Effects of Target Size and Symmetry on the Structure of Variability in Precision Aiming

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Abstract

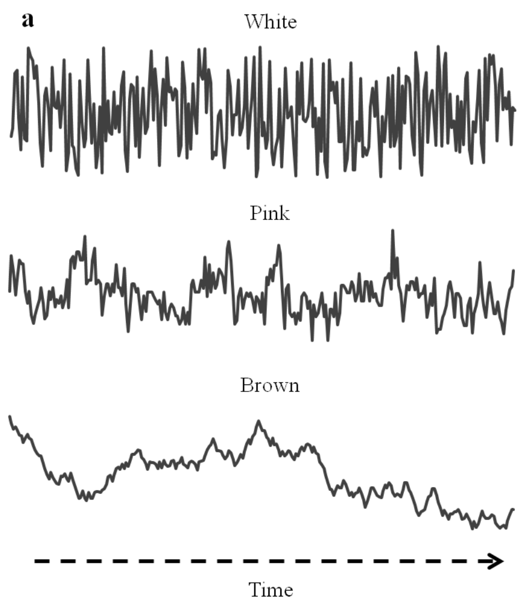
The current experiment investigated the effects of target size and symmetry on the dynamics of precision aiming. Participants were asked to sit on a chair and point at the center of four different targets (a small and big square target, and a horizontal and vertical rectangular target). The aiming movements were assessed using linear (root mean square) and non-linear fractal statistics (DFA and MFDFA). We found that participants spontaneously exhibited more movement in target dimensions with less spatial constraint (i.e., larger target dimensions). These larger movements, however, were more deterministic than the movements accompanying the smaller targets, indicating that more variation in aiming does not necessarily mean more random. Finally, even though participants' movements were multifractal, the different manipulations and task constraints had no effect on the width of the multifractal spectrum. These results suggest that human performance emerges from the complex relationship and interactions that exist between the perception and action capabilities of the human body and the physical environment.

Keywords: Cognitive science, psychology, action, motor control, complex systems, 1/f noise.

Introduction

Accuracy in tasks such as pistol shooting and archery depends on a person's ability to precisely aim at intended targets, which requires meticulous and refined control of the body and its relationship to the environment around it. Scholz, Schöner and Latash (2000) showed that expert shooters arrange the different components in their body into a motor synergy, coupling certain components to each other and therefore minimizing the necessary movements in order to be more precise. Complimentary research efforts have studied how different task constraints or elements of the physical environment affect how people move their bodies in order to aim precisely, such as target size (Ramenzoni et al., 2011) or distance (Balasubramaniam, Riley & Turvey, 2000). However, the effect that such environmental factors have on how people organize their bodies to achieve precision aiming has not yet been revealed in full detail.

Psychologists have traditionally evaluated the impact of task constraints on precision aiming (e.g., target size) using linear statistical tools, such as summarizing effects in means and standard deviations. Recently, statistical techniques allowing researchers to examine more complex aspects of such behavior have come to the fore, most notably, techniques that allow researchers to uncover the fractal structure in movement and behavioral variability (Gilden, 2001; Ihlen, 2012; Delignières & Marmelat, 2013). Fractal or *1/f* scaling refers to patterns in the variability of behavior that are long-term correlated such that deviations early in a recorded behavior are correlated with deviations that occur much later in the behavior. This kind of structure in variability is often referred to as "pink noise", denoting its difference from the highly irregular or random fluctuations of "white noise" and the highly regular or deterministic fluctuations of "brown noise" (see Figure 1). The degree to which a behavioral measurement series exhibits fractal scaling can be summarized by the Hurst exponent. The Hurst exponent (H) for white noise is 0.5 and for brown noise is 1.5, with pink noise in-between ($H \approx 1$) (Ihlen, 2012). Pink noise has been associated with signs of healthy functioning (for a review, Van Orden, Kloos & Wallot, 2009) in different human movement tasks, such as tapping (Kello et al., 2007; Delignières, Torre & Lemoine, 2008; Torre, Balasubramaniam & Delignieres, 2010), stimulus-response tasks (Holden, Choi, Amazeen & Van Orden, 2010), postural sway (Schmit, Regis & Riley, 2005; Schmit et. al., 2006), walking (Hausdorff, 2007) and eye-movement behavior (Coey et al., 2012).



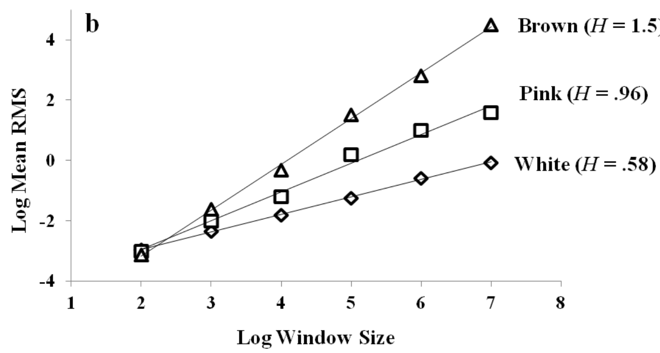


Figure 1: (a) sample time series of white noise depicting highly irregular or random fluctuations; brown noise, with highly regular or deterministic variability; and pink noise, located somewhere between random and deterministic fluctuations. (b) Plots obtained from a detrended fluctuations analysis (DFA) where the mean root mean square (RMS) is plotted against the window size both in log coordinates. The slope of the best fit line gives us the Hurst (*H*) exponent.

It is becoming increasingly apparent, however, that human behavior may in fact exhibit even more complex patterns of fluctuation than those that can be ascertained from standard fractal analysis. In these cases, the patterns cannot be captured by a single *H*, as the fractal scaling in the behavior might change over time during the course of measurement, or might be different at different scales of variability (Kantelhardt et al., 2002). Such “multifractal” patterns must, therefore, be characterized by their “multifractal spectrum”; a range of *H* values that collectively capture the complex structure inherent in a behavioral time series (e.g., Kuznetsov & Wallot, 2011; Kuznetsov et al., 2012). This spectrum of *H* can either be time-dependent or independent. When it is time-dependent it shows a pattern of long-range correlation where sections of rapid fluctuation are interspersed with sections of slow fluctuation and it is associated with intermittent processes (Kuznetsov & Wallot, 2011). Multifractal spectrums can also be time-independent due to the behavior being sampled having a frequency distribution with a long tail (Kantelhardt et. al., 2002).

These statistical properties are of interest to cognitive scientists primarily because they reveal something more about the underlying causal structure of human performance than do means and standard deviations (Gilden, 2001; Hausdorff, 2007; Kello et. al., 2007; Holden et. al., 2010; Kuznetsov & Wallot, 2011). For instance, the presence of monofractal or multifractal structure in human performance can provide insight about the degree to which a behavioral process is self-organized or emerges from interaction-dominant dynamics (Kuznetsov & Wallot, 2011; Van Orden et. al., 2009). Traditional linear statistical tools assume behavior to be static and self-contained, while monofractal and multifractal analyses reveal the strong relationship or coupling between people and their environment (Holden et. al., 2010).

It is for these reasons that the variation in human performance is seen as a balance between task constraints and a person’s ability or between involuntary and voluntary control (Van Orden et. al., 2009; Kloos & Van Orden, 2010). The embedded nature of human behavior can also be revealed by changes in monofractal or multifractal structure that result from subtle and sometimes non-obvious changes in environmental context or constraints (Chen et al., 2001; Balasubramaniam et. al., 2000; Ramenzoni et. al., 2011; Holden et. al., 2010). Depending on the nature of the task and the different constraints, the variability in behavior can go from overly random to more deterministic, or from overly deterministic to more random (Van Orden et. al., 2009; Kloos & Van Orden, 2010). However, the specific direction of change in variability is not yet fully understood and further study is needed.

The current study investigates the effect that subtle changes in the shape and symmetry of targets have on the dynamics of a participant’s precision aiming movements. Participants were instructed to complete the same precision aiming task, with the exact same instructions (i.e., point at the center of the target) over repeated trials. On any given trail, however, the shape and symmetry of the target was subtly changed to investigate how small changes in environmental task constraints can spontaneously reorganize the structure and variability of human behavior. In addition to performing a standard linear variability analysis (i.e., examined the RMS of movement), we conducted both a monofractal and multifractal analysis to better understand the effects that different targets had on the aiming movements of participants, and whether their movements became more deterministic or more random as constraints changed.

Materials and Method

Participants

Ten undergraduate students from the University of Cincinnati participated in the study for partial course credit.

Task, Materials and Procedures

Participants in this experiment were asked to point at targets presented on a display screen. There were four different grey colored targets: a big symmetric (6 cm x 6 cm), a small symmetric (3 cm x 3 cm), a vertical (3 cm x 6 cm), and a horizontal (6 cm x 3 cm). Asymmetric targets matched the dimensions of the small symmetric in the strictly constrained dimension and the big symmetric in the loosely constrained dimension (see Figure 2b), therefore the visual angle for both the big symmetric and the vertical targets was 3.12° and for the small symmetric and horizontal targets 1.56°. Additionally, the pointer had a visual angle of 0.93° When participants arrived they were greeted and then informed that for this experiment, a sensor would be attached to their index finger which would control the location of a small red square (1.8 cm x 1.8 cm) presented directly in front of them on a display screen. This sensor was part of a wired Polhemus magnetic motion tracking system (Polhemus Ltd, VT) and tracked and recorded the movements of the participants at 120 Hz. Once the sensor was attached, participants were seated on a chair located 110 cm away from the TV (Figure 2a).

There were a total of 16 trials; these were completed in blocks of four trials, such that each of the four targets was viewed in each block. The target viewed on any given trial in a four trial block was randomized. The participants were informed that their goal for the experiment was to hold the red square they controlled with the motion sensor in the center of the presented target for the 45 second length of each trial. For each trial, the participant was asked to start pointing at the center of the target, and then the trial started with the Polhemus system being calibrated and the recording of their movement. Participants were instructed to keep their left hand in their lap. After the participants were informed of the number of trials they were to complete, they were given about 25 seconds of practice controlling the red square with the large square target presented on the screen. Once the participant felt comfortable with the procedure, all 16 trials were completed with long breaks given if needed between every block of four trials, between each trial the participant was allowed to lower their hand and place it on their lap. Once the experiment was completed, participants were thanked for their time and debriefed.

Signal Processing and Measures

To examine the impact the different targets had on the participants' pointing movements, the first 4096 data points of the X (frontal, side-side movement) and Y (sagittal, up-down movement) position time series were extracted for analysis. The Z (back-and-forth) dimension of movement had little to no effect on task performance and was therefore not analyzed. Each dimension was analyzed separately to better understand the effect that the different target constraints posed on each of the degrees of freedom used by the participants.

Movement Variability. The root mean square (RMS) was calculated of both the X and Y position time series to examine the effects of the target manipulations on the stability of a participant's pointing movements.

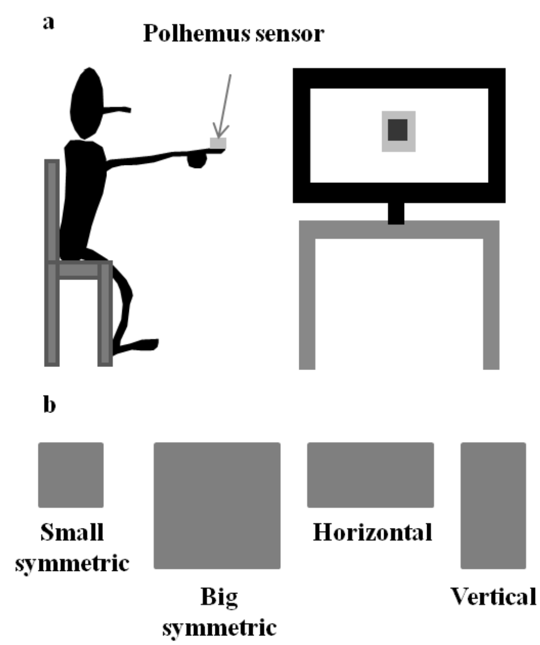


Figure 2: (a) Experiment set-up and (b) the four different targets used in the experiment

Fractal Analysis. Detrended fluctuations analysis (DFA) was employed to calculate the monofractal dimension of the X and Y positional time series for each trial. Detailed explanations of this method can be found in several articles (Delignières et. al., 2006; Ihlen, 2012; Delignières & Marmelat, 2013). Essentially, the time series is divided into windows of a particular size and the average variation (i.e., RMS) around a linear trend is calculated within each window. This procedure is then repeated for windows of different sizes. These averaged RMS are then plotted against the associated window size on log-coordinates. The slope of the best-fit line in this log-log plot represents the scaling relation and corresponds to the Hurst Exponent (H) of the time series (see Figure 1). For the current data we employed 50% overlapping window sizes from 16 to 1024 points. Additionally, surrogate time series were created for each time series by randomly shuffling the data points and then a DFA analysis was done to determine whether the fractal dimension observed was time-dependent and therefore a characteristic of long-range correlation.

Multifractal Analysis. Multifractal detrended fluctuation analysis (MFDFA) was used to determine the multifractal dimension present in each time series. This method follows the same steps as DFA, but does so with a scaling parameter (q) that allows for a calculation of H at different scales of variation in the time series. The final outcome of this procedure is the "width" of all the different H exponents present in the time series. If this width is equal to 0, then the monofractal dimension is enough to completely describe the behavior. For the current data we employed 50% overlapping window sizes from 16 to 1024 points and examined q's from -3.0 to +3.0 in .5 steps. The surrogate time series created were also analyzed through MFDFA to determine whether the spectrum observed was due to time-dependent fluctuations, or due to the frequency distribution of the behavior being sampled having a long tail.

Statistical Analyses. One way analyses of variance were computed for each measure in order to understand the effect that the different targets had on participants' behavior. If there was a significant difference, Tukey HSD post-hoc tests were performed.

Results

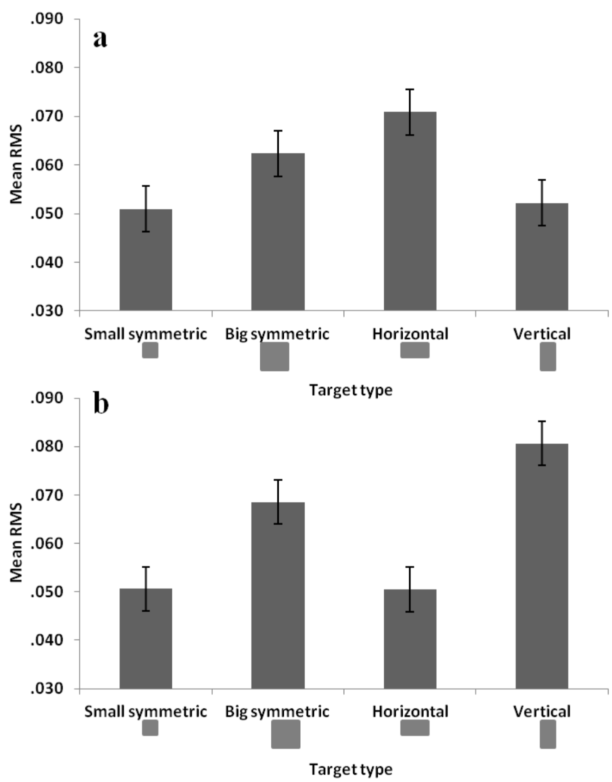


Figure 3: Mean root mean square of movement in the (a) X dimension (side-to-side) and in the (b) Y dimension (up-down) depending on target type. The error bars represent standard error of the mean.

RMS

Target type had a significant impact on the amount of side-to-side movement, F (3, 156) = 3.96, p = .009, η_p^2 = .07. Post-hoc tests revealed that there was significantly more movement for the horizontal target (M = .071) compared to the small symmetric target (M = .051, p = .003), and the vertical target (M = .052, p = .006; see Figure 3a), indicating that participants naturally exhibited more movement in the direction of less constraint.

Type of target also had a significant influence on the root mean square value of movement in the up-down direction, F(3, 156) = 10.43, p < .001, η_p^2 = .167. Post-hoc tests showed that there was significantly more up-and-down movement for the big symmetrical target (M = .069) compared to the small symmetric (M = .051, p = .03) and the horizontal targets (M = .05, p = .03). There was also significantly more up-down movement for the vertical target (M = .097) compared to the small symmetric (p <.001) and the horizontal targets (p < .001; see Figure 3b). Again, participants' movements seemed to spontaneously increase in the Y plane when the target was loosely constrained in this dimension as well. Thus, consistent with the result for the X dimension of movement, increases in participant movement variability appear to be a natural and spontaneous effect of the target size and shape.

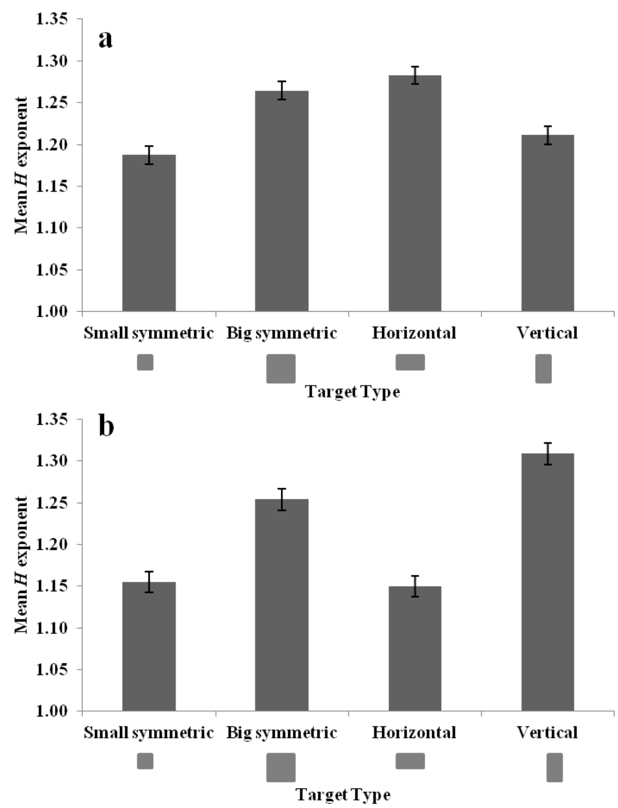


Figure 4: Mean Hurst, H, of (a) side-to-side movement and (b) up-down movement depending on target type. The error bars represent standard error of the mean.

Fractal Analysis

The analysis of the monofractal dimension, *H*, calculated using DFA, revealed that target type had a significant influence on the fractal structure of the participants' side-to-side movement, $F(3,156) = 17.20$, $p < .001$, $\eta_p^2 = .25$. Post hoc tests revealed that side-to-side movement in the big symmetric target was significantly "browner" ($H = 1.26$) than for the small symmetric target ($H = 1.19$; $p < .001$) and vertical target ($H = 1.21$; $p = .003$). Furthermore, the side-to-side movement of participants was significantly browner when pointing at the horizontal target ($H = 1.28$) than when pointing at the small symmetric target ($p < .001$) and vertical target ($p < .001$; see Figure 4a). This mirrors the results for RMS above, with participants' movement being browner in the targets where the X plane was loosely constrained and suggests that their movements became more deterministic when more freedom was allowed in the task. In other words, the participants moved more, but this increase in movement was also an increase in the level of determinism.

The fractal structure of the up-down movement of participants was significantly affected by the type of target they had to point at, $F(3,156) = 38.47$, $p < .001$, $\eta_p^2 = .43$. Post hoc tests revealed that participants' up-down movements were significantly browner when pointing at the vertical target ($H = 1.31$) than the big symmetric target ($H = 1.25$; $p = .01$), the horizontal target ($H = 1.15$; $p < .001$) or the small symmetric target ($H = 1.16$; $p < .001$; see Figure 4b). Consistent with the fractal analysis of X and the RMS for Y above, participants' movements were pinker in structure when the target was more constrained in the intended plane. This suggests that participants' movements became less correlated in time with increases in task constraint.

The DFA analysis of the surrogate time series resulted in white noise ($H \approx .5$) for every trial wiping out any correlation present in the collected data. This indicates that the above monofractal analysis performed on the recorded data is time-dependent and not an analysis artifact.

Multifractal Analysis

Participants' movements were found to be multifractal, with a one-sample t-tests demonstrating that the multifactal spectrum width for each movement dimension and for each target types were significantly different from zero (all $t(39) > 24.16$, $p < .001$). Although there was no effect of target type on multi-fractal width for participants' side-to-side movement, ($F(3,156) = .76$, $p = .518$), an effect of target type on multi-fractal width was found for the participants' up-down movement ($F(3,156) = 3.07$, $p = .03$, $\eta_p^2 = .06$). Pot-hoc analyses, however, revealed that the only significant difference was that participants' movement while pointing at the small symmetric target had a significantly wider Hurst spectrum (*H* width = .57) than while pointing at the vertical target (*H* width = .50, $p = .04$). Therefore, even though precision aiming shows multifractal spectrum characteristics, this measure does not capture the effects that size and symmetry of target have on the behavior as well as RMS and monofractal analyses do.

The surrogate time series also had a multifractal spectrum (*H* width $\approx$ .42) which suggests that the multifractal spectrum present in the data is not time-dependent, but rather is the result of the behavior having a long-tailed frequency distribution (Kantelhardt et. al., 2002).

Discussion

Our data indicate that changing some task constraints, while leaving the rest of the experiment the same, does change human performance behavior. In general, even though the participants in the current study were always told to point at the center of the target, they moved around more if more target space was available. In other words, looser constraints brought about more spontaneous movement variability. Additionally, this increase in movement variability brought about a more deterministic behavior, where looser constraints in a certain dimension resulted in a structure of variability closer to brown noise. This deterministic behavior was also shown to be the result of time-dependent long-range correlations. Finally, a multifractal analysis showed that the behavior was even more complex and that it could be represented by a multifractal spectrum, however, this multifractal spectrum did not characterize the influence of the different task constraints. Furthermore, the multifractal spectrum did not show a time-dependent pattern, it was instead due to the frequency distribution of the fluctuations of participants' movements.

These results support the idea that participants' behavior in the precision aiming task exhibit the characteristics of a strong relationship or coupling between the person and the environment, such that subtle changes in constraints bring about changes in the underlying dynamics of the movement. Additionally, the results are similar to those obtained by Balasubramaniam and colleagues (2000) where participants increased their overall movement in dimensions where more freedom was present, but that in turn this spontaneous increase in movement was more deterministic in nature. However, studies in different tasks, such as tapping or walking to a metronome have found the opposite results in which stricter control results in more random variability (for a review see Van Orden et. al., 2009 and Kloos & Van Orden, 2010). One idea that has been supported by the data available so far is that people's movement variability is a result of the balancing between involuntary control (overly random) and voluntary control (overly deterministic) that arises during a specific task in a specific context (Van Orden et. al., 2009; Kloos & Van Orden, 2010). If this is indeed the case, the results of the present study would suggest that participants impose further voluntary control to counteract the increase in spontaneous movement, so that they are able to successfully stay inside the target boundary. However, further research is needed to better understand the mutual influence that task constraints and participants' ability play on the production of a certain behavior.

In general, the results of the present study bring into question the standard belief in cognitive science of behavior being the result of participants' voluntary and cognitive control alone. Instead, it points to a more embodied or interaction-dominant approach in which participants and their physical environment interact and mutually influence each other. It is therefore objectionable to try to study behaviors by only looking at the participant and ignoring the environment. Instead the focus of research should be the coupling or relationship between the person and its physical environment.

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