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Recent literature suggests that gait dynamics plays a role in establishing healthy, adaptive gait behavior, and that illness or injury can alter the dynamic patterns of gait (termed fractal patterns). So called "dynamical diseases" change the fractal patterns in gait, hereby reducing adaptive gait ability and increasing fall-risk. Previous research has shown that fractal patterns in gait can be strengthened through the use of a fractal metronome stimulus. However, in previous research participants have consistently presented weaker fractal patterns than prescribed by the metronome, despite improvements from their baseline. One postulate is that this gap between the stimulus and the participants' response is due to the prescriptive nature of the stimulus – that is, the metronome is presented with no interaction with the user. If so, the introduction of real-time feedback regarding synchrony with the stimulus may be beneficial to strengthening fractal patterns. The purpose of this study was to examine the role of feedback in increasing synchrony with a fractal metronome stimulus, and in entraining fractal gait patterns. There were three hypotheses: First, feedback would elicit a stronger coupling between participants' gait dynamics and the dynamics of the stimulus relative to a non-feedback condition. Second, the addition of feedback to the visual metronome would lead to a stronger fractal pattern during the training and post-training (retention) phases. Third, participants with the strongest coupling during training would exhibit the strongest fractal patterns during training and post training. Results showed no difference in coupling

between feedback and non-feedback conditions. The addition of feedback to the fractal metronome led to no significant difference in fractal strength from baseline to training and baseline to retention. While greater coupling was correlated to stronger fractal patterns during training, there was no relationship between coupling and retention. This study was consistent with previous studies supporting the use of metronomes to alter gait dynamics, and was one of the first to examine feedback in conjunction with fractal gait training.

USING FEEDBACK ENHANCED VISUAL METRONOMES TO MANIPULATE GAIT DYNAMICS

by

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APPROVAL PAGE

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CHAPTER I

INTRODUCTION

It is difficult to overstate the importance of functional mobility for independent living and high quality of life. Ambulation or gait is a core factor in determining functional mobility, which refers to the ability to safely and effectively navigate through the environment. Categorized as a Basic Activity of Daily Living (James, 2014), safe and effective gait is considered instrumental to self-care and an independent lifestyle. Functional gait behavior is the product of many factors: balance, executive function, muscular strength, timing, and coordination. The complexity of gait provides many avenues by which deficiency can be introduced. Degradation of functional gait behavior can occur through injury, aging, or a multitude of diseases, including Parkinson’s, Multiple Sclerosis, and stroke. Worsening gait function is linked not only to decreased mobility, but also an increased risk of injury due to falling (Campbell et al., 1989). Fall risk is particularly prevalent in an elderly population, with up to 30% of community-dwelling adults over 65 reporting one or more falls within the past year (Shema et al., 2013). Clinical rehabilitative practice attempts to address these gait deficits and restore a higher level of functional mobility.

It has been acknowledged in recent decades that gait dynamics may play an important role in healthy adaptive gait behavior. The term “dynamical systems” describes systems, including the physiological, which evolve through different states as a function of time. When measuring biological signals across a span of time, minor fluctuations in the signal are evident, even when environment factors are unchanged. The historical view of variability is that it is “noise”- meaningless imprecision in the mechanisms of the system. This paradigm does not see system variability as being of particular importance; researchers are more typically concerned with measures of central tendency (i.e., the mean about which the variability occurs). Recently, research has begun to re-evaluate the importance of variability. Beginning with cardiac dynamics, researchers have started to view small fluctuations in time series as not only natural, but necessary for the health of the system.

Utilizing non-linear mathematical tools, it is possible to examine the structure of variability, in effect describing how related any series of points may be to any other series of points as a function of time. In this way, the structure of variability in a time-series can be classified on a spectrum ranging from complex (highly correlated) to uncorrelated (white noise). It is thought that healthy biological systems, such as gait or cardiac rhythms, should exhibit a specific class of fluctuation described as fractal patterns, which is characterized by repeated patterns of variability across time scales. A fractal pattern is characterized by both low frequency patterns, as well as high-frequency fluctuations. Healthy gait rhythms therefore fall between these two poles of the continuum. Maladaptive gait behavior may be a result of gait patterns shifting to either extreme. On the one hand highly structured systems are too rigid to meet altered demands from the environment, while on the other hand an unstructured signal lacks any sort of defined pattern that would allow for control. Therefore, healthy systems need some level of fractal noise to function, but a high level of variability leads to breakdown in functionality.

While yet to be put to clinical practice, it is thought that many gait dysfunctions can be treated via manipulation of underlying gait dynamics. So-called “dynamical diseases” may produce pathological gait behavior by driving gait patterns out of the healthy part of the spectrum, toward either of the two extremes. Attempts to manipulate gait dynamics, using rhythmic auditory and visual stimuli have been met with initial success. Rhea and colleagues (2014), have shown that synchronization to a visual metronome driven by a fractal signal can alter subjects’ position along the spectrum of gait variability. Participants exposed to highly correlated patterns are capable of entraining to those stimuli and changing their gait dynamics. However, no study has yet shown the ability to induce fractal patterns of specified strength: participants’ gait dynamics tend to be significantly less correlated than the stimulus to which they are exposed. The size of the “gap” between the stimulus and the resultant motor behavior has been shown to be a product of the presentation modality of the stimulus. The visual metronome manipulation task is ripe for enhancements which may increase its ability to alter gait dynamics

The purpose of this study was to examine the effect of extrinsic feedback on the resulting gait patterns when synchronizing to a visual metronome task. This study was a continuation of previous work by Rhea, Kiefer, and Wittstein (2014) and represents one possible avenue for addressing the gap between stimulus and output. It was postulated that real-time interactive feedback would enhance coupling to the metronome and in so doing strengthen fractal patterns in comparison to the non-feedback condition. Three hypotheses were tested:

Hypothesis 1: Feedback would elicit a stronger coupling (i.e., higher cross-correlation values) between participants' gait dynamics and the dynamics of the stimulus relative to a non-feedback condition.

Hypothesis 2: The addition of feedback to the visual metronome would lead to a stronger fractal pattern during the training and post-training (retention) phases.

Hypothesis 3: Participants with the strongest coupling during training would exhibit the strongest fractal patterns during training and post-training.

CHAPTER II

REVIEW OF THE LITERATURE

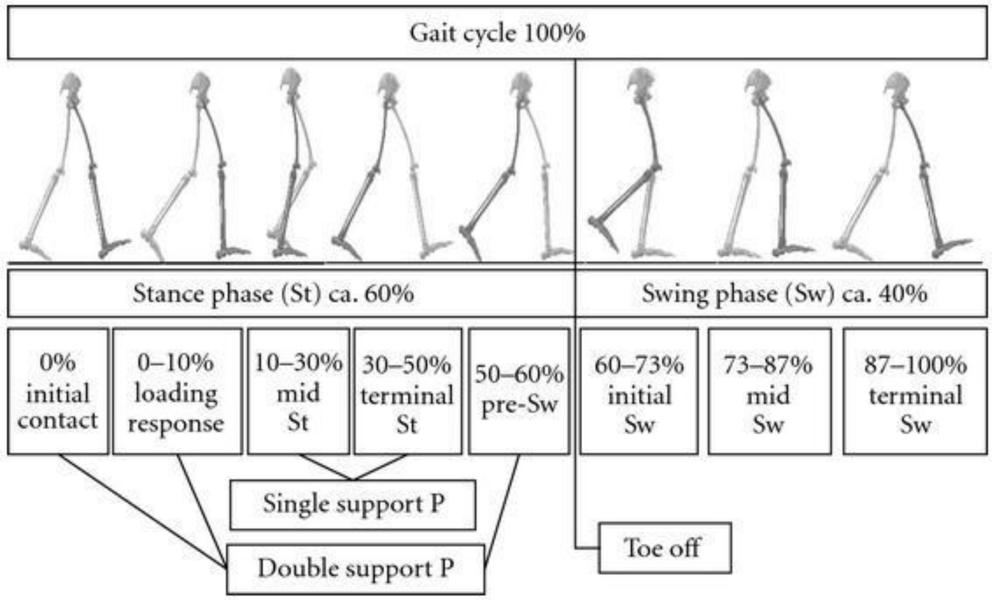
Overview

This chapter will explore the literature regarding: (1) the gait task, (2) the variability and adaptability hypothesis, (3) detrended fluctuation analysis, (4) origins of fractal noise, (5) sensorimotor and metronome synchronization, (6) cross-correlations in gait studies and (7) how feedback can be used to enhance sensorimotor synchronization. A summary will address opportunities for further research.

The Gait Task

Gait is a rhythmic, cyclic motion that progresses through limb-alternating stages during the course of a single cycle. Both limbs experience swing and stance phases in the course of a complete cycle, which is defined as from one heel strike to another with the same limb (Winter, 1991).The lower extremities oscillate through multiple states—left limb stance, dual limb stance, right limb stance—before returning to their previous state. The following figure illustrates the stages of a full gait cycle (Hartmann et al., 2010).

Figure 1. The Gait Cycle with Proportions for each Phase with Healthy Adult Gait



The lower extremities can be described mathematically as a pair of coupled oscillators; each limb progresses cyclically through stance phase, swing phase, and back again. While constantly in motion, each limb traces a mostly consistent pattern in space. During typical healthy gait neither limb operates independently. An increase in gait speed decreases stance times and increases swing times for both limbs symmetrically (Winter, 1991). Each limb moves in antisynchrony with each other, half a gait cycle apart. While one limb is in stance phase, the other swings, and vice versa. A vital feature of this system of coupled oscillators is its stability as limit-cycle oscillators. When subjected to a perturbation which disrupts the gait cycle, the limbs may briefly fall out of antisynchrony with each other, but will naturally and quickly recouple, reestablishing the previous pattern over the course of several strides. This behavior allows the gait cycle to recover following trips or slips that occur during navigation of the physical environment.

Pathological gait exhibits decreased adaptability to perturbation. Aging and illness are linked with maladaptive gait behavior and increased fall risk. This may be due to an altered gait cycle and reduced limb coupling. For example, hemiparetic gait is common in sufferers of stroke, where one limb is has significant muscular strength deficits in comparison to the other. This results in asymmetrical gait, with a shorter swing phase and ground clearance in the affected limb (Vaughan, et al., 1999). Asymmetrical or uncoupled limb oscillations may make it more difficult to establish and maintain stable gait cycles.

Variability and Adaptability Hypothesis

The adaptability of systems such as the gait cycle is thought to be linked to fluctuations of physiological variables (Glass & Mackey, 1988). Biological systems have been long recognized as exhibiting minor fluctuations as a function of time, even when systemic and environmental factors remain constant. Stable or homeostatic systems can be described mathematically as either steady states or oscillators. In these steady states, a given set of parameters will always produce a constant solution, which does not change as a function of time.. Steady state models do not provide adequate justification for the existence of observed biological variability. As such, variability has been historically considered meaningless noise — errors in measurement or methodology that were ignored in favor of mean values (Diniz et al., 2011).

Traditional measures of variability focused on the magnitude of variability, such as standard deviation or coefficient of variation, or standard error. These linear measures provide a narrow view of variability as a phenomenon. Later motor control paradigms linked the magnitude of variability to the health of a system, whereby increased variability was a sign of degraded accuracy of an individual's motor function. This view is supported by studies showing increased variability across motor tasks with advancing age and declining function (Roos et al., 1997).

This view, that variability across physiological systems is indicative of the failing health of these systems, rests upon the premise that successive fluctuations are entirely unrelated to each other. This form of unstructured, uncorrelated values is described as "white noise". However, it has been shown that fluctuations in biological systems are not uncorrelated white noise. Box and Jenkins (1976) published mathematical processes that allowed the examination of time series for dependence between successive data points, albeit on a short-term window of time. Correlations between successive points in a system can be observed over increasingly large time scales, suggesting that any individual value is an expression of all prior values in the series. This correlation of patterns in time series is known as self-similarity, fractal patterns, or 1/f noise.

Fractal patterns are present in numerous physiological systems, first evidenced in heartbeat time series (Peng et al., 1993), and later in gait stride times (Hausdorff et al., 1995). It is also present during finger-tapping (Gilden, Thornton, & Mallon, 1995) and metronome synchronization tasks (Torre & Delignières, 2008). Goldberger and colleagues (2002) link healthy behaviors to the presence of 1/f noise, a position reinforced by the weakening of fractal patterns due to injury, aging, or disease (Hausdorff, 2007; Hausdorff et al., 1997; Lipsitz & Goldberger, 1992). Healthy gait requires the presence of fractal fluctuations for proper motor function (Hausdorff et al., 1995). Herman et al (2005) showed that high level gait disorder is correlated with both increased fall risk and weak fractal patterns. It is hypothesized that the presence of minor fluctuations provides a system with the ability to adapt to perturbation. It is easy to imagine perturbations to the gait cycle: a physical obstacle may result in a trip, after which a healthy system may be able to recover and return to the original gait pattern. Too rigid of a gait pattern, i.e. overly correlated, would be unable to adapt to the perturbation. However, an under correlated gait pattern, i.e. white noise, lacks the structure necessary for a coordinated response and is similarly maladaptive. It is therefore thought that healthy adaptive behavior resides in an optimal zone; that is, neither too structured nor too noisy.

Detrended Fluctuation Analysis

Due the inability of traditional linear measures to capture the structure of gait variability, a non-linear dynamics approach is necessary. Detrended fluctuation analysis (DFA) is a metric that quantifies the strength of self-correlation in a time series, i.e. how strongly fractal patterns are expressed (Hausdorff et al., 1995). DFA was initially utilized to describe DNA sequences (Peng et al., 1994) and later applied more broadly to other physiological systems. DFA examines structure across increasingly large subsets of a times series in order to quantify long-range correlations on multiple time scales.

Calculation of DFA begins by demeaning all points of the time series (i.e., shifting the mean of the time series to zero) and then summing the points, as in Figure 2.

Figure 2. Calculation of Demeaning of Data

$$y(k) = \sum_{i=1}^{k}[S(i) - S_{ave}]$$

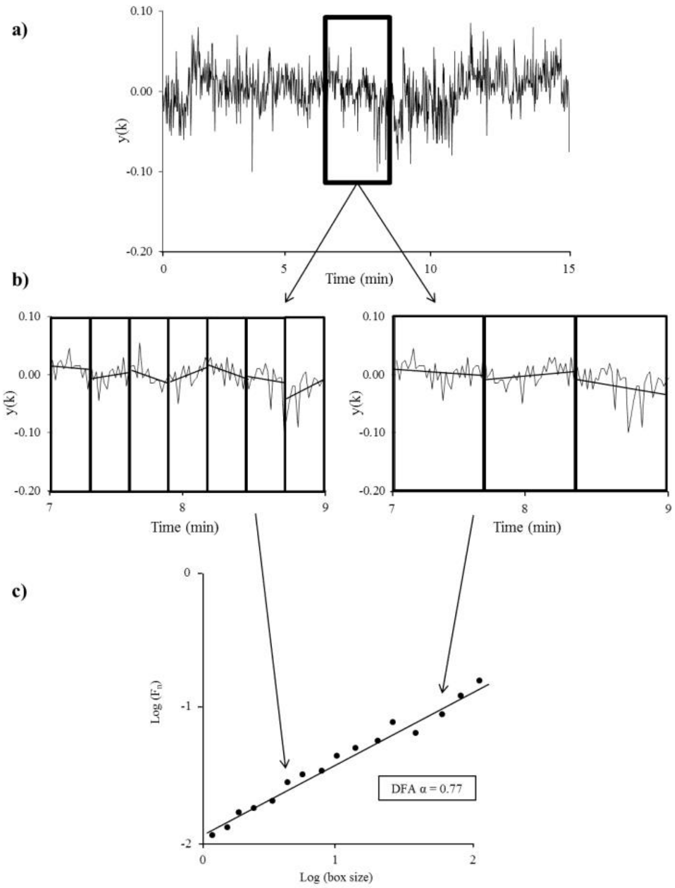
The average step interval is subtracted from value of each step interval S(i) to mean center the data (i.e., values now reflect variation about the average step interval). The y(k) time series is the summation of all demeaned y(k) values, which is then partitioned into discrete, smaller time series.. A polynomial curve is fitted to each sub-series, which range in size from 4 data points, to ¼ the length of the time series. The data in each sub-series is detrended by taking the magnitude of the difference between the trend values and the observed data. The amount of fluctuation within each section is computed using the Root Mean Square (RMS) method, depicted in Figure 3.

Figure 3. Root Mean Square Calculation for DFA

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n\,(k)]^2}$$

The logarithm of the RMS function is graphed as a function of the logarithm of the section size (number of data points in section) in a log-log plot. This process repeats iteratively with larger sections up to the maximum size. A line of best fit is constructed, the slope of which corresponds to the DFA alpha value of the time series. The entire DFA calculation is illustrated in Figure 4, from Rhea and Kiefer (2014).

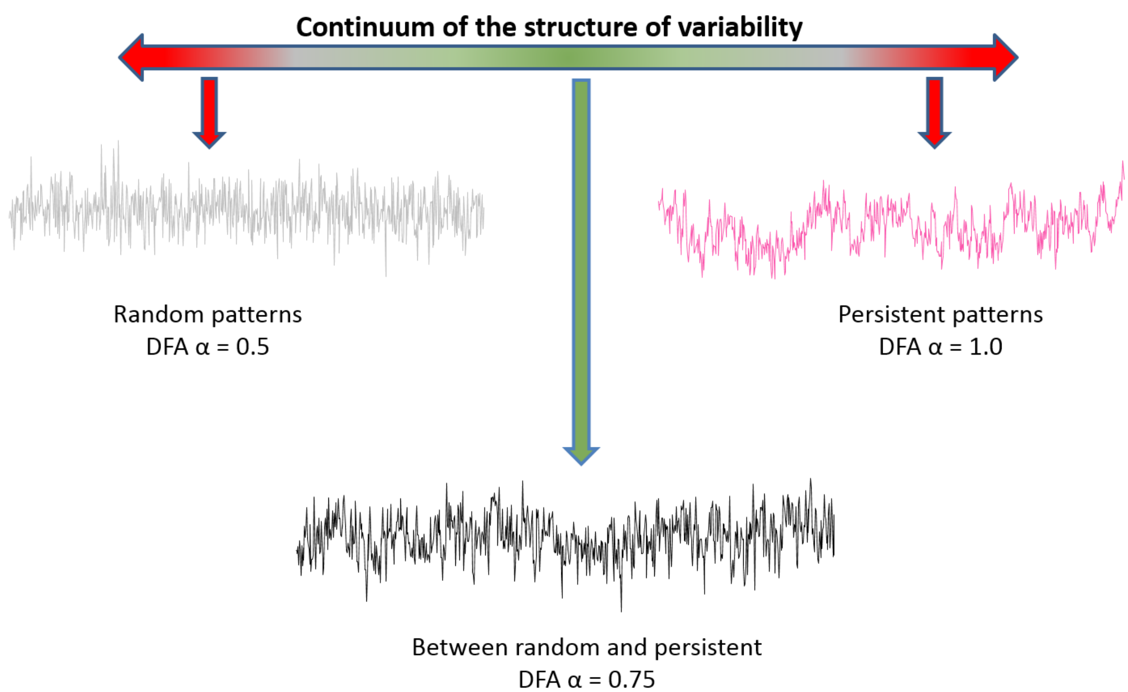
Figure 4. DFA Calculation, Adapted from Rhea and Kiefer (2014). Panel A illustrates an example demeaned time series. Panel B shows the process of partitioning the time series and calculating a line of best fit. Panel C presents the log-log plot of RMS and section size.



The DFA alpha metric provides a method of examining variability along a continuum, as shown in Figure 5 (adapted Rhea, Kiefer, D'Andrea, et al., 2014). Highly regular time series yield a DFA alpha of 1.0, while overly random series yield 0.5. Healthy adult gait usually has a DFA alpha value of around 0.75 (Hausdorff et al., 1995).

Older adults with gait and balance disorders exhibit DFA values close to 0.5, which may be related to decreased adaptability and greater fall risk (Hausdorff, 2007).

Figure 5. Examples of Time Series Depicting Random (DFA α = 0.50), Between Random and Persistent (DFA α = 0.75), and Persistent (DFA α = 1.0) Patterns. Adapted from Rhea, Kiefer, D'Andrea, et al. (2014).



Origins of Fractal Patterns

There is no consensus in the literature on the origin of fractal patterns in biological systems. The debate is divided primarily between two camps: those who believe fractal patterns can be caused "locally" by individual subsystems, and those who believe fractal patterns are an emergent property indicative of the complexity of a system (Diniz et al., 2011). In the former paradigm, 1/f noise can arise from a single aspect of the system, not the interaction of the system as a whole. Wing and Kristofferson (1973) posited rhythmic synchronization behavior required two components: a central internal timekeeper and a motor control process. The central timekeeper is considered the source of 1/f noise seen in the motor output (Gilden et al., 1995). The internal timekeeper is therefore responsible for adaptive responses to perturbations to the rhythm.

In contrast, the second school of thought views fractal patterns as arising from the interactions between various interdependent subcomponents of the system. A system exhibiting strong fractal patterns is thought to be more complex. A complex system lacks a central controller; instead, the subcomponents are free to behave within certain parameters, and self-organize dynamically into a coordinated system (Van Orden et al., 2003). This allows for emergent behavior and dynamically changing coordination based upon environmental changes. In this view, fractal patterns are indicative of complexity, and therefore emergent coordinated behaviors (West & Brown, 2005).

Sensorimotor Synchronization

Sensorimotor Synchronization (SMS), where motor behavior is temporally coordinated with an external stimulus, has been utilized to examine rhythmic behaviors. The primary method to examine SMS has been a finger tapping task in coordination with an audio or visual metronome. Humans are capable of synchronization to stimuli of various tempos with ease. To synchronize with an external event requires the capacity to anticipate the next occurrence of that event. Early studies (Woodrow, 1932) noted that participants' taps preceded each beat of a tempo-locked audio stimulus by an interval of milliseconds. This anticipatory tendency is quantified as the negative mean asynchrony (NMA).

Accepting the complexity hypothesis of fractal patterns, and rejecting the notion of an internal timekeeper requires an alternative explanation of humans' ability to successfully coordinate tapping intervals. Rather than rely on an internal timekeeper, Dubois (2003) developed the construct of strong anticipation to explain this ability. Strong anticipation models timing as an interaction between an organism and its environment as a single dynamical system. Instead of relying on previous data points to anticipate, hyperincursive reference to previous and successive data points is used by examining multiple time scales, not just the local scale (i.e., current moment). Global coordination between the organism and environment requires fractal time scaling. Inter-tap intervals for finger tapping tasks display fractal patterns consistent with coupling or entrainment. Studenka and Newell (2013) examined the role of what is termed prospective control (Lee, 1993). They utilized a force production task, where participants modulate the amount of force their fingers produced to fall in-line with a displayed force curve. Participants were presented with signals of varying regularity (sinusoidal wave and fractal patterns down to white noise), and were given prospective information (i.e., a visual representation of the force curve coming up) of varying durations. Their findings noted that less regular signals, such as fractal patterns, benefitted from larger prospective windows. This further supports the strong anticipation model by demonstrating the use of future data points across multiple timescales to inform the current moment.

Metronome Synchronization

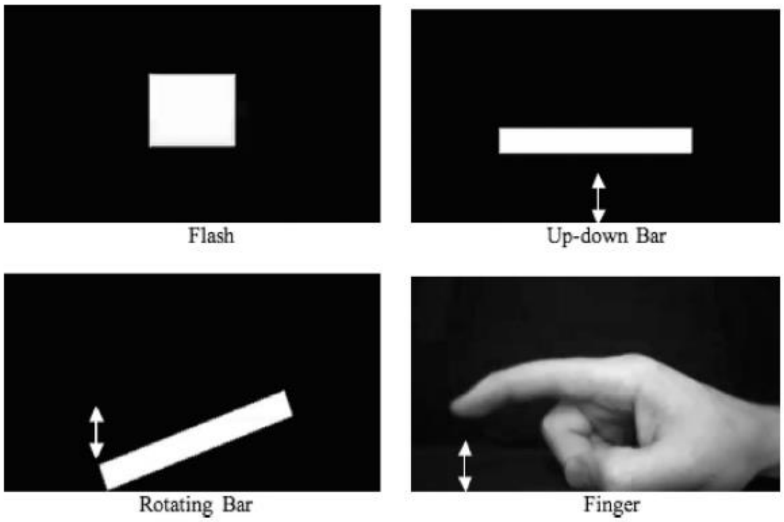
Given the established link between fractal patterns in stride time, gait complexity, and adaptive behavior, a new focus has developed in recent years on manipulating gait timing in order to entrain strong fractal patterns. This has been accomplished utilizing chaotic metronomes. Chaotic metronomes are ones that do not have a fixed period, but instead exhibit a form of structured noise. Stephen et al (2008) used a chaotic auditory metronome with a finger-tapping task, a scenario where local prediction should be impossible. They found that the structure of the participants' tapping was strongly correlated to the structure of the metronome (r=0.96). This favors strong anticipation, showing that participants can couple to the global time structure. The interaction between metronome and participant can be viewed through the dynamical systems framework as the coupling between the oscillating gait cycle and the external oscillator of the stimulus (Repp, 2005). This coupling relationship allows for entrainment of fractal patterns.

Previous work by Rhea and colleagues (2014a, 2014b) demonstrated the efficacy of visual metronome tasks at modulating participants' gait patterns, both when synchronizing to the metronome, in the 10 minutes immediately following removal of the stimulus. Study participants were tasked with synchronizing their self-paced gait cycle to a visual metronome projected on a screen in front of a treadmill with an underlying fractal pattern (DFA α= 0.98). Several modes of presenting the visual metronomes were utilized. Discrete, flashing foot prints and continuous sliding footprints successfully entrained stronger fractal patterns, pushing participants' mean DFA α significantly higher. Cross-correlational analysis of time lags showed a combination of proactive and reactive strategies necessary for entraining new patterns. This cross-correlational profile is consistent with previous findings from successful synchronization trials (Stephen et al., 2008).

However, a visual stimulus presented using a virtual avatar had the opposite effect, weakening participants' fractal patterns, resulting in participants exhibiting white noise patterns (Rhea et al 2014c). It was initially postulated that this stimulus was presenting extraneous information that only served to distract participants. A follow-up study utilized an eye-tracking head-mounted camera system to examine the focus of attention (MacPherson and Rhea, 2015). Results showed that participants attended specifically to the avatars' heel strike. Despite this, cross-correlational analysis found no evidence of the proactive/reactive strategies necessary for retention, suggesting that an avatar stimulus might not be a viable stimulus mode to develop fractal gait characteristics.

Data from a study by Hove et al. (2010) can be used to help explain the results from Rhea and colleagues' papers. Hove and colleagues examined the effect of different modes of visual stimuli in finger-tapping tasks, as shown in Figure 6.

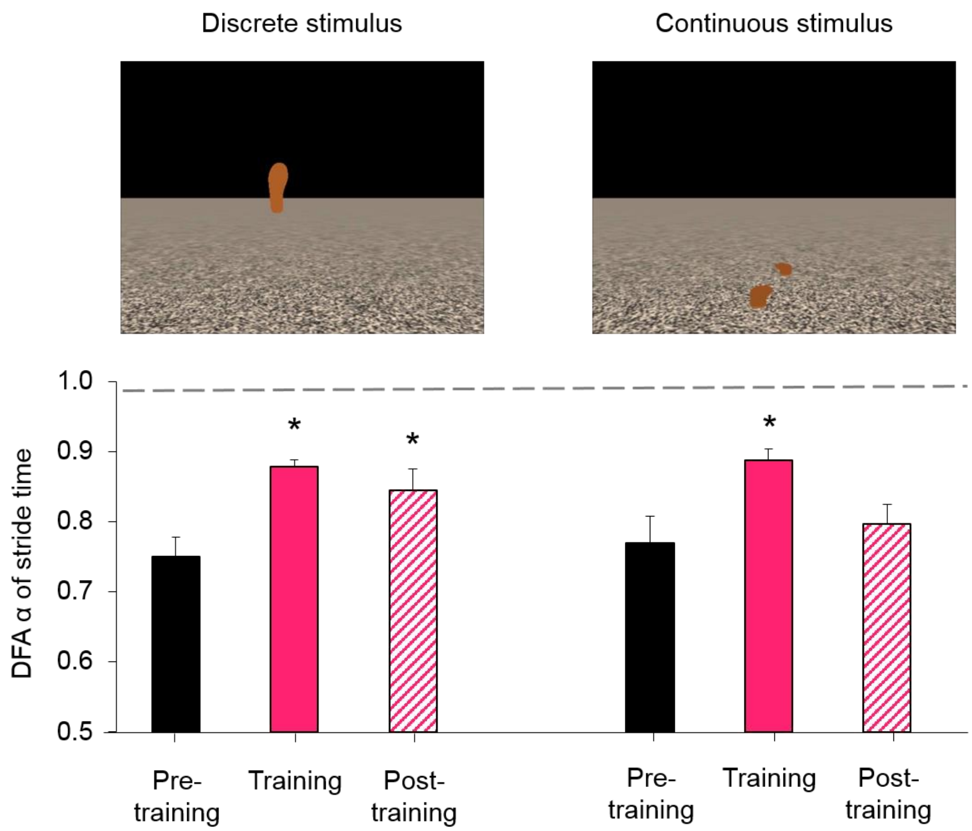
Figure 6. Various Presentation Modes for Visuomotor Synchronization Task, Adapted from Hove et al. (2010).



Their results let to the conclusion that continuous, motion-compatible stimuli induced the best performance at the task. It is thought that the visual system is not as adept at processing rhythmic information as the auditory system (Wright & Elliott, 2014). However, a combination of spatial and temporal information, such as a rhythmically moving bar, is better processed visually relative to a discrete stimulus, such as a flashing square. In a task such as gait, where optic flow is heavily weighted (Warren, 2006), this may be especially true. It is important to note that the “finger” condition—the video footage of a finger tapping—elicited poorer performance than the other spatiotemporal conditions. It is believed that biological representations of the task, such as the avatar metronome of Macpherson and Rhea (2015), is overly constraining. In a dynamical systems view, a system self-organizes in order to accomplish tasks, and is capable of near infinite solutions to a task. By presenting a full-body avatar, information is provided beyond timing of heel strike to include the whole gait cycle. Attempts to conform to this gait cycle constrains gait behavior, disrupting the self-organizing complexity of the system and reducing gait patterns to unstructured white noise (MacPherson & Rhea, 2015).

It is important to note that the fractal patterns produced when synchronizing to visual metronomes are not identically structured to the patterns of the stimulus. As shown in Figure 7, entrained patterns approach, but are lower than the target DFA α value of 0.98. The size of this gap differs based on presentation modality (Rhea, Kiefer, Wittstein, et al., 2014). In this case, participants were asked to synchronize to a discrete stimulus (flashing left and right foot prints) or a continuous stimulus (footprints that slide along the ground). However, in both presentation modes, the target values and the expressed values were significantly different. The difference between the target and expressed values may be indicative of the limitations of purely prescriptive visual metronomes. In order to more accurately manipulate fractal patterns, interactive methods of presenting the patterns may prove useful.

Figure 7. Participants' DFAα Values when Subjected to Two Presentation Modes of Visual Metronome. In each mode, DFA values while attending to metronome (Training) fails to reach the DFA level of the metronome (the dotted gray line). Adapted from Rhea, Kiefer, Wittstein, et al. (2014)

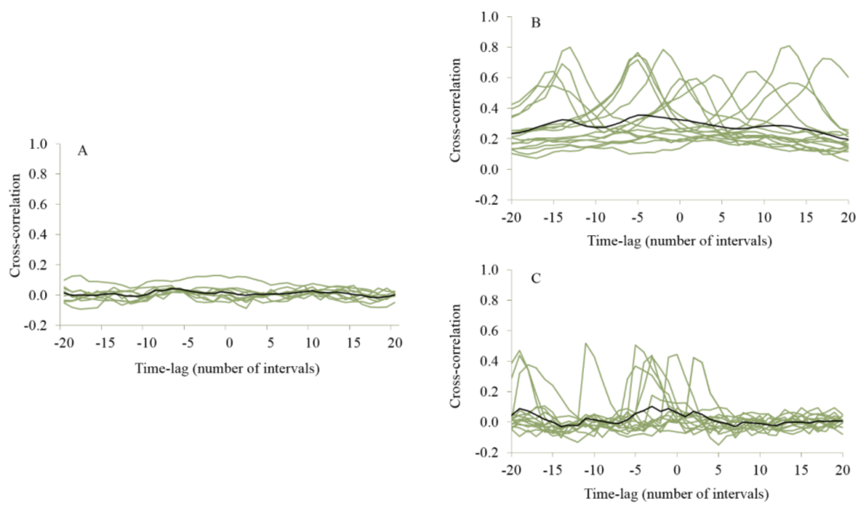


Cross-Correlation of Time Lags

Cross-correlational analysis is a tool that has been previously used to examine the coupling of two systems during an anticipatory task (Marmelat & Delignières, 2012) and during synchronization to a fractal gait metronome (Rhea, Kiefer, D'Andrea, et al., 2014). Cross-correlation compares the participants' stride time series to the series produced by the metronome, across a number of positive and negative time adjustments. Doing so allows for not only the correlation of time series (i.e. how well a participant mimicked the metronome) but also the assessment of strategy (anticipatory vs. reactionary). This can serve as a check to ensure that participants are in fact coupling to the metronome as instructed.

As shown in Figure 8, MacPherson and Rhea (2015) compared cross-correlational data between a fractal avatar metronome (A), a fractal discrete metronome (B), and a white noise discrete metronome (C). The discrete fractal metronome displays a moderate cross-correlation, with distinct peeks about the central point (no asynchrony). This is indicative of an ability to couple to the stimulus, with a variety of anticipatory and reactionary strategies amongst subjects. In contrast, the avatar cross-correlation is very low, similar to white noise, and entirely devoid of evidence for coupling strategies. This suggests that an avatar metronome task is not an achievable task, even in young healthy adults.

Figure 8. Comparison of Cross Correlation of Time Lags for Various Metronome Signals. Panel A shows correlation of participants' stride time series with a fractal avatar metronome. Panel B depicts correlations with discrete flashing fractal metronome. Panel C shows correlation with a white noise metronome. Adapted from MacPherson and Rhea (2015).



Extrinsic Feedback to Increase Synchrony

Schmidt and Lee (1988) describe feedback as essential to the process of learning new motor patterns. In many synchronization studies, such as those previously performed by Rhea and colleagues, participants were limited to receiving intrinsic feedback. This information is self-generated and may include proprioceptive information regarding the position of the foot or movements compared to internal rhythm-keeping. However, intrinsic feedback fails to provide definitive knowledge of results (i.e. success/failure at the task), and so performance may be further enhanced with the addition of extrinsic feedback. Augmented extrinsic feedback may be of use in complex skill acquisition and performance (Swinnen, 1996) Extrinsic information about performance has been shown to reduce absolute error in positioning tasks (Bilodeau, Bilodeau, & Schumsky, 1959), suggesting that the addition of extrinsic feedback to the fractal metronome paradigm utilized by Rhea and colleagues could enhance performance.

Extrinsic feedback in the context of a sensorimotor synchronization paradigm could take the form of visual or auditory cues indicating success or failure to synchronize with a metronome. For example, Aschersleben (2003) used visual feedback during an anticipatory synchronization task (i.e., finger tapping to a metronome) to reduce negative mean asynchrony, which increased participants' ability synchronize to a tempo-locked metronome. Kuznetsov and Wallot (2011) found that increased feedback reduced the presence of fractal patterns during tempo-locked finger tapping. In this context, a reduction of fractal patterns may be interpreted as evidence of the emergence of newly developed movement patterns as the system reorganizes in response to feedback. In the domain of continuous tasks, the effect of extrinsic feedback has been examined in isometric force production. Studenka and Newell (2013) found that when tracing irregular force production curves, the combination of prospective control (i.e. future curve information) and reactive feedback (i.e. previous curve information and personal performance) were correlated with increased performance.

Feedback scheduling for optimal motor performance and learning has been explored in previous research. Studies have examined both the relative frequency of feedback (how often it is received) and the timing of feedback (how quickly it is received after each trial). There is currently no strong consensus on optimal feedback scheduling.

A series of studies involving positioning tasks showed no differences in performance between 100% feedback (feedback after each trial) and a reduced frequency of feedback in either short term or long term retention tests in linear positioning tasks and in timing tasks (Sparrow, 1995). This suggests that the effect of feedback frequency on acquisition and retention may be specific to the task. In examining feedback timing, immediate knowledge of results has been shown to enhance motor performance, though this comes with the risk of developing feedback dependency (Anderson et al., 2001).

Real-time visual feedback has been used with some success in the field of gait rehabilitation (Barrios, Crossley, & Davis, 2010) to retain movement patterns. However, to the author's knowledge there is currently no data on the effect of extrinsic feedback on fractal pattern entrainment in gait.

Summary

The literature shows that fractal fluctuations in biological systems are correlated with the healthy function of those systems. Fractal fluctuations are thought to prepare the system for external perturbation, allowing the system to adapt to the disruption and resume normal function. In gait, weakening of fractal patterns is associated with maladaptive gait and increased fall risk. Pathological populations, such as sufferers of chronic stroke or Parkinson's disease, exhibit both poorer motor function and reduced DFA α values. The manipulation of gait dynamics to improve or restore healthy fractal patterns represents a promising new approach to gait rehabilitation. By temporally coordinating stride times with an external visual metronome, it is possible to entrain to alter fractal patterns, with evidence of short-term retention.

Despite the promise such interventions hold, there is a gap, both literally and figuratively, in our ability to push participants to desired DFA α values. Though it is possible to alter gait patterns toward the desired end of the spectrum, it has not been previously demonstrated that gait patterns can be trained to exhibit the DFA target provided by the stimulus. The extent to which gait patterns fall short of the goal appears to be affected by the presentation modality of the metronome, with biological forms having a detrimental effect.

To date, experimental interventions manipulating gait dynamics have been prescriptive. That is, a stimulus is presented and the participant is tasked with coupling to the stimulus. There is no interactivity between the participant and the stimulus. Feedback in other domains, such as finger tapping and isometric force production, has been shown to be beneficial to improving adherence to the task. Incorporation of interactive feedback stimulus may provide a tool for participants to adjust their performance in real time, decreasing the size of the gap between their performance and the target pattern. The proposed study intends to examine how this tool might be used.

CHAPTER III

OUTLINE OF PROCEDURES

Participants

20 young healthy adults (11 male and 9 female; height: 172.38±9.97 cm, weight: 70.57±10.69 kg, age: 23.47 ±3.85 years) were recruited as participants. The UNCG IRB approved all study procedures and all participants signed a consent form. Potential subjects were excluded for the following criteria: recent history of lower extremity injury; cardiac or respiratory illness; vision not corrected to normal; neuromuscular or balance disorders.

Instrumentation

The participants' gait dynamics data were collected using 12 Qualysis motion capture cameras (Gothenburg, Sweden) while on a Simbex Active Step treadmill (Lebanon, NH). Qualysis Track Manager were used to label anatomical landmarks, which were imported into Visual 3D software (C-Motion, Germantown, MD). Visual 3D were be used to create time-series of stride time. Matlab (MathWorks, Natick, MA) were used to compute detrended fluctuation analysis of the stride time time-series. Cross-correlation of time lags were calculated using custom Matlab scripts and Excel software. Participants also wore eye-tracking goggles (American Science Laboratories, Los Angeles, CA), which recorded participants' field of view, eye fixations and saccades during the experimental conditions. The eye-tracking data were used to determine whether the participants were looking proactively or reactively at the visual stimulus. However, that question is outside the scope of the manuscript associated with this thesis, so the eye-tracking data is presented in Appendix A.

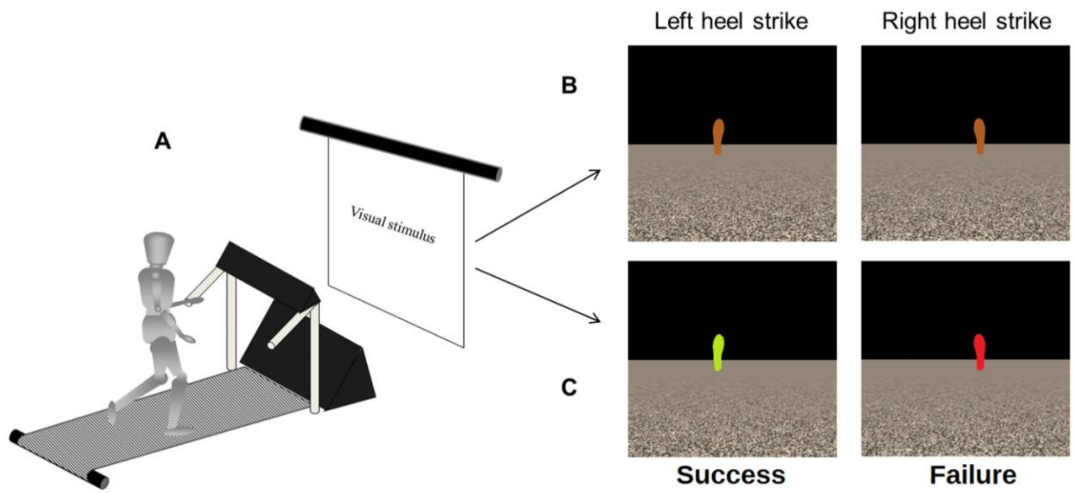
Procedure

All participants visited the lab on two separate days for testing, with 48 hours between the first and second sessions. Prior to the first session, participants completed a medical history and physical activity questionnaire. They also determined their self-selected walking speed by walking on a treadmill that started at 0 m/s and was slowly increased in speed until the participant indicated that was they were at their normal walking speed. Next, the participant started walking at 2.0 m/s and the treadmill speed was slowed down until they indicated that was their normal walking speed. The average speed was then taken as their self-selected walking speed if both speeds were within 10% of each other. Otherwise, the procedure was redone. This chosen speed was used for both sessions. The average preferred walking speed was 1.10+/-0.11 m/s.

In each session, participants completed a 30-minute treadmill walk that was administered in three 10-minute phases. The first 10 minute window was the pre-training phase (taken as a baseline), where participants walked at their self-selected speed with no stimuli present. The next 10 minute window (training phase) included synchronizing their heel-strikes during walking to a fractal visual metronome projected in front of them (Figure 9). Participants saw see one of two different visual metronomes each day (feedback or non-feedback conditions), the order of which was be counterbalanced. In the final 10 minute window (post-training phase), the metronome was removed, and participants continued walking at their self-selected pace. All three 10 minute phases were completed in succession, leading to 30 minutes of continuous walking per testing day.

The visual metronome used was identical to the one in experiment 2 of Rhea, Kiefer, Wittstein, et al., (2014), except one of the metronomes had a feedback feature. Both visual metronomes consisted of flashing left and right footprints, with a moving ground plane, and were presented 2 meters on a projection screen in front of the treadmill. The timing of the appearance of the footprints was fractal (DFA $\alpha = 0.98$), with a mean stride time of 1.17 ± 0.07 sec. In the non-feedback condition, the footprints remained a single color (brown, see panel B in Figure 9). In the feedback condition, the footprints were displayed in a color based on the participant's heel-strike—green if the participant’s corresponding heel was less than 2 cm vertically from the treadmill belt when the footprint appeared or red if they were above that threshold (see panel C in Figure 9). Thus, the participants were provided performance feedback on every step throughout the 10 minute training phase in the feedback condition.

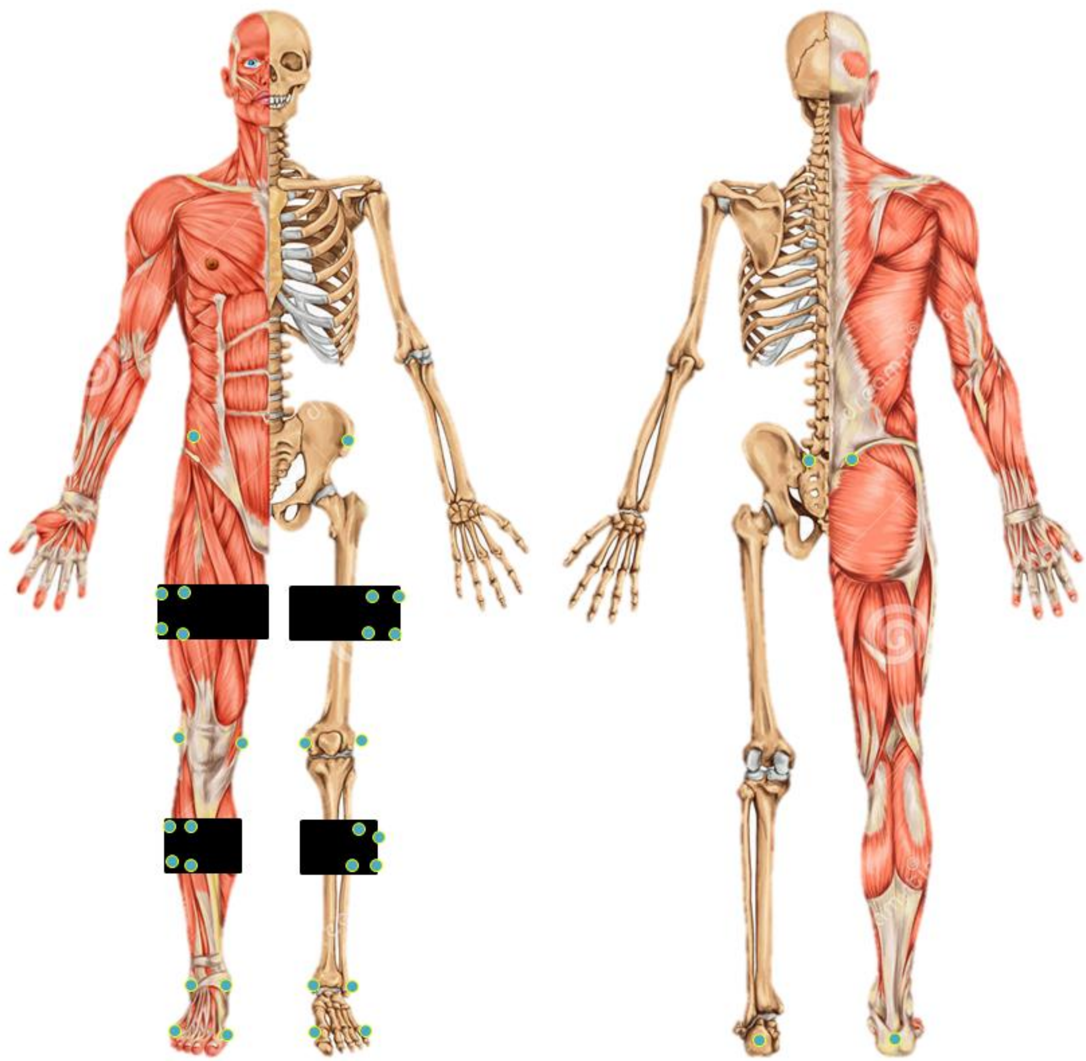
Figure 9. Concept of Visual Metronome Stimulus. Panel A depicts position of projected stimulus in relation to treadmill. Panel B shows heel strike stimulus in non-feedback condition. Panel C depicts success/failure feedback in the extrinsic feedback condition.



Participants also wore eye-tracking goggles (Applied Science Laboratories, Bedford, MA) during the synchronization phase of each session. These goggles recorded the scene from the perspective of the participant, as well as pupillary fixations and saccades at a rate of 30 Hz.

Gait data were collected using a 12-camera motion capture system (Qualisys, Gothenburg, Sweden) sampled at 200 Hz. Retro-reflective Qualisys markers were placed at anatomical landmarks on the body. Polymer panels with attached markers were placed on the lateral surface of the shank and thigh, with individual markers placed on the anterior and posterior superior iliac crests, the medial and lateral knee and ankles, the posterior aspect of the calcaneus, and the medial and lateral metatarsophalangeal joints. A total of 34 markers were applied to each subject, as shown in Figure 10

Figure 10. The Location of Panels and Individual Retro-Reflective Markers for Data Collection



The raw position time series data were reduced to inter-stride-interval (ISI) series using Visual3D (C-Motion, Germantown, MD). The resultant time series were processed to calculate two metrics. First, participants' gait timing was compared to that of the provided metronome using cross-correlational analysis. This analysis quantifies the coupling between the fractal gait patterns expressed by the participants to the fractal patterns presented by the visual metronome. The cross-correlation data were analyzed two ways. First, the peak correlation for each participant was examined to determine if their coupling to the metronome got stronger in the feedback condition. Second, the standard deviation of cross-coupling across participants across all time lags of interest (-20 to 20 samples) was examined to determine if participants were converging on a common coupling strategy within each metronome condition. Next, Detrended Fluctuation Analysis (DFA) α values were computed to measure the underlying dynamics of participants' stride intervals. The DFA and cross-correlational analyses were computed using custom Matlab software (Mathworks, Natick, MA).

Statistics

To address hypothesis 1 (influence of feedback on coupling to the fractal metronome) two separate two-tailed dependent-samples *t*-test were used. The first one was run on the peak correlation for each participant between the two metronome conditions in order to determine if their coupling to the metronome got stronger when feedback was present. The second one was run on the SD of cross-coupling across participants across all time lags of interest (-20 to 20 samples) to determine if participants were converging on a common coupling strategy within each metronome condition. Also, delta scores were calculated for both peak correlation and SD of the cross-coupling in order to examine changes in synchronization strategy.

To address hypothesis 2 (influence of feedback on fractal gait patterns), a 3 x 2 repeated measures ANOVA was run on participants' DFA α values, with phase (pre-training, training, and post-training) and condition (no feedback and feedback) as the within-subject factors.

To address hypothesis 3 (relation between coupling strength during training and retention) a Pearson correlation coefficient was calculated between the peak cross correlation values DFA α values during training and post-training. Significance for all tests were set *a priori* at $\alpha=0.05$

CHAPTER IV

MANUSCRIPT

Targeted for the journal Motor Control

Introduction

Functional gait, the capacity to navigate environmental obstacles effectively, is categorized as a Basic Activity of Daily Living (James, 2014), an activity that is essential to self-care and an independent lifestyle. While functional gait behavior is the product of many factors, it has been suggested in recent decades that the manner in which gait varies over time (termed gait dynamics) may reflect a person's functional capacity (Hausdorff, 2007; Rhea & Kiefer, 2014; Stergiou and Decker, 2011). That is, even when walking at a preferred pace on a treadmill, every step is slightly varied from the previous one. In young healthy adults, these gait dynamics exhibit a particular self-similar structure—termed fractal patterns. Aging, pathology, and disease leads to a weakening of the fractal patterns, and also corresponds to a decrease in functional mobility, as defined by an increase in fall rates and perceived limitations with respect to walking ability (Hausdorff, et al., 1997; Hausdorff, 2007). Thus, finding a way to strengthen the fractal patterns within gait dynamics may enhance functional mobility in aged and clinical populations.

Attempts to manipulate participants' fractal patterns using rhythmic auditory and visual stimuli have met with initial success (Hove et al., 2012;Kaipust et al., 2013;

Uchitomi et al., 2013; Marmelat et al., 2014; Roerdink et al., 2015; Terrier, 2016). For example, it has been shown that synchronization to a visual metronome driven by fractal patterns can alter subjects' position along the spectrum of gait variability (Rhea, Kiefer, Wittstein, et al., (2014). That is, participants who were asked to synchronize their stride timing to a metronome with strong fractal patterns were capable of entraining their gait patterns to the stimulus. However, it was observed that participants were only able to alter their gait dynamics roughly halfway between their baseline and the fractal strength prescribed by the metronome. It was proposed that the lack of specificity may have been due to the type of stimulus provided. Thus, experiment 2, Rhea, Kiefer, Wittstein, et al. (2014) compared visual metronomes driven by a fractal pattern, but presented either discretely or continuously. With both stimulus presentations, the participants were able to alter their gait dynamics halfway to the prescribed fractal strength, and retention (tested immediately after the 10 minute fractal gait training) was only observed after the discrete stimulus. Thus, it was postulated that participants' inability to reach the specified fractal strength may be due to other factors, such as the lack of feedback.

Although the role of feedback in motor control and learning is a well-studied topic, it has yet to be incorporated in fractal gait training. Interactive cuing has been explored (Hove et al., 2012; Uchitomi et al., 2013), but this method only takes the performers' past movement into account when producing the next stimulus cue, and it does not provide the participant with any information about their performance. Extrinsic feedback (i.e., externally provided feedback) has been shown to be useful in the acquisition of a new motor pattern (Swinnen, 1996). Feedback can be provided either after the completion of the motor task, or continuously during the execution of the motor task in order to guide participants as adjustments are made. The addition of extrinsic feedback to the fractal visual metronome may allow participants to couple more closely to the stimulus and may strengthen their fractal patterns to a greater extent.

The purpose of this study was to examine the effect of extrinsic feedback on the resulting gait patterns when synchronizing to a visual metronome task. This study is a continuation of previous work by Rhea, Kiefer, Wittstein et al. (2014) and represents one possible avenue for addressing the gap between stimulus and output. Three hypotheses were tested. First, feedback would elicit a stronger coupling (i.e., higher cross-correlation values) between participants' gait dynamics and the dynamics of the stimulus relative to a non-feedback condition. Second, the addition of feedback to the visual metronome would lead to a stronger fractal pattern during the training and post-training (retention) phases. Third, participants with the strongest coupling during training would exhibit the strongest post-training fractal patterns.

Methods

Participants

Nineteen young healthy adults (10 male and 9 female; height: 172.38±9.97 cm, weight: 70.57±10.69 kg, age: 23.47 ±3.85 years) participated in this study. All subjects were screened via self-report questionnaire for neurological conditions, cardiac or respiratory illness, or structural injuries that would degrade their gait performance. All participants were additionally screened for deficits in visual acuity (corrective lenses were permitted) and color-blindness that would affect their ability to synchronize to the provided metronome.

Ethics Statement

The University of North Carolina at Greensboro institutional review board approved all procedures, and all participants signed an informed consent form prior to participation.

Procedure

All participants visited the lab on two separate days for testing, with 48 hours between the first and second sessions. Prior to the first session, participants completed a medical history and physical activity questionnaire. They also determined their self-selected walking speed by walking on a treadmill that started at 0 m/s and was slowly increased in speed until participants indicated that was they were at their normal walking speed. Next, participants started walking at 2.0 m/s and the treadmill speed was slowed down until they indicated that was their normal walking speed. The average speed was then taken as their self-selected walking speed if both speeds were within 10% of each other. Otherwise, the procedure was administered again until both speeds were within the threshold of agreement. This chosen speed was used for both sessions. The average preferred walking speed was 1.10+/-0.11 m/s.

In each session, participants completed a 30-minute treadmill walk that was administered in three 10-minute phases. The first 10 minute window was the pre-training phase (taken as a baseline), wherein participants walked at their self-selected speed with no stimuli present. The next 10 minute window (training phase) included synchronizing their heel-strikes during walking to a fractal visual metronome projected in front of them (Figure 12). Participants followed one of two different visual metronomes each day (feedback or non-feedback conditions), the order of which was be counterbalanced. In the final 10 minute window (post-training phase), the metronome was removed, and participants continued walking at their self-selected pace. All three 10 minute phases were completed in succession, leading to 30 minutes of continuous walking per testing day.

The visual metronome used was identical to the one in experiment 2 of Rhea, Kiefer, Wittstein, et al. (2014), except one of the metronomes had a feedback feature. Both visual metronomes consisted of flashing left and right footprints, with a moving ground plane, and were presented onto a projection screen 2 meters in front of the treadmill. The timing of the appearance of the footprints was fractal (DFA $\alpha = 0.98$), with a mean stride time of 1.17 ± 0.07 sec (Figure 11). The mean stride time was chosen to closely match mean walking speed in healthy adults, and to be consistent with previous work, In the non-feedback condition, the footprints remained a single color (brown, see panel B in Figure 12). In the feedback condition, the footprints were displayed in a color based on the participant's heel-strike—green if the corresponding heel was less than 2 cm vertically from the treadmill belt when the footprint appeared or red if they were above that threshold (see panel C in Figure 12). The height of the calcaneus marker was tracked in real time by the metronome script, which made the determination of which color to display for each footprint. Thus, the participants were provided extrinsic feedback on every step throughout the 10 minute training phase in the feedback condition.

Figure 11. Time Series of Metronome Stride Intervals

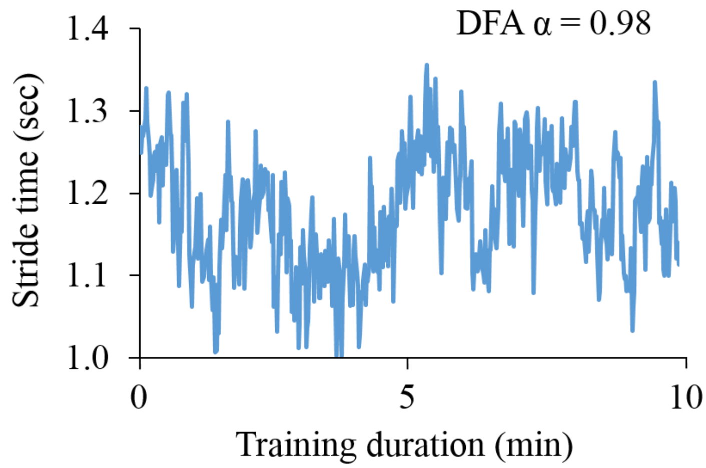
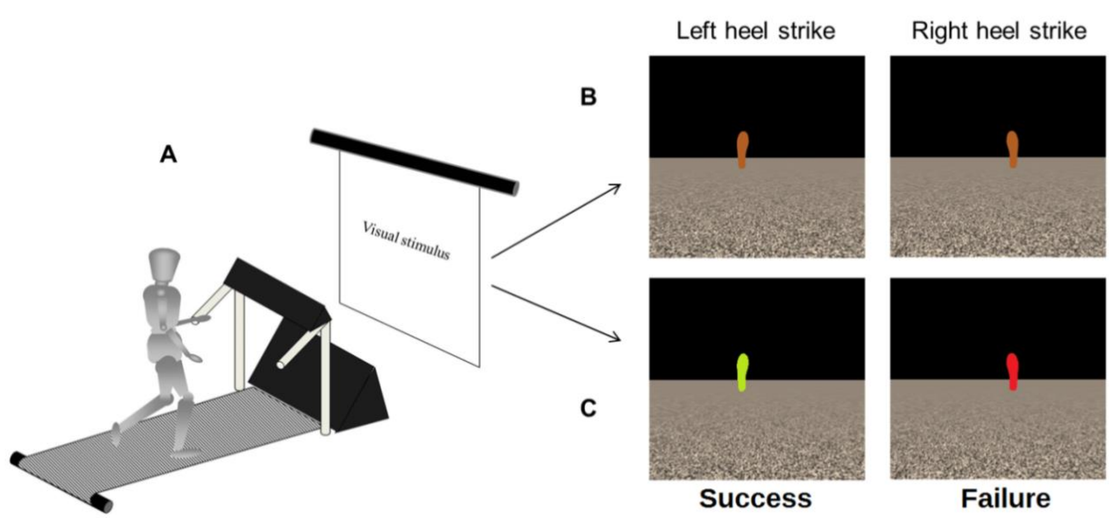


Figure 12. Concept of Visual Metronome Stimulus. Panel A depicts position of projected stimulus in relation to treadmill. Panel B shows heel strike stimulus in non-feedback condition. Panel C depicts success/failure feedback in the extrinsic feedback condition.



Gait data were collected using a 12-camera motion capture system (Qualisys, Gothenburg, Sweden) sampled at 200 Hz. Subjects were fitted with retroreflective markers on the posterior aspect of the heel. The raw position time series data were reduced to an inter-stride-interval (ISI) series using Visual3D (C-Motion, Germantown, MD). The resultant time series data were processed to calculate two metrics. First, participants' gait timing was compared to that of the provided metronome using cross-correlational analysis. This analysis quantifies the coupling between the fractal gait patterns expressed by the participants to the fractal patterns presented by the visual metronome. The cross-correlation data were analyzed two ways. First, the peak correlation for each participant across conditions was examined to determine if their peak correlation (i.e successful coupling to the metronome) increased in the feedback condition. Second, the standard deviation of cross-coupling across participants across all time lags of interest (-20 to 20 samples) was examined to determine if participants were converging on a common coupling strategy within each metronome condition. Next, Detrended Fluctuation Analysis (DFA) α values were computed to measure the underlying dynamics of participants' stride intervals. The DFA and cross-correlational analyses were computed using custom Matlab software (Mathworks, Natick, MA).

Statistics

To address hypothesis 1 (influence of feedback on coupling to the fractal metronome) two separate two-tailed dependent-samples *t*-test were used. The first one was run on the peak correlation for each participant between the two metronome conditions in order to determine if coupling to the metronome got stronger when feedback was present. The second one was run on the SD of cross-coupling across participants across all time lags of interest (-20 to 20 samples) to determine if participants were converging on a common coupling strategy within each metronome condition. Also, delta scores were calculated for both peak correlation and SD of the cross-coupling in order to examine changes in synchronization strategy.

To address hypothesis 2 (influence of feedback on fractal gait patterns), a 3 x 2 repeated measures ANOVA was run on participants' DFA α values, with phase (pre-training, training, and post-training) and condition (no feedback and feedback) as the within-subject factors.

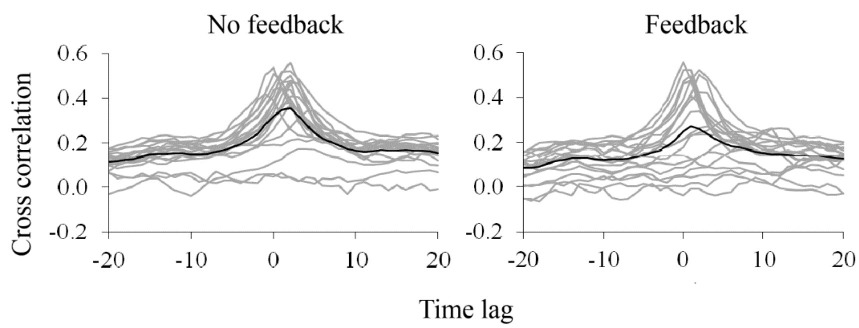
To address hypothesis 3 (relation between coupling strength during training and retention) a Pearson correlation coefficient was calculated between the peak cross correlation values and DFA α values during training and post-training. Significance for all tests were set *a priori* at α=0.05.

Results

Hypothesis 1: Influence of feedback on coupling to the fractal metronome

The cross-correlation analysis showed no differences between feedback and non-feedback conditions in the peak correlation, $t(18) = 1.90$, $p = .07$. However, the SD across time lags was smaller in the no feedback condition, $t(40) = 11.16$, $p < .001$ (Figure 13).

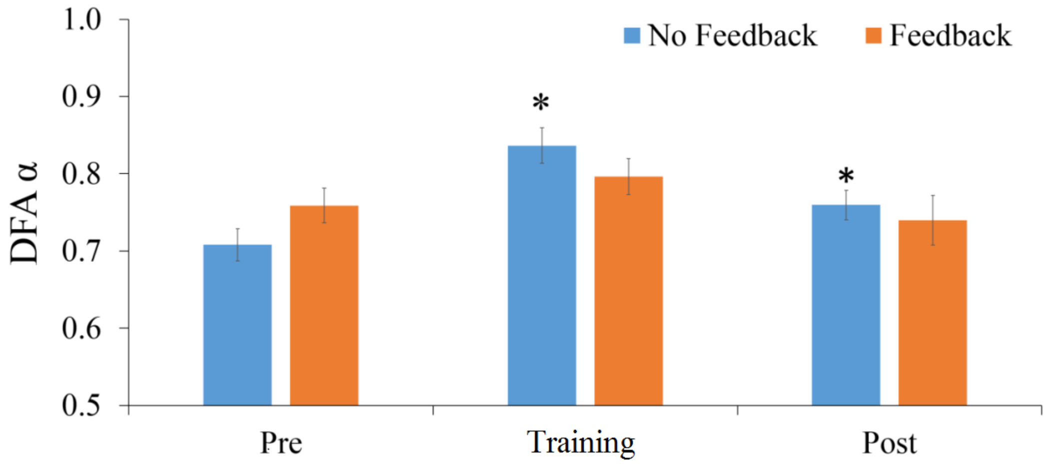
Figure 13. Cross Correlations of 40 Time Lags. Gray lines indicate each individual subject's data. The bold black lines indicate mean values across all subjects.



Hypothesis 2: Influence of feedback on fractal gait patterns

Analysis of DFA values showed that the feedback (with/without) × phase (pre/sync/post) interaction was significant, $F(2,36) = 3.49$, $p = .04$, partial $\eta^2 = 0.314$ (Figure 14). Follow-up tests showed the training and post-training phases were higher than the pre-training phase in the no feedback condition ($p \leq .02$), but no differences were observed in the feedback condition.

Figure 14. Mean DFA Values for Phase and Feedback Condition. Asterisks indicate significant increase from Pre-training within the metronome condition.



Hypothesis 3: Relation between coupling strength during training and retention

There was a significant correlation between peak cross-correlation during training and DFA values during training in both the feedback condition $r(17) = .769$, $p < 0.01$, and the non-feedback condition $r(17) = .787$, $p < 0.01$. However, there was no correlation between peak cross-correlation during training and DFA values during retention in either the feedback condition $r(17) = .15$, $p = .55$, or the non-feedback condition $r(17) = .28$, $p = .246$.

Discussion

The purpose of this study was to examine the utility of extrinsic feedback to enhance the effectiveness of fractal gait metronomes to alter fractal gait dynamics. It was hypothesized that the addition of feedback after each step would lead to stronger fractal gait patterns during training and retention, and that fractal strength would be correlated with stronger coupling to the visual metronome. The results show that feedback did not lead to stronger coupling in comparison to the non-feedback metronome, nor did it lead to stronger gait patterns during training or post-training. Further, coupling strength during training was not found to be correlated with the strength of the fractal gait patterns in the post-training phase.

The development of new fractal patterns can be compared to the learning of a new motor skill. In that context, a certain level of extrinsic feedback is known to aid in the accurate performance of a new motor skill. The guidance hypothesis of extrinsic feedback posits that extrinsic feedback serves to direct the participant toward desired modes of motor behavior more effectively than trial-and-error (Swinnen, 1996). This is useful to achieve the desired movement quickly during initial practice. It was postulated that this feedback mode would have enhanced participants' ability to couple to the fractal metronome. However, the addition of feedback to our visual metronome did not enhance fractal gait patterns.

The results for the non-feedback metronome were consistent with previous research using the discrete footprint metronome (Rhea, Kiefer, D'Andrea, et al., 2014; Rhea Kiefer, Wittstein, et al., 2014). Participants' fractal patterns were strengthened in the current study, and there is evidence of short-term retention of these patterns after 10 minutes of training. It is interesting to note that while the peak cross-correlation did not change when feedback was added, the SD across time lags was increased. This suggest that participants converged on a more common synchronization strategy in the non-feedback condition, but exhibited varied strategies once feedback was added. This observation suggests extrinsic feedback provided in a continuous manner may not be the most salient information for this type of task. In order to successfully synchronize to a fractal metronome, a certain level of prediction about the next time interval between footprint flashes is necessary. This anticipation has been termed *strong anticipation* as first defined by Dubois et al. (2003) and empirically shown in human timing patterns by Stephen et al. (2003). The strong anticipation framework suggest that humans are sensitive to fractal patterns when attempting to synchronize to a stimulus with a varying time interval. The derivation of this sensitivity is still an empirical question. Data in the current study suggest that immediate extrinsic feedback on synchronization performance does not elicit stronger fractal gait patterns during or after training. Since the strong anticipation framework suggests that humans are sensitive to fractal patterns, and such patterns require a relatively long time to evolve, focusing the participants in on their most recent behavior may have caused them to not attend to their longer-term evolving behavior, which may account for the "predictability" when feedback was added to the fractal metronome. Thus feedback using a larger retrospective windowed approach may allow participants to better attune to the underlying fractal patterns of the stimulus, potentially leading to stronger coupling. Such a windowed approach, both retrospective and prospective, has been shown to enhance synchronization behavior (Studenka & Newell, 2013).

There are at least two potential reasons why the addition of feedback did not enhance fractal gait patterns. The first is the introduction of feedback increased the variability of participants' cross-correlations. Participants may be demonstrating more widely differing abilities to integrate the feedback into their synchronization strategy. Or conversely, the increased variability may show varying degrees to which participants were successfully able to ignore the negative aspects of the metronome, be that over-exposure or a negative affective response induced by repeated discouraging feedback. Secondly, immediate feedback after each trial may induce an overreliance on the feedback for performance. The guidance hypothesis also asserts that too frequent feedback may cause the participant to rely on the feedback when executing the motor task, rather than engaging in the development of a self-centered movement strategy. Thus, when frequent feedback is removed, performance has been shown to degrade (Winstein & Schmidt, 1990). In the current study, when extrinsic feedback was removed post-training, no retention was observed, suggesting that little or no actual motor learning took place.

This study was intended to set the groundwork for future studies into feedback-based fractal interventions. As such, the selected frequency of feedback was chosen as an initial point of entry into the feedback domain. The presentation of the feedback was also chosen so as not to alter the appearance of the metronome more than necessary, in order to facilitate comparison to previous work. In future studies, a more altered visual feedback may prove beneficial. In particular, future work would reduce the frequency of feedback. The feedback presented in this study was designed to be an indicator of when participants' fell out of sync with the metronome. In future work, a bandwidth approach, where participants only received feedback when they are no longer in synchrony should be explored.

In conclusion, this study demonstrates that the addition of extraneous feedback on every step during a fractal gait training session does not lead to stronger fractal patterns. It is likely that less frequent feedback would be beneficial in this context. However, the optimal profile of the feedback schedule has yet to be determined. While fractal gait training shows some promise, researchers should continue to use motor learning principles to guide the development of their protocol in order to get the desired motor output.

CHAPTER V

DISCUSSION

Functional mobility, specifically the ability to adapt gait to perturbations, may be related to underlying patterns in individuals' strides. This specific form of variability, termed "Fractal Patterns" correlate to functional movement behaviors and decreased fall risk. However, these patterns weaken with age or pathology. Interventions designed to strengthen fractal patterns in gait may be of clinical utility in addressing fall risk. Fractal visual metronomes have been successfully utilized to strengthen fractal patterns in both patients with pathology and healthy participants. However, the degree to which fractal metronomes can alter gait dynamics appears related to presentation modality, with no current method able to induce fractal patterns of specific strength. That is, participants' dynamics remain present consistently weaker than the frac tal patterns prescribed by the metronome stimulus. While this gap between stimulus and participants' dynamics may represent a ceiling effect for this intervention, exploring other methods of enhancing the visual stimulus may yield a breakthrough treatment for dynamical diseases.

A limitation of previous work with fractal metronomes is the prescriptive nature of the stimulus, involving no direct interaction between the participants' actions and the stimulus received. This study was intended to move away from a non-interactive, prescriptive stimulus toward a more user-interactive metronome. To that end, this study compared a non-feedback metronome to one where participants received feedback about their timing after every step. The aim of adding feedback was to increase participants' ability to actively synchronize with a dynamic metronome, and in so doing, more closely mimic the strong fractal dynamics driving the metronome stimulus.

It was determined that this form of constant extrinsic feedback did not improve the efficacy of the metronome While it is acknowledged that extrinsic feedback can be beneficial, is plausible that feedback on every step is detrimental to performance. A limitation of this study was a lack of post-training affective questionnaires, which may have been able to address the question of whether feedback after every step was distractionary or frustrating. Motor control/learning research shows that constant feedback is not a best practice, so future research should explore distributed feedback in the context of the gait synchronization task. The feedback provided was intended to signal to participants when they fall out of synchrony with the metronome, hopefully earlier than they would have been able to perceive unaided. A bandwidth form of feedback may be less distractionary or frustrating to participants' while still achieving the desired effect.

REFERENCES

Aschersleben, G. (2003). Effects of training on the timing of repetitive movements. In S. P. Shohov (Ed.), *Advances in psychology research* (pp. 15–30). Huntington, NY: Nova Science Publishers.

Bilodeau, E. A., Bilodeau, I. M., & Schumsky, D. A. (1959). Some effects of introducing and withdrawing knowledge of results early and late in practice. *Journal of Experimental Psychology*, *58*(2), 142–144. http://doi.org/10.1037/h0040262

Box, G. E. P., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control. Oakland: Holden-Day.

Campbell, A. J., Borrie, M. J., & Spears, G. F. (July 01, 1989). Risk Factors for Falls in a Community-Based Prospective Study of People 70 Years and Older. *Journal of Gerontology*, *44,* 4.)

Diniz, A., Wijnants, M. L., Torre, K., Barreiros, J., Crato, N., Bosman, A. M. T., … Delignières, D. (2011). Contemporary theories of 1/f noise in motor control. *Human Movement Science*, *30*(5), 889–905. http://doi.org/10.1016/j.humov.2010.07.006

Dubois, D. M. (2003). Mathematical Foundations of Discrete and Functional Systems with Strong and Weak Anticipations. In M. V. Butz, O. Sigaud, & P. Gérard (Eds.), *Anticipatory Behavior in Adaptive Learning Systems* (pp. 110–132).

Springer Berlin Heidelberg. Retrieved from http://link.springer.com/chapter/10.1007/978-3-540-45002-3_7

Dubois, D. M., Butz, M. Z., Olivier, S., & Pierre, G. (2003). Anticipatory Behavior in Adaptive Learning Systems. LNAI, 2684, 110-132.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science, 267*(5205), 1837–1839. http://doi.org/10.1126/science.7892611

Glass, L., & Mackey, M. C. (1988). *From Clocks to Chaos: The Rhythms of Life*. Princeton University Press.

Hartmann, M., Kreutzpointner, F., Haefner, R., Michels, H., Schwirtz, A., and Hass, J. (2010). Effects of Juvenile Idiopathic Arthritis on Kinematics and Kinetics of the Lower Extremities Call for Consequences in Physical Activities Recommendations. *International Journal of Pediatrics*, 2010. Retrieved from Http://dx.doi.org/10.1155/2010/835984.

Hausdorff, J. M. (2007). Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking. *Human Movement Science*, *26*(4), 555–589. http://doi.org/10.1016/j.humov.2007.05.003

Hausdorff, J. M., Mitchell, S. L., Firtion, R., Peng, C. K., Cudkowicz, M. E., Wei, J. Y., & Goldberger, A. L. (1997). Altered fractal dynamics of gait: reduced stride-interval correlations with aging and Huntington's disease. *Journal of Applied Physiology*, *82*(1), 262–269.

Hausdorff, J. M., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of Applied Physiology*, *78*(1), 349–358.

Herman, T., Giladi, N., Gurevich, T., & Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a "cautious" gait: why do certain older adults walk fearfully? *Gait & Posture*, *21*(2), 178–185. http://doi.org/10.1016/j.gaitpost.2004.01.014

Hove, M. J., Spivey, M. J., & Krumhansl, C. L. (2010). Compatibility of motion facilitates visuomotor synchronization. *Journal of Experimental Psychology: Human Perception and Performance*, *36*(6), 1525–1534. http://doi.org/10.1037/a0019059

Hove, M. J., Suzuki, K., Uchitomi, H., Orimo, S., & Miyake, Y. (2012). Interactive rhythmic auditory stimulation reinstates natural 1/f timing in gait of Parkinson's patients. *PloS one*, *7*(3), e32600.

James, A. B. (2014). Activities of daily living and instrumental activities of daily living. In: Schell, B. A. B., Gillen, G., & Scaffa, M. (Eds.), Willard and Spackman's Occupational Therapy (12th ed). Philadelphia: Lippincott, Williams & Wilkins.

Kaipust, J. P., McGrath, D., Mukherjee, M., & Stergiou, N. (2013). Gait variability is altered in older adults when listening to auditory stimuli with differing temporal structures. *Annals of biomedical engineering*, *41*(8), 1595-1603

Lee, D. N. (1993). Body–environment coupling. In *The perceived self: Ecological and interpersonal sources of self-knowledge* (pp. 43–67). New York, NY, US: Cambridge University Press.

Lipsitz LA, & Goldberger AL. (1992). Loss of “complexity” and aging: Potential applications of fractals and chaos theory to senescence. *JAMA*, *267*(13), 1806–1809. http://doi.org/10.1001/jama.1992.03480130122036

Marmelat, V., & Delignières, D. (2012). Strong anticipation: complexity matching in interpersonal coordination. *Experimental Brain Research*, *222*(1-2), 137–148. http://doi.org/10.1007/s00221-012-3202-9

Marmelat, V., Torre, K., Beek, P. J., & Daffertshofer, A. (2014). Persistent fluctuations in stride intervals under fractal auditory stimulation. *PLoS One*,*9*(3), e91949.

Peng, C.-K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical Review Letters*, *70*(9), 1343–1346. http://doi.org/10.1103/PhysRevLett.70.1343

Repp, B. H. (2005). Sensorimotor synchronization: A review of the tapping literature. *Psychonomic Bulletin & Review*, *12*(6), 969–992. http://doi.org/10.3758/BF03206433

Rhea, C. K., Kiefer, A. W., D’Andrea, S. E., Warren, W. H., & Aaron, R. K. (2014). Entrainment to a real time fractal visual stimulus modulates fractal gait dynamics. *Human Movement Science*, *36*, 20–34. http://doi.org/10.1016/j.humov.2014.04.006

Rhea, C. K., Kiefer, A. W., Wittstein, M. W., Leonard, K. B., MacPherson, R. P., Wright, W. G., & Haran, F. J. (2014). Fractal Gait Patterns Are Retained after Entrainment to a Fractal Stimulus. *PLoS ONE*, *9*(9), e106755. http://doi.org/10.1371/journal.pone.0106755

Rhea, C. K., Wittstein, M. W., Kiefer, A. W., & Haran, F. J. (2013). Retaining fractal gait patterns learned in virtual environments. In *2013 International Conference on Virtual Rehabilitation (ICVR)* (pp. 264–269). http://doi.org/10.1109/ICVR.2013.6662069

Roerdink, M., Daffertshofer, A., Marmelat, V., & Beek, P. J. (2015). How to sync to the beat of a persistent fractal metronome without falling off the treadmill?. *PloS one*, *10*(7), e0134148.

Roos, M. R., Rice, C. L., & Vandervoort, A. A. (1997). Age-related changes in motor unit function. *Muscle & Nerve*, *20*(6), 679–690. http://doi.org/10.1002/(SICI)1097-4598(199706)20:6<679::AID-MUS4>3.0.CO;2-5

Schell, B. A. B., Gillen, G., & Scaffa, M. (Eds.), Willard and Spackman's Occupational Therapy (12th ed). Philadephia: Lippincott Williams & Wilkins.

Shema, S., Brozgol, M., Dorfman, M., Maidan, I., Yannai, O. W., Giladi, N., … Mirelman, A. (2013). Clinical experience using a 5 week treadmill training program with virtual reality to enhance gait. In *2013 International Conference on Virtual Rehabilitation (ICVR)* (pp. 249–253). http://doi.org/10.1109/ICVR.2013.6662067

Sparrow, W. A. (1995). Acquisition and retention effects of reduced relative frequency of knowledge of results. *Australian Journal of Psychology, 47,* 2, 97-104.

Stephen, D. G., Stepp, N., Dixon, J. A., & Turvey, M. T. (2008). Strong anticipation: Sensitivity to long-range correlations in synchronization behavior. *Physica A: Statistical Mechanics and Its Applications*, *387*(21), 5271–5278. http://doi.org/10.1016/j.physa.2008.05.015

Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection?. *Human Movement Science*, *30*(5), 869-888.

Studenka, B. E., & Newell, K. M. (2013). Visual information for prospective control of tracking irregular target paths with isometric force production. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(6), 1557–1567. http://doi.org/10.1037/a0031744

Swinnen, S. P. (1996). Information Feedback for Motor Skill Learning: A Review. In H.N. Zelaznik (Ed.), *Advances in motor learning and control*. (pp 37-66). Champaign, IL: Human Kinetics

Terrier, P. (2016). Fractal fluctuations in human walking: comparison between auditory and visually guided stepping. *Annals of biomedical engineering*, 1-9.

Torre, K., & Delignières, D. (2008). Unraveling the finding of 1/f β noise in self-paced and synchronized tapping: a unifying mechanistic model. *Biological Cybernetics*, *99*(2), 159–170. http://doi.org/10.1007/s00422-008-0247-8

Uchitomi, H., Ota, L., Ogawa, K. I., Orimo, S., & Miyake, Y. (2013). Interactive rhythmic cue facilitates gait relearning in patients with Parkinson's disease. *PloS one*, *8*(9), e72176.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General*, *132*(3), 331–350. http://doi.org/10.1037/0096-3445.132.3.331

Vaughan, C., Davis, B., & O'Connor, J. (1999). *Dynamics of Human Gait*. Kiboho Publishers. Retrieved from http://www.kiboho.co.za/GaitCD/GaitBook.pdf

Warren, W. H. (2006). The dynamics of perception and action. *Psychological Review*, *113*(2), 358–389. http://doi.org/10.1037/0033-295X.113.2.358

West, G. B., & Brown, J. H. (2005). The origin of allometric scaling laws in biology from genomes to ecosystems: towards a quantitative unifying theory of biological structure and organization. *Journal of Experimental Biology*, *208*(9), 1575–1592. http://doi.org/10.1242/jeb.01589

Wing, A. M., & Kristofferson, A. B. (1973). Response delays and the timing of discrete motor responses. *Perception & Psychophysics*, *14*(1), 5–12. http://doi.org/10.3758/BF03198607

Winstein, C. J., & Schmidt, R. A. (1990). Reduced frequency of knowledge of results enhances motor skill learning. Journal of Experimental Psychology: Learning, Memory, and Cognition, 16(4), 677.

Woodrow, H. (1932). The effect of rate of sequence upon the accuracy of synchronization. *Journal of Experimental Psychology*, *15*(4), 357–379. http://doi.org/10.1037/h0071256

Wright, R. L., & Elliott, M. T. (2014). Stepping to phase-perturbed metronome cues: multisensory advantage in movement synchrony but not correction. *Frontiers in Human Neuroscience*, *8*. http://doi.org/10.3389/fnhum.2014.00724

APPENDIX A

EYE-TRACKING DATA

Methods

To determine whether they were visually anticipating or reacting to the visual cue, participants wore eye-tracking goggles (Applied Science Laboratories, Bedford, MA) during the synchronization phase of each session (see Figure 13). These goggles recorded the scene from the perspective of the participant, as well as pupillary fixations and saccades at a rate of 30 Hz. Rate of anticipation was quantified by examining the five frames (160ms) preceding the appearance of each footprint for every step. It was determined if the participant's eye motion over this window trended toward the left or the right. If eye motion trended toward the left prior to the appearance of a left footprint, the participant was said to have anticipated that footprint. Anticipation for the right footprint was calculated similarly.

Figure 15. ASL MobileEye Eye Tracking Headset.

Results

Analysis of eye tracking data showed, consistent with the cross-correlation data, a split between reactionary and anticipatory. During the non-feedback condition, participants anticipated the arrival of the next footfall 49.90 ± .004 percent of the time, and 50.16±.005 percent during the feedback condition.