Movement Kinematics and Fractal Properties in Fitts' Law Task

by

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ABSTRACT

Fractal analyses examine variability in a time series to look for temporal structure or pattern that reveals the underlying processes of a complex system. Although fractal property has been found in many signals in biological systems, how it relates to behavioral performance and what it implies about the complex system under scrutiny are still open questions. In this series of experiments, fractal property, movement kinematics, and behavioral performance were measured on participants performing a reciprocal tapping task. In Experiment 1, the results indicated that the alpha value from detrended fluctuation analysis (DFA) reflected deteriorating performance when visual feedback delay was introduced into the reciprocal tapping task. This finding suggests that this fractal index is sensitive to performance level in a movement task. In Experiment 2, the sensitivity of DFA alpha to the coupling strength between sub-processes within a system was examined by manipulation of task space visibility. The results showed that DFA alpha was not influenced by disruption of subsystems coupling strength. In Experiment 3, the sensitivity of DFA alpha to the level of adaptivity in a system under constraints was examined. Manipulation of the level of adaptivity was not successful, leading to inconclusive results to this question.

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CHAPTER 1

INTRODUCTION

Fractal property has been reported in many physiological and psychological signals. Examples include heartbeat interval, postural sway, reaction time, intralimb coordination, team communication, among others. However, what fractal property implies about the measured system is still an oft-debated question. In this series of experiments, we look at fractal property of movement data obtained from the well-studied reciprocal tapping task. In Experiment 1, we coupled performance measures with fractal parameters to determine whether fractal property characterizes behavioral performance. In Experiments 2 and 3, we manipulated the parameters of the reciprocal tapping task to test two claims on the meaning of fractal property: that fractal measures characterize the degree of coordination or integration of multiple subsystems operating on different time scales, and that fractal measures reflect a complex system adapting to difficult task demands.

Fractal property in cognition and behaviors

Fractal property refers to a set of parameters in dynamic system theory that characterizes how a complex system produces dynamic, emergent behaviors. One explanation of fractal property suggests that because subsystems in a complex system tend to operate on different time scales, time series data of complex systems tend to display long-range correlations, indicating that processes on longer time scales are interacting with processes on shorter time scales. Fractal analyses therefore focus on analyzing changes in variability as a function of scale in time series data. This fractal analysis stands in contrast to traditional analyses where variability is treated as noise that interferes with measurement of the mean.

Whereas this theoretical framework offers a compelling perspective on how cognitive processes and behaviors can be understood, evidence supporting the notion that fractal analyses are actually tapping into the cohesiveness of a system have often times been correlational in nature. For example, Goldberger et. al. (2002) showed that variation in heartbeat intervals of healthy individuals exhibited more pronounced fractal property than did interval variability of individual with heart diseases. Similarly, stride interval in healthy adults showed more prominent fractal property compared to stride interval in individuals with Parkinson's disease (Hausdorff, 2009). In posture control, research showed differential non-linear parameters on posture sway of patients recovering from stroke (Roerdink, De Haart, Daffertshofer, Donker, Geurts, & Beek, 2006). Although it is possible that these fractal analyses are sensitive to the robustness of the complex cardiovascular and sensorimotor systems, many alternative explanations exist.

Another related issue concerns how fractal property is interpreted. Van Orden, Holden, and Turvey (2003) argued that fractal property reflects the ability of a complex system to react and adapt to environmental constraints. Likens, Fine, Amazeen, and Amazeen (2015) argued that fractal property depends on the degree of control exerted on behavior. Valdez and Amazeen (2008) asserted that fractal property arises from the summation of signals originating from subsystems operating on different time scales. Dotov, Nie, and Chemero (2010) suggested that fractal property is indicative of the coupling strength between various systems, whether intrapersonal, interpersonal, or even human-machine coupling. The wealth of competing explanations for fractal property can cause confusion over the interpretation of data and the generation of accurate predictions.

The goal of the current study is to examine fractal property of a well-studied movement task, the reciprocal tapping task, in order to 1) verify the sensitivity of fractal analyses to changes in performance, and 2) differentiate between two common interpretations of fractal property: system adaptivity/flexibility and coupling strength/coordination between subsystems. For the first question, if fractal measurements reflect the well-adapted operation of a complex system, we should see a correlation between measured fractal property and traditional indexes of performance. To answer the second question, we separately test whether fractal measures respond appropriately to manipulations that heavily influence either coupling strength between subsystems, or level of system adaptivity. If fractal measures capture the coupling strength between multi-scaled processes in a complex system, then disruption to these couplings (such as between the visual and the motor system, or between motor planning and motor control) will result in deteriorated fractal metrics. However, if fractal measures instead capture the degree to which a complex system is flexibly adapting to task constraints, then manipulation of the level of adaptation in a system should result in directional changes in fractal metrics.

Goal-directed aiming task

Woodworth (1899) first brought attention to goal-directed movements as a viable window into the cognitive processes underlying movement control. In the subsequent centuries since this study was published, researchers have developed several variations of the task and several theories on contributing factors influencing movement performance and variability (Elliott, Helsen, & Chua, 2001). Of interest to our purpose is the reciprocal tapping task introduced by Fitts (1954). In this task, participants are instructed to make several rapid aiming movements, moving back and forth between targets of varying distances and sizes. One advantage of using Fitts' task is that the measures of participants' performance, task difficulty, movement profile, and speed-accuracy variability are well studied. Equally important, researchers have documented several manipulations of the task that probe the contribution of motor planning, motor control, and the visual feedback loop, three subsystems that we will manipulate. This allows us to test the hypothesis that fractal analyses are indicative of the integration of multiple systems. Last but not least, the continuous movements in this task allow us to generate enough time series data for the fractal analyses.

Woodworth (1899) first proposed the two-component model for movements during a goal-directed aiming task. Each movement consisted of two components: an initial impulse phase and a control phase. The initial impulse was associated with centralized control and planning, whereas the control phase was associated with online adjustments using visual feedback. By manipulating visual information, Woodworth (1899) and subsequently Keele and Posner (1968) (also Zelaznik, Hawkins, and Kisselburgh, 1983) were able to demonstrate that vision plays a critical role in rapid, accurate aiming movements, especially during the rapid online control phase. However, Smith and Bowen (1980), using visual feedback delay, and Elliott (1988), using no-vision periods prior to the beginning of movement, found that vision can affect the early planning phase as well. Separately, motor planning, motor control, and visuomotor feedback have all been showed to be important for high performance in goal-directed aiming tasks. Presumably, all three subsystems also need to be well-coordinated to produce the desired outcome.

Fractal analyses have previously been used to study the temporal structure of variability in rapid goal-directed aiming tasks. Miyazaki, Kadota, Kudo, Masani, and Ohtsuki (2001) detected long-range correlations at different kinematics markers across trials of a discrete aiming task. The fractal measure was strongest at peak acceleration, decreasing in strength at subsequent markers (peak velocity and peak deceleration) in the movement. The authors postulated that neuronal-motor coordination led to stronger long-range correlations at movement's start, whereas constraints imposed by the target reduced fractal property at movement's end. However, this runs counter to some arguments presented above that task constraints, or a system's adapting to such constraints, increase fractal property. Valdez and Amazeen (2008) similarly showed higher fractal property at peak velocity when participants were moving at preferred speed than at high speed. The authors suggested that at preferred speed, signals from motor planning and motor control had time to combine, resulting in long-range correlation in the movement data. At higher speed, reliance on online control process abolished coordination between systems so a weaker long-range correlation was found. In both studies, a question remains open regarding the behavioral outcome of high fractal property. Does higher fractal property translate to higher performance? Or to rephrase the question, is coordination between systems the optimal strategy for favorable outcome in an aiming task? We attempted to answer this question in experiment 1.

CHAPTER 2

EXPERIMENT 1

In Experiment 1, we tested whether interference between the motor system and the visual feedback loop resulted in lower performance and a concurrent reduction of measured fractal property. Interference was created by introducing visual feedback delay (Elliott, 1988) in a reciprocal tapping task.

Methods

Participants

Twenty participants (11 males, 9 females) were recruited for the experiment in exchange for course credit. Participants were healthy adults with no impairments in vision or movement.

Design

Similar to Fitts' (1954) design, participants were instructed to alternatively tap two target areas as often as possible, while still maintaining accuracy. Participants performed this task by monitoring a crosshair tracking their movements on a computer screen. The delay between the real movement and the on-screen representation was manipulated. After a practice trial, each participant performed three randomly ordered trials with either no delay, 133ms of delay, or 266ms of delay. Each trial, including the practice trial, lasted 4 minutes, with 1 minute of rest in between.

Apparatus

Participants sat in front of a table measuring 70cm x 120cm x 75cm. Their dominant hand index finger rested on a marked dot on the table at the beginning of each trial. The surface of the table was otherwise unmarked. Projected onto the wall in front of the participant were two 10-cm-wide, vertical target areas, a horizontal line indicating the table surface, and a red moving crosshair showing the position of the participant's index finger in vertical and horizontal space. The two target areas were positioned to the left and right of the participants. The targets were 1m apart on the projected screen, which translated to 30cm of actual movement for the participant. To capture the participant's movement, a single infrared-emitting diode was attached to the tip of the index finger, with an Optotrax 3020 motion-capture camera recording the movement at a sampling rate of 30Hz.

In no-delay trials, the projected crosshair displayed a representation of the current position of the diode on the participant's finger. In the delayed trials, the projected crosshair displayed the recorded position of the diode either 133ms or 266ms prior to the current position. Since delayed display requires some initial data to be recorded, the crosshair in delayed trials switched from live display to delayed display at 500ms into each trial. Most of this first 500ms is taken up by startup transience as participants begin their trials.

Procedure

At the beginning of every trial, the participant put his or her finger on a marked dot located in between the target zones. At the computer's signal, the participant lifted the finger off of the table and attempted to tap the table at the location corresponding to target zones projected on the screen. Participants were instructed to alternate between the two targets as quickly as possible while still maintaining accuracy. If they missed a target, they were encouraged to move on to the next target instead of correcting for errors. There was otherwise no constraint on their speed/accuracy priority. The procedure was approved by the Institutional Review Board at Arizona State University.

Kinematic analysis

The side-to-side movement of each participant was extracted from the recorded data and analyzed. Prior to any analysis, a 12Hz Butterworth low pass filter was applied to the time series. The data was centered and a peak finder algorithm applied to identify the furthest points in both left and right directions (peak amplitude) and time position for each aiming movement. Time intervals between peak amplitudes were calculated for subsequent fractal analysis. Movement distance, movement time, and standard deviation of the peak amplitudes were calculated. As outlined by Fitts and Peterson (1964), the effective width of the target, as derived from participants' actual movement, was calculated as 4.133 times the standard deviation of peak amplitudes. Then, the effective index of difficulty was calculated as

$$eID = log_2\left(\frac{mean\ movement\ distance}{effective\ width} + 1\right)$$

Participants' effective index of performance was then calculated as:

$$eIP = \frac{eID}{mean\ movement\ time}$$

In the original Fitts' (1954) experiment, the width of the presented target and the distance between targets were used to calculate the index of difficulty of the task given to participants. Therefore, every participant shared the same index of difficulty for a given version of the task. However, even when all participants were presented with the same task, their performance naturally differed. This difference in performance was previously only captured by the mean movement time term in the calculation for the index of performance. On the other hand, the effective index of difficulty more accurately captured performance and accuracy by using participants' movement data. Assuming that the distribution of peak amplitudes follows a normal distribution, effective width represents 96% of possible endpoints around mean peak amplitude, thus giving us an approximation of the width of the target as performed by each participant. Likewise, mean movement distance gives us an approximation of the distance between targets based on each participant's movement data. Thus, the effective index of difficulty can be interpreted as how hard did a participant perform in a given task condition.

A one-way repeated measures ANOVA was conducted to look at the effect of visual feedback delay on mean movement distance, mean movement time, effective index of difficulty, and effective index of performance.

Fractal analysis

Detrended fluctuation analysis (DFA; Peng, Buldyrev, Havlin, Simons, Stanley, & Goldberger, 1994) was used to detect the presence of long-range correlation within the peak intervals time series. DFA measures the power log scaling relationship between variability and time scale by dividing the time series into bins of increasingly smaller sizes. At each bin size (or time scale), each segment of data is centered, detrended, and the RMS residual calculated. The amount of variability at each bin size is plotted against bin size in a log-log plot, and a linear regression equation is fitted onto these data. The slope of this line indicates the degree to which the variability in the data scale as a function of how extended in time the segments are. A slope (alpha) of 0.5 indicates no long-range correlation (e.g. white noise), while the slope between 0.5 and 1.0 indicates persistent long-range correlation (e.g., pink noise[1]) (see Wagenmakers, Farrell, & Ratcliff, 2004; Hausdorff et. al., 1995 for an in-depth overview). Because the analysis parses out local trends in the data, DFA is advantageous for analyzing non-stationary data such as the strongly oscillatory pattern in the current data.

DFA is commonly used to assess long-range correlation in physiological data. For example, Hausdorff et. al. (1995) used DFA to look at the existence of long-range correlation in stride interval data. Not only did they find evidence that stride interval data exhibited long-range correlation, the authors also demonstrated this type of signal can be artificially created by a central pattern generator model wherein each stable pattern (or signal frequency) can only transitioned to a limited set of nearby states. This model resembles our own motor system, where there is interdependency between several processes (such as sensory processing, higher order goal-oriented control, motor planning, current muscle states, feedback-based motor control, environmental constraints, etc.). Hausdorff et. al. (1995) concluded that the combination of these factors resulted in the observed power-law correlation between variability and scale. Jordan, Challis, and Newell (2006) also used DFA to look for long-range correlation in stride intervals during running. However, the conclusion they drew was that high DFA slope at preferred speed reflected greater adaptive control rather than greater coordination of related systems. We

[1] Unlike white noise, where the power of every frequency band is the same, pink noise generally has high power at low frequencies and low power at high frequencies. The linear power law relationship between frequency and power in pink noise signals indicates long range dependency across the entire signal.

will further test whether DFA slope represents coordination or adaptivity in Experiments 2 and 3.

Similar to kinematic measures, a one-way repeated measures ANOVA was used to analyze the effect of visual feedback delay on DFA alpha.

Results

Due to technical errors, one trial from participant number 5 and two trials from participant number 8 were lost. Additionally, during trial 3 (at 266ms delay), participant 14 moved the finger in an anti-phasic pattern with the crosshair, resulting in qualitatively different movement pattern as well as an alpha value in the outlier range. Data from this trial was excluded from the analysis.

Mean movement distance

The omnibus ANOVA test indicated that there was a significant main effect of visual feedback delay on mean movement distance, F (2,32) = 35.92, $p < 0.01$, as well as a significant linear increase in mean movement distance as delay increased, F (1,16) = 54.98, $p < 0.01$. Post hoc tests indicated that there were significant differences of mean movement distance between all delay conditions (No delay M = 296.94, SD = 2.59; 133ms delay M = 305.13, SD = 2.55; 266ms M = 311.81, SD = 3.23). As delay increased, participants' mean movement distance progressively got longer.

Mean movement time

The omnibus ANOVA test indicated that there was a significant main effect of visual feedback delay on mean movement time, F (2,32) = 45.31, $p < 0.01$, as well as a significant linear increase in mean movement time as delay increased, F (1,16) = 65.64, $p < 0.01$. Post hoc tests indicated that there were significant differences of mean movement time between all delay conditions (No delay $M = 29.35$, $SD = 12.66$; 133ms delay $M = 35.74$, $SD = 12.13$; 266ms $M = 48.35$, $SD = 14.33$). As delay increased, participants' mean movement time progressively got longer.

Effective index of difficulty

There was a significant effect of delay on participants' effective index of difficulty, $F\ (2, 32) = 6.739$, $p = .004$, as well as a significant linear decrease in effective difficulty as delay increased, $F\ (1, 16) = 7.75$, $p = .013$. Post hoc tests showed that the effective index of difficulty between no-delay condition ($M = 3.05$, $SD = .14$) and 133ms delay condition ($M = 2.93$, $SD = .1$) was not significantly different ($p = .198$), but there was a significant different between 133ms delay and 266ms delay ($M = 2.69$, $SD = .09$) as well as between no delay and 266ms delay. As delay increased, the effective difficulty of the task as calculated from participants' movement decreased. Although the task itself becomes more difficult as delay increased, participants were behaviorally performing an easier version of the task with progressively wider targets, perhaps as a coping mechanisms to visual feedback delay.

Effective index of performance

There was a significant effect of delay on participants' effective index of performance, $F\ (2, 32) = 40.46$, $p < .001$, as well as a significant linear decrease in effective performance as delay increased, $F\ (1, 16) = 51.34$, $p < .001$. Post hoc tests showed that the effective index of performance between no delay ($M = .12$, $SD = .01$), 133ms delay ($M = .09$, $SD = .01$), and 266ms delay ($M = .06$, $SD = .01$) were all significantly different ($p \leq .001$).

Detrended fluctuation analysis

Detrended fluctuation analysis was applied to the peak interval time series. Bin sizes started from 256 data points for fast participants, or 128 data points for slow participants, with a scaling factor of 2. Mean alpha slope for no delay trials is $M = .76$, $SD = .15$, for the 133ms delay $M = .67$, $SD = .28$, and for the 266ms delay $M = .59$, $SD = .21$. There was a significant effect of delay on alpha, $F\ (2, 32) = 4.03$, $p = .027$. Linear trend analysis was significant ($p = .007$). Post hoc tests indicated that the alpha slope in no-delay trials was significantly higher than in 266ms delay trials ($p = .019$), but no other pairwise comparisons were significant. Overall, the evidence suggested that participants exhibited more pink noise signals in the no-delay trials, and more white noise (i.e. random noise) signals in the delayed trials.

Correlation

One of the main goal of Experiment 1 was to examine the sensitivity of the DFA alpha value and standard performance measure. As such, we performed a correlation test, looking at the relationship between alpha slope and the effective index of performance (see Figure 1). Two-tailed Pearson's correlation test showed $R = .54$, $p < .001$, indicating a moderate positive relationship between the effective index of performance and DFA alpha. To account for within-subjects shared variance, we used an MLM model with DFA alpha as the outcome, the index of performance as the predictor, and subject number as the Level 2 identifier. The model included random effects for the intercept and the slope of the index of performance, and an unstructured covariance matrix. The results showed an estimated fixed intercept of .39, $t\ (19) = 5.48$, $p < .001$. The estimated fixed slope for the index of performance was 3.22, $t\ (18) = 4.43$, $p < .001$. At an index of performance of 0, the average alpha value was .39. For every one point increase in the index of performance, the alpha value increased by 3.22.

Discussion

As expected from previous reports, visual feedback delay both interfered with speed and accuracy of movement (Smith, 1972; Smith & Bowen, 1980). Increases in visual delay linearly increased both mean movement time and mean movement distance. Mean index of difficulty and index of performance both decreased linearly with increases in delay, indicating that participants were lowering the difficulty of the movement task and achieving lower performance overall. Analysis using DFA alpha revealed a similar trend. As delay increased, variability in movement showed weaker and weaker indication of long-range correlation, transitioning from a more pink noise signal to a more white noise (i.e. random) signal. Evidence from the correlation test and the MLM analysis both indicated a positive correlation between the index of performance and DFA alpha. The evidence presented suggested that DFA analysis was sensitive to changes in behavioral performance.

CHAPTER 3

EXPERIMENT 2

We have showed that DFA alpha slope is sensitive to performance levels. However, it remains unclear as to what aspects of the visuomotor system dynamic induced this change in fractal property. One hypothesis is that visual feedback delay negatively affects both motor control and motor planning. As mentioned, visual disruption during different stages of the movement can influence both motor control and planning (Keele & Posner, 1968; Elliott, 1988). Since visual delay persisted before, during, and after each movement cycle in the current design, it is reasonable to assume that the coordination between vision and the motor system was disrupted. If we accept previous interpretations of the DFA alpha as an indication that signals from multi-scaled processes are coordinating and combining, then such disruption as described would result in a signal with weaker fractal property. Experiment 2 tests this hypothesis further by introducing additional disruption to the coordination between motor control and planning. This perturbation can be induced by blocking vision between the two target areas.

There is evidence suggesting that coordination between motor planning and control occurs in the middle stages of aiming movement. Valdez and Amazeen (2008) found strongest fractal signals at peak velocity, then weaker signals at both the preceding (peak acceleration) and following (peak deceleration) kinematic markers. From a signal summation perspective, this pattern matches the integration between a decaying motor planning signal and a starting motor control signal. Because motor control depends on visual information for feedback, blocking vision in the middle region should prevent motor control processes from integrating early on in the movement. At the same time, this manipulation should leave both motor planning and motor control processes relatively intact, as explained in the next paragraph. The goal of the manipulation is to maximally interfere with the signal summation process, while minimizing interference to motor planning and motor control processes.

Early research in motor control have separately showed that both motor planning and control can function without vision in the middle of the movement. Carlton (1981) reported that accuracy and movement time in aiming movements were not negatively impacted even when up to 50% of the first part of movement distance was blocked from view, suggesting that vision at early stages of movements were not required for effective feedback-based motor control. Similarly, Henson (1978) used eye saccadic data to show that secondary saccades, which presumably provide visual information for motor error correction, only covered the last 10% of movement distance. Regarding motor planning, Carlton's (1981) results also indicated that motor planning did not rely on vision since the entire first half of the movement was blocked with no negative effect on performance. However, it is worth noting that the starting position of a movement in discrete aiming tasks is fixed. As such, motor planning might not rely on vision as much as with reciprocal aiming tasks, where the starting position varies every cycle.

If DFA alpha measures coordination between multi-scaled processes within a system, this visual disruption, which prevents motor planning signals from combining with motor control signals until a late stage, will result in an alpha value closer to 0.5 above and beyond the effect of visual feedback delay. Furthermore, if performance depends on a well-coordinated system, we will see further reduction in performance measures despite evidence suggesting that both motor planning and motor control can separately function in a discrete aiming task.

Methods

Participants

Twenty-five participants were recruited for the experiment in exchange for course credit. Participants were healthy young adults with no vision or movement impairments. Due to technical errors, the data from one trial was lost (participant 19, trial 2). In addition, participants moved the crosshair in an anti-phasic pattern in three trials (participant 2, trial 3 and 4, and participant 10, trial 6). Data from these trials were excluded from the analysis.

Design

Experiment 2 followed a 2x3 design with two within-subject independent variables. Similar to Experiment 1, participants alternatively tapped between two target areas under three different delay conditions. Additionally, in half of the trials, 40% of the area between the two targets was also blocked so that participants could not see the crosshair representing their finger's position in space. Overall, each participant performed 1 practice trial followed by 6 4-minute trials (one for each of the six conditions in the 2x3 design) in randomized order. The practice trial had no delay and no visual blocking.

Apparatus and Procedure

The equipment configuration and trial-by-trial procedure in Experiment 2 was unchanged from Experiment 1. For trials where vision was blocked, the computer automatically shades 40% of the area between the two target zones the same color as the crosshair, making movements of the crosshair within this region effectively invisible.

When the crosshair comes within 10% of total distance to a target area, the area from the 10% mark to the midway mark was shaded. This shaded region switched to the opposite side when the crosshair got close to the other target area. This way, at the beginning of every movement, only the area immediately around the starting position, and half of the area near the target were visible.

Analysis

Pre-processing procedures similar to those done in Experiment 1 were applied to calculate the kinematic measures as well as the alpha slope from DFA. A two-way repeated measures ANOVA was then used to analyze the main effect of visual feedback delay and vision block, and any interaction effect on performance measures (mean movement distance, mean movement time, effective index of difficulty, and effective index of performance) and DFA alpha. Additionally, a correlation test was run to test the relationship between DFA alpha and the effective index of performance.

Results

Mean movement distance

The repeated measures ANOVA indicated that there was a significant main effect of visual feedback delay on mean movement distance, F (2,42) = 115.57, $p < .001$ as well as a significant linear increase in mean movement distance as delay increased (no delay M = 294.99, SD = 6.05, 133ms delay M = 301.81, SD = 5.29, 266ms delay M = 307.72, SD = 7.12, F (1,21) = 146.95, $p < .001$). Post hoc pairwise comparisons indicated that there were significant differences between mean movement times at all delay conditions (all $p < .001$). There was also a significant main effect of vision block on mean movement distance, F (1,21) = 8.07, p = .01. Participants in vision block trials (M =

302.51, $SD = 6.40$) moved a longer distance compared to their own performance in full vision trials ($M = 300.50$, $SD = 5.57$). There was no significant interaction between visual feedback delay and vision block, $F(2,42) = .08$, *ns*.

Mean movement time

There was a significant main effect of visual feedback delay on mean movement time, $F(2,42) = 70.16$, $p < .001$, along with a significant linear increase in mean movement time as delay increased (no delay $M = 26.23$, $SD = 7.83$, 133ms delay $M = 32.17$, $SD = 7.81$, 266ms delay $M = 41.24$, $SD = 12.12$, $F(1,21) = 84.23$, $p < .001$). Post hoc pairwise comparisons showed that there were significant differences between the mean movement times at all delays. The main effect of vision was not significant, $F(1,21) = 2.65$, *ns*, as was the interaction effect between visual feedback delay and vision block, $F(2,42) = 1.14$, *ns*. Overall, participants moved slower as delay increased, but vision block had no effect on their movement time (with vision block $M = 34.00$, $SD = 9.19$, with full vision $M = 32.43$, $SD = 9.02$).

Effective index of difficulty

There was a significant main effect of visual feedback delay on the effective index of difficulty, $F(2,42) = 45.56$, $p < .001$. Effective index of difficulty linearly decreased as delay increased (no delay $M = 3.12$, $SD = .24$, 133ms delay $M = 2.97$, $SD = .28$, 266ms delay $M = 2.78$, $SD = .28$, $F(1,21) = 100.97$, $p < .001$). Post hoc pairwise comparisons showed that there were significant differences between the effective index of difficulty at all delays (all $p < .001$). There was no significant main effect of vision block, F (1,21) = 2.62, *ns*, or of the interaction effect between visual feedback delay and vision block on the effective index of difficulty, F (2,42) = 1.35, *ns*. Participants performed effectively easier movements as delay increased, but did not significantly changed movement difficulty as a result of vision block.

Effective index of performance

There was a significant main effect of visual feedback delay on the effective index of performance, F (2,42) = 123.76, $p < .001$. Effective index of performance linearly decreased as delayed increased (no delay M = .13, SD = .03, 133ms delay M = .097, SD = .02, 266ms delay M = .072, SD = .02, F (1,21) = 161.98, $p < .001$). Post hoc pairwise comparisons showed that there were significant differences between the effective index of performance at all delay (all $p < .001$). There was also a significant main effect of vision block, F (1,21) = 6.24, $p = .021$. Participants in vision block trials had lower effective performance (M = .096, SD = .02) than compared to their performance in full vision trials (M = .103, SD = .02). There was no significant interaction between visual feedback delay and vision block, F = .05, *ns.*

Detrended fluctuation analysis

Similar to the procedure described in Experiment 1, detrended fluctuation analysis was applied to the peak interval time series to calculate the alpha slope. There was a significant main effect of visual feedback delay on alpha, F (2,42) = 11.92, $p < .001$. Linear trend test indicated that alpha linearly decreased as delay increased (no delay M = .79, SD = .18, 133ms delay M = .73, SD = .14, 266ms delay M = .61, SD = .20, F (1,21) =

18.67, $p < .001$). Post hoc pairwise comparisons showed that alpha slope at 266ms delay condition was significantly lower than alpha slopes at 133ms delay or no delay ($p = .006$ and $p < .001$, respectively), and that the difference in alpha slope between 133ms delay and no delay approached significance ($p = .056$). The main effect of vision block on alpha was not significant, F (1,21) < .001, *ns*. Neither was the interaction effect between visual feedback delay and vision block, F (2,42) = 2.56, $p = .089$. Similar to Experiment 1, the results suggested that participants performed closer to the pink noise threshold (alpha of 1.0) at lower delay and closer to the white noise threshold (alpha of 0.5) at higher delay. However, there was no difference in alpha slope when we compared vision block trials and full vision trials.

Since the interaction effect was close to significance, we attempted an exploratory analysis of the simple effects of vision on alpha value at each delay conditions. The analysis revealed that at no delay, the mean alpha difference between vision block and full vision was $M = .06$, $SD = .2$, $p = .151$. At 133ms delay, the mean alpha difference was $M = -.01$, $SD = .21$, $p = .857$. At 266ms delay, the mean alpha difference was M = -.05, $SD = .17$, $p = .165$ (see Figure 2).

Correlation

DFA alpha and the effective index of performance was correlated to examine whether the relationship we found in Experiment 1 could be replicated. Two-tailed Pearson's correlation test showed $R = .49$, $p < .001$, indicating a moderate positive relationship between the effective index of performance and DFA alpha. A MLM model predicting alpha using the index of performance as a predictor and subject number as the

Level 2 identifier was used. The model included random effects for both the index of performance and the intercept, and an unstructured covariance matrix. The estimated fixed intercept was .44, t (24) = 6.73, p < .001. The fixed slope for the index of performance was 2.76, t (24) = 5.16, p < .001. At an index of performance of 0, the average alpha value was .44. For every one point increase in the index of performance, alpha increased by 2.76 points.

Discussion

Experiment 2 was designed to test whether DFA's reactivity to performance stemmed from a sensitivity to a system's ability to communicate and coordinate between multiple component subprocesses. Using visual feedback delay, we disrupted the link between the visual system and the motor system. Using region blocking, we disrupted the link between motor control and motor planning, while leaving the core functionality of both components relatively unaffected.

The results replicated findings in Experiment 1. Participants' alpha value changed from closer to 1.0 (pink noise) when performing under no delay to closer to 0.5 (white noise) when performing in high delay. This change in alpha also correlated with concurrent changes in the effective index of performance, indicating that DFA alpha is sensitive to performance.

When we compare vision block trials and full vision trials, the data from the analysis of the effective index of performance suggested that vision block and visual feedback delay independently contributed to changes in performance, seemingly driven mainly by changes in the mean movement distance. Looking at the analysis on alpha, we did not detect any change in alpha as a function of vision blocking despite the reported change in performance. One implication is that DFA alpha is not sensitive to the performance measure per se, but rather to a third variable that is also influencing performance. Another implication is that this third variable is not the degree to which signals from subprocesses in a system can smoothly incorporate. This interpretation runs counter to previous research that argued for the coordination/coupling strength position (Dotov et. al., 2010; Valdez & Amazeen, 2008).

However, if we consider the exploratory analysis and observe the mean trends, a different picture emerges. No effect of vision block on alpha was detected because this effect changed as a function of visual feedback delay. At no delay, participants seemed to have higher alpha in vision block trials compared to in full vision trials. At high delay, participants seemed to have lower alpha in vision block trials compared to in full vision trials. With no delay and blocked vision, perhaps participants were forced to use longer range motor planning processes (to overcome the blocked region) and shorter range motor control processes (to compensate for the smaller region with vision). The combination of these signals could resulted in more pronounced long-range correlation in the interval time series. Attempts to employ the same strategy on trials with high delay may not be successful due to the additional interference, especially on online visual feedback processes. This interpretation would still suggest that alpha is not directly sensitive to performance measure, but it would support existing literature on the sensitivity of alpha to signal summation in a system.

CHAPTER 4

EXPERIMENT 3

An alternative interpretation of DFA alpha is that this measure indicates the level of flexible adaptivity in a system in response to environmental, or task, constraints (Van Orden et. al., 2003; Gorman, Amazeen, & Cooke, 2010). A hallmark of well-functioning complex systems is that they are able to adapt to external perturbation, often reorganizing into qualitatively distinct stable patterns in doing so. A smoothly operating system has a tendency to maintain homeostasis, giving it the ability to resist outside disruption. In most circumstances, complex systems are constantly subjected to outside influences. These influences cause random variations around the innate system-generated stable signal, leading to the type of structured, long-term correlated signals that non-linear analyses are designed to detect. Once disrupted, however, the ability of the system to maintain stability is compromised, leading to a more random signal. The goal of Experiment 3 is to test this hypothesis by manipulating the degree to which the visuomotor system adapts to cope with visual feedback delay and examining the effect of flexibility on performance and DFA alpha.

As reported in Experiment 1, as visual feedback delay increased (i.e. increasing disruption in the system), participants' observed effective index of difficulty decreased. We interpreted this as indicating that participants were reducing the level of difficulty in the motor portion of the task in response to worsening visual condition. In other words, the effective index of difficulty was capturing participants' adaptation to visual perturbation. Manipulation of this index will allow us to examine a system's performance and fractal measure at different levels of adaptivity. If DFA is sensitive to the system's adaptivity, then lower adaptation levels will have alpha values closer to 0.5 than at higher adaptation levels. Adaptation level should also translate to stronger performance.

Fitts (1954) originally calculated the index of difficulty based on the width of the targets and the distance between the targets to indicate the difficulty of the presented version of the task. Fitts and Peterson (1964) later updated this calculation to include other variables by using participants' actual movement data (variability around movement end points and mean movement distance). Despite this, the effective index of difficulty was still dependent on the parameters of the presented task stimuli. By changing the task constraints, namely target width, we can induce changes in the observed effective index of difficulty.

Methods

Participants

Twenty-four participants were recruited into the experiment in exchange for class credit. Participants were young, healthy adults with no visual or movement impairments. Two participants (number 9 and 17) failed to follow instructions and were not included in the analysis. Participants in two trials performed the task using an anti-phasic movement pattern (participant 1, trial 7, and participant 14, trial 9). Additionally, data for one trial was lost due to technical error (participant 18, trial 4). These three trials were not included in the analysis.

Design

Experiment 3 followed a 3x3 within-subject ANOVA design. Similar to previous experiments, participants performed a reciprocal tapping task under 3 delay conditions in randomized order. After these trials were completed, participant's effective indices of difficulty at each delay levels were calculated. Participant then repeated each delay condition two more times. However, instead of performing the same task, participants was given a modified task that reflected an enhanced or attenuated level of adaptivity. For example, a modified task at high delay might have a smaller target size to simulate the level of movement difficulty previously seen in an easier low delay trial. The order of the 6 subsequent trials was also randomized. Overall, participants performed 9 4-minute trials and 1 practice trial.

Apparatus and Procedure

The equipment configuration and trial-by-trial procedure in Experiment 3 were unchanged from Experiment 1. Each participant's effective index of difficulty was calculated immediately after each of the first three standard trials. The differences between observed indices in different delay conditions were added to or subtracted from observed value to create new effective indices of difficulty that simulate scenarios where participants' adaptivity was above or below the observed level. An elevated effective index of difficulty would imply that a participant was not adequately compensating to a given task difficulty (by performing simpler movement). Thus, to induce a higher effective index of difficulty, the target width would need to be narrowed. Conversely, a lowered effective index of difficulty would imply overcompensation, and would need to be implemented with wider target width.

The displayed target width was calculated based on the effective width using the new effective index of difficulty. The effective width eW_j when a participant was overcompensating at delay j was calculated as:

$$eW_{j\_ov} = \frac{MD_j}{2^{eID_{j\_ov}} - 1}$$

For example, the effective width in a delay 2 trial (133ms) needed to simulate an overcompensated trial was:

$$eW_{2\_ov} = \frac{MD_2}{2^{eID_{2\_ov}} - 1}$$

The displayed target width was then adjusted proportional to the *calculated* eW: *observed* eW ratio. For a detailed example, refer to the Appendix.

Analysis

Pre-processing procedures similar to those done in experiment 1 were applied to calculate the kinematic measures as well as the alpha slope from DFA. As a manipulation check, the effect of width manipulation on effective width and effective index of difficulty in simulated trials were compared to the observed index using a one-way ANOVA to verify that trials of the same level of difficulty had similar reported indices, regardless of delay condition. Then, a two-way repeated measures ANOVA was used to analyze the main effects of visual feedback delay and adaptivity on both performance measures and DFA alpha. Because standard baseline trials were not randomized with simulated trials, the main effect analyses will only look at under-compensated versus over-compensated trials. Once again, the DFA alpha was correlated with index of performance.

Results

Manipulation checks

Target width was adjusted based on each participant's performance in the standard baseline trials. On average, under-compensated trials had target widths that were

10.5%, 11.1%, and 23.5% smaller than baseline at no delay, 133ms delay, and 266ms delay respectively. Over-compensated trials had target widths that were 7%, 17.6%, and 18.4% larger than baseline at no delay, 133ms delay, and 266ms delay respectively. A one-way ANOVA was used to examine whether the width adjustment had an effect on participants' effective width and effective index of difficulty. There was no significant effect of width adjustment on effective width, F (2,42) = .12, *ns* (baseline M = 47.93, SD = 10.14, under-compensated M = 47.86, SD = 20.52, over-compensated M = 49.08, SD = 15.6). Similarly, there was no significant effect of width adjustment on participants' effective index of difficulty, F (2,42) = .52, *ns* (baseline M = 2.91, SD = .26, under-compensated M = 2.97, SD = .43, over-compensated M = 2.91, SD = .45). The width adjustment manipulation was not successful at altering participants' movement properties, and more specifically, their effective index of difficulty. Since a causal relationship between changes in target width and participants' effective index of difficulty could not be established, under-compensated and over-compensated trials will be renamed narrow and wide trials for simplicity and clarity of interpretation.

Mean movement distance

A 2 (width: narrow and wide, baseline not included) x 3 (visual feedback delay: no delay, 133ms delay, and 266ms delay) repeated measures ANOVA was used to test for the main effects and the interaction between width and delay on mean movement distance. There was a significant main effect of delay on mean movement distance, F (2,36) = 111.55, $p < .001$ (no delay M = 292.29, SD = 5.96, 133ms delay M = 298.39, SD = 6.57, 266ms delay M = 305.75, SD = 6.80). Similar to Experiment 1 and 2, as delay increased, participants' movement distance increased. There was also a significant main effect of width on movement distance, F (1,18) = 11.51, $p < .001$ (narrow M = 300.21, SD = 6.23, wide M = 297.41, SD = 6.39). Participants went longer distance with narrow targets compared to wide targets. The interaction effect was not significant, F (2,36) = 2.02, *ns*.

Mean movement time

A 2x3 repeated measures ANOVA was used to test for the main effects and the interaction between width and delay on mean movement time. There was a significant main effect of visual feedback delay on movement time, F (2,36) = 57.59, $p < .001$ (no delay M = 29.30, SD = 21.77, 133ms delay M = 35.58, SD = 20.67, 266ms delay M = 43.73, SD = 25.10). As delay increased, participants' movement time got longer. There was also a significant main effect of width on movement time, F (1,18) = 11.19, p = .004 (narrow M = 37.70, SD = 22.88, wide M = 34.70, SD = 21.96). Participants took longer to move between targets when the targets were narrow compared to when the targets were wide. The interaction effect was not significant, F (2,36) = 1.01, *ns*.

Effective index of difficulty

A 2x3 repeated measures ANOVA was used to test the main effects and the interaction term of delay and width on the effective index of difficulty. There was a significant main effect of visual feedback delay on the effective index of difficulty, F (2,36) = 31.97, $p < .001$ (no delay M = 3.15, SD = .51, 133ms delay M = 2.99, SD = .44, 266ms delay M = 2.78, SD = .36). In accord with results from the one-way ANOVA reported above, there was no effect of width on the effective index of difficult, F (1,18) = 1.09, *ns* (narrow M = 3.00, SD = .43, wide M = 2.95, SD = .45). The interaction effect was also not significant, F (2,36) = 1.78, *ns*.

Effective index of performance

A 2x3 repeated measures ANOVA was used to test the main effects and the interaction term of delay and width on the effective index of performance. There was a significant main effect of visual feedback delay on the effective index of performance, F (2,36) = 131.61, $p < .001$ (no delay M = .13, SD = .03, 133ms delay M = .10, SD = .03, 266ms delay M = .08, SD = .03). There was also a significant effect of width on the effective index of performance, F (1,18) = 9.31, p = .004 (narrow M = .098, SD = .03, wide M = .11, SD = .03). The interaction effect was not significant, F (2,36) = .504, *ns*. Overall, as delay increased and width decreased, participants' performance got worse.

Detrended fluctuation analysis

Similar to Experiment 1 and 2, detrended fluctuation analysis was applied to peak intervals data series. The repeated measures ANOVA results indicated that there was a significant main effect of delay on DFA alpha, F (2,36) = 3.45, p = .043 (no delay M = .80, SD = .19, 133ms delay M = .76, SD = .2, 266ms delay M = .69, SD = .23). As delay increased, DFA alpha moved further away from 1.0 (pink noise) and closer to 0.5 (white noise). The difference between DFA alpha in narrow trials and DFA alpha in wide trials approached significance, F (1,18) = 3.25, p = .088 (narrow M = .73, SD = .19, wide M = .77, SD = .17). The interaction effect was not significant, F (2,36) = .49, *ns*. The mean trend suggested that participants performed closer to 1.0 (pink noise) in wide trials than they did in narrow trials.

Correlation

We correlated DFA alpha with participants effective index of performance. The Pearson's Correlation test matched results found in Experiment 1 and 2, R = .51, p <

.001. There was a moderate positive correlation between alpha and the effective index of performance. A MLM model predicting alpha using the index of performance as a predictor and subject number as the Level 2 identifier was used. The model included random effects for both the index of performance and the intercept, and an unstructured covariance matrix. The estimated fixed intercept was .51, t (21) = 6.79, $p < .001$. The fixed slope for the index of performance was 2.65, t (21) = 4.46, $p < .001$. At an index of performance of 0, the average alpha value was .51. For every one point increase in the index of performance, alpha increased by 2.65 points.

Discussion

The goal of Experiment 3 was to test the hypothesis that fractal analysis such as the DFA measures a system's ability to flexibly adapt to changing environment. By changing the width of the target areas in the reciprocal tapping task, we aimed to manipulate level of adaptivity in the visuomotor system in response to visual feedback delay, as conveyed by the effective index of difficulty. This manipulation would then allow us to examine whether system flexibility is one of the underlying causes of changes in DFA alpha values.

The manipulation checks indicated that the width manipulation was not successful. As seen in Table 1, when target width was reduced to simulate participants not adequately compensating for task difficulty, the observed effective index of difficulty largely matched our target values. However, when target width was increased to simulate a scenario where participants compensate more than what we observed in baseline trials, we instead found that the effective index of difficulty stayed at baseline level or even increased. In other words, participants were not decreasing the difficulty of the task they performed even when there was an option to do so. One simple explanation could be that participants had gained a level of automaticity with the baseline target width so they performed at this level whenever possible. In narrow width trials, successful completion of the task required them to change their movement parameters to a higher difficulty. However, in wide width trials, they could perform the baseline level of difficulty and still satisfy the requirement of the test. Regardless, the reduction in the range of effective indices of difficulty negatively impacted the statistical power of the experiment.

The results once again replicated the principal finding of Experiment 1, namely that DFA alpha was closer to pink noise when delay was low, and closer to white noise when delay was high. This indicated that movement variability at low delay showed strong presence of long-term correlation, relative to movement variability at high delay. DFA alpha also moderately correlated with the index of performance, signaling that fractal analysis of variability was sensitive to some aspect of behavioral performance.

When comparing participants' performance between narrow trials and wide trials, the results indicated that performance was higher in wide target trials. This result is consistent with a wealth of literature on the reciprocal tapping task. In terms of DFA alpha, the direction of the means suggested that movement variability in wide target trials might be closer to pink noise than in narrow target trials. Considered alongside the partial success of our manipulation, this pattern of data appeared promising. However, we clearly need a more effective manipulation to arrive at a conclusive answer to this hypothesis.

CHAPTER 5

CONCLUSION

In this series of experiments, we explored the possibility of analyzing movement variability as a way to measure generalized performance in movement task. In Experiment 1 and subsequent replications, we established that the alpha exponent, as derived from applying detrended fluctuation analysis to the peak interval time series of a reciprocal tapping task, showed sensitivity to participants' performance.

More specifically, we showed that as delay in visual feedback increased, DFA alpha linearly decreased between 1.0 and 0.5. Concurrently, we observed a linear decrease in various performance measures. As delay increased, participants were making longer movements, moving slower, performing less demanding movements, and showing lower index of performance. Finally, the index of performance moderately correlated with DFA alpha. These results established a clear causal effect of visual feedback delay on both performance and on the temporal structure of variability in participants' movements. This connection between behavioral performance and variability structure adds to a body of evidence that have often relied on comparisons across age groups or patient populations (Stergiou & Decker, 2011). DFA alpha's sensitivity to performance also opens up the possibility of using fractal analyses to assess traditionally difficult-to-measure skills such as musical performance, skilled tool use (see Bril, Rein, Nonaka, Wenban-Smith, & Dietrich, 2010), or any non-speed skills (skills in which the speed of execution is not the primary predictor of performance).

Furthermore, recall that DFA alpha of 0.5 indicates a lack of long-range correlation, whereas an alpha of 1.0 indicates persistent long-range correlation in the time series. The results showed that participant's movement variability at low delay were closer to 1.0, and movement variability at high delay were closer to 0.5. These findings suggested that there were inherent structure and interdependency nested within the movement variability in the "normal" (low delay) condition, and that this temporal structure was disrupted when a time lag was introduced into the system. Experiments 2 and 3 examined in greater details the effect of disruption on movement variability and performance.

In Experiment 2 and 3, we tested two major interpretations of the DFA alpha value by manipulating the task environment of the reciprocal tapping task. In Experiment 2, we examined whether DFA alpha changes as a function of the degree to which subcomponent signals in a system can be smoothly combined. By blocking a portion of the task space, we presumably prevented signals from motor control and motor planning processes from combining early in the movement. The results showed that alpha was not affected by vision blocking, which implied that smooth integration of subcomponent signals was not a major driver of DFA alpha value. This account contradicts previous works supporting this view. An alternative explanation involving the interaction between vision blocking and visual feedback delay can explain the pattern of the data, and will need to be further examined in subsequent experiments.

In Experiment 3, we examined whether DFA alpha changes as a function of the degree to which a system can flexibly adapt to changing task environment. By manipulating the effective index of difficulty in each trial (through manipulation of the target width), we simulated conditions in which participants either under-compensated or overcompensated for the task difficulty. Unfortunately, our manipulation was only partially successful. However, the pattern of data appeared to support the notion that flexible adaptation to a task environment has an impact on DFA alpha value.

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APPENDIX A

EXAMPLE OF CALCULATIONS USED TO ADJUST TARGET WIDTH IN EXPERIMENT 3

To demonstrate the steps taken to calculate the target widths used in Experiment 3, we will use the data from Participant 1 as an example. After performing the first 3 standard trials (at 3 delay conditions), the participant's effective indices of difficulty at no delay, 133ms delay, and 266ms delay were 2.76, 2.49, and 2.18, respectively. We start by calculating the difference between the indices:

$$D1 = 2.76 - 2.49 = 0.27$$

$$D2 = 2.49 - 2.18 = 0.31$$

Using these differences, we calculate the target effective index of difficult in simulated trials. At no delay, the target for effective indices of difficulty for under-compensated and over-compensated trials equal the baseline plus or minus D1, respectively:

$$eID_{1\_Un} = 2.76 + D1 = 3.03$$

$$eID_{1\_Ov} = 2.76 - D1 = 2.49$$

At high delay, the calculations for target effective indices of difficulty are identical, except D2 is used instead of D1. At moderate delay (133ms), under-compensated target is calculated as baseline at moderate delay plus D1, whereas over-compensated target is calculated as baseline minus D2.

Next, we calculate the target effective width of the simulated trials. For example, the target effective width of the over-compensated trial at no delay is:

$$eW_{1\_ov} = \frac{MD_1}{2^{eID_{1\_ov}-1}} = \frac{286.21}{2^{2.49}-1} = 61.98$$

Given the observed effective width at no delay is 49.38, the width of the target areas in the over-compensated trial at no delay will be increased by 61.98/49.38 = 1.26 times.

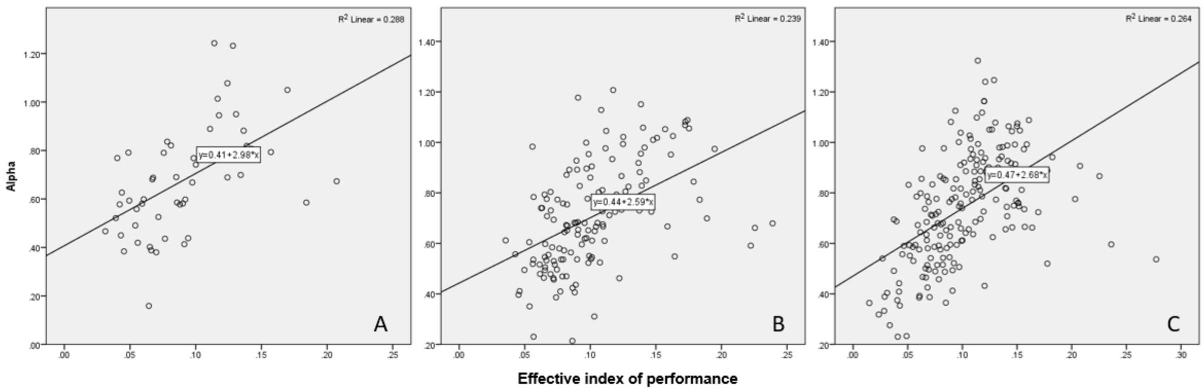

Figure 1. Scatterplots showing the relationship of the effective index of performance and DFA alpha. A – Experiment 1; B – Experiment 2; C – Experiment 3.

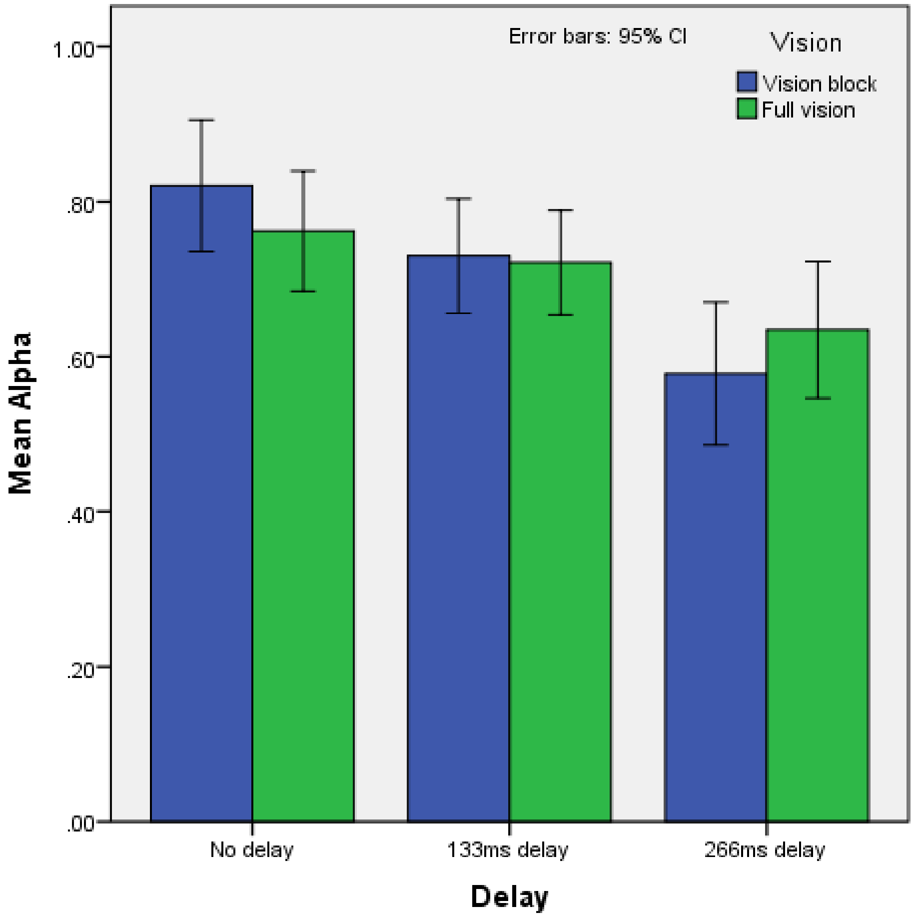

Figure 2. DFA alpha as a function of visual feedback delay and vision block.

Effective index of difficulty	No delay	133ms delay	266ms delay
Under-compensate	Target: 3.11 Observed: 3.15	Target: 3.05 Observed: 3.06	Target: 2.99 Observed: 2.81
Baseline	Observed: 3.05	Observed: 2.99	Observed: 2.73
Over-compensate	Target: 2.99 Observed: 3.16	Target: 2.73 Observed: 2.94	Target: 2.47 Observed: 2.75

Table 1. Effective index of difficulty (EID) by visual feedback delay (no delay, 133ms, and 266ms) and condition (under-compensate, baseline, and over-compensate). Target: EID calculated after based on each participant's performance in baseline trials. Target width is adjusted based on Target EID. Observed: EID as calculated from participant's movement data.