A COMPARISON OF FIXATION AND FRACTAL MEASURES OF EYE MOVEMENT WHEN VIEWING PICTURES WITH AFFECTIVE VALENCE

by

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ABSTRACT

The goal of this research was to evaluate fractal statistics as an alternative method of quantifying eye movement when viewing pictures of different affective valence. Eye movement researchers have traditionally used measures of fixations and saccade variability to differentiate viewing patterns across affective picture groups and individual differences that relate to these fixation statistics. Research examining fixation statistics when viewing pleasant and unpleasant pictures has both found and failed to find differences between metrics. Inconsistent findings appear to be driven by the sensitivity of fixation metrics, as well as differing methodologies. Eye tracking with contemporary tracking devices produces voluminous time series data ideal for analytical approaches that quantify patterns occurring on a temporal scale; fractal dimension and lacunarity are two types of fractal statistics that characterize temporal and spatial patterns. Variogram, Madogram, and Hall-Wood estimates of fractal dimensionality, lacunarity slopes, and fixation indices were calculated for time series data generated by individuals viewing sequences of pictures with unpleasant, pleasant, or neutral valence. Nature target pictures were embedded within each picture group to evaluate carry over effects from viewing affective pictures. Fractal statistics were compared to fixation statistics and their ability to differentiate eye movement across picture groups using a series of linear mixed models where fractal statistics and fixation statistics were treated as outcome variables. Fractal

dimensions were unable to differentiate eye movement in pleasant and unpleasant picture groups, displaying a similar pattern to fixation statistics, except for number of fixations, which differed across pleasant and unpleasant picture groups. Fractal dimensions were, however, able to differentiate pleasant/unpleasant pictures when compared to neutral picture groups, also consistent with the pattern observed with fixation statistics. Emotional reactivity, trait anxiety, depression, and state affect were included as random effects to examine the ability of individual differences to predict the outcome and control for factors that have the potential to influence eye movement. Fixation statistics were not predicted by individual differences whereas fractal dimensions were predicted by emotional reactivity, but only for y-axis eye movement. Target pictures were viewed differentially depending on which affective picture group they were presented in; however, differences between unpleasant and pleasant picture groups remained elusive. Eye movement was largely similar across pleasant and unpleasant picture groups whether using fractal or fixation statistics. Lacunarity proved most effective in differentiating eye movement across pictures groups where less negative slopes were associated with the unpleasant picture group. Fractal statistics appear to be equally as useful as fixation statistics for the purpose of differentiating eye movement across affective picture groups. Fractal statistics also appear to be a sensitive measure of individual differences in emotional reactivity. Overall these results support the inclusion and consideration of fractal statistics in the analysis of eye movement.

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CHAPTER 1

INTRODUCTION

Fractal and other nonlinear time series analyses are increasingly being utilized by social and behavioral science researchers to describe patterns, characteristics, and individual differences in psychological research (Lewis, 2005; Thelen & Smith, 1992). The driver behind this trend is a collective belief that quantitative descriptions are only as insightful as the statistical method being calculated to inform them. When measurement of a particular phenomenon generates a fine resolution of data over time, researchers have an opportunity to evaluate and combine statistical methods that can both quantify dynamic processes *and* statistical moments (e.g., Renaud, Décarie, & Bouchard, 2004; Renaud et al., 2009). The overarching theme of this research is how fractal statistics can be a complimentary set of statistical metrics and included in traditional statistical models to yield novel results.

Fractal time series analyses are data hungry and thus limited in their research applications (Liebovitch & Toth, 1989). Studies examining time series dynamics (of which fractal statistics are one approach) tend to be limited to physiological, motor movement, and other domains of research that produce voluminous data over time (Brown & Liebovitch, 2010). Eye movement is an area of psychological research that lends itself to both parametric and fractal analytical approaches (Aks, 2005; Aks, Zelinsky, & Sprott, 2002). Numerous researchers have utilized time series analyses to understand patterns in oculomotor movement (Aks, 2005; Fairbanks & Taylor, 2011; Renaud, Décarie, & Bouchard, 2004; Renaud et al., 2009) and other cognitive-perceptual phenomena (Gilden, Thorton, & Mallon, 1995; Kelso, 1995; Port & Van Gelder, 1995; Pressing, 1999; Ward, 2002).

Fixation statistics of oculomotor movement commonly treat variability in the time series as noise rather than effects of interest (e.g., Maljkovic & Nakayama, 1994) and fixation features are extracted as signal. In contrast, from a time series approach, we begin by asking about how a phenomenon changes over iterations in time; erratic fluctuations become key to understanding the system (Gilden, 1997). Saccades, for example, are typically averaged across movements and yet it has been shown that saccades exhibit temporal and spatial dependence that can be described as 1/f noise (a power density that is inversely proportional to the frequency of the time series; Gilden, 1997; Gilden, Thorton, & Mallon, 1995). Stated clearer, the time series of saccade lengths takes the form a power law function, which suggests long-range relationships across resolutions of the time series (Brockmann & Geisel, 2000).

Aks (2005) examined oculomotor movement in the context of a visual search task and observed a power law relationship between fixations and time. The findings indicated that temporal dynamics of oculomotor movement provide information about fixations across time that was not explained by known mechanisms (i.e., inhibitory tagging processes; Klein, 1988) but rather contingencies existed across fixations themselves.

Commonly used fixation metrics may capture some, but not all, patterns in eye movement. Given that eye movement is controlled by the complex interaction between multiple systems across multiple scales (physical and temporal), researchers are increasingly turning to approaches that describe the dynamics of the time series in an effort to understand patterns in eye movement (Aks, 2005), efficiency in visual search behavior (Fairbanks & Taylor, 2011), and cognitive-affective mechanisms that impact these processes (Lewis, 2005; Scherer, 2009a, 2009b).

Figures 1.1 and 1.2 are examples of x-axis eye movement data for two individuals viewing four different pictures (A, B, C, D). Common fixation metrics (number of fixations, mean saccade length, and mean fixation duration) could be extracted from these time series and provide a limited but meaningful description. The remaining variability in the eye time series would be ignored. Ignoring the remaining features of the time series would not be problematic if the question being asked was where and what a person was looking at. Fractal statistics would alternatively describe the statistical self-affinity of the time series (scale invariance) that arises from long-range autocorrelations and how the time series occupies two-dimensional space. To the extent that a researcher is attempting to differentiate patterns in eye movement based on experimental manipulation of viewing content or individual differences in emotional lability, fractal statistics appear to be a promising complimentary approach.

There remains debate among researchers and methodologists about the value of adopting a fractal time series approach to measuring and quantifying psychological phenomenon (Delignieres et al., 2006). Given data demands, limited evidence as to the experimental value of fractal statistics, and the need to learn a new set of estimation procedures, there is a high bar for making a persuasive argument.

This research has two principle aims: (1) contrast fixation and fractal statistics of eye movement and evaluate their ability to differentiate affective picture groups and target pictures embedded within picture group, and (2) examine individual differences in emotional lability (anxiety, emotional reactivity, and depression) as predictors of fixation and fractal metrics. Eye movement researchers often find differences in fixation statistics when viewing high and low arousal pictures but fail to find differences across high and low valence. This research introduces a novel integration of fractal statistics in quantifying eye movement and attempts to show that valence of affective pictures can be detected with fractal statistics (fractal dimension and lacunarity slope; Smith, Lange, & Marks, 1996).

Eye Movement

Bradley et al. (2011) observed that eye movement patterns changed as a function of intensity of pleasantness/unpleasantness of pictures drawn from the International Affective Picture System (IAPS; Lang & Bradley, 2007). They counterbalanced complexity and valence to separate perceptual characteristics of the picture (i.e., contour, novelty, and brightness) from the affective valence of the picture. They found a main effect of complexity and valance intensity but not a pattern unique to pleasant or unpleasant valence. Eye movement being influenced only by valence level and complexity would suggest that all information differentiation is occurring at the level of higher order cognitive processing and not in the way eyes attend to available information in the field of vision.

Research from the clinical literature has reliably demonstrated the impact that anxiety and depression, either state or trait, has on eye movement. In a modified probe detection task, anxious individuals displayed heightened attentional vigilance (reduced orienting response times and increased fixation duration) to threatening pictures compared to nonanxious individuals (Mogg, Bradley, De Bono, & Painter, 1997; Mogg, Bradley, Miles, & Dixon, 2004). Depressed individuals show increased sensitivity in attending to both sad and angry faces compared to nondepressed individuals, and at a lesser degree of emotive expression to target picture faces (Joorman & Gotlib, 2006; 2007). Further, similar patterns of findings are present in experiments with patients who have arachnophobia (spiders) or ophidiophobia (snakes) (Öhman, Flykt, & Esteves, 2001; Peira, Golkar, Larsson, & Wiens, 2010). Taken in sum, eye movement is influenced by affect and affective processes even in the absence emotionally salient stimuli.

Researchers have recently begun to examine how pictures of different affective quality influence later eye movement. In one such study, Kaspar et al. (2013) examined the affect of affectively salient pictures on eye movement on subsequent viewing behavior of nature pictures. The researchers presented pleasant, unpleasant, and neutral pictures in sequence with nature pictures interspersed throughout, measuring mean fixation duration, mean saccade length, and a measure of entropy (spatial dispersion) for each picture viewed. Approximately 45 pictures were shown in each sequence where pleasant, unpleasant, and neutral pictures were presented in different experimental conditions. Unpleasant pictures were associated with longer fixations, shorter saccades, and reduced entropy when viewing secondarily presented neutral target pictures. These results both support and conflict with the findings of Bradley et al. (2011) which found that eye movements did not change as a function of valence but rather the arousal or complexity of the picture alone. Consistent with Bradley and colleagues (2013), Kaspar et al. (2013) found that positive and negative priming pictures were viewed similarly but also found that target pictures had different fixation statistics across pleasant and unpleasant picture contexts. The changes in eye movement were occurring in the subsequent viewing of neutral pictures. Utilizing a fractal time series approach may reconcile some of these inconsistencies.

Fractals

Fractals are geometric objects that do not conform to Euclidian geometric descriptions (Mandelbrot, 1983). There are different categories of fractal forms: statistical (scaling relationships) and mathematical (precise rules for their construction, e.g., Koch curves). Both can be described as being spatial or temporal physical objects (coastlines compared to heart rate variability). Strange attractors are conceptual fractal objects that live within chaotic dynamical system state spaces and are characterized by a fractional dimension (for a comprehensive review of these topics, see Theiler, 1990). A key feature of fractal patterns is self-similarity across resolutions and changing statistical moments depending on the resolution of the data.

Renaud et al. (2009) illustrated the value of fractal statistics by examining eye movement patterns of male pedophilic sex offenders. They used fixation duration, number of fixations, average saccade length, and the correlation dimension (not emphasized here but a related dimension estimation technique similar to the fractal dimensions described in the following section) to differentiate between eye movement directed at neutral, juvenile, and adult female avatars. Only the estimate of fractal dimension was able to differentiate pedophiles from individuals with age-appropriate sexual attraction (number and duration of fixations and saccade length). Normative sexual profiles were characterized by correlation dimensions near 1.85 for neutral and juvenile avatars and approximately 1.5 for the age appropriate opposite sex avatar. Pedophiles were characterized by lower dimensionality across the three avatar pictures, indicating that the dynamic of eye movement for pedophiles is similar across juvenile and adult viewing (see Figure 1.3).

There are multiple fractal dimension estimation techniques. Gneiting, Ševčíková, and Percival (2012) have written a comprehensive review of the different approaches. The authors describe three categories of estimation: 1) box-counting, 2) variation estimators, and 3) spectral estimators. Upon comparison, some estimation methods are more accurate than others where those with greater precision in identifying the true fractal dimension with less error about the dimension estimate are considered superior. Of the three categories, box counting and variation estimators were most accurate. More specifically, a modified box counting method – the Hall-Wood method – outperformed the traditional box counting method (Hall & Wood, 1993). Of the variation and spectral estimates, the Variogram estimator (Carr & Benzer, 1991) was the most accurate and the Madogram estimator more suitable for statistical assumptions.

For the Hall-Wood estimator, a time series graph is covered in a single box (a rectangular selection of values). At the first iteration, the initial box is divided into four quadrants, or smaller boxes. The second iteration divides each of the four quadrants into four sub-quadrants. The procedure continues until the box size is at the finest resolution of the data. A plot is then generated regressing log $N(\varepsilon)$ on log (ε) with an OLS regression fit line added. $N(\varepsilon)$ represents the number of boxes required at a given resolution to cover the data and (ε) represents the resolution. The slope of the fit line is the estimate of the fractal dimension. The weakness of this approach is that as $(\varepsilon) \rightarrow 0$, information is lost, and yet it is when $(\varepsilon) \rightarrow 0$ that the underlying scaling relationship is most pronounced. Hall and Wood (1993) introduced a modified version of the box-counting estimator that is able to function at the smallest resolution of observation in the time series. The Hall-Wood method avoids the loss of information due to the boxing method described above and does not rely on researcher judgment in determining the box size.

The Variogram dimension is calculated by taking samples of pairs of points (of varying distances) along the time series and calculating the differences between their vertical values. The dimension is taken as the slope of the log-log plot between the expected differences and the observed differences between pairs of points (Klinkenberg, 1994).

Madogram estimates were calculated as well, as there is literature suggesting that Madogram estimates of fractal dimension are more amenable to statistical assumptions (Gneiting, Ševčíková, & Percival, 2012). The Madogram dimension is very similar to the Variogram procedure, however estimated with a power index of one instead of two. All three methods will be calculated for eye movement in this study.

Figure 1.4 shows a simulated example of how fractal dimension estimates might appear in eye movement patterns. The simple line in element A has a dimension of one (consistent with a Euclidean estimate); element B depicts data generated from a Brownian motion process (semirandom) and approaches a dimension of two; element C has a dimension between one and two (1.6). A *fractional* dimension is characteristic of fractal patterns and has been found to be descriptive of many biological (Goldberger & West, 1987) and physical systems (Takayasu, 1982) and, more relevantly, eye movement patterns (Renaud, Décarie, & Bouchard, 2004; Renaud et al., 2009).

The fractal pattern (C.) depicted above could be a bird's eye view of a monkey's foraging behavior (Ramos-Fernandez et al., 2004) or a person's eye movement pattern in a visual search task (Fairbanks & Taylor, 2007). Brownian motion consists of random turns and fixed length steps at each iteration, whereas fractal patterns have unique distributional qualities in the length of a step at a given iteration; in the context of eye movement, there are many short saccades and fewer long-range saccades (Brockmann & Geisel, 2000).

Saccade length probability densities follow a power law function and have been described using Lévy flight mathematical functions (Boccignone & Ferraro, 2004); this pattern of occupying space represents an optimal method for exploring a given location for a goal relevant target. Little is known about how fractal dimensions of eye movement might differ as a function of affective valence of what is being viewed. Is the fractal patterning in eye movement something that is physiologically fixed within a limited range or the does the fractal dimension of eye movement change across functional contexts or constraints, i.e., affective content? Some eye movement patterns may show a similar fractal dimension and yet differ in their specific temporal course or spatial representation; lacunarity is one analytical tool for further differentiating fractal patterns

(Mandelbrot, 1983).

Lacunarity

Fractals can have the same geometric dimension and yet wildly different qualitative features. Mandelbrot (1983) proposed the lacunarity statistic as a measure for differentiating the *texture* or *clumpiness* of fractal patterns. Lacunarity is a measure of the heterogeneity or nonuniformity of a time series or spatial object and has been successfully applied in biological and ecological research to understand phenomena as diverse as extinction events, cell morphology, and dispersion of animals and insects (Plotnick & Sepkoski, 2001; Plotnick et al., 1996; Smith, Lange, & Marks, 1996). The calculation of lacunarity itself does not assume any underlying properties of the time series and thus can be used on any time series or spatial distribution of data. Lacunarity analysis is a relatively simple statistical calculation. A moving box of length *t* is placed at the beginning of the time series and the values that fall within that box are summed and the mean calculated. The box is then slid one time step in the sequence such that it overlaps with the last value in the prior box and the sum is calculated again. This is repeated across all box sizes up to *N/2*. The procedure is performed for the variance at each step as well. The calculation of lacunarity at a given window step is

$$\Lambda(r) = \frac{s^2(r)}{\bar{s}^2(r)} + 1$$

where $s^2(r)$ is the variance of each window and $\bar{s}^2(r)$ is the mean. Lacunarity at each window size is logged and plotted with logged window size. The fitted OLS regression line represents the scaling relationship across resolutions, or the constancy in dispersion across scales. Lacunarity slopes can be used to evaluate variability in lacunarity across time series and individuals. When used in combination with the fractal dimension, lacunarity provides an additional description and differentiation of fractal forms. Figure 1.5a depicts two fractal patterns each with a fractal dimension of 1.67. A dimension estimate alone does not differentiate the two patterns whereas lacunarity does; A. has a mean lacunarity of 1.07 and B. a mean lacunarity of 1.25. Figure 1.5b (reproduced from Plotnick et al., 1996) shows the log-log plot of lacunarity and window size (labeled *box size*) for various time series with known distributional patterns; most noticeably, lacunarity is able to differentiate clustered, fractal, and random dispersions. Currently, there is no easily implemented method for calculating lacunarity for time series, particularly hundreds of time series. A function in R was developed for this study using the R statistical programming language to calculate lacunarity in large batches. This will be a substantive contribution to the psychological literature given the general applicability of the procedure.

The principle aim of this research was to examine how eye movement statistics differ across affective picture groups and neutral pictures embedded in those groups, and whether fractal statistics can add to our understanding of eye movement. Bradley et al. (2011) and Kaspar et al. (2013) found somewhat competing effects when looking at fixation statistics across pleasant and unpleasant pictures, where Kaspar and colleagues utilized a novel target picture approach. This research extends their work. The secondary aim is to compare fixation and fractal statistics in their relationship to individual differences of affective lability. Can fractal statistics capture aspects of between-person affective variability that fixations statistics cannot?

Hypotheses

1. Mean fixation duration, mean number of fixations, and average saccade length were expected to be indistinguishable across pleasant and unpleasant picture groups but differentiate pleasant/unpleasant pictures from neutral. Unpleasant and pleasant picture groups were not expected to differ from each other on these metrics.
2. Average fractal dimension estimates (Variogram, Madogram, & Hall-Wood) were expected to be lower for unpleasant pictures compared to pleasant and neutral picture groups. Fractal estimates were expected to be lowest for the unpleasant picture group and the neutral pictures the highest values, but clearly distinct from the pleasant picture group. This finding would suggest that eye movement when viewing unpleasant and unpleasant pictures can be differentiated with a more sensitive analytical approach.
3. Higher lacunarity slope (less negative) values were expected to be observed in unpleasant picture groups and be progressively steeper across pleasant and neutral.
4. Anxiety and emotional reactivity were expected to be negatively associated with fractal dimensions.
5. Target pictures embedded in affective picture groups were expected to have different fractal dimensions across picture groups, and differ in mean fixation duration, mean number of fixations, or mean saccade length.

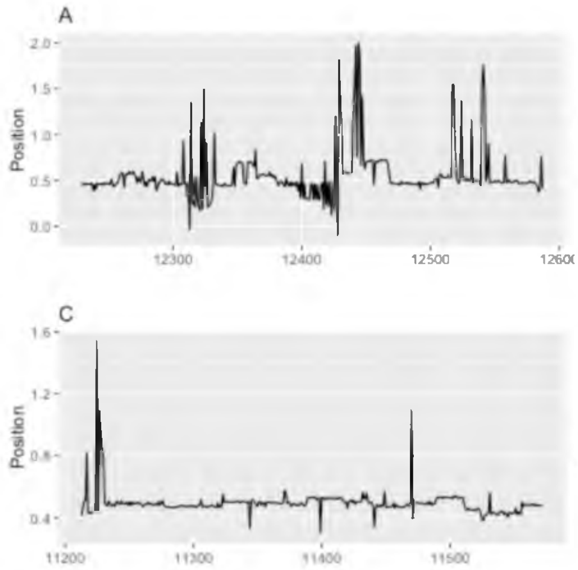


Figure 1.1. X-axis eye movement across different pictures for an individual

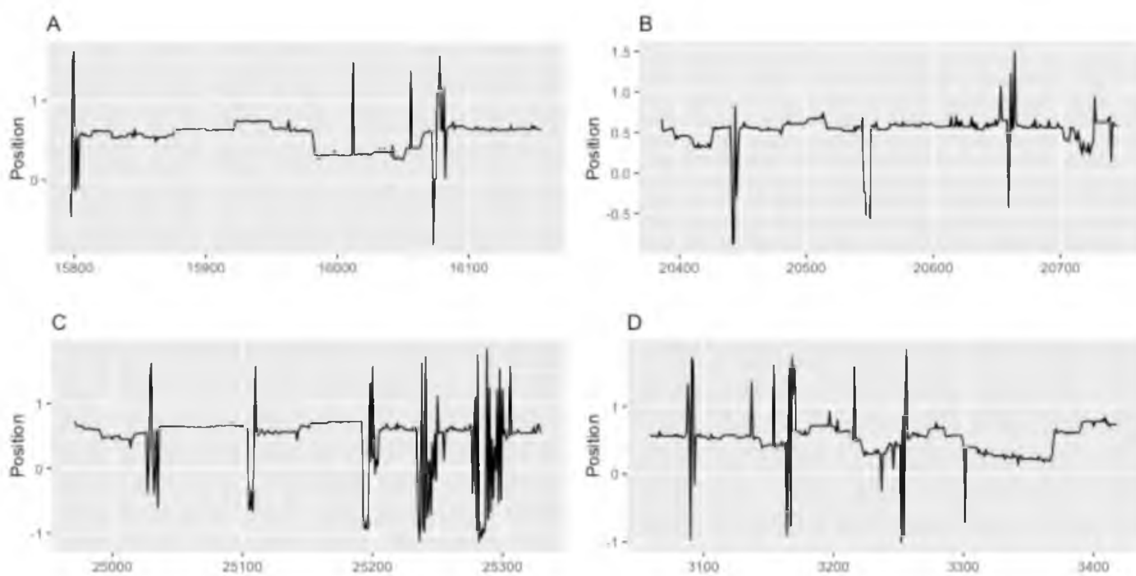


Figure 1.2. X-axis eye movement across different pictures for an individual

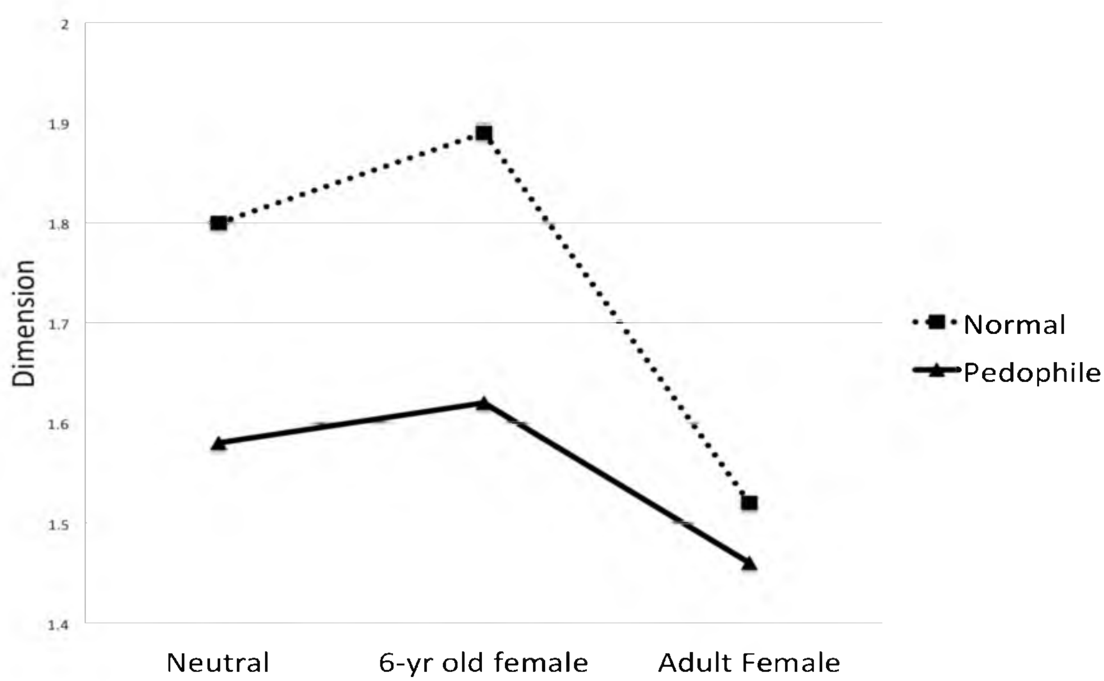


Figure 1.3. Fractal dimensions for pedophile and nonpedophile eye movement

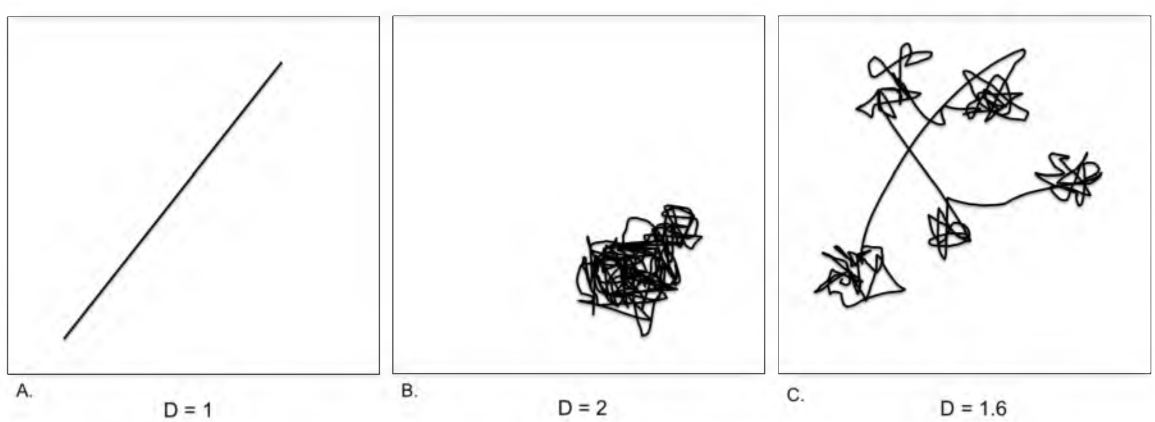
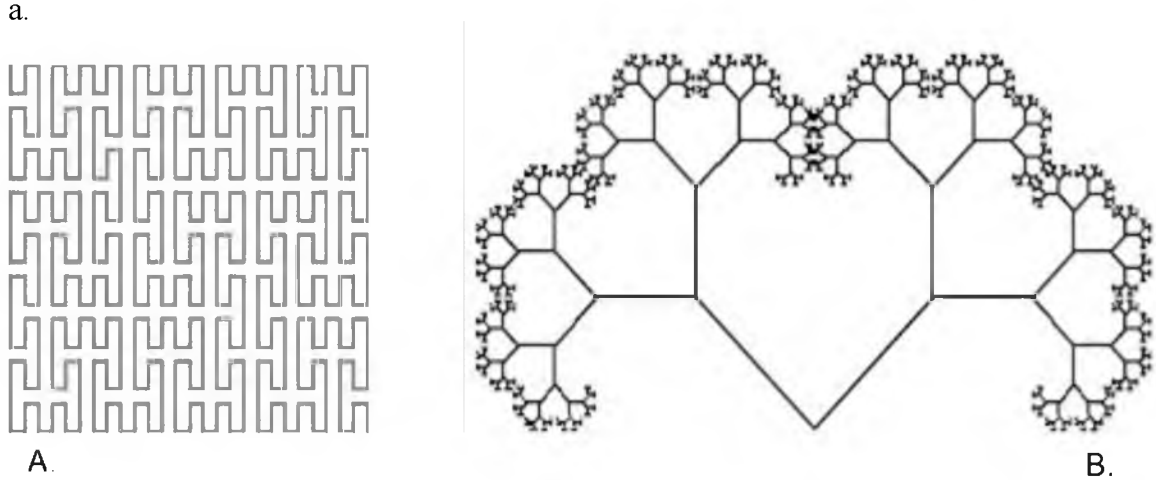


Figure 1.4. Hypothetical fractal dimensions in two-dimensional viewing space

a.



b.

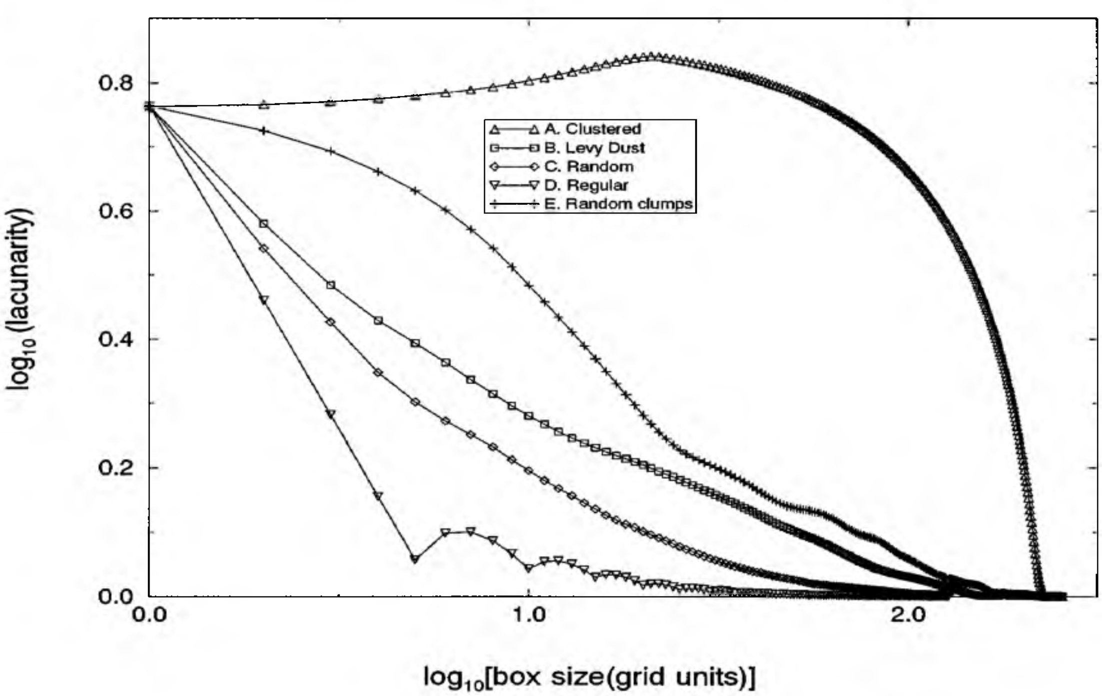


Figure 1.5. Comparing fractal dimensions and lacunarity

a. Fractal A (D=1.67, L=1.07), Fractal B (D=1.67, L=1.25)

b. Lacunarity plots of simulated data to highlight differences in expected slope

CHAPTER 2

METHOD

Participants

Eighty-three participants were recruited from the undergraduate psychology student research pool at the University of Utah. The single exclusion criteria was participants not be dependent on eyeglasses; contact lenses were allowed and addressed in the analyses. Participants were remunerated in the form of participation credits that are used to earn extra credit in courses or to meet course requirements. An alternative procedure was provided if the individual was unable to or uninterested in participating in the study. Participants ranged in age from 18 to 64 years old ($M = 22.5$, $SD = 6.4$) and were predominantly Caucasian (73%; 7.2% African American; 9.6% Asian; and 9.6% who reported another ethnic category), and non-Hispanic (78%).

Apparatus

An Arrington ViewPoint Monocular Eye Tracker® (PC-60) was used to record eye movements of participants' right eye at a rate of 60 Hz. Stimuli were presented and eye movement data compiled using EyeLab software (Webb, A. K., Honts, C. R., Kircher, J. C., Bernhardt, P., Cook, A. E., 2008). Stimuli were presented on a 20" Dell

LCD monitor.

Stimuli

Pleasant (n = 46), unpleasant (n = 46), and neutral pictures (n = 46) were selected from the International Affective Picture System database (IAPS; Lang & Bradley, 2007) and used as stimuli. The number of pictures that could be presented using Eye Lab was limited. Random samples of pleasant, unpleasant, and neutral pictures were selected from those used in Bradley et al. (2011). The pictures used by Kaspar et al. (2013) were not appropriately matched in arousal and appeared biased in the content of the picture descriptions (pleasant pictures consisted primarily of puppies and babies and did not include romantic pictures; unpleasant pictures avoided gory pictures). The use of these pictures has been well validated as an affect induction technique and they are commonly used in eye movement and affect research (Kaspar et al., 2013; Lang & Bradley, 2007). Unpleasant and pleasant pictures were matched in mean and variance of arousal level (unpleasant: arousal, M = 5.65 (SD = 2.19); valance, M = 2.84 (SD = 1.69); pleasant: arousal, M = 4.96 (SD = 2.26), valence, M = 6.98 (SD = 1.67); neutral: arousal, M = 3.27 (SD = 1.99), valence, M = 4.91 (SD = 1.39). Twenty-nine emotionally neutral fractal pictures were also selected from the picture repository at *chaotic n-space network;* http://www.cnspace.net/ and did not have standardized ratings. This provided two types of neutral to compare viewing behavior of pleasant and unpleasant to. Nine nature target pictures were imbedded in the viewing sequence of each of the prior picture categories to evaluate eye movement carry over in picture viewing behavior (arousal, M = 4.41 (SD = 2.40), valence M = 7.13 (SD = 1.52)).

The following is a list of pictures used in the study: Pleasant: 1340, 1500, 1850, 2208, 2304, 2510, 2791, 4608, 4640, 4653, 4666, 4687, 5000, 5030, 5200, 5300, 5480, 5621, 5779, 5890, 5900, 7260, 7270, 7280, 7282, 7284, 7289, 7330, 7350, 7352, 7400, 7470, 7481, 8041, 8080, 8090, 8116, 8162, 8300, 8320, 8380, 8420, 8465, 8502, 8510, 8531; Unpleasant: 1050, 1051, 1280, 1303, 2120, 2590, 2691, 2730, 2800, 3030, 3064, 3168, 3181, 3500, 3550, 5600, 5970, 5971, 6020, 6230, 6250, 6260, 6370, 6821, 6830, 6838, 7380, 9001, 9006, 9010, 9090, 9102, 9180, 9181, 9252, 9290, 9300, 9440, 9470, 9480, 9560, 9561, 9592, 9800, 9921; Neutral: 2200, 2206, 2214, 2221, 2230, 2270, 2280, 2381, 2383, 2410, 2480, 2495, 2514, 2516, 2518, 2570, 2749, 2752, 2830, 2850, 2870, 5120, 5731, 6150, 7010, 7100, 7110, 7140, 7150, 7180, 7190, 7205, 7211, 7224, 7234, 7490, 7500, 7510, 7560, 7590, 7595, 7700, 7705, 7950, 9210; Target pictures: 5210, 5250, 5600, 5700, 5725, 5780, 5814, 5900, 7580.

Procedure

Participants were provided with consent forms before beginning the experimental procedure. They were instructed to read the form thoroughly as the research assistant read it to them before signing it. The research assistant emphasized details of the consent related to their exposure to pictures that they may find disturbing or explicit, and that they could withdraw from the study at any time. An alternative activity of equal remuneration was offered to participants who chose not to continue with the study procedure (this occurred twice). After signing the consent form, participants completed demographic, emotional reactivity, anxiety, and depression surveys using Qualtrics survey administration software. Participants also completed measures of state affect before and after the experimental procedure (PANAS; Watson, Clark, & Tellegen, 1988).

Participants were randomly assigned to conditions that dictated in which order they would view picture sequences based on a predefined condition assignment sheet. Conditions consisted of ACBD, ADBC, BCAD, and BDAC (A – unpleasant, B – pleasant, C – neutral, and D – fractal neutral) where pleasant and unpleasant and categories of neutral pictures were counter balanced. Each condition received the same task introduction that described what the experiment would entail. Because the experimental procedure was automated through Eye Lab, the delivery of stimuli and instructions was identical for each viewing period and participant.

Two computers were arranged side-by-side on a table. The first computer was used for administering the psychometric surveys and the second was equipped with EyeLab and Arrington ViewPoint software, and the Arrington eye tracker. Participants completed demographic and psychometric surveys then moved to the computer equipped with the eye tracker. The eye-tracker was positioned on the head much like a pair of glasses and the infrared sensor adjusted as to place the pupil in position to be measured (indicated by a stable red circle around the pupil). Once fashioned, the eye tracker was calibrated in the ViewPoint software. Calibration consisted of instructing the participant to focus their gaze on a series of green squares appearing and disappearing on a grey background on the monitor. The researcher verified a successful pattern of fixations and repeated the process if the calibration fixations deviated from rectangular. Some participants were not able to achieve a successful calibration due to astigmatisms or an inability to securely position the eye tracker 'glasses' (the loss of participants due to these reasons in addressed in the Data Preparation section). EyeLab was opened and the participant was told to “view the pictures as you would any sequence of pictures and press the spacebar when you are ready to begin.”

The picture presentation sequence consisted of viewing four picture groups (unpleasant, pleasant, neutral, neutral fractal) in the order dictated by the condition they were assigned to. Once the picture presentation sequence began, the participant viewed each picture for 6 seconds followed by 2 seconds of grey screen before the next picture was presented. The process was repeated consecutively through the four picture groups. The target pictures were embedded within each picture group and appeared on average after every fifth picture. Fewer target pictures were embedded in the fractal picture (D) sequence as there were fewer pictures presented in that group overall (due to a limited number of suitable pictures in the repository where they were sourced).

At the end of the picture viewing period, participants removed the eye tracker and were repositioned in front of the survey computer where they completed postexperiment measures of positive and negative affect (PANAS) and a cognitive processing task to evaluate the extent to which they could identify pictures previously seen and pictures that were not in the picture groups. Once complete, the participant was debriefed about the purpose of the study and thanked for their contribution to basic psychological science.

Psychosocial Measures

Individual differences in emotional arousal were measured using the Emotional Reactivity Scale (Melamed, 1994; *M* = 36.95, *SD* = 9.84). The scale consists of 6-items rated on a 1 to 6 scale (1 = very uncharacteristic of me, 2 = very uncharacteristic of me), that measure an individual’s tendency toward heightened arousal to both positive and negative emotionally valanced stimuli (e.g., ''Whenever I think about an unpleasant event that once happened to me I get upset about it all over again'') (α = .60).

Trait anxiety was measured using the Spielberger (1983) State-Trait Anxiety Inventory (*M* = 40.58, *SD* = 10.45). The trait items from Spielberger's Inventory (20 items; Spielberger, 1983) were rated on a 1 to 4 scale (1=almost never, 2=sometimes, 3=often, 4=almost always). Validity and reliability of this widely used scale are well established (α = .88). The measure evaluates an individual's anxious feelings and cognitions at a general level (e.g., "I worry too much over something that really doesn't matter" "I lack self-confidence" "I feel that difficulties are piling up so that I cannot overcome them").

The Beck Depression Inventory (BDI II; Beck et al., 1961) was administered to examine depressive symptoms (*M* = 10.1, *SD* = 8.15). The 21-item inventory includes questions about behaviors, cognitions, and depressive symptoms, such as hopelessness and irritability, and changes in lifestyle (sleep, diet, sex, etc.). The measure has been widely and reliably used to measure depression in both clinical and nonclinical samples (α = .91).

Pre- and postexperiment positive and negative affects were assessed using the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). The PANAS is a 20-item scale that yields two 10-item scales, one for positive affect (α = .90) and one for negative affect (α = .89). The PANAS is widely used and validated as a measure of state affect (positive affect pre, *M* = 28.59, *SD* = 8.04; positive affect post, *M* = 23.19, *SD* = 8.94; negative affect pre, *M* = 15.18, *SD* = 6.92; negative affect post, *M* = 14.35, *SD* = 6.01).

Cognitive processing was examined by having participants view a series of randomly selected pictures from the picture groups (IAPS and fractal) and a series of pictures that were not seen prior. Pictures were presented in random order on a computer screen while the participant rated the pictures as having been seen or not. Participants recognized previously seen pictures with 86.8% accuracy and identified unseen pictures with 98% accuracy.

Analytic Strategy and Data Preparation

Fractal estimates, lacunarity calculations, statistical models, and data manipulation were performed with the statistical programming language R. Fractal dimension estimates were calculated using the fractaldim package. Lacunarity was calculated using a function in R written for this study (Appendix D). Linear mixed models were estimated using the lme4 package.

Three methods for calculating fractal dimensions were used: Variogram, Madogram, and Hallwood. Lacunarity was calculated consistent with Plotnick (1996). These methods are amenable to calculating estimates on single vector time series data and as such, x- and y-axes time series' were analyzed separately (8.6 million unique measurements per time series). Fractal dimensions and lacunarity slopes were calculated for each picture x and y time series. For example, each picture a participant viewed generated six fractal dimensions, and two lacunarity slopes. The slope of lacunarity (a linear fit of the relationship between log(boxsize) and log(lacunarity)) is the metric of analysis most commonly used in lacunarity analyses (Plotnick, 1996; Smith, Lange, & Marks, 1996).

X and y time series were not linearly detrended or lagged before the calculation of lacunarity but rather used in their entirety (consistent with prior applications of the method; Plotnick et al., 1996). In calculating fractal dimension estimates, multiple lags and window sizes were explored. The Mutual Information Criterion (Liebert & Schuster, 1989) was calculated for a random subset of 20 x and y time series. The resulting plots (interpreted much like scree plots) did not show an inflection point at a particular lag but linearly decreased up to the maximum value. Dimension results specifying a lag and window size for the estimate were compared to estimates when the function was allowed to use its default settings. The results indicated no difference and the default settings for the dimension estimates were used.

Fractal dimension and lacunarity calculations were then aggregated within person, within picture group, yielding mean fractal dimensions and lacunarity calculations for each picture group. The lacunarity calculations proved to be particularly expensive computationally and as a result were unable to be calculated on a personal computer. These calculations were performed using Domino Data Lab and a virtual machine hosted by Amazon Web Services that allowed for an R script to be run over days using 32GB of RAM across 15 cores.

Fixation statistics of eye movements were extracted using EyeLab and included a calculation of mean number of fixations, mean fixation duration, and mean saccade length. Areas of Interest were defined as the entire screen (of which the pictures fully filled). Fixations were adjusted in EyeLab to be accurately positioned on the AOIs. The resulting extracted data consisted of feature measurements for each participant viewing each picture across the four picture groups. The data frame consisted of 16364 rows of unique calculations. Values of mean fixation duration, mean number of fixations, and mean saccade length were aggregated across pictures within a condition, within a participant.

Each of these fixation statistics along with the fractal time series statistics were predicted using linear mixed effects models to control for the dependency within-person while being predicted by picture group. Additionally, a series of linear mixed effects models were estimated where the outcomes were predicted by picture condition and individual difference variables and covariates. Finally, models were evaluated where an interaction term was created between lacunarity slopes and picture group and used to predict fractal dimensions (consistent with Mandelbrot's recommendation to simultaneously evaluate the dimension and texture of the temporal-spatial pattern).

Fractal dimensions and lacunarity estimates were not normally distributed (as would be expected given the known power-law distributional characteristics of fractal statistics). As a result, each fractal statistic was transformed using a lognormal transformation (modified to account for negative values in the lacunarity calculations). All transformed and nontransformed fractal statistics failed Shapiro-Wilk normality tests with similar results (W = .82 to .92, for all tests $p < .000$) and yielded similar patterns in model coefficients (see Appendix B for density plots of dependent variables by picture group).

Missing data occurred due to participant astigmatisms, unique contact lenses, or technical issues with the eye tracker or survey software that prevented data collection. As a result, the final number of participants that contributed data to the analyses was 68. Because the data were believed to be missing at random and the individuals who could not provide data were not different from those who did participate (similar demographics and psychosocial profiles) it was not considered a concern for the analyses. Estimation of missing data was not appropriate given the time series approach to the analyses and the inability to account for missing data in EyeLab when features were extracted with that software.

CHAPTER 3

RESULTS

Overview

Fixation measures of occulomotor movement were examined first, followed by fractal statistics (estimates of Variogram, Madogram, and Hall-Wood fractal dimensions, and lacunarity slopes), where each dependent variable was predicted by affective picture group. Before fractal dimensionality and lacunarity can be argued to be valuable statistics for understanding complex patterns in eye movement time series data, it is important to first understand what fixation statistics of eye movement can explain and where they outperform or deviate from fractal statistics. The overarching goal was to evaluate whether the dependent variable could be predicted by affective picture group. Secondarily, individual differences associated with emotional arousal and covariates that may impact eye movement were evaluated in each model. Finally, the set of target pictures that were embedded in each affective picture group were examined in a similar fashion to evaluate if eye movement when viewing target pictures differed as a result of the affective picture sequence that contained them. Correlations between study variables and descriptive statistics are included in Appendix A.

Fixations Statistics and Pictures Groups

Mean fixation duration, mean number of fixations, and mean saccade length were predicted in linear mixed effects models, where the participant identification variable was included as a random effect and picture group was included as a fixed effect. Target pictures were removed so that fixation metrics from affective pictures could be analyzed distinctly. The equation for these models took the following form:

```
Fix_metric ~ as.factor(pic_cond) + (1|studyid)
```

Mean fixation duration was not significantly predicted by picture group. Mean number of fixations did differ by picture group where mean number of fixations was highest for the unpleasant picture group and significantly different from pleasant, neutral, and fractal neutral picture groups.

Eye movement across picture groups was also different for mean saccade length where mean saccade length was longer when viewing unpleasant pictures compared to the two neutral picture groups. No differences were found between unpleasant and pleasant picture groups (Table 3.1).

Individual Tukey contrasts were calculated to compare fixation statistics by picture group using an ANOVA function of the mixed model object. This permitted the comparison of all picture groups. The models took the following form:

```
anova(mod <- lme(fix_metric ~ pic_cond, random=~1 | studyid, method="ML",
data=data))
summary(contrasts <- glht(mod, linfct=mcp(cond="Tukey")))
```

Because the lme procedure above did not permit missing data, the analyses were conducted on the same data set used above but with missing cases removed (n = 272 compared to n = 266). Post hoc contrasts are presented in summary form in Table 3.2.

The contrasts failed to show a difference between unpleasant and pleasant picture groups as reported earlier, suggesting that the finding was dependent on few cases. Mean saccade length was found to be different between pleasant and neutral picture groups; however, the difference between unpleasant and other picture groups appeared to be the primary influence on group differences.

The pattern of differences between picture groups across fixation statistics is presented in Figure 3.1. There is little variability in mean fixation duration across picture groups and a more distinct pattern for mean number of fixations and mean saccade length. Mean number of fixations and mean saccade length were highest for unpleasant pictures and progressively lower across pleasant and neutral pictures with a slight increase for the fractal neutral picture group.

The findings presented above are consistent with prior literature, which shows that when matched on picture arousal level, higher and lower affective valence of pictures is not detectable with fixation statistics. The same analyses were conducted for estimates of fractal dimension and lacunarity slopes.

Fractal Statistics and Picture Groups

Linear mixed effects models were estimated, where Variogram dimension, Madogram dimension, Hall-Wood dimension, and Lacunarity slope were individually predicted by the factorial fixed-effect of picture group (separately for x- and y-axis time series'). Participant identification was included as a random effect. Eight models were estimated. The equation for the linear mixed model took the following general form:

Fract_metric ~ as.factor(pic_cond) + (1|studyid)

Variogram, Madogram, and Hallwood fractal dimensions of x-axis eye movement were significantly predicted by picture group (Table 3.3). Unpleasant pictures had lower average dimensions than neutral and fractal neutral picture groups. The models failed to show differences between pleasant and unpleasant picture groups for x-axis eye movement, consistent with prior literature that failed to find eye movement differences due to picture group valance.

Variogram and Madogram fractal dimensions of y-axis eye movement were significantly predicted by picture group (Table 3.4); however, only differences between unpleasant and fractal neutral picture groups were found. The Hall-Wood dimension was not predicted by picture group. Y-axis fractal dimension estimates were sensitive to differences between unpleasant and neutral fractal picture groups but again unable to differentiate unpleasant and pleasant picture groups.

Individual Tukey contrasts were calculated to compare fixation statistics by picture groups using an ANOVA function of the mixed model object. This permitted the comparison of all picture groups. The models took the following form:

```
anova(mod <- lme(frac_metric ~ pic_cond, random=~1 | studyid, method=“ML”,
data=data))
summary(contrasts <- glht(mod, linfct=mcp(cond=“Tukey”)))
```

The results are presented in summary in Table 3.5. The majority of significant tests were driven by the difference between unpleasant and neutral picture groups, for both x- and y-axis time series. X-axis eye movement time series’ across all dimensions was more sensitive to picture group than y-axis eye movement. Fractal dimension was unable to differentiate eye movement between unpleasant and pleasant picture groups in any comparison.

Examining means of the fractal dimensions for y-axis eye movement across picture groups revealed a similar pattern to that of x-axis data although it was less pronounced (Figure 3.3). Mean dimension was lowest for unpleasant picture groups and progressively higher across pleasant and neutral groups. The Hall-Wood method again was least able to differentiate picture groups; however, there was little variability in fractal dimension for y-axis eye movement overall. Lower fractal dimensions can be interpreted to mean that the pattern of eye movement when viewing unpleasant pictures was constrained or less variable in how the time series' filled dimensional space. This finding is consistent with the increased number of fixations observed for the unpleasant picture group.

Lacunarity slopes were significantly predicted by picture group across x- and y-axis eye movement (Table 3.6). For x-axis eye movement, unpleasant and pleasant picture groups were significantly different from one another as was unpleasant and fractal neutral groups. For y-axis eye movement, lacunarity slope was significantly predicted by the two neutral picture groups and was approaching significance for the unpleasant and pleasant picture group comparison. Lacunarity slopes for the unpleasant picture group were less negative than the other picture groups, indicating that the pattern of eye movement was more restricted in terms of values in the time series as well as showing less scale invariance across window sizes. This pattern of results is consistent with the observation that fractal dimensions were lower for unpleasant pictures than the other picture groups.

Mean lacunarity slopes by picture group are presented in Figure 3.4. The mean slope for the unpleasant picture group is clearly less steep than the other picture groups for x and y axis data. Lacunarity slopes were larger in absolute value for y-axis data but a similar pattern across picture groups was found.

Effect sizes were calculated using an approximation of Cohen's D estimate of effect size (condition difference divided by square root of the variance component from a model without the condition effect) and are reported for all significant comparisons. While the effects are not individually large, the relative comparison of those for lacunarity to the others indicates that lacunarity is not only able to differentiate unpleasant and pleasant picture groups but with fairly robust effect (Table 3.7)

Examining Covariates

Linear mixed models were expanded to include individual difference measures of emotional lability. The equation including covariates took the following general form for all models examining covariates:

Fix_metric ~ as.factor(pic_cond) + emotional_reactivity + depression + anxiety + positive_affect + negative_affect + age + contacts + sex + (1|studyid)

Mean fixation duration, mean number of fixations, and mean saccade length were not predicted by any individual difference variables or covariates. Emotional reactivity, anxiety, and depression were not meaningful predictors of fixation statistics in the context of viewing affective picture groups (see Appendix C for detailed model summaries). Picture group remained predictive of fixation statistics in the same pattern as when picture group was included alone.

Fractal dimensions were each predicted individually by picture group, individual differences, and covariates. Emotional reactivity significantly predicted Variogram, Madogram, and Hall-Wood dimensions for y-axis eye movement ($\beta_{emotional\_reac} = -.005$).

A summary of significant effects is presented in Table 3.8 and model results are reported in Appendix C. Picture group again remained predictive of fractal dimensions in the same pattern as when picture group was included alone.

Fractal dimensions of vertical eye movement appear to be sensitive to emotional reactivity. While analytically more complicated, separating x and y time series' uniquely allowed for an examination of differences across vertical and horizontal eye movement. Higher emotional reactivity was associated with more dimensionally constrained viewing behavior but only along the vertical axis of eye movement.

Lacunarity slopes for x- and y-axes were examined in two linear mixed models where participant identification was included as a random effect, and emotional reactivity, depression, anxiety, age, positive affect, negative affect, sex, and contacts as fixed effects. There were no significant effects predicting x-axis lacunarity slope; however, anxiety approached significance ($\beta_{emotional\_reac} = -.004$, $p = .093$). Similarly, there were no significant effects when predicting lacunarity slope for y-axis (see full results in Appendix C). The unpleasant picture group was still significantly different from the other three picture groups when controlling for individual differences and covariates.

Consistent with Mandelbrot's recommendation that fractal dimension and fractal texture (lacunarity) be used in combination to differentiate fractal forms, linear mixed models were examined where an interaction term between lacunarity slope and picture group was used to predict fractal dimensions. None of the models examining the interaction term were significant. The null findings are not presented here.

Eye movement and Target Pictures

Fixation Statistics

The final question this study attempted to answer was whether target pictures were viewed differently when embedded in affective picture groups. Kaspar and colleagues (2013) found that pleasant and unpleasant pictures were not viewed differently (across fixation statistics) but neutral pictures following pleasant and unpleasant picture sequences were. The following analyses examined how the same set of target pictures was viewed across picture groups. Target picture eye movement was examined using the same modeling framework as the affective picture models.

Mean fixation duration, mean number of fixations, and mean saccade length were individually predicted by picture condition in linear mixed models where participant identification was included as a random effect. Target pictures embedded in the unpleasant picture group were not viewed differently from the pleasant picture group. Significant differences were observed between the unpleasant picture group and the neutral picture group when predicting mean number of fixations and mean saccade length. Mean number of fixations was also different across unpleasant and neutral fractal picture groups. Target pictures in the context of unpleasant pictures were viewed with fewer fixations (Table 3.9). These results fail to support the same effect observed by Kaspar et al. (2013) where both pleasant and unpleasant picture sequences influenced later viewing of target pictures.

The pattern of effects and mean comparisons between pictures groups supports the proposition that number of fixations and mean saccade length are sensitive to the affective valence of the picture group in which the target pictures were viewed (Figure

3.5). While the effect between unpleasant and pleasant picture groups did not rise to the level of interpretation, the neutral picture groups had approximately the same average values whereas unpleasant and pleasant pictures groups showed qualitative difference.

Fractal Statistics

Fractal dimensions for target pictures, across x- and y-axis data, were predicted by picture group in linear mixed models with participant identification included as a random effect. The pattern of findings was similar to that of the fixation statistics. Across x and y time series', target pictures embedded in the unpleasant picture group had a lower fractal dimension than the other picture groups. X-axis fractal dimensions for target pictures in the unpleasant picture group were significantly lower than each of the neutral picture groups (which were quite similar) but not meaningfully different from the pleasant picture group (Table 3.10).

X-axis eye movement when viewing neutral target pictures differed as a function of the affective picture sequence in which they were viewed. Pleasant and unpleasant picture groups appear to be different from neutral pictures but neither affective nor neutral groups were different from each other (Figure 3.6).

Y-axis fractal dimensions for target pictures in the unpleasant picture group were significantly lower than those in the neutral fractal picture group across all dimensions and different from the neutral picture group only when predicting the Hall-Wood dimension (Table 3.11). Across all comparisons, target pictures viewed in the unpleasant picture group had lower fractal dimensions, though not meaningfully different from target pictures in the pleasant picture group (Figure 3.7).

Table 3.1. Fixation statistics predicted by picture group

Average Fixation Duration - Affect Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	0.296	0.007	88.3	40.81	0.000	***
Unpleasant:Pleasant	0.00	0.00	195.1	-0.61	0.540	
Unpleasant:Neutral	0.00	0.00	195.1	1.05	0.290	
Unpleasant:Fractal	0.00	0.00	195.5	0.98	0.330	
Random Effects	***Variance***	***SD***				
Participant	0.003	0.054				
Residual	0.001	0.025				

***p<.001, **p<.01, *p<.05, .P<.10

Average Number of Fixations - Affect Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	11.281	0.527	79.8	21.42	0.000	***
Unpleasant:Pleasant	-0.54	0.25	195	-2.16	0.032	*
Unpleasant:Neutral	-1.12	0.25	195	-4.43	0.000	***
Unpleasant:Fractal	-0.73	0.26	195.3	-2.80	0.006	**
Random Effects	***Variance***	***SD***				
Participant	16.700	4.090				
Residual	2.150	1.470				

***p<.001, **p<.01, *p<.05, .P<.10

Average Saccade Length - Affect Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	5.272	0.197	130.8	26.8	0.000	***
Unpleasant:Pleasant	0.06	0.18	193.9	0.31	0.756	
Unpleasant:Neutral	-0.55	0.18	193.9	-3.04	0.003	**
Unpleasant:Fractal	-0.38	0.19	195.1	-2.06	0.041	*
Random Effects	***Variance***	***SD***				
Participant	1.530	1.240				
Residual	1.110	1.050				

***p<.001, **p<.01, *p<.05, .P<.10

Table 3.2. Fixation statistics – model contrasts between picture groups

Affective Picture Contrasts	Fixation Duration	Number of Fixations	Saccade Length
Unpleasant - Pleasant			
Unpleasant - Neutral		***	*
Unpleasant - Fractal Neutral		*	
Pleasant - Neutral			**
Pleasant - Fractal Neutral			.
Neutral - Fractal Neutral			

***p<.001, **p<.01, *p<.05, .P<.10

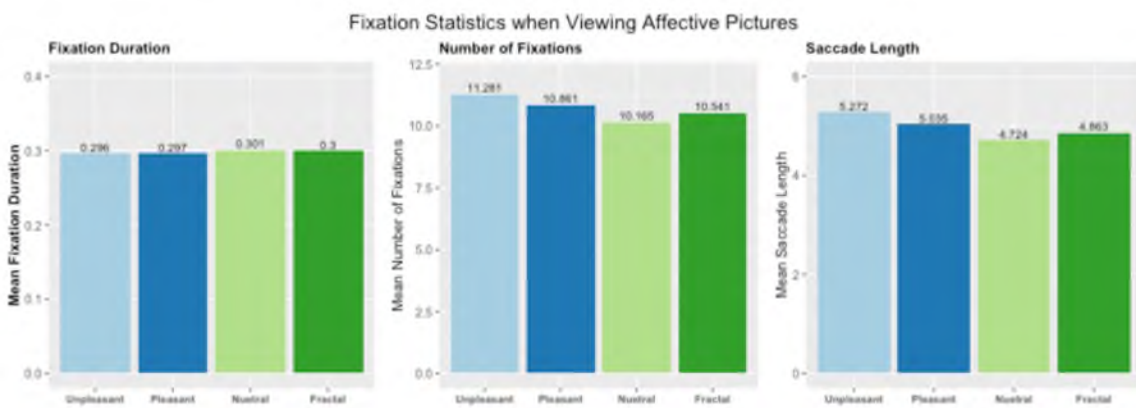


Figure 3.1. Fixation statistic by picture group

Table 3.3. Fractal dimensions predicted by picture group – x-axis

Predicting Variogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.779	0.018	82.2	96.64	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	1.41	0.159	
Unpleasant:Neutral	0.03	0.01	201	3.61	0.000	***
Unpleasant:Fractal	0.03	0.01	201	3.04	0.003	**
Random Effects	***Variance***	***SD***				
Participant	0.020	0.141				
Residual	0.003	0.055				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.727	0.021	78.2	83.79	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	1.14	0.258	
Unpleasant:Neutral	0.04	0.01	201	3.96	0.000	***
Unpleasant:Fractal	0.03	0.01	201	3.18	0.002	**
Random Effects	***Variance***	***SD***				
Participant	0.026	0.161				
Residual	0.003	0.054				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.691	0.018	82.5	96.62	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	0.56	0.577	
Unpleasant:Neutral	0.03	0.01	201	3.06	0.003	**
Unpleasant:Fractal	0.03	0.01	201	3.05	0.003	**
Random Effects	***Variance***	***SD***				
Participant	0.018	0.134				
Residual	0.003	0.053				

***p<.001, **p<.01, *p<.05, .P<.10

Table 3.4. Fractal dimensions predicted by picture group – y-axis

Predicting Variogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.760	0.022	78.6	81.63	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	1.03	0.305	
Unpleasant:Neutral	0.01	0.01	201	1.35	0.180	
Unpleasant:Fractal	0.03	0.01	201	3.48	0.001	***
Random Effects	***Variance***	***SD***				
Participant	0.028	0.168				
Residual	0.003	0.057				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.766	0.020	76.6	90.59	0.000	***
Unpleasant:Pleasant	0.00	0.01	201	0.50	0.614	
Unpleasant:Neutral	0.01	0.01	201	0.72	0.474	
Unpleasant:Fractal	0.02	0.01	201	2.24	0.026	*
Random Effects	***Variance***	***SD***				
Participant	0.024	0.154				
Residual	0.002	0.047				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.729	0.016	81	105.53	0.000	***
Unpleasant:Pleasant	0.00	0.01	201	-0.11	0.920	
Unpleasant:Neutral	0.00	0.01	201	0.26	0.790	
Unpleasant:Fractal	0.01	0.01	201	1.48	0.140	
Random Effects	***Variance***	***SD***				
Participant	0.016	0.127				
Residual	0.002	0.047				

***p<.001, **p<.01, *p<.05, .P<.10

Table 3.5. Fractal dimensions – model contrasts between picture groups

Affective Picture Contrasts	Variogram X	Madogram X	Hall-Wood X	Variogram Y	Madogram Y	Hall-Wood Y
Unpleasant - Pleasant						
Unpleasant - Neutral	**	***	*			
Unpleasant - Fractal Neutral	*	**	*	***		
Pleasant - Neutral		*	.			
Pleasant - Fractal Neutral			.	.		
Neutral - Fractal Neutral						

***p<.001, **p<.01, *p<.05, .P<.10

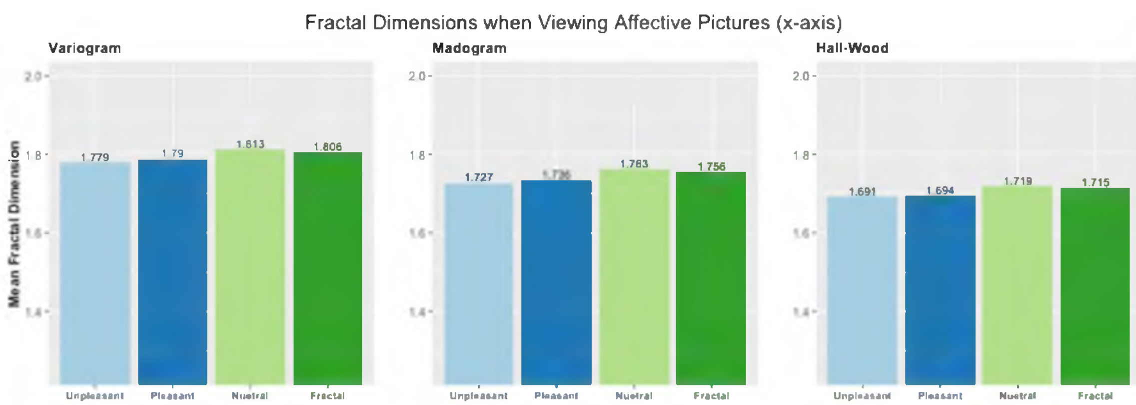


Figure 3.2. Fractal dimensions by picture group – x-axis

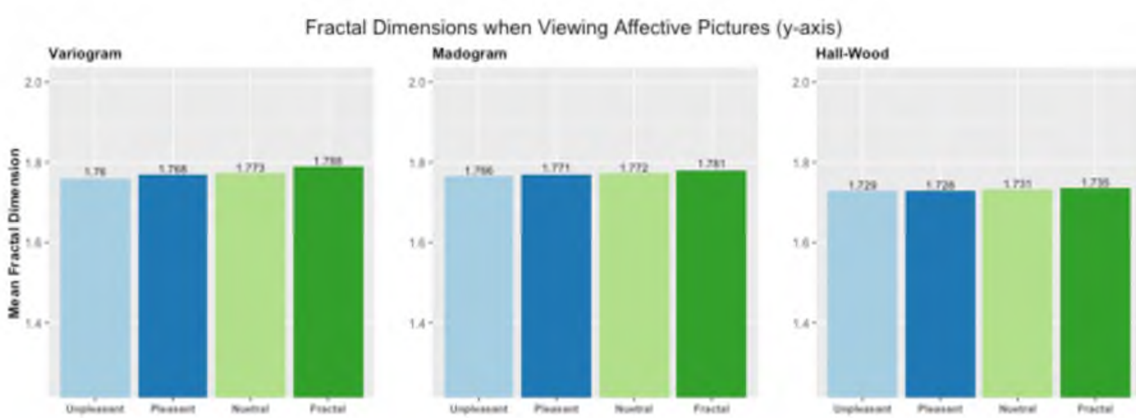


Figure 3.3. Fractal dimensions by picture group – y-axis

Table 3.6. Lacunarity predicted by picture group – x- and y-axis

Average Lacunarity Slope X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	-0.059	0.013	93.7	-4.52	0.000	***
Unpleasant:Pleasant	-0.03	0.01	201	-3.14	0.002	**
Unpleasant:Neutral	-0.01	0.01	201	-1.63	0.104	
Unpleasant:Fractal	-0.02	0.01	201	-2.61	0.010	**
Random Effects	***Variance***	***SD***				
Participant	0.009	0.095				
Residual	0.002	0.049				

***p<.001, **p<.01, *p<.05, .P<.10

Average Lacunarity Slope Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	-0.144	0.020	110	-7.28	0.000	***
Unpleasant:Pleasant	-0.03	0.02	201	-1.74	0.084	.
Unpleasant:Neutral	-0.04	0.02	201	-2.29	0.023	*
Unpleasant:Fractal	-0.04	0.02	201	-2.26	0.025	*
Random Effects	***Variance***	***SD***				
Participant	0.018	0.136				
Residual	0.008	0.091				

***p<.001, **p<.01, *p<.05, .P<.10

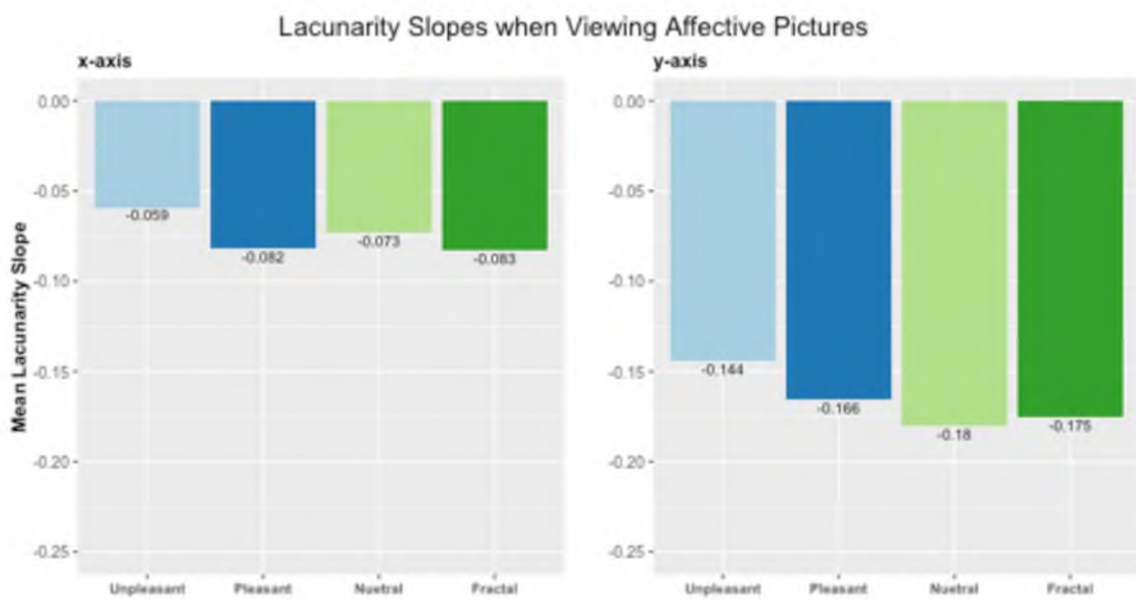


Figure 3.4. Lacunarity by picture group – x- and y-axis

Table 3.7. Cohen's D for significant picture contrasts

Group Comparison	Fixation Duration	Number of Fixations	Mean Saccade	Variogram - X	Madogram - X	Hall-Wood - X	Variogram - Y	Madogram - Y	Hall-Wood - Y	Lacunarity Slope - X	Lacunarity Slope - Y
Unpleasant - Pleasant		0.13								0.32	0.22
Unpleasant - Neutral		0.27	0.45	0.21	0.25	0.23					0.29
Unpleasant - Fractal Neutral		0.18	0.31	0.21	0.19	0.23	0.21	0.13		0.21	0.29
Pleasant - Neutral											
Pleasant - Fractal Neutral											
Neutral - Fractal Neutral											

Table 3.8. Significant individual difference predictors of fractal dimensions

Model Group	**Pictures**	**Time Series**	**Model**	Emotional Reactivty	Depression	Anxiety	Age	Positive Affect	Negative Affect	Contacts	Sex
Fractal	Affect	x-axis	Variogram								
			Madogram								
			Hall-Wood								
	Affect	y-axis	Variogram	*							
			Madogram	*							
			Hall-Wood	*							

***p<.001, **p<.01, *p<.05, .P<.10

Table 3.9. Fixation statistics for target pictures predicted by picture group

Average Fixation Duration - Target Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	0.307	0.009	109.8	34.83	0.000	***
Unpleasant:Pleasant	-0.01	0.01	192.7	-0.88	0.380	
Unpleasant:Neutral	0.00	0.01	192.6	-0.15	0.880	
Unpleasant:Fractal	-0.01	0.01	193.4	-1.01	0.310	
Random Effects	***Variance***	***SD***				
Participant	0.004	0.060				
Residual	0.002	0.040				

***p<.001, **p<.01, *p<.05, .P<.10

Average Number of Fixations - Target Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	10.508	0.557	91.9	18.85	0.000	***
Unpleasant:Pleasant	-0.55	0.36	193	-1.55	0.122	
Unpleasant:Neutral	-0.91	0.35	193	-2.56	0.011	*
Unpleasant:Fractal	-0.79	0.37	193.4	-2.16	0.032	*
Random Effects	***Variance***	***SD***				
Participant	16.830	4.100				
Residual	4.210	2.050				

***p<.001, **p<.01, *p<.05, .P<.10

Average Saccade Length - Target Pictures						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	5.185	0.257	193.5	20.15	0.000	***
Unpleasant:Pleasant	-0.36	0.30	189.8	-1.21	0.229	
Unpleasant:Neutral	-0.68	0.30	189.5	-2.31	0.022	*
Unpleasant:Fractal	-0.13	0.30	191.7	-0.43	0.668	
Random Effects	***Variance***	***SD***				
Participant	1.500	1.230				
Residual	2.950	1.720				

***p<.001, **p<.01, *p<.05, .P<.10

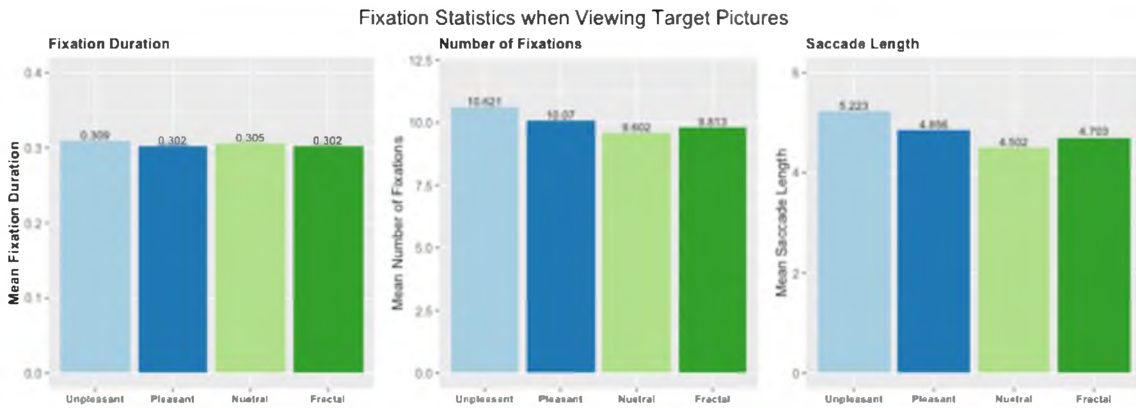


Figure 3.5. Fixation statistics for target pictures across picture groups

Table 3.10. Fractal dimensions for target pictures predicted by picture group – x-axis

Predicting Variogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.779	0.020	96.5	90.49	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	0.60	0.550	
Unpleasant:Neutral	0.03	0.01	201	2.61	0.010	*
Unpleasant:Fractal	0.03	0.01	201	2.20	0.029	*
Random Effects	***Variance***	***SD***				
Participant	0.020	0.142				
Residual	0.006	0.078				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.730	0.022	89.2	79.33	0.000	***
Unpleasant:Pleasant	0.00	0.01	201	-0.19	0.852	
Unpleasant:Neutral	0.03	0.01	201	2.14	0.033	*
Unpleasant:Fractal	0.04	0.01	201	2.92	0.004	**
Random Effects	***Variance***	***SD***				
Participant	0.026	0.163				
Residual	0.006	0.077				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.683	0.019	116.3	86.68	0.000	***
Unpleasant:Pleasant	0.01	0.02	201	0.85	0.394	
Unpleasant:Neutral	0.04	0.02	201	2.62	0.009	**
Unpleasant:Fractal	0.05	0.02	201	2.90	0.004	**
Random Effects	***Variance***	***SD***				
Participant	0.017	0.130				
Residual	0.009	0.094				

***p<.001, **p<.01, *p<.05, .P<.10

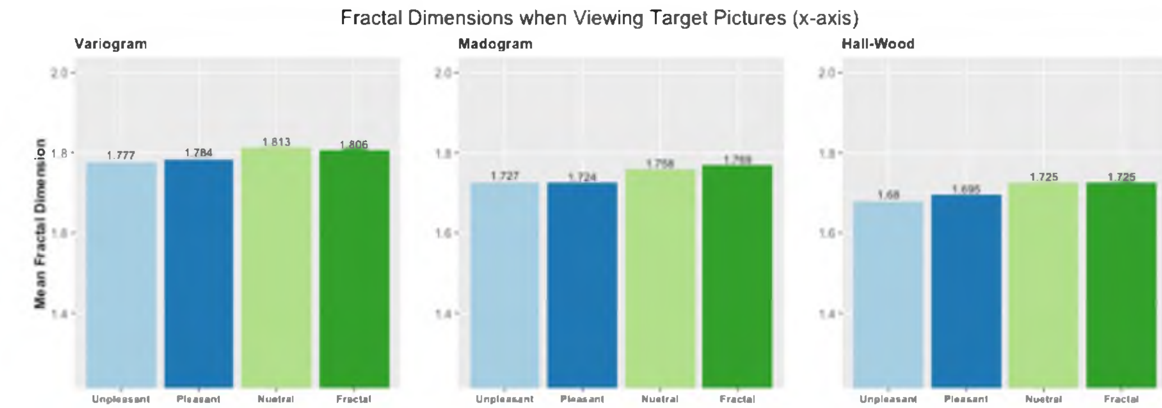


Figure 3.6. Fractal dimensions for target pictures across picture groups – x-axis

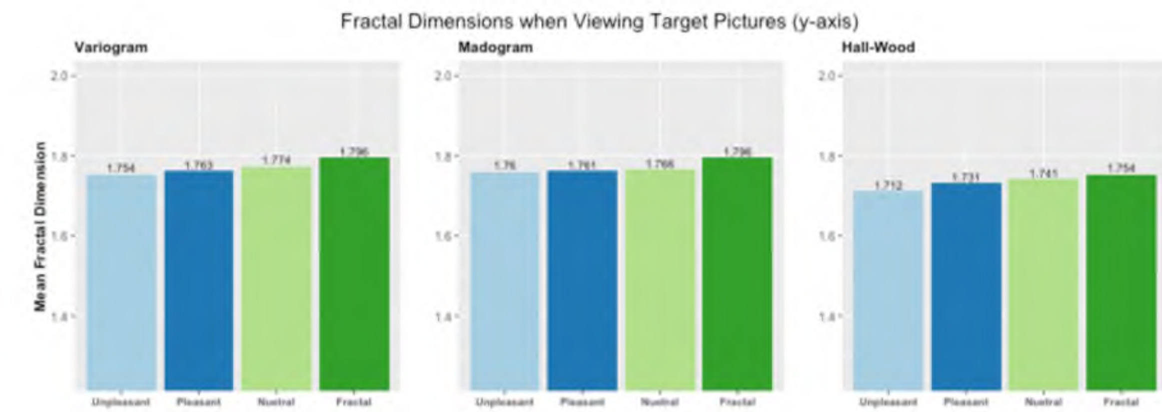


Figure 3.7. Fractal dimensions for target pictures across picture groups – y-axis

Table 3.11. Fractal dimensions for target pictures predicted by picture group – y-axis

Predicting Variogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.753	0.022	82.4	80.11	0.000	***
Unpleasant:Pleasant	0.01	0.01	201	1.09	0.278	
Unpleasant:Neutral	0.02	0.01	201	1.81	0.071	.
Unpleasant:Fractal	0.05	0.01	201	4.45	0.000	***
Random Effects	***Variance***	***SD***				
Participant	0.028	0.168				
Residual	0.004	0.066				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.761	0.020	81.3	87.38	0.000	***
Unpleasant:Pleasant	0.00	0.01	201	0.34	0.731	
Unpleasant:Neutral	0.01	0.01	201	0.54	0.591	
Unpleasant:Fractal	0.04	0.01	201	3.71	0.000	***
Random Effects	***Variance***	***SD***				
Participant	0.024	0.156				
Residual	0.003	0.059				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	1.714	0.018	101.5	98.13	0.000	***
Unpleasant:Pleasant	0.02	0.01	201	1.61	0.109	
Unpleasant:Neutral	0.03	0.01	201	2.19	0.030	*
Unpleasant:Fractal	0.04	0.01	201	3.55	0.000	***
Random Effects	***Variance***	***SD***				
Participant	0.015	0.124				
Residual	0.005	0.074				

***p<.001, **p<.01, *p<.05, .P<.10

CHAPTER 4

DISCUSSION

The primary goal of this study was to compare fractal statistics to fixation statistics of eye movement across affective picture groups and attempt to show that fractal statistics can detect differences between eye movement in unpleasant and pleasant picture groups in a way that fixation statistics cannot. This expectation was born out for lacunarity only; however, fractal dimensions proved to be sensitive to emotional lability individual differences.

Prior research failed to find differences between mean fixation duration and mean saccade length across pleasant and unpleasant picture groups (Bradley et al., 2011; Kaspar et al., 2013). The findings presented here are consistent with that. Mean number of fixations, however, was different across picture groups. Interestingly, this is not a statistic that was reported by Kaspar et al. (2013). Bradley et al. (2011) failed to find differences in mean number of fixations across pleasant and unpleasant picture groups; however, differences were found in this study. Bradley and colleagues (2011) trimmed the data by 225ms prior to beginning their calculation of fixation parameters. It is possible that their method of data preparation contributed to the failure to find an effect in their study and an ability to find the effect in this study. Their rationale was that fixations increase in occurrence after the 225ms point. Mean number of fixations appears to hold promise for differentiating picture groups when eye movement data are used in their entirety.

Fractal dimensions were able to differentiate eye movement across picture groups with approximately the same efficacy as fixation statistics. Dimensions derived from x-axis eye movement were sensitive to differences between picture groups. Unpleasant and pleasant picture groups were consistently different from the two neutral picture groups (although the precise pattern varied depending on the dimension). Fractal dimensions for pleasant and unpleasant picture groups were not found to be different from each other in any analysis. There are a few reasons why this might be the case. It is possible that there is not a difference between eye movement when viewing pleasant and unpleasant picture groups; however, the lacunarity finding contests this. Analyzing x- and y-axis eye movement separately may take away from how they would be able to describe eye movement together in Cartesian space. Box-counting methods for two-dimensional data are potential solutions but computationally more complicated than fractal estimates for one-dimension time series data.

While lacunarity slope for x- and y-axis eye movement was not predicted by any individual difference variables, lacunarity for x-axis time series' was able to clearly differentiate eye movement between pleasant and unpleasant picture groups. This suggests that horizontal eye movement displays differential heterogeneity in dispersion across resolutions of the time series dependent on the picture group being viewed. Less negative slopes were found for the unpleasant group when compared to pleasant and neutral picture groups. A less negative slope can be interpreted to mean that there is less scale-invariance in lacunarity or less systematic clumping of values across resolutions. A time series of constant values would yield a lacunarity value of 0 and value of -1.0 would indicate homogeneity of dispersion across window sizes. This is consistent with the interpretation of different fractal dimensions where unpleasant pictures were viewed with greater eye movement rigidity than other picture groups.

Emotional reactivity consistently predicted fractal dimensions for y-axis eye movement, where higher emotional reactivity was associated with lower fractal dimensions. Correlations between study variables showed a negative relationship between fractal dimension and negative affect-related individual difference variables. While the raw magnitude of difference was small, having a trait-level tendency toward emotional arousal was associated with more random-like eye movements in a more constrained dimensional space. This finding is consistent with research in clinical samples showing rigidity in eye movements of individuals high in anxiety and blood-injury fear (Mogg & Bradley, 2005; Mogg, Bradley, Miles, & Dixon, 2004).

Mogg and colleagues (2004) investigated attentional bias and anxiety when viewing threat scenes in an attempt to test what they describe as the *vigilance-avoidance hypothesis* (initial vigilance for high threat information followed by avoidance of the threat information). Interestingly, and consistent with the findings presented here, Mogg and colleagues (2004) found no impact of anxiety on eye movement over the entire duration of stimulus presentation but did observe an effect of anxiety on initial orientation to threatening pictures. This finding may explain the absence of an effect of anxiety, as the analyses presented in this research spanned the entire viewing period. Secondarily, their research showed that individuals with high blood-injury fear engaged in avoidance strategies, such that reaction times to probes following threat pictures were longer than reaction times following nonthreat pictures. Blood-injury fear was not measured in this study but should be considered as a covariate in future work.

The depression (Beck, 1961) and anxiety (Spielberger, 1983) measures used in this study are inherently self reflective (e.g., “I feel nervous” or “I am sad all of the time”), and thus impact of these constructs should be most pronounced in contexts salient to the self. Had the image content been self-relevant, these variables may have been more predictive of eye movement. The construct of emotional reactivity is capturing the extent to which pleasant and unpleasant emotional states persist over time, which is what would have had to have been occurring for eye movement patterns to be found to be different across individuals (as the eye movement time series were not broken into smaller time segments). Emotional reactivity predicted fractal dimensions beyond picture group, indicating that regardless of picture content, individuals high in emotional reactivity were viewing pictures in a more constrained fashion.

While emotional reactivity is a distinct construct and effects were not found for anxiety or depression in this study, lower fractal dimensions for individuals high in emotional reactivity are consistent with the pattern observed by Mogg and colleagues (1997; 2004), particularly for those with blood-injury fear. Lower fractal dimensions appear to be associated with pattern of reduced orienting time and increased fixation duration. Interestingly, fixation statistics were not associated with measures of emotional arousability.

The goal in examining target pictures embedded in each group was to replicate Kaspar et al., (2013) and show that neutral target pictures are viewed differently when couched in a sequence of pleasant or unpleasant pictures. Fixation statistics were not different for target pictures across affective picture group. All three fractal dimensions were significantly predicted by picture group; however, none of the contrasts revealed a difference between target pictures in the pleasant and unpleasant picture groups. As mentioned in the methods section, Kaspar et al. (2013) did not equate pleasant and unpleasant pictures on arousal level. Secondarily, their choice of pictures seemed biased in that pleasant pictures primarily included babies and puppies and unpleasant pictures uniquely focused on figure/ground unpleasant pictures of people.

All fractal dimension estimates were highly correlated with each other and with fixation measures. The strong negative correlation between fractal dimensions and fixation metrics was somewhat surprising, and indicated that while fractal statistics proved to be more sensitive across analyses, they nonetheless have a strong relationship with fixation metrics. Across all analyses, vertical eye movement was a better differentiator of picture groups. Vertical (y) measures of eye movement could have been taking place at any value of x and yet fractal dimension of vertical eye movement was consistently predicted by emotional reactivity. This may have something to do with the scan patterns of individuals with high emotional reactivity such that they are seeking information in the visual field high and low in addition to left and right. Further analysis is required to understand the nature of the importance of vertical eye movement for detecting differences across picture groups. There may be neurological mechanisms related to arousal that also influence oculomotor muscle systems; however, research has failed to find such an effect (Lang et al., 1998).

This research suggest that both fractal and fixation statistics are valuable descriptors of eye movement and yet have different sensitivities. Specifically, fractal dimensions and fixation statistics showed a similar pattern of differentiating picture groups but fractal dimensions were able to detect differences in emotional reactivity. The correlation between all fractal dimensions, fixation duration, and number of fixations ranged from -.53 to -.66. If fractal dimension are an approximation for eye movement rigidity, high rigidity was associated with increased number of fixations and fixation duration. The relationship makes sense when thinking about how fixations and fixation duration are calculated. Measuring eye movement at 60hz means we have an x and y data point every 60th of a second. When those data points remain in proximity to each other over some duration, they are considered a fixation. They are essentially measures of clumps of values and the duration that a clump of values persists. Fractal dimensions are calculated similarly but with differences, where a statistic is calculated for different sized windows of the time series without a priori expectations as to what defines clusters in the data. By doing this across resolutions, or increasingly small window sizes of the time series, clusters of values are detected when the window size becomes sufficiently small. The key difference is that the final dimension is the slope of the relationship of the statistic and the window size from which it was derived. This method captures both clumpiness in the data and how the clumps scale across resolutions of the time series while the order of the time series is preserved.

The temporal and scaling qualities of fractal dimensions may be necessary for differentiating individual differences in emotional arousability given the relationship found between emotional reactivity and fractal dimension. Individuals high in emotional reactivity were expected to view affective pictures in a more rigid fashion. This was not apparent in the fixation statistics, but when examining how eye movement was scaled across resolutions of the data in time, a relationship emerged. Emotionally reactive individuals may be viewing pictures in a limited region of the area of interest. Lower fractal dimensions imply a more tightly wound region of eye movement, as if the individual attends to affectively salient content in the picture then hovers in the general area, or is less exploratory. This finding is at least conceptually similar to the cognitive quickness and stickiness of affect associated with emotionally reactive individuals. Given the number of analyses conducted in this study, it cannot be said with certainty that the finding is not spurious. Given the promising pattern of findings, this research should be replicated and extended.

Lacunarity was not sensitive to differences in emotional arousal individual differences but was able to uniquely differentiate pleasant and unpleasant picture groups with a robustness that fractal dimensions and fixation statistics could not. Promisingly, the lacunarity statistic is the most intuitive calculation presented here. Lacunarity was not correlated with fractal dimensions or fixation statistics, suggesting that it is describing unique characteristics of eye movement. This is interesting as lacunarity, much like the fractal dimension calculation, preserves the temporal structure of the time series and examines the scaling of the mean and variance across resolutions of the data. Because lower lacunarity slopes represent more constant values in eye movement (lower lacunarity slopes for unpleasant pictures), the time series may be capturing how x-axis eye movement is more constant when there is greater eye movement only along the y-axis. Alternatively, unpleasant pictures could have prompted individuals to overly fixate on the picture or to look away and fixate. The lack of differences observed in number of fixations and fixation duration would indicate that if this is occurring, it is happening in a restricted viewing space. Unpleasant pictures were associated with longer average saccade length, which partially supports the hypothesis that participants are looking away. With all of these considerations in mind, lacunarity remains the only metric that was able to differentiate eye movement across pleasant and unpleasant picture groups. Lacunarity should be strongly considered as a robust statistic for quantifying and differentiating patterns in eye movement.

Both the time series methods and linear mixed models are highly sensitive to missing data, and hence there were slightly variable sample sizes across tests. Paying special mind to avoiding missing data in the methodology is critical for the success of these analyses. These methods can also be quite computationally intensive as the calculation of lacunarity required the deployment of a virtual machine and nearly 23 hours of run-time. Methods for increasing the efficiency of this process should be explored. At minimum, researchers should be conscientious of the length and number of time series being generated for analysis. Finally, the fractal statistics require time series and fractal libraries built for R. R supports a number of unique libraries for time series and other nonlinear analyses. Learning new software and methods can be a hurdle for some researchers, but many resources exist to overcome these hurdles.

When asking research questions about how patterns in eye movement across viewing conditions or emotional states are different within or between people, fractal ststistics that incorporate the temporal order and scaling properties of the time series are highly recommended. If where or what an individual is looking at is important, then areas of interest and how fixations statistics map on to the areas of interest is a robust methodology, as fractal statistics lose that resolution of description. In order of complexity and interpretability, lacunarity should be considered first, followed by Hall-Wood box-counting, Variogram, and Madogram dimension estimates. Lacunarity appears most robust for differentiating viewing contexts and fractal dimensions may hold promise for understanding how individual differences are associated with viewing patterns.

CHAPTER 5

CONCLUSION

This research shows that fractal statistics can uniquely add to our understanding of individual differences in eye movement and differentiate viewing patterns across affective picture groups. When the measurement method and hypotheses permit, eye movement researchers should consider the use of time series data and fractal statistics, specifically lacunarity for differentiating viewing patterns and fractal dimensions for detecting individual differences in emotional arousability. Fixation statistics are extremely valuable for understanding what an individual is directing attention to and in what fashion (e.g., looking for a long or short time), but they fail to describe details of eye movement that are occurring in time across all resolutions of the eye movement time series. Time and space can be straightforwardly incorporated in traditional research methods to further our understanding of eye movement and how it differs across contexts and individuals.

APPENDIX A

DESCRIPTIVE STATISTICS

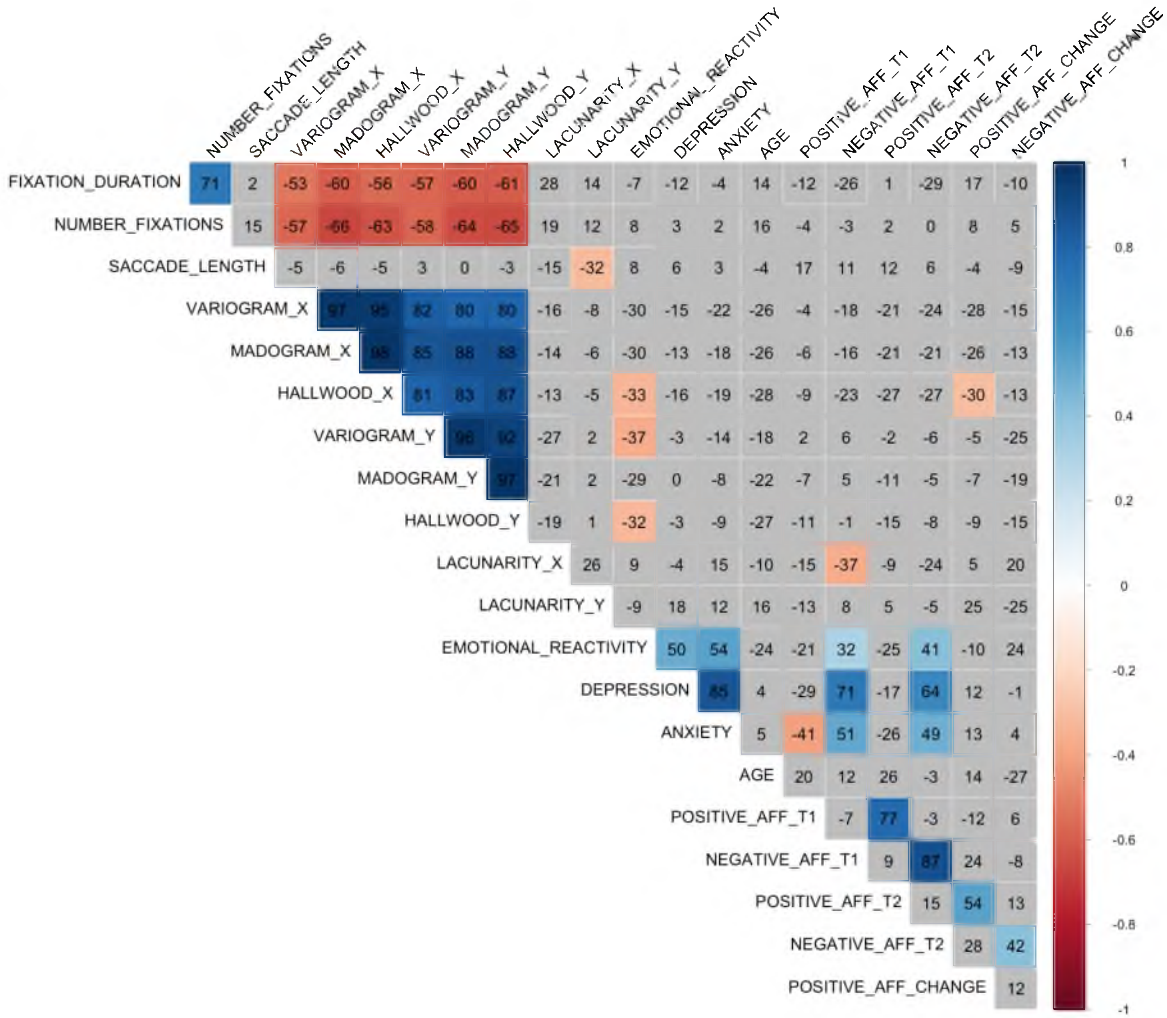


Figure A.1. Zero-order correlations between study variables (color indicates significance at p < .05) aggregated at the level of participant, where values are represented in percentage form for clearer display.

Table A.1. Fractal metrics – affective pictures

Statistic	Lacunarity Slope X	Lacunarity Slope Y	Variogram X	Madogram X	Hall-Wood X	Variogram Y	Madogram Y	Hall-Wood Y
N	272	272	272	272	272	272	272	272
Min	-0.76	-0.94	1.26	1.29	1.29	1.29	1.41	1.40
Max	0.02	0.00	1.99	1.99	1.94	2.00	2.00	1.97
Media	-0.04	-0.11	1.85	1.80	1.74	1.83	1.83	1.76
Mean	-0.07	-0.17	1.80	1.75	1.71	1.77	1.77	1.73
SE.mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Variance	0.01	0.03	0.02	0.03	0.02	0.03	0.03	0.02
SD	0.11	0.16	0.15	0.17	0.14	0.18	0.16	0.13

Table A.2. Fractal Metrics – target Pictures

Statistic	Lacunarity Slope X	Lacunarity Slope Y	Variogram X	Madogram X	Hall-Wood X	Variogram Y	Madogram Y	Hall-Wood Y
N	272	272	272	272	272	272	272	272
Min	-0.76	-0.94	1.28	1.28	1.21	1.28	1.36	1.34
Max	0.02	0.00	2.00	2.00	1.99	2.00	2.00	2.00
Media	-0.04	-0.11	1.84	1.79	1.74	1.83	1.82	1.75
Mean	-0.07	-0.17	1.80	1.75	1.71	1.77	1.77	1.74
SE.mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Variance	0.01	0.03	0.03	0.03	0.03	0.03	0.03	0.02
SD	0.11	0.16	0.16	0.18	0.16	0.18	0.17	0.14

Table A.3. Fixation metrics – affective pictures

Statistic	Mean Fixation Duration	Mean Number of Fixations	Mean Saccade Length
N	266	266	266
Min	0.1	1	0
Max	0.47	19.02	15.27
Median	0.31	11.41	5.01
Mean	0.30	10.68	5.05
SE.mean	0.00	0.27	0.10
Variance	0.00	18.95	2.62
SD	0.06	4.35	1.62

Table A.4. Fixation metrics – target pictures

Statistic	Mean Fixation Duration	Mean Number of Fixations	Mean Saccade Length
N	264	264	264
Min	0.11	1.00	0.00
Max	0.50	20.43	24.08
Median	0.31	10.13	4.78
Mean	0.30	10.00	4.90
SE.mean	0.00	0.28	0.13
Variance	0.01	20.78	4.40
SD	0.07	4.56	2.10

APPENDIX B

DENSITY PLOTS

Density plots depicting the distributional characteristics of dependent variables across affective and target pictures by picture group.

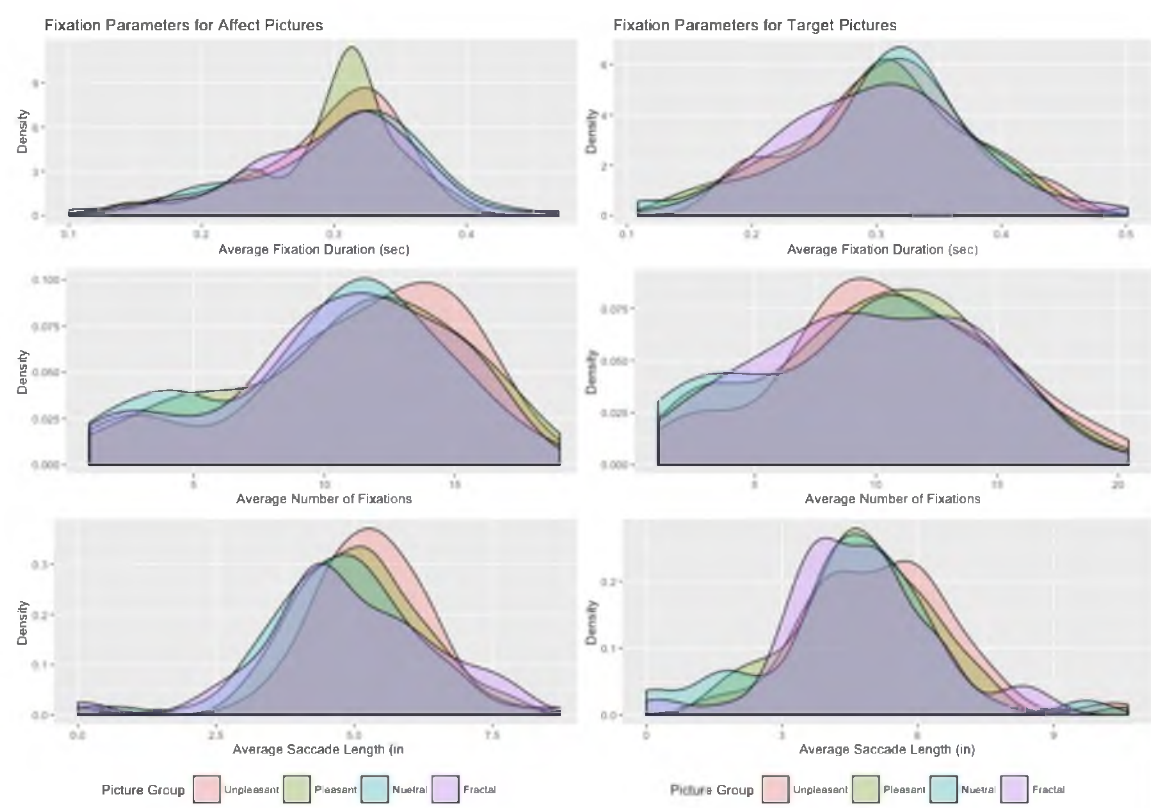


Figure B.1. Fixation statistics – affective and target pictures

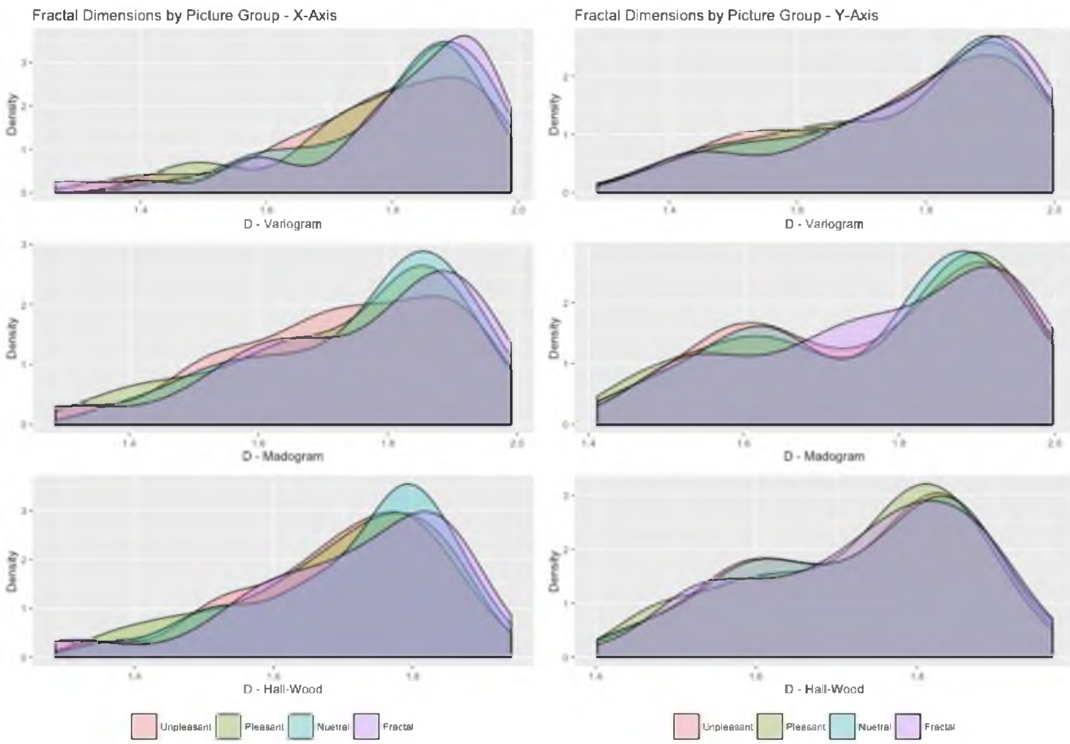


Figure B.2. Fractal dimensions – affective pictures

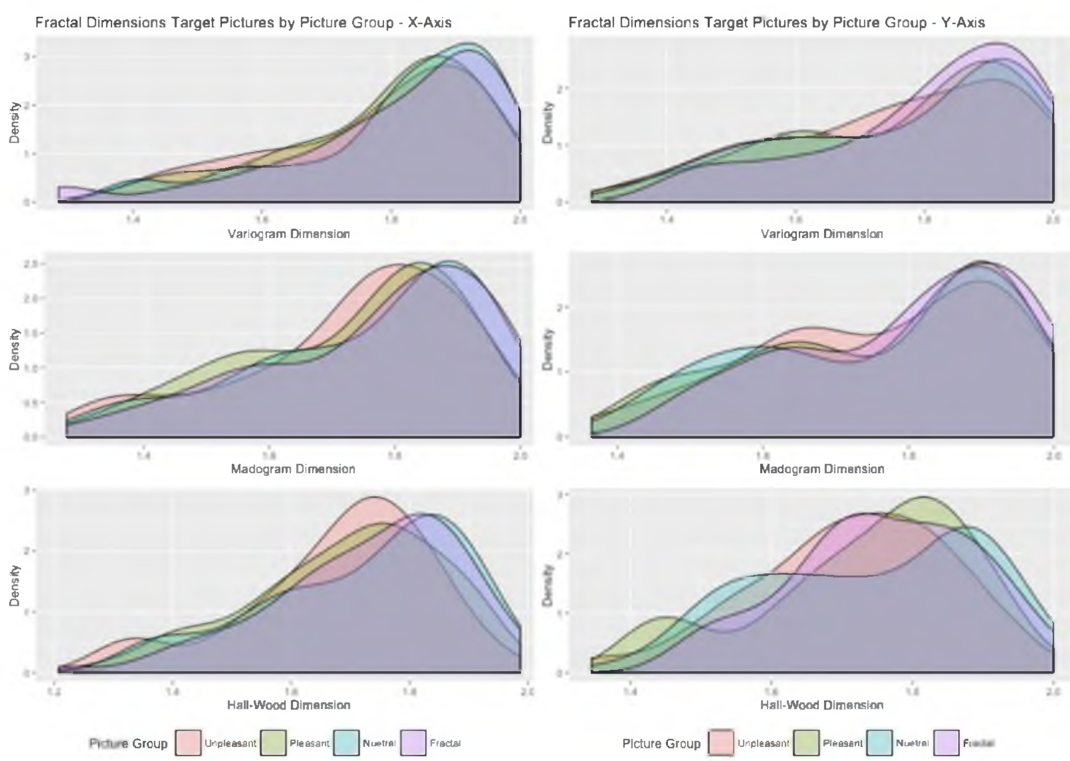


Figure B.3. Fractal dimensions – target pictures

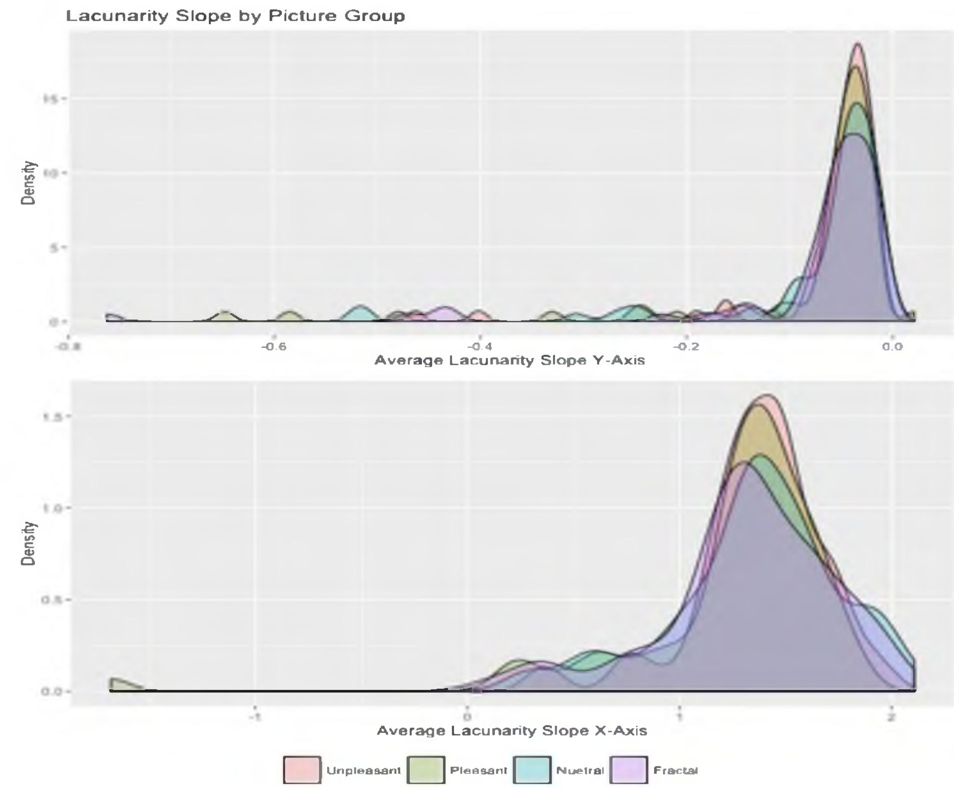


Figure B.4. Lacunarity – affective pictures

APPENDIX C

MODEL SUMMARIES

Table C. 1 Linear models - fixation statistics

Average Fixation Duration - Affect Pictures						
Fixed Effects	*Estimate*	*se*	*df*	*t*	*p*	
Intercept	0.329	0.073	57.3	4.54	0.000	***
Emotional Reactivity	0.001	0.001	57.1	0.82	0.410	
Depression	-0.001	0.001	57.4	-0.74	0.460	
Anxiety	0.000	0.001	57.1	0.34	0.730	
Age	0.001	0.001	57	0.97	0.340	
Positive Affect	-0.001	0.001	57	-1.44	0.160	
Negative Affect	-0.001	0.001	57.6	-0.75	0.460	
Contacts	-0.021	0.015	57.1	-1.36	0.180	
Sex	-0.002	0.015	57	-0.14	0.890	
Unpleasant:Pleasant	0.00	0.00	189.1	-0.54	0.590	
Unpleasant:Neutral	0.00	0.00	189.1	1.10	0.270	
Unpleasant:Fractal	0.00	0.00	189.4	0.84	0.400	
Random Effects	*Variance*	*SD*				
Participant	0.003	0.055				
Residual	0.001	0.025				

***p<.001, **p<.01, *p<.05, .P<.10

Average Number of Fixations - Affect Pictures						
Fixed Effects	*Estimate*	*se*	*df*	*t*	*p*	
Intercept	12.419	5.418	57.2	2.29	0.026	*
Emotional Reactivity	0.106	0.068	57	1.55	0.126	
Depression	0.022	0.112	57.2	0.2	0.844	
Anxiety	-0.077	0.093	57.1	-0.83	0.410	
Age	0.116	0.086	57	1.35	0.181	
Positive Affect	-0.085	0.074	57	-1.15	0.255	
Negative Affect	-0.003	0.091	57.4	-0.04	0.972	
Contacts	-0.603	1.140	57	-0.53	0.599	
Sex	-0.906	1.100	57	-0.82	0.414	
Unpleasant:Pleasant	-0.58	0.26	189	-2.24	0.026	*
Unpleasant:Neutral	-1.13	0.26	189	-4.37	0.000	***
Unpleasant:Fractal	-0.76	0.27	189.2	-2.84	0.005	**
Random Effects	*Variance*	*SD*				
Participant	17.410	4.170				
Residual	2.210	1.490				

***p<.001, **p<.01, *p<.05, .P<.10

Average Saccade Length - Affect Pictures						
Fixed Effects	*Estimate*	*se*	*df*	*t*	*p*	
Intercept	6.335	1.813	56.9	3.49	0.001	***
Emotional Reactivity	-0.003	0.023	56.2	-0.11	0.912	
Depression	0.038	0.037	57.1	1.02	0.312	
Anxiety	-0.026	0.031	56.4	-0.85	0.401	
Age	-0.012	0.029	56.1	-0.41	0.686	
Positive Affect	0.007	0.025	56.1	0.28	0.779	
Negative Affect	-0.008	0.031	57.6	-0.28	0.783	
Contacts	-0.083	0.381	56.2	-0.22	0.828	
Sex	0.007	0.367	56.1	0.02	0.984	
Unpleasant:Pleasant	0.05	0.18	188.2	0.25	0.802	
Unpleasant:Neutral	-0.58	0.18	188.2	-3.16	0.002	**
Unpleasant:Fractal	-0.39	0.19	189	-2.07	0.040	*
Random Effects	*Variance*	*SD*				
Participant	1.720	1.310				
Residual	1.110	1.050				

***p<.001, **p<.01, *p<.05, .P<.10

Table C. 2. Linear models - fractal dimensions x-axis time series

Predicting Variogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.074	0.192	57	10.81	0.000	***
Emotional Reactivity	-0.002	0.002	57	-0.65	0.519	
Depression	0.000	0.004	57	0.03	0.973	
Anxiety	-0.002	0.003	57	-0.71	0.480	
Age	-0.002	0.003	57	-0.7	0.490	.
Positive Affect	-0.003	0.003	57	-0.96	0.342	
Negative Affect	-0.001	0.003	57	-0.2	0.838	
Contacts	-0.019	0.040	57	-0.46	0.648	
Sex	0.012	0.039	57	0.32	0.753	
Unpleasant:Pleasant	0.01	0.01	195	1.49	0.138	
Unpleasant:Neutral	0.03	0.01	195	3.52	0.001	***
Unpleasant:Fractal	0.03	0.01	195	3.12	0.002	**
Random Effects	***Variance***	***SD***				
Participant	0.022	0.148				
Residual	0.003	0.056				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.017	0.216	57	9.34	0.000	***
Emotional Reactivity	-0.003	0.003	57	-1.13	0.262	
Depression	0.000	0.004	57	0.06	0.949	
Anxiety	-0.001	0.004	57	-0.27	0.789	
Age	-0.004	0.003	57	-1.13	0.262	
Positive Affect	-0.002	0.003	57	-0.53	0.596	
Negative Affect	-0.001	0.004	57	-0.19	0.848	
Contacts	-0.002	0.045	57	-0.05	0.963	
Sex	0.008	0.044	57	0.18	0.857	
Unpleasant:Pleasant	0.01	0.01	195	1.21	0.226	
Unpleasant:Neutral	0.04	0.01	195	3.90	0.000	***
Unpleasant:Fractal	0.03	0.01	195	3.40	0.001	***
Random Effects	***Variance***	***SD***				
Participant	0.028	0.167				
Residual	0.003	0.054				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.051	0.178	57	11.55	0.000	***
Emotional Reactivity	-0.003	0.002	57	-1.35	0.183	
Depression	0.000	0.004	57	0.03	0.973	
Anxiety	-0.001	0.003	57	-0.43	0.667	
Age	-0.003	0.003	57	-1.07	0.288	
Positive Affect	-0.003	0.002	57	-1.18	0.244	
Negative Affect	-0.001	0.003	57	-0.24	0.810	
Contacts	-0.009	0.037	57	-0.25	0.806	
Sex	-0.010	0.036	57	-0.26	0.793	
Unpleasant:Pleasant	0.01	0.01	195	0.60	0.547	
Unpleasant:Neutral	0.03	0.01	195	2.94	0.004	**
Unpleasant:Fractal	0.03	0.01	195	3.06	0.003	**
Random Effects	***Variance***	***SD***				
Participant	0.019	0.136				
Residual	0.003	0.053				

***p<.001, **p<.01, *p<.05, .P<.10

Table C. 3 Linear models – fractal dimensions y-axis time series

Predicting Variogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.120	0.221	57	9.61	0.000	***
Emotional Reactivity	-0.006	0.003	57	-2.19	0.032	*
Depression	0.003	0.005	57	0.65	0.517	
Anxiety	-0.002	0.004	57	-0.46	0.649	
Age	-0.005	0.003	57	-1.38	0.173	
Positive Affect	0.000	0.003	57	-0.08	0.933	
Negative Affect	0.003	0.004	57	0.84	0.405	
Contacts	-0.010	0.046	57	-0.22	0.824	
Sex	-0.005	0.045	57	-0.11	0.914	
Unpleasant:Pleasant	0.01	0.01	195	1.02	0.309	
Unpleasant:Neutral	0.01	0.01	195	1.17	0.243	
Unpleasant:Fractal	0.04	0.01	195	3.57	0.000	***
Random Effects	***Variance***	***SD***				
Participant	0.029	0.170				
Residual	0.003	0.057				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Madogram Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.035	0.202	57	10.1	0.000	**
Emotional Reactivity	-0.005	0.003	57	-2.03	0.047	*
Depression	0.002	0.004	57	0.5	0.617	
Anxiety	0.000	0.003	57	-0.12	0.905	
Age	-0.004	0.003	57	-1.34	0.186	
Positive Affect	-0.001	0.003	57	-0.24	0.813	
Negative Affect	0.001	0.003	57	0.34	0.738	
Contacts	0.015	0.042	57	0.36	0.722	
Sex	-0.004	0.041	57	-0.1	0.924	
Unpleasant:Pleasant	0.00	0.01	195	0.42	0.675	
Unpleasant:Neutral	0.01	0.01	195	0.64	0.524	
Unpleasant:Fractal	0.02	0.01	195	2.40	0.017	*
Random Effects	***Variance***	***SD***				
Participant	0.024	0.156				
Residual	0.002	0.048				

***p<.001, **p<.01, *p<.05, .P<.10

Predicting Hall-Wood Dimension: Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	2.056	0.163	57	12.65	0.000	**
Emotional Reactivity	-0.005	0.002	57	-2.45	0.017	*
Depression	0.001	0.003	57	0.44	0.658	
Anxiety	0.000	0.003	57	-0.17	0.869	
Age	-0.004	0.003	57	-1.42	0.160	
Positive Affect	-0.002	0.002	57	-0.72	0.473	
Negative Affect	0.001	0.003	57	0.22	0.827	
Contacts	0.006	0.034	57	0.19	0.854	
Sex	-0.015	0.033	57	-0.46	0.644	
Unpleasant:Pleasant	0.00	0.01	195	-0.18	0.861	
Unpleasant:Neutral	0.00	0.01	195	0.22	0.830	
Unpleasant:Fractal	0.01	0.01	195	1.50	0.134	
Random Effects	***Variance***	***SD***				
Participant	0.016	0.125				
Residual	0.002	0.048				

***p<.001, **p<.01, *p<.05, .P<.10

Table C. 4 Linear models - lacunarity

Lacunarity Slope X-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	-0.178	0.126	57.2	-1.41	0.164	
Emotional Reactivity	0.000	0.002	57	0.28	0.782	
Depression	-0.002	0.003	57	-0.83	0.411	
Anxiety	0.004	0.002	57	1.71	0.093	.
Age	0.000	0.002	57	0.03	0.978	
Positive Affect	-0.001	0.002	57	-0.36	0.722	
Negative Affect	-0.003	0.002	57	-1.52	0.135	
Contacts	-0.002	0.027	57	-0.06	0.950	
Sex	0.029	0.026	57	1.15	0.256	
Unpleasant:Pleasant	-0.03	0.01	195	-3.19	0.002	**
Unpleasant:Neutral	-0.01	0.01	195	-1.70	0.090	.
Unpleasant:Fractal	-0.02	0.01	195	-2.75	0.007	**
Random Effects	***Variance***	***SD***				
Participant	0.009	0.095				
Residual	0.002	0.050				

***p<.001, **p<.01, *p<.05, .P<.10

Lacunarity Slope Y-Axis						
Fixed Effects	***Estimate***	***se***	***df***	***t***	***p***	
Intercept	-0.296	0.192	57.3	-1.54	0.128	
Emotional Reactivity	0.001	0.002	57	0.23	0.819	
Depression	0.001	0.004	57	0.26	0.795	
Anxiety	0.001	0.003	57	0.3	0.763	
Age	0.003	0.003	57	1.04	0.303	
Positive Affect	-0.002	0.003	57	-0.69	0.492	
Negative Affect	0.000	0.003	57	-0.14	0.892	
Contacts	0.032	0.040	57	0.79	0.436	
Sex	0.008	0.039	57	0.22	0.830	
Unpleasant:Pleasant	-0.03	0.02	195	-1.66	0.098	.
Unpleasant:Neutral	-0.04	0.02	195	-2.23	0.027	*
Unpleasant:Fractal	-0.03	0.02	195	-2.00	0.047	*
Random Effects	***Variance***	***SD***				
Participant	0.020	0.143				
Residual	0.008	0.091				

***p<.001, **p<.01, *p<.05, .P<.10

APPENDIX D

R SCRIPT FOR LACUNARITY FUNCTION

```
## Calculating lacunarity in R.

library(dplyr)
library(doMC)
library(zoo)

load("revised_compiled_data.rda")
compiled_data_1 <- compiled_data %>%
  filter(picture != "blank.PSG") %>%
  na.omit

registerDoMC(detectCores()-1)
lac <- function(data, variable, windowSize){
  rollapply(data[,variable],windowSize, sum, na.rm = TRUE, fill = NA)
}

bob <- function(data, variable, smallWindow, largeWindow){
  foreach(i=smallWindow:largeWindow, .combine = 'rbind', .errorhandling = "remove")
 %dopar% {
    # message = i
    ll <- lac(data, variable, windowSize = i)
    data.frame(
      Mean = mean(ll, na.rm = TRUE)
      ,Variance = var(ll, na.rm = TRUE)
      , WindowSize = i
    )
  }
}

StudyIDs <- unique(compiled_data_1$studyid)
nStudyIDs <- length(StudyIDs)

lac_all_x <- foreach(k = 1:nStudyIDs, .combine = 'rbind') %do% {
```

```
  message(k)
  StudyIDCompiled <- filter(compiled_data_1, studyid == StudyIDs[k])

  PicIDs <- unique(StudyIDCompiled$picture)
  nPicIDs <- length(PicIDs)

foreach(j = 1:nPicIDs, .combine = 'rbind') %do% {

  PicIDCompiled <- filter(StudyIDCompiled, picture == PicIDs[j])

  picRes <- bob(PicIDCompiled, 'ALX', 2, 150)

      data.frame(
         picRes
        ,picture = rep(PicIDs[j], nrow(picRes))
        ,studyid = rep(StudyIDs[k], nrow(picRes))

        )
   }
}

save(lac_all_x, file = "lac_all_x.rda")
```

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