden, Choi, Amazeen, & Van Orden, 2010). On the other hand, some findings have demonstrated a clear fractal
organization in tasks for which people have some expertise (e.g., after intensive training; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). In other words, fractal exponents – while illustrative of the system’s coordination – might need to be interpreted in the context of a specific task for which some level of mastery is required. Therefore, it could be necessary to introduce a set of task manipulations, taking into account the subject’s expertise and the level of randomness of the task, in order to explore changes in fractal organization.

Pilot experiment was implemented in order to understand both how to represent the coordination of global Gestalts and local features by a fractal dimension; and how fractal exponents can be modulated by task’s constrains and specific skill of individuals (Castillo, Kloos, Vanderburgh & Holden, 2011). In this preliminary study seventy undergraduate students participated in one of four experimental conditions. The general task was to decide as quickly as possible whether two stimuli matched in the local elements, in the global pattern or in none of the two. In all conditions trials differed in whether there was a local match, a global match, or neither. Furthermore, the nature of elements was varied to be either familiar or novel. Finally the possibility to anticipate the next trial category was manipulated in that the order of trials was either random or sequential.

In terms of coordination of local and global aspects, fractal analyses indicated that all experimental conditions were different from Pink Noise (1/f noise). Nonetheless, the only experimental condition that systematically stayed away from White Noise was when familiar stimuli were administered randomly. Even though trials were randomly administered to control the learning and priming effects, this condition had a slight long-term correlation through the trials. Thus, there was no traditional explanation in order to justify why the reaction times remain related between them in the time.

Additionally, sequential procedure generated a different organization in the reaction times than random procedure. Reaction times of sequential mode appeared more close to pink noise only in the

---

1. 1/f or pink noise is a concept developed in fractal geometry. It is associated to complex systems whose components interact on multiple time scales to self-organize their behavior. Variability of repeated measurements in human performances exhibits this kind of noise (Holden, 2005; Van Orden, Holden, & Turvey, 2003).
waves of long frequency and high amplitude of the spectrum. In general terms, the pattern of the spectral plots of random and sequential procedures were very different. While spectral plots of random conditions showed the traditional linear organization of frequency-amplitude points, spectral plots of the sequential conditions had a pattern in which emerged a series of waves of high amplitude and median frequency and they did not fall within the typical linear orientation. This phenomenon was attributed to recurrent pattern of stimuli presentation in which sequences of trial were repeated again and again, affecting the speed of reaction times and therefore their variability. According to this preliminary evidence, it was possible to conclude that reaction times in a categorization task possess a scale-invariant among trials that partially resembles the fractal structure observed in other cognitive tasks.

In summary, grouping many relatively small elements into a global configuration and the segmentation of few large elements are faster, effortless, and more accurate; whereas grouping a few relatively large elements and the individuation of many small elements is slower, requires attention and the performance is less accurate. Considering this interaction, it is important to note that perception of global configurations tends to occur more frequently than the perception of local elements. This bias has shown to be resistant to experimental manipulations on the number, position, shape, and separation between elements that are part of a display. On the other hand, in several experiments, the global aspects and local details have been continuously organized hierarchically in which small elements are nested in large wholes (e.g., a large H letter made up of small S letters). Given this organization, it is more difficult to detect the alternation of the coordination of the attention to local and global elements, because immediately the attention is focused on global forms in detriment of the elements that constitute the whole.

In order to obtain a measure of coordination between the perception of global configurations and local elements, reaction times of each trial could be analyzed by mean of spectral analysis. This analysis provides an estimation of the coordination that occurs at different time scales. The final value obtained is a fractal exponent. If exponent is close to 1, it indicates a high level of similarity between different
systems at different time scales, while a value close to 0 is indicative of lack of coordination between different kinds of time scales (Holden, 2005).

In reaction times of various types of human performance have been reported exponents close to fractal organization. Fractal exponents also have been found in visual search tasks, a phenomenon rather close to the perceptual categorization of stimuli. Considering the foregoing, it was predicted that reaction times in this new categorization task, in which global configurations and local elements are not nested hierarchically, had a fractal organization.

Finally, the fractal exponents obtained with other experimental tasks have shown to be sensitive to task’s constrains and individuals’ abilities. For example if participants have some expertise in some task, exponents estimated from reaction times are close to $1/f$ noise. Additionally, when randomness is introduced to the task, fractal values are moved to ranges that are indicating a random organization of reaction times, very close to white noise.

1.3) Overview of Experiments

Two experiments were implemented with the intention of obtaining a measure of the coordination of local and global aspects during a categorization task. The task was to decide whether two stimuli matched in some aspect (e.g., in their overall Gestalt) or not. In some trials, stimuli had the same contour around a string of elements (Shape-Match trial), and in other trials, stimuli shared an element (Element-Match trial). In filler trials, stimuli differed both in overall contour and individual elements (No-Match trial). Importantly, global and local aspects of the stimuli were likely to have similar salience, creating some degree of competition of attention. The assumption was that such competition might maximize the degree to which global and local attributes need to be coordinated. Therefore, this coordination might be characterized by fractal exponents, which in turn, might be susceptible to constraints in task and participants.

The first experiment was conducted in order to test the effect of two of the task constraints. The first experiment manipulated whether the correct response of the next trial could be predicted from the answer of the previous trial. In some conditions, trials were presented in a random order, and in other
conditions, trials were presented in a predetermined sequence that allowed participants to anticipate the next trial. The idea was that predictability might increase the fractal exponent, while added randomness decreases the fractal exponent (Holden et al., 2011). Another factor manipulated in the first experiment pertained to the participants’ skill. In particular, in some conditions the stimuli were either highly familiar to the participants or not. Here, it was assumed that a greater familiarity was associated a greater skill identifying the stimuli. The main idea was that fractal exponents, close to pink noise, must appear more clearly with familiar stimuli, than novel stimuli (Wijnants et al., 2009).

Taking into account the results of the first experiment, the second experiment was conducted in order to reduce and focus the attentional requirements of the original task. Here, the structure of experimental task was modified in such a way that the competition for attentional resources was decreased. In particular, participants were instructed to make a decision by considering only one trial category: the global pattern or the local element. In some conditions, they were asked to make a decision by focusing attention exclusively on local elements, while in other conditions they were asked to make a decision focusing attention on global shapes.

Additionally, this ad-hoc manipulation had two underlying assumptions based on previous antecedents. The first assumption was related to an investigation conducted by McIlhagga (2008), who found a fractal organization in a visual search task. However, this was only in one of the search conditions. This antecedent allowed me to guess that in this categorization task, there might not be the same level of attention given to local elements than global configurations. The second assumption was based on general characteristics of tasks in which \(1/f\) noise has been reported. These tasks have been very simple, repetitive, and with few constraints, where almost nothing changes from trial to trial, and the primary source of variation is the variation endogenous to the behavior that is measured (Holden et al., 2011; Kello, Anderson, Holden, & Van Orden, 2008).

In integrating this information, it was deduced that by simplifying the task in which participants pay attention to one aspect of the stimulus, should increase the value of the fractal exponents. Thus, it was
hypothesized that the coefficients obtained in the second experiment should be higher than those obtained in the first experiment.

II) Experiments

2.1) Experiment 1

In this experiment two independent factors were manipulated. The first one, named the stimuli familiarity, for which the local elements in a stimulus were depicted by consonants letters or novel geometric figures. The second one, named the predictability of the next trial, produced by the method of presentation of trials was characterized by trials following a random order or sequential order. Combining the two factors, four experimental conditions were generated. In two of these conditions, stimuli consisted of familiar elements (i.e., letters), and trials were presented either randomly or in a repeating sequence. In the two other experimental conditions, stimuli consisted of unfamiliar elements (i.e., tetragons), and trials were again presented either randomly or in a repeating sequence.

2.1.1) Method

Participants: A total of 32 undergraduate (10 men and 22 women) were randomly assigned to one of four experimental conditions \((n = 8\) per condition). Inclusion criteria were that participants were English speakers with no reported history of vision impairments. The age ranged between 18.17 to 55.17 years of age, with a mean of 23.57 years, and a standard deviation of 7.26 years. Among conditions, no difference was found for gender distribution, \(\chi^2(3) = .58, p = .90\); and there was no difference in mean age, \(F(3, 28) = .97, p = .42\). Additional five participants were tested but not included in the final sample due to technical errors \((n = 4)\), or because of not meeting the accuracy criterion \((n = 1, see Procedure)\).

Materials: Two kinds of elements were used for the experimental stimuli: letters or tetragons. Letters consist of lower-case consonants that differ in their contour (see Figure 2, top panel). The contour was a square for four of the letters \((c, s, x, z)\), a low rectangle (i.e., a rectangle that reaches below the line) for another four of the letters \((p, q, g, y)\), and a high rectangle (i.e. a rectangle that sits on the line) for the remaining four letters \((b, h, f, l)\). Tetragons are geometric figures (squares and rectangles) that were equivalent to the lower-case consonant letters (see Figure 2, bottom panel).
Elements were grouped into strings of three, with the restriction that no element was repeated within a string. Depending on the contour of an element, 24 uniquely shaped strings were possible (see Table 2 for a schematic representation of the unique string shapes).

Table 2

Unique String Shapes Represented Schematically as a Function of Elements Types.

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>112</td>
<td>121</td>
<td>211</td>
<td>221</td>
<td>212</td>
<td>122</td>
<td></td>
</tr>
<tr>
<td>113</td>
<td>131</td>
<td>311</td>
<td>331</td>
<td>313</td>
<td>133</td>
<td></td>
</tr>
<tr>
<td>223</td>
<td>232</td>
<td>322</td>
<td>332</td>
<td>323</td>
<td>233</td>
<td></td>
</tr>
<tr>
<td>123</td>
<td>132</td>
<td>231</td>
<td>213</td>
<td>312</td>
<td>321</td>
<td></td>
</tr>
</tbody>
</table>

Note: The numerals 1, 2, and 3 signify the three different types of elements (letters/characters): lower-rectangle (p, q, g, y), square (s, c, x, z), and upper-rectangle (h, b, f, l) respectively. Each configuration shown in rows 1-3 (when the string contains two letters of the same type) was used in 48 unique strings; and each configuration in row 4 (when the string contains one letter from each type) was used in 64 unique strings.

Strings were then combined into pairs according to the following specifications: pairs matched in one element (i.e., ‘Element-Match category’, Figures 2A and 2D); they matched in overall shape (i.e., ‘Shape-Match category’, Figures 2B and 2E), or they matched neither in overall shape nor in an element (‘No-Match category’, Figures 2C and 2F). Using an iterative process, there were 440 unique Shape-Match trials, 440 unique Element-Match trials, and 220 unique No-Match trials. Care was taken to ensure that a particular element (e.g., the letter z) appeared equally often within the left and right string of a pair.

Table 3 shows the number of times that an element appeared in a certain position in the trials across pair type. The 1,100 trials were programmed to appear either in a random or a nonrandom sequential pattern. In the random conditions, the trials were grouped into five blocks of 220 trials (88 Shape-Match trials, 88 Element-Match trials, and 44 No-Match trials). Within each block, the trials were presented randomly. In contrast, in the sequential conditions, trials appeared in a pre-determined order. As depicted in Table 4, the first sequence started with one No-Match trial, followed by two Shape-Match trials, and then by two Element-Match trials. This sequence was repeated six times (30 trials total). In the second sequence, there were first two No-Match trials, followed by four Shape-Match trials, and then
followed by four Element-Match trials. This sequence was repeated seven times (70 trials total). Finally in the third sequence, there were first three No-Match trials, six Shape-Match trials, and six Element-Match trials. This sequence was repeated eight times (120 trials total). This 3-sequence pattern was repeated until 1,100 trials were completed.

Figure 2

Figure 2. Example of slides used in Experiments. Top panel shows two strings stimuli of three letters each (each stimuli yielding a particular shape outline), and the instruction to participants. A. Trial of Element-Match category; B. Trial Shape-Match category, and C. Trial of No-Match category. Bottom panel shows two strings slides of three tetragons each, and the instruction to participants. D. Trial of Element-Match category; E. Trial of Shape-Match category, and F. Trial of No-Match category.

All experiments were performed and registered with a laptop with an Intel Core Duo processor of 2.40 GHz, and 1.58 GHz, with 2.96 GB RAM memory with Superlab pro version 2.0. For each trial, reaction time and response was recorded.
Table 3
*Number of Times that an element (Consonant or Tetragon) Appear in a Certain Position in a String.*

<table>
<thead>
<tr>
<th>Shape-Match</th>
<th>Element-Match</th>
<th>No-Match</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Left</td>
<td>Middle</td>
</tr>
<tr>
<td>Lower-Rectangle letter/symbols</td>
<td></td>
<td></td>
</tr>
<tr>
<td>g</td>
<td>34, 33</td>
<td>34, 32</td>
</tr>
<tr>
<td>p</td>
<td>34, 34</td>
<td>31, 31</td>
</tr>
<tr>
<td>q</td>
<td>34, 34</td>
<td>31, 31</td>
</tr>
<tr>
<td>y</td>
<td>34, 35</td>
<td>31, 33</td>
</tr>
<tr>
<td>Square-Shaped letter/symbols</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>32, 31</td>
<td>33, 35</td>
</tr>
<tr>
<td>s</td>
<td>32, 31</td>
<td>35, 33</td>
</tr>
<tr>
<td>x</td>
<td>31, 33</td>
<td>35, 33</td>
</tr>
<tr>
<td>z</td>
<td>31, 31</td>
<td>33, 35</td>
</tr>
<tr>
<td>Upper-Rectangle letter/symbols</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b</td>
<td>35, 34</td>
<td>35, 34</td>
</tr>
<tr>
<td>f</td>
<td>35, 34</td>
<td>35, 35</td>
</tr>
<tr>
<td>h</td>
<td>34, 35</td>
<td>35, 33</td>
</tr>
<tr>
<td>l</td>
<td>34, 35</td>
<td>32, 35</td>
</tr>
</tbody>
</table>

*Note:* Each cell provides two frequencies, one for the elements (letters or symbols) appearing in the left string on a slide, and one for the elements appearing in the right string on a slide.
Table 4  
*Sequential Structure of Sequential-Order Condition.*

<table>
<thead>
<tr>
<th>Block</th>
<th>Sequence</th>
<th>Pattern</th>
<th>Number of Repetitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>N S S E E</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>N N S S S S E E E E</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>N N N S S S S S S S E E E E E E E E</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>N S S E E</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>N N S S S S E E E E</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>N N N S S S S S S S S S E E E E E E E E E</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>N S S E E</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>N N S S S S S S S S E E E E E</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>N N N S S S S S S S S S S S E E E E E E E E E</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>N S S E E</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>N N S S S S S S S S E E E E E</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>N N N S S S S S S S S S S S E E E E E E E E E</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>N S S E E</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>N N S S S S S S S S E E E E</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>N N N S S S S S S S S S S S E E E E E E E E</td>
<td>8</td>
</tr>
</tbody>
</table>

*Note:* N, S and E refer to trial category (No-Match; Shape-Match, Element-Match, respectively). These experiments are organized according to a nonrandom pattern (Sequential Condition). The first sequences always start with one trial of the No-Match category, followed by two trials of the Shape-Match category and trials of the Element-Match category. The number of each trial is increased in the following sequence, maintaining the proportionality between the three types of categories, in which the categories Shape-Match and Element-Match are twice the No-Match category.
**Procedure:** Participants were tested individually in the laboratory. Instruction was identical across all conditions, with the only difference pertaining to the differences in elements (letters vs. tetragons). Tetragons were referred to as ‘symbols’ or ‘characters’. In particular, participants were instructed: “Your task is to compare two letter strings (or two symbol strings). Do they match in a letter (or character), in overall shape, or not at all?” Participants were given a numeric keypad for which the numbers 1, 2 and 3 had been covered with the letters S, N and L (or C), to correspond to the answer categories ‘Shape-Match’, ‘No-Match’, and ‘Element-Match’ (letter or character), respectively.

A brief training followed during which participants were presented with two stimuli at a time. They were shown (e.g., for a pair that matched in shape): “Look at the two strings below. They do not share a letter (or character), but together, they have the same overall shape. So in this case, you have to press S for ‘Same Shape’.” Participants were also told: “Sometimes the shapes will appear in mirror image, like below. But these shape to NOT match. So in this case, you should NOT press S.” They were then presented with nine feedback trials, three of each category of trials. For each trial, the instruction appeared: “Look at the two strings below. Do they match in letter (or character), in shape, or not at all?” Once a response was selected, the participant received feedback on the computer (Yes. Good Job! or No. Let's try again!), and, in the case of incorrect responses, the experimenter explained the error. At the end of the training, the instructions read: “Now you are ready. So the experiment will last about 60 minutes. Make sure to be as quick and precise as possible.”

The experimenter supervised the participant during instruction and training and then left the room for the participant to complete the task. A total of 1,100 trials followed, advancing immediately after the participant pressed a key on the number pad. Participants had to perform correctly in at least 825 trials (75% accuracy) to be included in the final sample.

**2.1.2) Results and Discussion**

Using Matlab® routines, reaction times greater than 10,000 milliseconds and shorter than 300 milliseconds were eliminated. Of the resulting time series, reaction times 3 or more standard deviations above or below the participant’s average were eliminated (cf., Holden, 2005; Holden, Choi, Amazeen, &
Van Orden, 2010). Data were then analyzed in terms of (1) proportion of correct responses, (2) mean and standard deviation of reaction times, and (3) fractal exponent resulting from the spectral analysis of each time series. Each of these results is described in turn.

2.1.2.1) Proportion of Correct Answers.

As depicted in Figure 3, the mean proportion of correct answers was above 87% in all conditions and across all types of trials. The proportion of correct answers were submitted to a 2-by-2-by-3 mixed Analysis of Variance, with familiarity of the element (letters vs. tetragons), and predictability of the next trial (sequential vs. random) as between-subject factors, and trial category (Shape-Match vs. Element-Match vs. No-Match) as the within-subject factor.

Figure 3

![Figure 3](image-url)

**Figure 3.** Means and standard errors of average of the proportion of correct answers for each experimental condition.

A main effect was found for trial category, $F(2, 27) = 21.41, p < .001, \eta^2_p = .61$, with higher proportion of correct performance on Shape-Match trials ($M = .96$) than on Element-Match trials ($M = .90$), Bonferroni adjusted, $p < .001$. No other pairwise comparison was significant, $ps > .16$. The
difference between Shape-Match and Element-Match category was modulated by a significant familiarity by trial category interaction, $F(2, 27) = 5.93, p < .001, \eta^2_p = .31$. In particular, the effect of trial category (difference between Shape-Match and Element-Match category) was more pronounced for unfamiliar stimuli ($M = .96$, vs. $M = .88, F(2, 27) = 24.74, p < .001, \eta^2_p = .65$), than for familiar stimuli ($M = .96$ vs. $M = .93, p > .08$).

Furthermore, there was a marginally significant familiarity by predictability interaction, $F(1, 28) = 3.78, p = .06, \eta^2_p = .12$. When stimuli were presented randomly, the proportion of correct answers was higher with familiar ($M = .96$) than unfamiliar stimuli ($M = .90, F(1, 28) = 5.74, p = .023, \eta^2_p = .17$); whereas there was no differences when the stimuli were presented sequentially ($M = .94$ vs. $M = .95), p > .72$. Additionally, even though the 3-way interactions was not significant, $F < .65, p > .53$, simple effects analyses revealed that the proportion of correct answers was higher on Shape-Match trials with unfamiliar elements, administered sequentially ($M = .99$) than Shape-Match trials with familiar elements administered randomly ($M = .94), F(1, 28) = 4.34, p = .046, \eta^2_p = .13$.

In summary, results on accuracy indicated that participants were more precise on Shape-Match trials than on Element-Match trials. In other words, they were more accurate identifying the match in global configurations than in local aspects, especially with unfamiliar stimuli. In addition, evidence indicated that familiar stimuli were categorized more accurately than unfamiliar stimuli, at least with trials presented randomly. That is, the familiarity of elements improved accuracy overall across trial categories when trials were presented randomly. Finally, sequential presentation was beneficial in terms of accuracy, however only considering Shape-Match trials with familiar stimuli.

2.1.2.2) Mean and Standard Deviation of Reaction Times.

Figures 4 and 5 depict means and standard deviations of reaction times respectively. Two 2-by-2-by-3 mixed Analysis of Variance were conducted, one for average reaction time, and one for the standard deviation of reaction times, with familiarity and predictability as the between-group factors, and trial category as the within-subject factor.
In terms of average reaction time, all three main effects were significant. In particular, there was an effect of trial category, \( F(2, 27) = 66.97, p < .001, \eta^2_p = .83 \), with slowest reaction times for No-Match trials (\( M = 3.9 \) sec.), followed by Element-Match trials (\( M = 2.5 \) sec.), and followed by Shape-match trials (\( M = 2.1 \) sec.), Bonferroni-adjusted ps < .03. There was furthermore an effect of familiarity of stimuli, \( F(1, 28) = 8.22, p = .008, \eta^2_p = .23 \), with longer reaction times for unfamiliar stimuli (\( M = 3.20 \) sec.) than familiar stimuli (\( M = 2.46 \) sec.). Finally, there was a main effect of predictability, \( F(1, 28) = 6.33, p = .018, \eta^2_p = .18 \), with longer reaction times when stimuli were administered randomly (\( M = 3.16 \) sec.) than when stimuli were presented sequentially (\( M = 2.51 \) sec.).

In terms of standard deviation, results show only a significant effect of trial category, \( F(2, 27) = 5.82, p = .008, \eta^2_p = .30 \), with more variability on No-Match trials (\( M = 1.98 \) sec.) than on Element-Match trials (\( M = 1.78 \) sec.), Bonferroni-adjusted, \( p = .01 \). No other pairwise differences turned up significant, \( ps > .16 \); and none of the interactions turned up significant, \( p > .10 \).
Summarizing these findings, although variability in reaction time on Shape-Match and Element-Match trials were almost identical, participants were faster on Shape-Match trials than Element-Match trials. Furthermore, participants were faster with familiar than unfamiliar stimuli, and also they were faster with stimuli presented sequentially than stimuli presented randomly.

2.1.2.3) Spectral Analyses.

A Spectral Analysis (SA) is used here to provide a characterization of the correlational structure of fluctuations in a series of response time measurements. It decomposes a trial series into a set of regular oscillations, component waves with particular frequencies and amplitudes. As such, SA approximates an irregular, empirical time series with a set of idealized, periodic sine and cosine functions. The result of SA, the power spectrum of the signal, includes a set of coefficients that characterize the relative amplitudes of all the wave forms, ordered from lowest to highest frequency. Using the slope of the regression line through the power spectrum, it is possible to determine the value of the scaling exponent...
alpha in $1/f^\alpha$. Response time series usually yield negatively accelerated slopes indicate pink noise. In contrast, slopes that are statistically equivalent to zero suggest white noise (Holden, 2005).

Two Matlab® programs were deployed to estimate the fractal exponent. The first program generates a plot of amplitude (power) against frequency of each sine wave describing a participant’s time series, in log-log coordinates. Accumulative plot can then be generated for each experimental condition to summarize the average amplitude for each of the frequencies across group performance. Such cumulative graphs are shown in Figure 6, separated by experimental condition, reflecting a 127-point power spectrum, and based on a trials series of 1024 reaction times. The second program yields a direct estimation of the exponent, for the complete spectrum or some portion thereof, by selecting some points of 127-point power spectrum. Using this estimation procedure, value close to 0 are classified as White Noise, and values close to 1 (alpha * -1), are classified as Pink Noise.

**Figure 6**

![Figure 6](image)

*Figure 6. Cumulative graphs for four experimental conditions. Top panel shows information about conditions that were exposed to trials of familiar stimuli randomly presented (left), and conditions that were exposed to trials of unfamiliar stimuli randomly presented (right). Bottom panel shows information about experimental conditions that were exposed to trials of familiar stimuli sequentially presented (left), and conditions that were exposed to trials of unfamiliar stimuli sequentially presented (right). In a rectangle is framed in the interference pattern consisting of waves of high amplitude and median frequency.*
For random procedure, regardless familiarity of stimuli, exponents were very close to white noise, ranging between .08 and .13. By contrast, for the sequential procedures, mean exponents were slightly higher, ranging between .28 and .19 respectively.

Looking at Figure 6, note the difference in the general shape of the spectral plots between random and sequential procedure. While the spectral plots of random-procedure conditions show the traditional linear organization of frequency-amplitude points, spectral plots of the sequential-procedure conditions have a very different pattern. This latter spectrum has a series of waves of high amplitude and median frequency (circumscribed with a rectangle), and these frequency-amplitude points do not fall within the typical linear orientation. Analyzing the power spectrum of each participant tested with the sequential procedure, the distinctive feature of spectral plots appeared on frequencies equal or higher than the 15th bin. This interference pattern was isolated by calculating the slopes of the power spectra of the first fifteen points of 127-point power spectrum (11.81 ≈ 12%). The analyses reported below were performed with 12% and 100% of the power spectrum.

Averages of alpha exponents for each experimental condition are shown in Figure 7, estimated across trial categories for each subject. Data on the 100% spectrum were submitted to a 2 (familiarity) by 2 (predictability of the next trial) Analysis of Variance (see Figure 7, top panel). It only revealed a significant effect of mode, \( F(1, 28) = 8.15, p = .008, \eta^2_p = .23 \), with higher alpha values in the sequential presentation mode (\( M = .19 \)) than the random presentation mode (\( M = .09 \)). Complementary, using one-sample \( t \) tests, average alpha values for each experimental condition was compared against White Noise (\( \alpha = 0 \)). Results indicated that all average alpha values were statistically different from White Noise, \( ts (7) \geq 2.39, ps \leq .05 \). When the 2-by-2 ANOVA was repeated with the 12% of power spectrum (see Figure 7, bottom panel), there was only a marginally significant effect of predictability of the next trial, with a higher average exponent in the sequential procedure than the random procedure (\( M = .16 \) vs. \( M = .04 \)), \( F(1, 28) = 2.96, p = .10, \eta^2_p = .10 \). However, unlike the findings with 100% spectrum, one-sample \( t \)-tests
revealed that only one condition yielded an exponent that was significantly different from white noise: sequential presentation of stimuli with unfamiliar elements, \((M = .21), t (7) = 3.22, p = .015\). All other mean differences did not reach significance \(p_s > .12\).

**Figure 7**

*Figure 7.* Means and standard errors of the average of alpha’s exponents for each experimental condition. Top panel shows information averages with 100% of the spectrum, and bottom panel shows the averages with 12% of the spectrum, wavelength of high amplitude and low frequency.
In sum, analysis of the cumulative spectral graphs for each experimental condition only showed differences associated with the predictability of the next trial. The first difference states that sequential procedures generated higher values of fractal exponents than random procedures. The second difference, pointed out that in sequential procedures appears a pattern of interference high amplitude and median frequency. Nevertheless, analysis of variance shown that the only condition that kept its trend, both with the 100% and 12% of the power spectrum, was when unfamiliar stimuli were sequentially presented.

In this experiment, using a improved speed categorization task, it was possible confirm that, regardless of the familiarity of the stimulus and the procedure, Alpha’s values extracted with spectral analysis had an organization that moves away from the White Noise, similar to that obtained by other visual search and discrimination tasks (McIlhagga, 2008). However, none of the experimental conditions in this experiment had coefficients close to $1/f$ noise. Something that McIlhagga’s study has been found.

Even though prior results were indicating that systematically familiar stimuli administered randomly stayed away from white noise (Castillo et al, 2011), in this case the results were in the opposite direction. Because only when unfamiliar stimuli were administered sequentially alpha exponents were different from white noise. According to these facts the hypothesis that anticipated higher alpha values with familiar stimuli was not supported. However, there was partial support for the hypotheses that proposed higher coefficients under a decreased randomness, defined as greater predictability of the next trial in the sequential procedure.

2.2) Experiment 2

Even though the stimuli were created with the goal of matching the salience of global vs. local features, detecting a match in the global configuration turned out to be easier than detecting a match in local features. Taking into account these findings from Experiment 1, it would be informative to simplify the experimental task, asking the participant to make decision only based on one feature (either the global shape or the local element). This was done in Experiment 2. Instead of being given three answer options (Element-Match, Shape-Match or No-Match), participants were given only two answer options ("yes" or "no"), and they had to make a decision either in terms of shape-match or in terms of element match. Eight
experimental conditions were generated using the same two factors of stimuli familiarity (letters vs. tetragons) and predictability (sequential vs. random), plus the new factor of decision type (attention centered on shapes vs. attention centered on elements).

2.2.1) Method

Participants: A total of 64 undergraduate students (22 men and 42 women) were randomly assigned to one of the eight experimental conditions ($n = 8$). Inclusion criteria were that participants were English speakers with no reported history of vision impairments. Ages ranged from 17.8 to 56.3 with a mean of 22.7 and a standard deviation of 6.7 years. Among conditions, no difference was found for gender distribution $\chi^2 (7) = 9.69, p = .21$, but there was a difference in mean age $F (7, 56) = 2.35, p = 0.04$. However, given that age was not a significant contributor to any of the dependent variables, this difference was ignored. An additional six participants were tested but not included in the final sample due to technical error ($n = 2$), or not meeting the accuracy criterion ($n = 4$).

Materials: The stimuli were the same ones used in Experiment 1.

Procedure: Participants were tested individually in the laboratory. Instruction was identical across all conditions, with the only difference pertaining to the differences in stimuli (letters vs. tetragons) and what kind of decision participants had to make (attention centered on shapes vs. attention centered on elements). In particular, participants were instructed during training: “Your task is to compare two letter strings (or two symbols strings).” In the element-decision conditions, participants were asked “Do they match in a letter (or character)?” And in the shape-decision conditions, participants were asked, “Do they match in shape?” Participants were given a numeric keypad in which the numbers 1 and 3 had been covered with the letters Y and N, to correspond to “Yes” and “No” options, respectively. The training phase was identical to training phase of Experiment 1. At the end of the training, experimenter pointed to

---

2 The Pearson’s correlation coefficient was calculated between age and proportion of correct answer, mean and standard deviation of reaction time (separately for Shape-Match, Element-Match, and No-Match trials), and alpha exponents (with 100% and 12% of power spectrum). Results showed that the age variable had an association close to zero with the dependent variables (range of $r_{xy}$ was $\pm .12$, $ps \geq .34$.)
the participant that the same question responded during the training should be answered throughout all experimental trials.

2.2.2) Results and Discussion

Reaction times were submitted to the same analyses as in Experiment 1, and results are presented separated by dependent variable.

2.2.2.1) Proportion of Correct Answers

Figure 8 depicts means and standard errors of the proportion of correct answers for all experimental conditions, separated by decision type (top panel: attention on shapes; bottom panel: attention to element). The proportion of correct answers was over 83% in all experimental conditions. Visual inspection of the plots suggests that the mean proportion of correct answer was over 90% in the shape-decision conditions, independently of the other factors. However, for element decision, Element-Match trials had a lower proportion of correct answers (86%) than Shape-Match trials (98%) and No-Match trials (98%).

The proportion of correct answers was submitted to a 2-by-2-by-2-by-3 Mixed Analysis of Variance, where between-subject factors were the stimuli familiarity (letters vs. tetragons), the predictability of the next trial (sequential vs. random), and the type of decision (attention centered on elements vs. attention centered on shapes). Repeated measures were the three trials categories (Shape-Match vs. Element-Match vs. No-Match).

A main effect was found for trial category, $F(2, 55) = 73.50, p < .001, \eta^2_p = .73$. The proportion of correct answers for No-Match trials ($M = .98$) was higher than for Shape-Match trials ($M = .97$), both of them being higher than for Element-Match trials ($M = .90$), Bonferroni-adjusted $ps < .001$. This effect was modulated by a significant category-by-familiarity interaction, $F(2, 55) = 3.50, p = .037, \eta^2_p = .11$. Specifically the difference between No-Match trials and Shape Match trials was only apparent with familiar stimuli (No-Match: $M = .98$; Shape-Match: $M = .96$; Element-Match: $M = .91$), Bonferroni-adjusted $ps < .001$. By contrast, when were used unfamiliar stimuli, No-Match trials ($M = .98$) and Shape-
Match trials \((M = .98)\) yielded comparable accuracy, \(p > .13\) (while performance lower in Element-Match trials; \(M = .89\)), Bonferroni-adjusted \(ps < .001\).

**Figure 8**

![Figure 8](image.png)

Figure 8. Means and standard errors of average of the proportion of correct answers for each experimental condition. Top panel shows information about decisions centered on shapes, and bottom panel about decisions centered on elements.
Another interaction was detected, namely between trial category and type of decision, $F(2, 55) = 39.43, p < .001, \eta^2_p = .59$. In particular, when participants had to decide on elements (element decision), No-Match trials ($M = .99$) did not differ from Shape-Match trials ($M = .99, p > .99$), but both had a proportion of correct answers significantly higher than trials of Element-Match trials ($M = .86$), Bonferroni-adjusted $p < .001$. On the other hand, when participants had to decide whether trials were just matching in shape configurations (attention centered on shape), trials of No-Match trials ($M = .98$) had a proportion of correct responses significantly greater than trials of Shape-Match trials ($M = .95$), and Element-Match trials ($M = .94$), which in turn did not differ between them, $p > .99$.

A significant interaction was detected among trials category, procedure and competition for attentional resources, $F(2, 55) = 3.96, p = .03, \eta^2_p = .13$. Trials of the Shape-Match trials were found to have a slightly high proportion of correct answers when attention was focused on elements than when attention was focused on shapes. And this pattern was similar in both, sequential procedure ($M = .99$ vs. $M = .95$), $F(1, 56) = 22.62, p < .001, \eta^2_p = .29$; and random procedure ($M = .98$ vs. $M = .95$), $F(1, 56) = 14.12, p < .001, \eta^2_p = .20$. By contrast, trials of the Element-Match category had a marked higher proportion of correct answers when the attention was centered on shapes, than on either, sequential procedure ($M = .84$ vs. $M = .96$), $F(1, 56) = 5.83, p = .019, \eta^2_p = .09$, or random procedure ($M = .87$ vs. $M = .92$), $F(1, 56) = 31.10, p < .001, \eta^2_p = .36$. Finally, for trials of No-Match category, no differences were observed in the proportion of correct answers. In all cases the accuracy was over 98% regardless of the type of procedure and type of competition for attentional resources, $p > .08$.

In general terms, the trend was that trials of Shape-Match category had a greater proportion of correct answers than trials of Element-Match category, either with familiar and unfamiliar stimuli, as well as when participants were focusing attention on elements. However, the most notable result was that when participants were paying attention on global configurations, they demonstrated higher accuracy on trials of the Element-Match category than of the Shape-Match category. On the contrary, when
participants were paying attention on local aspects, they had a higher proportion of correct answers with the trials of the Shape-Match category than Element-Match category.

2.2.2.2) Mean and Standard Deviation of Reaction Times.

Figures 9 and 10 are depicting graphs of means and standard deviations of reaction times, respectively. The means and standard deviations of reaction time were submitted to a 2-by-2-by-2-by-3 Mixed Analysis of Variance, where the principal effects were the familiarity of the stimuli (letters vs. tetragons), the predictability of the next trial associated to the procedure of presentation of stimuli (sequential vs. random), and the competition for attentional resources (attention centered on elements vs. attention centered on shapes). Repeated measures were the three trials categories (Shape-Match vs. Element-Match vs. No-Match categories).

Three main effects were significant statistically. The first one was stimuli familiarity, where participants took less time with familiar stimuli \( (M = 1.61 \text{ sec.}) \) than with unfamiliar stimuli \( (M = 2.14 \text{ sec.}) \), \( F(1, 56) = 18.98, p < .001, \eta^2_p = .25 \). The second one was the type of decision, in which participants who were focusing attention on global shapes \( (M = 1.48 \text{ sec.}) \) took less time than participants that were focusing attention on local elements \( (M = 2.28 \text{ sec.}) \), \( F(1, 56) = 42.87, p < .001, \eta^2_p = .43 \).

The last significant main effect was trial category, \( F(2, 55) = 19.15, p < .001, \eta^2_p = .41 \). Exploring the differences, Participants were found to take less time with Element-Match trials \( (M = 1.71 \text{ sec.}) \), than Shape-Match \( (M = 1.93 \text{ sec.}) \), and No-Match trials \( (M = 1.99 \text{ sec.}) \), Bonferroni-adjusted \( ps < .001 \). However, no differences were found between Shape-Match and No-Match trials were not found differences, \( p > .13 \).

A significant interaction was found between trials category and procedure, \( F(2, 55) = 4.51, p = .015, \eta^2_p = .14 \). In this effect, when stimuli were randomly presented, participants took less time with Element-Match trials \( (M = 1.79 \text{ sec.}) \) than Shape-Match \( (M = 2.09 \text{ sec.}) \) and No-Match trials \( (M = 2.07 \text{ sec.}) \), Bonferroni-adjusted \( ps < .001 \). Nevertheless, when stimuli were sequentially presented, participants took less time with Element-Match \( (M = 1.63 \text{ sec.}) \), and Shape-Match trials \( (M = 1.77 \text{ sec.}) \), than No-
Match trials \((M = 1.91 \text{ sec.})\), Bonferroni-adjusted \(ps < .001\). No differences were found between strings of Shape-Match and Element-Match trials, \(p > .09\).

**Figure 9**

*Means and standard errors of the average of reaction time for each experimental condition. Top panel shows information about decisions centered on shapes, and bottom panel about decisions centered on elements.*
The second interaction effect was between trial category and type of decision, $F(2, 55) = 23.79, \ p < .001, \ \eta^2_p = .46$. It suggests that when the attention was centered on elements, participants took longer in No-Match trials ($M = 2.53$ sec.), followed by trials of Shape-Match trials ($M = 2.35$ sec.), and finally Element-Match trials ($M = 1.95$ sec.), Bonferroni-adjusted $ps < .001$. Nonetheless, when participants were centered on global configurations, significant differences were not detected among the three types of trials, $ps > .43$.

**Figure 10**

*Figure 10.* Means and standard errors of the average of standard deviation of reaction time (sec.) for each experimental condition. Top panel shows information about decisions centered on shapes, and bottom panel about decisions centered on elements.
For standard deviations of reaction times, no significant main effects were observed (Figure 10). However, a significant interaction was observed between stimuli familiarity and type of decision, $F(1, 56) = 4.24, p = .04, \eta^2_p = .07$. With regard to familiar stimuli, similar levels of variability in decision making were found between times when attention was centered on elements ($M = .84$ sec.) and when it was centered on shape ($M = .95$ sec.) were similar, $p = .66$. By contrast, when were used unfamiliar stimuli, the variability of decision when attention was centered on elements ($M = 1.53$ sec.) was significantly greater than variability of decision when attention was centered on shapes ($M = .90$ sec.), $F(1, 56) = 6.11, p = .017, \eta^2_p = .10$.

Another significant interaction was between procedure by type of decision, $F(1, 56) = 4.03, p = .05, \eta^2_p = .07$, indicating that when trials were randomly presented, no significant differences were observed between variability of decisions when attention was centered on elements ($M = 1.08$ sec.) and when decision were centered on shapes ($M = 1.18$), $F(1, 56) = .16, p = .69$. In contrast, when trials were sequentially presented, the variability of decision when attention was centered on elements ($M = 1.29$ sec.) was significantly higher than variability of decision centered on shapes ($M = .67$ sec.), $F(1, 56) = 5.93, p = .018, \eta^2_p = .10$.

In sum, participants were faster identifying familiar stimuli than unfamiliar stimuli, and at the same time they were faster when attention was focused on global configurations than on local aspects. However, a peculiar behavior was observed for reaction times in both its averages and variability. Unlike the results of the first experiment, participants were faster with Element-Match trials than Shape-Match trials. This general trend was maintained when stimuli were presented randomly and when participants were instructed to make decisions focusing attention on local aspects. In terms of variability, when unfamiliar stimuli were used or when stimuli were presented sequentially, the variability was greater with decisions centered on local aspects than decisions focused on global shapes.
2.2.2.3) Spectral Analyses.

As illustrated in Figure 11, the cumulative graphs of 127-point power spectrum, based on 1024 reaction times, for four experimental conditions in which the participant had to make decision focused on elements.

**Figure 11**

*Figure 11. Cumulative graphs for four experimental conditions in which the participant had to make decision focused on elements. Top panel shows information about conditions that were exposed to trials of familiar stimuli randomly presented (left), and experimental conditions that were exposed to trials of unfamiliar stimuli randomly presented (right). Bottom panel shows information about experimental conditions that were exposed to trials of familiar stimuli sequentially presented (left), and experimental conditions that were exposed to trials of unfamiliar stimuli sequentially presented (right). In a rectangle is framed in the interference pattern consisting of waves of high amplitude and median frequency.*

There it is possible to observe that when random procedure was used, with familiar and unfamiliar stimuli (top, left and right panel), exponents were very close to White Noise, ranging between .13 and .15. By contrast, when experiments were conducted with sequential procedure, with familiar and
familiar stimuli (bottom panel, left and right), exponents were slightly higher, fluctuating between .23 and .26 respectively. In addition, only in the sequential procedures was a pattern detected that modifies the linear organization of the trend. A very similar phenomenon that was observed in the first experiment, in which emerged a series of waves of high amplitude and median frequency (circumscribed with a rectangle).

In Figure 12 are plotted the cumulative graphs for four experimental conditions in which the participant had to make decision focused on shapes. Following the previous trend, the two experimental conditions that received the trials in a random way (top panel, left and right), experienced lower alpha values, ranging between .20 and .16. On the other hand, the exponent values of the two conditions that received the sequential procedure were fluctuating between .33 and .21 (bottom panel, left and right). In the two experimental conditions in which sequential procedure was used, an interference pattern appears. Even when if this pattern is compared with the pattern appeared in the first experiment, it looks more attenuated. It is also noteworthy that the alpha exponent of the group that received sequential procedure and familiar-letters stimuli (bottom left panel) appeared with a steeper slope than the other three experimental conditions.

In the same form as in Experiment 1, analyzing the power spectrum of each participant tested with the sequential procedure, the distinctive feature of spectral plots appeared on frequencies equal or higher than the 15th bin. This interference pattern was isolated by calculating the slopes of the power spectra of the first fifteen points of 127-point power spectrum (11.81 ≈ 12%). So thus, the analyses were performed and reported with 12% and 100% of the power spectrum.

Alpha’s exponents estimated for each participant in each experimental condition were submitted to a 2-by-2-by-2 Analysis of Variance, where the familiarity of the stimuli (letters vs. tetragons), and the predictability of the next trial associated to the procedure of presentation of stimuli (sequential vs. random), and the type of decision (centered on elements vs. centered on shapes) were principal effects.

Figure 12
Figure 12. Cumulative graphs for four experimental conditions in which the participant had to make decisions focused on shapes. Top panel shows information about conditions that were exposed to trials of familiar stimuli randomly presented (left), and experimental conditions that were exposed to trials of unfamiliar stimuli randomly presented (right). Bottom panel shows information about experimental conditions that were exposed to trials of familiar stimuli sequentially presented (left), and experimental conditions that were exposed to trials of unfamiliar stimuli sequentially presented (right). Here is not a rectangle because the interference pattern of waves of high amplitude and median frequency does not appear.

For exponents estimated with 100% of the power spectrum (Figure 13, top panel), a significant main effect, where exponents generated under sequential procedure (M = .23) were higher than exponents obtained under random procedure (M = .14), $F(1, 56) = 12.86, p = .001, \eta^2_p = .19$.

A significant marginal interaction was observed among stimuli familiarity, procedure, and type of decision, $F(1, 56) = 3.14, p = .082, \eta^2_p = .05$. When participants received trials of familiar stimuli sequentially presented, and they made decisions centered on global configurations, the exponents were...
significantly higher ($M = .30$) than with unfamiliar stimuli ($M = 0.18$), $F (1, 56) = 5.67, p = .021, \eta^2_p = .09$.

**Figure 13**

![Mean of Scaling Exponent](image)

**Mean of Scaling Exponent**

(100% of Spectrum)

Figure 13. Means and standard errors of the average of alpha’s exponents for each experimental condition. Top panel shows information averages estimated with 100% of the spectrum, and bottom panel shows the averages estimated with 12% of the spectrum that represent wavelength of high amplitude and low frequency.

For exponents estimated with 12% of the power spectrum (Figure 13, bottom panel), a significant main effect found was type of decision. Here participants made decisions by focusing attention on shapes...
(\(M = .31\)). The exponents were significantly higher than exponents of participant were making decisions focusing attention on element (\(M = .12\)), \(F(1, 56) = 7.06, p = .01, \eta^2_p = .11\).

Also, a significant marginal interaction effect was observed between stimuli familiarity, procedure, and type of decision, \(F(1, 56) = 3.26, p = .076, \eta^2_p = .06\). When participants received trials sequentially, and made decisions centered on global configurations, exponents with familiar stimuli (\(M = .61\)) were significantly higher than with unfamiliar stimuli (\(M = .21\)), \(F(1, 56) = 8.06, p = .006, \eta^2_p = .13\).

Summarizing these results, the procedure and the type of decision were factors that independently were modulating the intensity of the alpha’s exponents. As initially hypothesized, sequential procedure facilitated that exponents were away from white noise, but an interference pattern appeared to alter the linear organization of slopes. This interference could be attributable to the recurrent pattern in which the strings were appearing. However, it was not a general phenomenon, because when trials of familiar stimuli were sequentially presented and decisions were focused on shapes configurations, the behavior of alpha exponents also turned away from White Noise and the interference pattern was attenuated.

Finally, even though these two main effects were relevant, the most robust effect was the interaction between type of decision, the familiarity of the stimuli, and the procedure, both with 100% and 12% of the spectrum. Analyzing this effect, it was clear that alpha’s exponents were rose, approaching pink noise (1/\(f\) noise). Especially, when experimental task was implemented with a sequential procedure, the decision was centered on global shapes, and the stimuli were familiar.

2.2.2.4) Effect associated with the competition for attentional resources.

Experiment 1 suggests that, in comparison to Experiment 2 and according to the nature of the task, participants were keeping in mind three categories of responses while they were responding. However, in the second one, although the participants were trained to distinguish the three possible categories of trials, the task was posed so that the participants were attending on a single aspect of each trial. From this clear distinction, it was proposed that in Experiment 1 there was greater competition for attentional resources than in the Experiment 2.
In order to test the hypothesis about the competition for attentional resources, alpha’s exponents from the first and second experiments were analyzed and simultaneously compared. Participants of the first experiment were labeled as a group of higher competition for attentional resources, because they were attending simultaneously to both, global and local aspects. In contrast, participants of the second experiment were classified as a group with less competition for attentional resources. They were attending to one attribute (global aspects or local aspects) when they were classifying trials.

Alpha’s exponents (estimated with 100% and 12% of the spectrum) were submitted to 2-by-2-by-3 Analysis of Variance, in which the main effects were procedure (sequential vs. random), stimuli familiarity (letters vs. tetragons) and competition for attentional resources during the decision (centered on element vs. centered on shape vs. centered on both, elements and shapes).

For exponents estimated with 100% of the spectrum, differences by procedure were detected (Figure 14, top panel). In this case the participants who received trials sequentially obtained alpha’s exponents higher ($M = .21$) than those who received trials randomly ($M = .12$), $F (1, 84) = 20.97, p < .001, \eta^2_p = .20$.

For the exponents estimated with 12% of the power spectrum (Figure 14, bottom panel), two of three main factors were significant statistically: both procedure and competition for attentional resources in the decision. Participants who received trials sequentially ($M = .24$) had exponents significantly higher than who received trials randomly ($M = .11$), $F (1, 84) = 5.75, p = .019, \eta^2_p = .06$. On the other hand, differences were attributable to competition for attentional resources during the decision, $F (1, 84) = 6.45, p = .002, \eta^2_p = .13$. The alpha’s exponent of participants who had to make decision centered on the global aspects ($M = .31$) was significantly higher than participants who had to make decision centered on local aspects ($M = .12$), and centered on both aspects ($M = 0.10$), Boherroni adjusted $ps < 0.01$. However, no significant differences were found between participants who had to make decision centered on local aspects and those whom had to make decision centered on both aspects were no significant differences ($p > .89$).
A complementary finding was a marginally significant interaction among stimulus familiarity, procedure, and competition for attentional resources in the decision, \( F (2, 84) = 2.98, p = .056, \eta^2_p = .07. \)

Exploring this effect, it was found that when stimuli were sequentially administered, and participants had to make decision focusing on the global aspects, exponent value was significantly higher with familiar stimuli (\( M = .61 \)) than with unfamiliar stimuli (\( M = .21 \)), \( F (1, 84) = 9.60, p = .003, \eta^2_p = .10. \)

**Figure 14**

![Figure 14](image)

**Figure 14.** Means and standard errors of the average of alpha’s exponents for each experimental condition, summarizing data from experiments 1 and 2. Top panel shows information averages estimated with 100% of the spectrum, and bottom panel shows the averages estimated with 12% of the spectrum that represent wavelength of high amplitude and low frequency.
In summary, the results show that procedure, defined as the predictability of the next trial, was one of the most important factors. These results confirming that when trials were administered sequentially, exponents were higher than those obtained with random procedure. Additionally, when only the waves of high amplitude and low frequency (12% of the spectrum) were selected, and when decision was centered on global aspects, exponents were higher than decision was centered on local elements and decision was centered on both aspects. Finally, in one experimental condition alpha values were higher systematically. In this condition participants were centered on global shapes, and responded to familiar stimuli (letters) presented sequentially.

III) General Discussion

The objective of this research was to investigate how human beings are coordinating attention to the local elements and global configurations in a perceptual categorization task. It was expected that in the analysis of the reaction times of this task, a long-term correlation would emerge between the trials. It was anticipated if a coordinative process exists, then the process can be described according to a mathematical construct called a fractal (Gilden, 2001; Holden, 2005). Mathematical and natural Fractals have certain properties such as self-similarity and scale invariance (Brown & Liebovitch, 2010; Holden, Van Orden & Turvey, 2009). The processes involved in the perception of local elements and global entities are expressed at different time scales. If these processes have a coordinative process among them, it was hypothesized that process should possess self-similarity and scale invariance.

The hypothesis was formulated by considering previous findings in which a fractal organization has been reported on motor, perceptual and cognitive tasks (Hollis, Kloos, & Van Orden, 2009). These previously mentioned tasks have demonstrated that the variability in such tasks have a fractal organization close to 1/f noise, and that this scaling parameter tends to be ubiquitous and pervasive in the adaptative functioning of humans (Kello, Anderson, Holden, & Van Orden, 2008; Kello & Van Orden, 2009).

In this task, not only was there an expected fractal organization of reaction times, but also that fractals scaling were sensitive to the subject’s characteristics and task’s constraints. Thus, it was
anticipated that fractal organization would be closer to 1/f noise with familiar stimuli, and with a procedure of presentation of trials, it would become possible to predict the category of membership of the next trial (Holden, Choi, Amazeen, & Van Orden, 2011; Wijnants et al., 2009).

On other hand, in terms of the traditional paradigm of stimuli processing, it was expected that this new categorization task increased the competition between local and global elements. Intentionally, stimuli were created to mitigate the nested character of local elements into global configurations (Kimchi et al, 2005). It was assumed that this new stimuli would make more salience of coordination between global and local elements. Also, a more careful and fast performance was predicted with familiar stimuli, and with a procedure in which it became possible to predict the category of membership of the next trial.

In both experiments, the global aspects (shapes configurations) were better identified than the local aspects. Unlike other studies, in which local elements are nested in a global shape forming a hierarchy (e.g., large letters written with small letters), here the global and local aspects were designed in such way that they were not forming a strict hierarchy. In these terms, it was expected to neutralize the shape’s bias, whose effect has shown to be resistant to manipulations of size, alignment, sparcity, and number of elements (Burack, Enns, Iarocci, & Randolph, 2000; Dukette & Stiles, 1996; Enns & Girgus, 1985; Kimchi, 1990, 2005). However, in concordance with these antecedents in the current experiments, the shape’s bias was again observed, despite the hierarchy between local and global aspects was attenuated markedly with the strings of letters and even more with strings of tetragons.

In the first experiment, fractal values of each experimental condition were modest. Analyzing the 100% and 12% of the power spectrum, the fractal parameters were located in a range where they were not completely random (White Noise) and clearly they were not fractal (Pink Noise). The explanation for these modest fractal values was attributed to the cognitive load imposed by the experimental task. Participants should pay attention to three types of categories of tests: shape-match, element-match, and no-match. This type of task was far from the traditional tasks in which there has been found an organization fractal of the performance. These tasks are not only repetitive, but also have a minimum of
difficulty with very few restrictions, and where the primary source of variation is the internal variation generated by the subject's behavior (Kello, et al, 2008).

Concomitantly, an interference pattern was observed in the two sequential procedures (letters and tetragons). This pattern was attributed to the repetitive nature of the trials. Recurrence was imposed by the order of the trials. It was not generated by the behavioral fluctuation of the subject, but rather by the structure of the task. The second experiment was designed as a form to reduce the complexity of the task based on the assumption that one way to simplify the task was to reduce cognitive load. If in Experiment 1, participants had to pay attention to the three categories in this new experimental version, participants had to pay attention to one of the categories. Specifically, if the trials were part of the shape-match or element-match categories.

When the experimental task was simplified, the results were different patterns of performance and fractal organization, compared to the first experiment. For example, the proportion of correct answers and reaction times were associated in different ways between the types of strings, depending on what experiment was performed. In the first experiment, a greater number of correct responses were associated with a decreased reaction time on the trials of the Shape-Match option, compared with trials of Element-Match option. By contrary, in the second experiment, a higher proportion of correct answers on the trials of the Shape-Match option were linked to an increased average of response times. In synthesis, if during Experiment 1 a high level of efficiency was observed, with higher accuracy and faster reaction times, during Experiment 2, greater accuracy was associated with slower reaction times.

What kind of phenomenon or process could explain this difference? Whether in the implementation of the first experiment, a greater competition for attentional resources was predicted because participants had to make a decision considering three options for response. In the second experiment, lower competition for attentional resources was predicted because the participant must make a dichotomous decision about the presence or absence of a single attribute. If the explanation were based on cognitive load associated with attentional resource competition, the second experiment should have obtained a greater proportion of correct answers; or faster reaction times, or both at once. However, the
proportion of correct answers was similar between the two experiments, and contrary to expectations, participants took more time with the strings of the shape-match option in the second experiment. Complementary to this finding, it was also observed that when the instruction was to focus attention on global aspects, the proportion of correct responses decreased slightly in trials of the Shape-Match category, and this proportion increased with the trials of the Element-Match category. And by contrary, when attention was centered on elements of the string, the proportion of correct answers was notoriously lower with trials of Element-Match option than with trials of the Shape-Match option.

Taking into account these results together one can conclude that attentional control was generating a deleterious effect on the ability to identify categories that must be identified. In specific terms, a deleterious effect was more intense for detection of local details than global configuration (Shape’s bias). And paradoxically, in general terms, a deficitary performance identifying categories that had to be attended, and an improved performance identifying categories that had to be neglected. Probably, the simplification of the task, understood as focusing attention on one aspect of string, restricted the degrees of freedom during this categorization task. This restriction on the degree of freedom produced an increasingly voluntarily attentional control, which has been demonstrated to have a differential effect in tasks with low level of difficulty (Kimchi, 2009; Nasr, 2010).

For the analysis of fractal exponents, there were observed similarities and differences between the two experiments that are pointing in the same direction. In both experiments, the predictability of the next trial associated to the procedure presentation of stimulus was one of the most significant effects. It had been established that the introduction of randomness in the procedures into trails produced ‘whitening’ of the signal, making reaction times tend to white noise (Holden, Choi, Amazeen, & Van Orden, 2011). These two experiments were implemented under the opposite assumption. Here, it was assumed that the introduction of cues, such as the recurrence of a given sequence, could reduce the randomness. From this recurrence, participants could learn to anticipate the next trial, facilitating the emergence of a fractal organization. Experimental conditions, following sequential procedure, obtained alpha values that were away from the white noise, compared with conditions following random procedure.
However, when trials were sequentially presented, an emerging interference pattern was detected in the power spectrum. The pattern was constituted by wave of high amplitude and median frequency, which were attributed to the type of sequencing used. This interference, which had been observed in pilot experiments, was identically replicated for the first experiment. But, during the implementation of the second experiment, this pattern was depending on where the attention was oriented on local or global aspects. In this case, the interference pattern was most noticeable in the experimental conditions where participants were focusing attention on local aspects. When the decision was focused on global aspects, the interference pattern decreased. This result was even clearer when familiar stimuli were administered sequentially.

These exponents cannot be fully explained by competition of attentional resources or cognitive load. When participants of the second experiment were paying attention to a single attribute of the string, it was assumed the cognitive load was lower than participants in the first experiment. It seems that the performance was not related to how many aspects the participants were paying attention, but which feature of the string the attention was directed to. In this case, higher alpha exponents were obtained when attention was centered on global configurations. Nonetheless, when the attention was centered only on local elements or when attention was placed on local and global aspects at the same time, both conditions obtained almost the same exponent alpha, close to white noise.

In a lesser extent, stimuli familiarity demonstrated to be a factor modulating both performance and the fractal organization of the response times. With familiar stimuli, it was hypothesized that performance would be more efficient, and fractal exponents were closer to 1/f noise. Assuming the findings of other researchers, where expertise was associated with higher fractal exponents (Wijnants et al, 2009). In the current experiments, it was observed that a better performance and high alpha exponents with familiar than unfamiliar stimuli partially supported the hypothesis stating that expertise is associated with fractal organization of reaction times.

However, stimuli familiarity was interacting with the procedure and with a specific type of decision. Decision focused on the global aspects of the strings. Based on this triple interaction effect, it is
evident that is not enough to affirm that a particular categorization task has a fractal organization in its reaction times. Because according to these results, it is necessary to specify under what conditions fractal organization emerges. In this case, it is possible to posit -answering the research question- that when participants have the knowledge or expertise with the stimulus (letters). The trials are sequentially organized according to a recurrent pattern, in such way that participants can make predictions about the next trial. And the attention is focused on identifying the overall shapes; the fractal exponents emerge closer to $1/f$ noise.

From these results, there are several questions unanswered. One such question is related to the analysis of the behavior of participants focusing their attention to the no-match option. This untested condition potentially has similarities to those found in a visual search task (McIlhagga, 2008). In his experiments, 2,700 random trials were separated between targets absent versus targets present. Then the gaps were filled with an estimation that does not generate White Noise. This author obtained a distribution of power-laws only for target absent condition. Probably, is pertinent to assume that in this perceptual categorization task, the fractal organization will be more intense when global and local aspects are absent.

Another issue to explore in these experiments is related to the characteristics of the distributions (Holden, Van Orden, & Turvey, 2009). In this thesis, there were not any distributions performed for analysis in each of the experimental conditions. However, it is possible to conjecture that doing this type of distributional analysis, a higher proportion of power-law distributions will appear in the group that had highest fractal exponents (Letter-Sequential-Focused on shape) and a higher proportion of log-normal and exponential distributions will appear in the other experimental conditions. Following the guidelines of some authors, the analysis should focus on identifying weak and false power-law distributions. The central idea associated to this additional contrast is that power-law distributions are scales invariant because the shape of the function is the same at every magnitude, and this relation “takes the form $f(x) = Kx^{-\alpha}$, where $K$ is the constant of proportionality and the exponent $\alpha$ characterizes the distribution” (Brown & Liebovitch, 2010, p. 6).
An evident characteristic of power law distributions is that their tails are thicker than log-normal or exponential distributions. This trait makes possible to differentiate power law distributions from log-normal and exponential distributions. Other characteristic of power law distributions is that they plot the size-frequency relation as a straight line on a log-log plot. If the relation is linear, then it is possible to conclude that distribution is approximated by a power law and then the data are fractal (Brown & Liebovitch, 2010; Clauset, Shalizi, & Newman, 2007; Newman, 2005; Perline, 2005).

In synthesis, if we want to state, in a reliable form that there is some specific condition in which this perceptual categorization task has a coordinated process; and that this process is fractal. Then it should be not only detected by spectral analysis, but also it should be detected by a power-law distribution analysis.
IV) References


