AN ANALYSIS OF THE RELATIONSHIP BETWEEN COMPLEXITY AND GAIT ADAPTABILITY

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ABSTRACT

The presented sequence of studies considers theoretical applications from Complexity Science and Chaos Theory for gait time-series analysis. The main goal of this research is to build on insights from a previous body of knowledge, which have identified measures derived from Complexity Science and Chaos Theory as critical markers of gait control. Specifically, the studies presented in this dissertation attempt to directly test whether characterizing gait complexity relates to an ability to flexibly adjust gait. The broader impact of this research is utilizing measures of complexity to characterize gait control, and as a tool for rehabilitation which have both gained momentum in fall prevention research.

Through a series of four studies, this dissertation was designed to test the theoretical viewpoint that complexity is related to gait control, particularly gait adaptability. Firstly, I sought to develop a paradigm for reliably entraining gait complexity with the use of several auditory fluctuating timing imperatives which, differed based on specified fractal characteristics. I also sought to quantify the duration of the retention of gait complexity, following entrainment. Thirdly, I assessed whether attentional demands required during entrainment were affected by the fractal characteristics of a fluctuating timing imperative. Lastly, I applied the developed paradigm to evaluate the theoretical relationship between gait complexity and stepping performance.

The findings from this dissertation have developed a framework for assessing gait control. This series of projects has determined that a fluctuating timing imperative can reliably prescribe the gait pattern of healthy individuals towards a particular complexity.

The use of a fluctuating timing imperative leads to entrainment of the stimulus complexity. Furthermore, once the timing imperative has ceased, there is a brief period of complexity retention in the walking pattern. This dissertation has also confirmed that entraining complexity to a fluctuating timing imperative does not alter the attentional demands associated with entrainment. However, entraining gait to fluctuating timing imperatives of different complexities alters the stepping strategy that is adopted. Lastly, this dissertation has shown that synchronizing gait to a fixed-interval stimulus following entrainment, depends on the complexities of the gait pattern.

DEDICATION

This work is dedicated to my parents, fiancé, sister and brother-in-law who have shown me unconditional love and support from start to finish.

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LIST OF ABBREVIATIONS

ASYN – Asynchrony

ASYN$_E$ – Entrainment phase asynchrony

ASYN$_P$ – Post-entraintment phase asynchrony

COV – Coefficient of variation

DFA – Detrended fluctuation analysis

DST – Dynamical Systems Theory

ENT – Entrainment phase

FFT – Fast Fourier transform

FSI – Fractal scaling index

FULL – first post-entrainment window

HC – Heel-contact

IBI – Inter-beat interval

IFFT – Inverse fast Fourier transform

INT – Intermediate window

ISI – Inter-stride interval

LHEEL – Left heel

PN – Pink noise

POS – Post-entrainment phase

PRT – Probe reaction time

PWS – Preferred walking speed

PWS$_L$ – Lower bound preferred walking speed

PWS$_U$ – Upper bound preferred walking speed

REB – Research ethics review board

RHEEL – Right heel

RMS – Root mean square

RN – Red noise

RT – Reaction time

SD – Standard Deviation

SEM – Standard error of mean

SES – Sessions

SHORT – Short window

SWIN – Synchronization window

TI – Timing imperative

UN – Uncued

WIN – Window

WN – White noise

SECTION ONE

INTRODUCTION

CHAPTER ONE

REVIEW OF LITERATURE

1.0. Background

A central component to independent living is mobility, which is defined as the capability to navigate the surrounding environment; to displace the body from one location to another (Shumway-Cook, 2007). Gait is a fundamental aspect of mobility and can be assessed from a system point-of-view. Any measurable behaviour (i.e., actions such as stepping performance) produced by the gait system derives from mechanical, sensory and cognitive interactions.

Shumway-Cook and Woollacott (2007) developed a framework for studying the control of gait system behaviour based on three fundamental goals of walking: progression, biomechanical stability, and adaptability. Progression is defined as displacement of the body, in the typically desired forward direction, by repetitive and rhythmic stepping. Biomechanical stability refers to maintaining the body's center-of-mass, over a changing base-of-support and from expected or unexpected perturbations, during progression. Lastly, adaptability, as stated in the current framework, is the ability to modify stepping, away from the basic pattern, in response to expected and unexpected perturbations (Shumway-Cook and Woollacott, 2007). Progression, stability and adaptability can be thought of as fundamental objectives to the gait system and control of walking. The gait system achieves its underlying objectives within an information-rich environment. Therefore, internal demands (e.g., anxiety and balance confidence) and external demands (e.g., physical obstacles, changes in surface, changes in direction) necessitate stepping adaptations. When considering the current framework of gait control with populations of differing walking capacity (such as stroke patients, fall-risk individuals, elderly adults, and young adults), there are clear differences in gait performance.

For example, an examination of falls among community-dwelling stroke survivors reported that 71 percent (%) of falls were due to tripping (34%), slipping (25%), and misplaced steps (12%) (Berg et al., 1997). When testing the ability of elderly low-risk fallers and elderly high-risk fallers to make foot adjustments in a multi-target stepping task, the elderly high-risk group failed to avoid targets accurately 17% of the time compared to 15% observed in low-risk elderly adults (Yamada et al., 2011). Special and pathological populations appear to experience difficulty controlling their gait, particularly when encountering situations that require step adjustments. Yet, there is no true clinical test of walking adaptability (Balasubramanian, et al., 2014).

Systems theory proposes that patterned behaviour, observed in certain objects in nature, can be understood by framing the object as a function of interacting and bounded elements (Rousseau, 2015). A system is an object that is composed of a finite number of elements, which interact in some manner to produce an output (Rickles et al., 2007). Linear systems (e.g., simple harmonic motion) are composed of elements (e.g., mass, spring, damper) that produce output that is a summation of the elements. This is known as the superposition principle. Systems become increasingly complex as the number of elements involved increases. Systems also become increasingly complex as time influences interactions between elements. Both the time and the number elements ultimately impact the output of the system.

Gait is a complex task. Due to the dynamic nature of gait, stepping performance changes with time (Hausdorff et al., 1995). Accordingly, to understand how stepping performance is controlled, gait must be assessed from a broad viewpoint (i.e., systems viewpoint). The gait system is a subset of interacting elements (i.e., mechanical, sensory, and cognitive) within the broader motor control system. The gait system generates locomotor behaviour (i.e., rhythmic stepping). In line with Shumway-Cook and Woollacott (2007) theory on assessing the control of gait, the gait system ascribes to the previously mentioned three fundamental goals of walking: progression, stability and adaptability. Examining gait performance from a systems perspective can help interpret behavioral patterns related to function, relative to the gait system's goals.

Dynamical Systems Theory (DST) suggests that time-evolving systems demonstrate non-linear behaviour relative to the system’s objective. Dynamical systems can be modeled on a set of non-linear differential or difference equations, to define short-term and long-term changes in system states (McCamley and Harrison, 2016). Hence, motor control theories (e.g., Optimal Movement Variability and Loss of Complexity theories) seek to understand locomotor behaviour from a systems viewpoint by interpreting dynamical output (e.g., stepping pattern), in relation to the fundamental goals of the task (e.g., progression, stability, adaptability).

Within the realm of dynamical systems exists a smaller branch of non-linear (complex) dynamical systems, and an even fewer number of systems that display chaotic behaviour. Due to the intricate nature of highly complex dynamical systems, a formal science called Complexity Science has been developed to understand the complex patterns observed in many natural systems (e.g., cardiorespiratory system, biological movement system, and the stock market).

Investigations utilizing numerical methods derived from Complexity Science and Chaos Theory have been applied to gait time-series. These investigations have enhanced current knowledge of what is considered a "healthy gait" (Hausdorff et al., 1995; Dingwell & Cusumano, 2000; Kurz, et al., 2005; Granata & Lockhart, 2008). The *loss of complexity* hypothesis developed by Lipsitz & Goldberger (1992) suggests that a system in a steady-state (i.e., rest or free-running) lacking physiological complexity, is associated with poor adaptive capacity. Proponents of the Dynamical Disease Theory suggest that healthy physiological control systems are embedded in dynamical fluctuations, and that pathology arises when the dynamic fluctuations become rigid or too random (Rhea and Kiefer, 2014).

Hausdorff's (1995; 2001; 2007) work examining gait rhythm revealed complexity within a series of stride intervals (i.e., time between successive ipsilateral heel contacts). Furthermore, complexity observed in a series of stride intervals is sensitive to changes in walking speed (e.g., preferred, slower and faster than preferred), age differences (e.g, young adults and elderly adults), disease (e.g., Parkinson's and Huntington's) and fall-risk individuals (i.e. healthy elderly and fall-risk elderly) (Jordan et al., 2005; Hausdorff et al., 1997; Frenkel-Toledo et al., 2005; Herman et al., 2005). This, coupled with evidence indicating that elderly fallers experienced 53% of falls due to trips and slips (Lord & Rochester, 2007), suggest that complexity may underscore important information regarding the control of gait, and may distinguish healthy from pathological gait. Interestingly, Hausdorff's work (1995; 2001) found that when healthy individuals are asked to time their heel contact to the beat of a fixed interval timing imperative (i.e., a metronome with a fixed frequency), their typical level of gait complexity "breaks down" and approaches randomness. In the two decades after Hausdorff's (1995) seminal work, a number of articles have highlighted the presence of complexity and its importance in gait (Dingwell and Cusumano, 1999; Decker et al., 2010; Harbourne and Stergiou, 2009).

Amidst encouraging results that implicate complexity as an indicator of gait control, additional experimental efforts are needed to directly link gait complexity and gait adaptability. Recent evidence suggests that gait complexity can be primed using a fluctuating timing imperative (i.e., a metronome with a fluctuating frequency). Specifically, cueing steps to a fluctuating timing imperative can lead to matching gait dynamics with the stimulus dynamics (Hunt et al 2012; Marmelat et al., 2014; Rhea et al 2014). Additionally, it appears that entrainment of gait complexity using a fluctuating timing imperative can be retained in the short-term (Rhea et al., 2014). Recent findings provide an opportunity to directly test the relationship between gait complexity and gait control, specifically adaptability.

1.1. Variability, Complexity and Chaos

Over the past five decades, research has shown that the difference between skilled and unskilled movements is the development of an "optimized" motion. "Optimized" can be defined as little to no inconsistency between repetitive motions (i.e., stable motion). Mastering walking entails supporting the center-of-mass over the base-of-support, allowing step adjustments to be made while progressing the body forward in space. However, even when stepping is mastered, only rarely will two or three consecutive strides demonstrate identical movement execution. This is due to an inherent level of variability within the optimized human movement system.

Variability has been established as a fundamental feature of the human motor control system. In the 1920s, Nikolai Bernstein demonstrated a clear example of biological variability in human performance with the technique of kimocyclography (which is akin to modern day optoelectronic motion analysis) (Latash, 2014). Bernstein tracked the motion of a hammer and arm during a repetitive hammer strike being performed by professional blacksmiths. It was observed that highly skilled individuals can strike a target consistently using a hammer.

The key finding from this work, which has shaped the modern view of biological variability, is that the magnitude of spatial deviation of the hammer tip (e.g., output variability) was less than the magnitude of spatial deviation of the arm joint angles (e.g., coordinative variability) (Latash et al., 2002). Bernstein is now famously quoted as saying the blacksmiths performed, “repetition without repetition”. The blacksmiths example provided evidence of the complexities involved with repetitive human performance.

Human performance researchers consider variability to be an indicator of movement proficiency. Variability measures the amount of dispersion that occurs amongst repeated measurements of a movement. Large variability indicates poor consistency in movement, whereas small variability shows greater consistency in movement. Traditionally, variability has been quantified using statistical metrics (such as the standard deviation or root mean square) that quantify the magnitude of "error" around the average performance (van Emmerick, 2016).

Variability of movement tasks can be observed in both space and time (i.e., are spatiotemporal). Regarding gait, stepping is viewed as a pseudo-periodic movement, whereby steps are repeated to form a basic rhythm. During steady-state walking, successive steps demonstrate small deviations (i.e., a magnitude of "error") in speed, duration and distance in healthy individuals (Vaughan, 2003). The magnitude of variability is linked to balance during gait, and has an association with the risk of falling (Maki, 1997). Accordingly, an abnormally low or high magnitude of variability in spatiotemporal gait parameters is an indications of fall-prone individuals (Brach et al., 2005).

Despite such findings, it is questionable whether characterizing the magnitude of spatiotemporal gait variability is a true indication of gait control. Bruijn (2013) presented the following example to clarify the idea of control and variability: consider subject A and subject B, both with identical anthropometrics and similar step width variability, but subject A has a considerably narrower step width than B. When experiencing a lateral perturbation of equal magnitude, Subject A can be considered more at risk of losing balance at any step. Thus, determining gait proficiency from the magnitude of variability is, at best, an indirect relationship.

The magnitude of variability poses a theoretical limitation in quantifying the control of gait. When considering metrics such as the standard deviation or root-mean square, past and future observations are considered independent from each other. Alternatively, there is evidence to suggest that past and future steps are time-dependent.

These connections are called long-range correlations and indicate a patterned connection between past and future strides (Hausdorff, 2005, Rhea and Kiefer, 2014). Utilizing metrics aimed at quantifying the pattern of variability can lead to understanding how a system is controlled and the level of gait proficiency. For example, a "proficient walker" (e.g., a healthy young adult), will demonstrate a particular patterned variability that may represent an ability to behave flexibly in a changing environment. More specifically, this means constraining the typical pattern of stepping to a defined variability, so that slight environmental changes do not destabilize the walker, and appropriate detection of environmental changes is enabled. In contrast, a "novice walker" (e.g., early childhood), may lack an appropriate patterned variability. Accordingly, they may demonstrate an inability to correctly modify or adjust steps due to an overly variable stepping pattern, or they may demonstrate an overly constrained stepping pattern that is sensitive to minor stepping changes (Figure 1-1). Simply measuring the magnitude of deviation of a time series will not distinguish between a skilled and unskilled walker.

The research that has examined patterns of variability in gait has been informed by cardiac rhythm research (Lipsitz et al., 1990; Schwartz et al., 1991). Though the inter-beat interval of the heart is under autonomic control and gait is under somatic control, both rhythms demonstrate periodicity with underlying patterned fluctuations. An interest in the pattern of gait variability (more specifically the complexity) has since surfaced in the past two decades, and is also associated with fall-risk (Hausdorff, 2007).

The Optimal Movement Variability hypothesis proposes that a particular level of variability is the result of a highly functional system (Stergiou et al., 2006; Stergiou and Decker, 2011). Motor control theories that are based on motor schemas have defined variability (quantified as the standard deviation) as a non-iterative error term that is added to the true behaviour of the system. This, by definition, implies that error in motor is a random process that is added to the overall true process. In fact, “error” that is considered related to previous “error” is multiplicative, and it operates as a feedback and influences future iterations. Feedback systems (e.g., gait system) behave in a non-linear

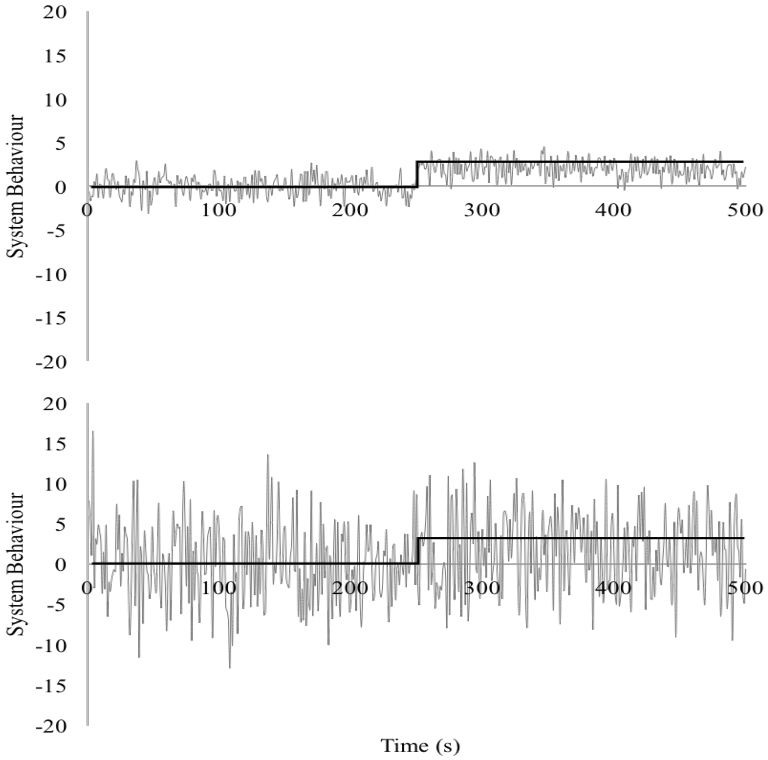

Figure 1-1: Conceptual images of two systems with differing sensitivity to perturbations (black lines). Top: a highly rigid system that will sense slight perturbations. Bottom: a system with five times (5x) the variability of the top image, and when faced with a perturbation of the same magnitude as the top system, it will not require any change in behaviour (unlike the behavioral change seen in the top image). Figure created by author.

fashion. Aggregating the number of non-linear interactions within a system increases the likelihood of producing patterns that are multiplicative (i.e., fractal-like).

1.1.1. Time-series (pattern of) variability

Evaluating any system's underlying control mechanisms requires understanding the evolution of time-varying behavioural changes. Measurements taken as time changes can result in an ordered set of numbers, known as a time-series. A time-series is a set of numbers that depends on the sequential order of the numbers. For example, in two sequences that contain the same elements, each will have identical means and standard deviations (first and second moments). However, the order of the elements will demonstrate dependence, meaning that the current element depends on the previous element.

A discrete time-series can be defined as:

$$X_t = \{x_t + \ x_{t+1} \ldots x_{t-1}\} \qquad (1)$$

where t represents an index within the time-series X. A discrete time-series is a set of data points that is sampled at regular, equal intervals over a defined period. This differs from a continuous time-series. In a continuous time-series, two points (t_1 and t_2), potentially have a countless number of points between them (Myers, 2016).

Time-series can have several core features that offer insight into the pattern of variability over time. In stochastic (i.e., random) time-series, each index at t_1, $t_2 \ldots t_{n-1}$ is independent from each other and does not demonstrate any dependence. Many of the time-series models (e.g., autoregressive moving averages) developed since the 1970s in economics and inferential statistics have been based on probability theory, and have thus been concerned with stochastic processes (Kirchgässner et al., 2013). However, in the movement sciences, most if not all time-varying processes include some level of determinism; that is, the process has some level of prediction. It is likely that movement signals contain both deterministic and stochastic components (Bruijn et al., 2013; van Emmerick et al., 2016). A signal containing purely a deterministic process (e.g., Lorenz attractor) can have a mean and variance that change with time (i.e., a trend). These processes are considered non-stationary. In contrast, a stochastic process has stationary properties; that is, the process has a mean and a variance that do not change. A classically modelled stochastic process is a white-noise signal, with zero mean and a fixed (i.e., finite) variance. Gait time-series demonstrate a level of non-stationarity and it is suggested that such non-stationarities are due to a complexity with fractal-like properties (Hausdorff et al., 2007; Sejdic et al., 2012).

The goal of time-series analysis is to determine time-evolving patterns within the signal. For example, time-series analysis can determine patterns for prediction, for forecasting, or for developing control schemes (Myers, 2016). DST has driven the development of several metrics that are used to quantify variable patterns in many physiological time-series. The metrics use to characterize variable patterns give insight into the underlying mechanisms of such processes. For example, these analyses have been applied to cardiac rhythms (Lipsitz et al., 1990; Schwartz et al., 1991), brain wave activity (Abasolo et al., 2008), and other motor control tasks (Sethi et al., 2013; Latash, 2014). All of the aforementioned applications have revealed complexity (as opposed to randomness) in steady-state conditions.

The fractal scaling index, Lyapunov exponents, and entropy statistics (e.g., sample, approximate, multiscale) are measures designed to quantify fluctuation patterns over time (i.e., the variable patterns) that are observed in gait (Bruijn et al., 2014). Computational assumptions limit the utility of such measures (see Wurdeman, 2016; Yentes, 2016; McGrath, 2016 for review). For example, use of the maximum Lyapunov and approximate entropy measures require stationarity in the data set being analyzed (Myers, 2016). Concerning steady-state gait, the stride interval time-series typically approaches 1/f scaling (i.e., pink noise, which is a non-stationary process) and any analysis of the underlying process in such a time-series requires selection of a method impervious to non-stationarities.

1.1.2. What is complexity?

Complexity is considered to be a novel, unifying term in the natural sciences (Ladyman et al., 2013). Yet, a formal mathematical definition of complexity does not exist. (Ladyman et al., 2013). Some believe that defining complexity may be domain specific (Ladyman et al., 2013). In creating a working definition of complexity for this dissertation, I will begin with the term system. "System" was previously defined as an object that is composed of connected elements. Complex systems include many interacting and bounded elements (Rickles et al., 2007). Specifically, the gait system includes muscles, bones, and joints (i.e., mechanical elements), nerve endings and neurons (i.e., neural elements), and executive functions (i.e., cognitive elements) that interact to produce lower-limb locomotor output that satisfies the goals of the walking (Figure 1-2). These components interact across various time scales. The aggregate

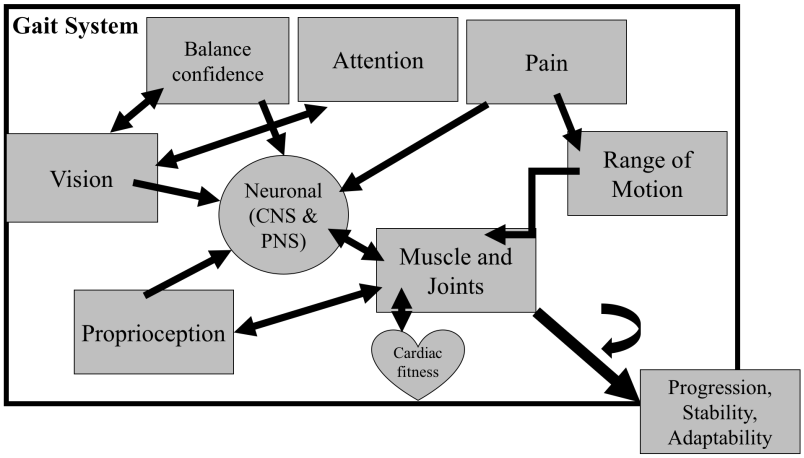

Figure 1-2: Conceptual image of gait system complexity. The gait system is a highly composite system, with many interacting components (straight arrows), that produces non-linear behaviour (represented by the half-circle arrow). Note that the cognitive, sensory, and mechanical components of the system interact with each other owing to a highly complex interconnected gait system. Interactions combined produce behaviour that is non-linear. Figure created by author and adapted from Hausdorff et al., 2001.

behaviour (e.g., variability of stepping) of all incumbent processes produces a non-linear pattern. Accordingly, complexity will be defined here as non-linear output from a highly composite system that demonstrates scale-invariance. Scale-invariance means that regardless of the scale at which the output is viewed, the characteristics (e.g., pattern of variability) of the corresponding system are similar. Behaviour at one scale will be a multiple of another scale. This is formally known as a power-law:

$$f(x) = kx^{\alpha} \qquad (2)$$

where α represents the multiplicative scaling factor which characterizes the non-linear behaviour of $f(x)$. The fractal scaling index thereby measures the level of complexity (Katz, 2016).

A purely scale-invariant time series is one where $\alpha = 1.0$, and this process is otherwise known as pink noise. In contrast, a process $\alpha > 1.5$ is known as brown noise. A completely random (i.e., stochastic and uncorrelated across time) process is one where $\alpha \approx 0.5$, and is otherwise known as a white noise (Figure 1-3). A periodic time series such as a sine wave approximates $\alpha \approx 0$.

Figure 1-3 is a conceptual diagram that demonstrates the relationship between the fractal scaling index measure and the associated level of complexity across several known time series. The level of complexity refers to the magnitude of correlation across scales. Anti-persistence and persistence describe the quality of complexity. Anti-persistence is a time-series feature that demonstrates error-correcting (i.e., is qualitatively similar to a stationary process). This means that statistically, within the time series, a value above the mean is likely to be followed by a value below the mean. In contrast, persistence is a time-series feature that demonstrates short-range or long-range correlations. This means that a value above the mean will likely be followed by another value above the mean (i.e., is qualitatively similar to a non-stationary process) (Terrier, 2016).

Several qualitative features, as described in this paragraph are generally accepted as hallmarks of systems that display purely complex behavior. One such feature, previously mentioned, is non-linearity. Non-linearity means that the system does not behave in a proportional matter. Accordingly, small changes to the current system state do not necessarily reflect a proportional change in output (i.e., output is not the sum of the behavior of each element).

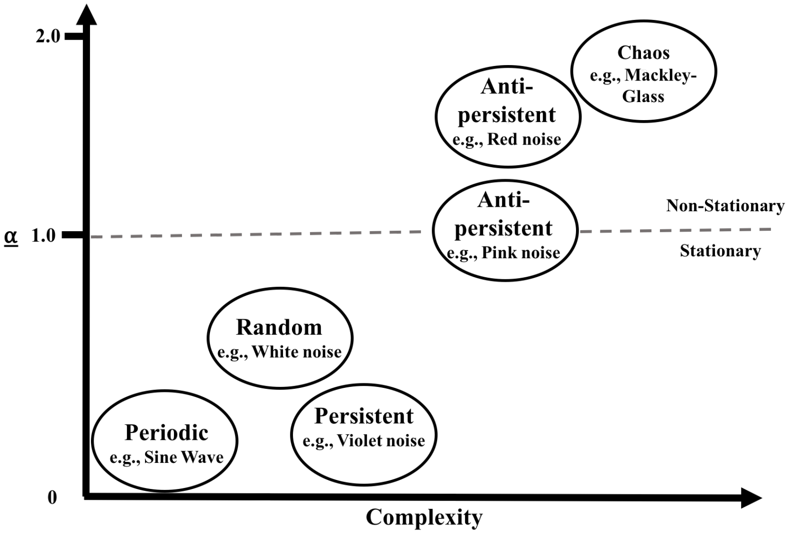

Figure 1-3: The relationship between the level of complexity and associated fractal scaling index measure, with example time-series. Figure created by author.

Another such feature is limited predictability, where complex systems display behavior that is the result of environmental feedback. These systems are considered sensitive to initial conditions, and any slight change in the initial conditions and environment can alter the evolution of the output.

A third such feature is self-organization, where elements of a complex system interact in a parallel and distributed manner (Sleimen-Malkoun et al., 2014). This means that there is no central control. Rather, a complex system uses bottom-up control. This is believed, at a behavioural level, to allow adaptable behaviour to be "regular without being regulated" (Harrison and Stergiou, 2015). Self-organization in human movement has explained the phenomena of motor coordination of the pelvis-trunk (van Emmerick, 1994) and of bilateral finger coordination (Haken, 1985).

The most recognized example of self-organization in human movement is the Haken-Kelso-Bunz (HKB) model of bilateral finger coordination. The HKB model depicts that when a person attempting to abduct and adduct their pointer fingers in anti-phase (that is, one finger is abducted while the other is adducted), the phase coordination will eventually change to in-phase (that is, both fingers either adducted or abducted at the same time) at a critical frequency (McCamley and Harrison, 2016). This example is an example of self-organization because at a critical frequency, the coordination of both fingers spontaneously changes from anti-phase to in-phase. Another example of self-organized behaviour is the presence of 1/f fractal scaling in steady-state human gait (Hausdorff, 2007; McCamley and Harrison, 2016). This l/f fractal scaling characteristic allows for constrained but adaptive gait at preferred walking frequencies (Hausdorff, 2007; McCamley and Harrison, 2016).

A fourth such feature is emergence. Self-organized behaviour results in the emergence of an output that is the result of precise interactions of the systems' individual elements (i.e., systems compositional complexity). The output cannot be dissected, and are conditioned by the task and the environment. Arguably, self-organization and emergence are closely linked (Addiscott, 2011). Rhea (2014) demonstrated that changes in local gait dynamics emerge to accommodate the dynamics of a fluctuating timing imperative. The features of complex systems listed above occur in many biological systems (Addiscott, 2011).

1.1.3. What is chaos?

Nested within dynamical systems and connected to complex systems is a sub-class of systems called chaotic systems (Figure 1-4). Chaotic systems are considered completely deterministic, and can only be modeled by knowing the initial conditions of the system. Currently, several chaotic systems can be modeled mathematically, such as the logistic equation, the Lorenz equations, and the Mackey-Glass equation. This is because chaotic systems can be defined by known parameters. As the defined parameters evolve, chaos appears qualitatively.

Chaotic systems are highly sensitive to initial conditions (Rickles et al., 2007; Decker et al., 2010). This sensitivity leads to "constrained randomness," which is popularly known as the Butterfly Effect (Rickles et al., 2007; Decker et al., 2010). Specifically, "constrained randomness" is qualitative behaviour that appears variable but is constrained within a set limit of trajectories. As a result, chaotic systems demonstrate "unusual geometric properties" (McCamley and Harrison, 2016). Lyapunov exponents can provide a metric of chaotic behaviour and the presence of a chaotic attractor. Modeling studies using passive dynamic walkers have demonstrated that the oscillation between limbs is embedded in a chaotic attractor (Kurz et al., 2005). Also, Lyapunov exponents have shown sensitivity to different age groups based on stride-to-stride fluctuations (Buzzi et al., 2003). Therefore, it appears that gait time-series contain deterministic components.

1.1.4. Chaos vs. complexity?

It is important to note that not all chaotic systems are complex (Figure 1-4). Chaotic systems are considered deterministic. In contrast, complex systems are not completely deterministic, and therefore there is inherent uncertainty in a complex system. The biggest difference between complexity and chaos is that chaotic systems operate in a closed environment, where the parameters defining the dynamics are known. In contrast, complex systems operate in an open environment.

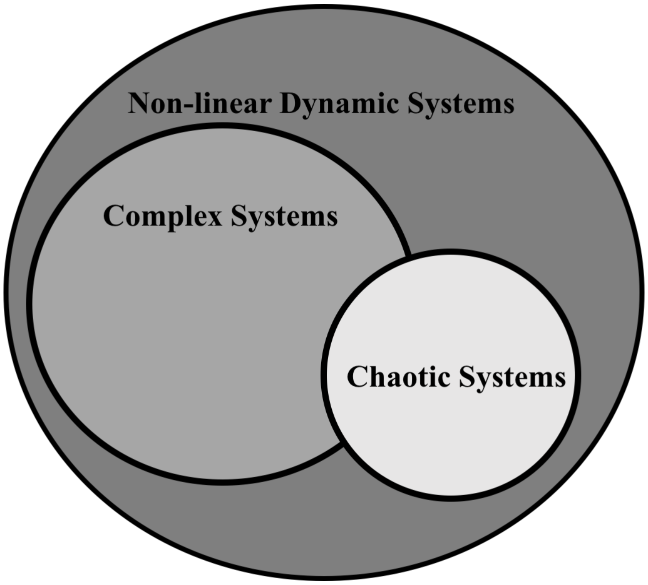

Figure 1-4: Complex and chaotic systems are nested within non-linear dynamical systems. All chaotic systems are not considered complex systems. Complex systems are believed to lie on the "edge of chaos", but the two differ in that complex systems do not contain purely deterministic components like chaotic systems. Figure created by author and adapted from McCamley and Harrison, 2016.

It is generally impractical to determine a system's initial conditions. However, if the system's initial conditions are known, one can determine when chaotic behaviour will occur. In contrast, complex systems produce emergence from self-organization due to interactions with the environment (Bar-Yam, 2011). Therefore, in true complex systems, there is limited predictability even if the initial conditions are well-known. Furthermore, chaotic systems can be used to predict future states of the system. Complex systems cannot be used for such predictions. However, understanding complex systems can reveal aspects of the underlying control mechanisms that govern the system.

1.2. Gait Adaptability and Complexity

Gait adaptation is a necessary process of functional mobility, particularly in a continually changing environment. Environmental threats to steady-state gait (i.e., the presence of obstacles, changes in terrain, oncoming traffic) require adjustments to be made in gait pattern.

The intersection between adaptability and complexity is not well understood (van Emmerick et al., 2017). Yet numerous studies point to the idea that complexity is related to adaptability (Harbourne and Stergiou, 2009; Manor et al., 2010; Rhea and Kiefer, 2014; Harrison and Sterigou, 2015). Before an analysis concerning the relationship between complexity and adaptability can be performed, gait adaptability must be defined. For this dissertation, gait adaptability is defined as the process of adjusting the typical gait pattern to meet environmental demands (Balasubramanian et al., 2014).

Navigating external demands can be classified into two main strategies: avoidance and accommodation. Avoidance strategies can be accomplished in a single stride, and they typically involve navigating an obstacle in one's path. These strategies often utilize visual-motor integration. More specifically, avoidance strategies include adjustments in the kinematics of lower-limb movements based on visual feedback from various characteristics of the obstacle (Reitdyk et al., 2006; Perry et al., 2009). For exmaple, visualization of the avoidance target at least one stride prior to crossing an obstacle is necessary for successful negotiation (Patla, 1992). Additionally, while performing an avoidance maneuver, visual information of the target is more important than visual information of the foot position (Rietdyk and Rhea, 2006).

Alternatively, accommodation involves gait modifications that are long-term and involve at least two strides (e.g., modifying the timing of successive steps different surfaces) (Shumway-Cook and Woollacott, 2007). Accommodation is needed when surfaces are irregular or uneven, and when the temporal demands of walking are changed (e.g., crossing an intersection).

Accommodation has been studied less than avoidance. However, an investigation comparing walking over a rock surface, with level ground walking, found that there was adaptation of spatiotemporal gait parameters and kinematics (Gates et al., 2012). Specifically, when traversing the rock surface, the magnitude of variability of the spatiotemporal parameters (step length, step width, and duration) increased (Gates et al., 2012). As such, both avoidance and accommodation strategies involve changes that can be captured by the parameters of gait kinematics.

The working definition of adaptability outlined above is in accordance with the three-component neural control model of walking (Shumway-Cook and Woollacott, 2007). In this model, adaptability and stability are connected, in that a step adjustment can help maintain biomechanical stability. From a biomechanical perspective, an individual can achieve stability (i.e., not fall over) even when the center-of-mass moves outside of the base-of-support, as is the case with steady-state gait.

In line with this thinking, adaptability and stability become connected in their function, because a spatial or temporal adjustment of the foot (i.e., gait adaptations) is one of the best methods for avoiding a fall (i.e., maintaining stability) (Nonnekes et al., 2009). Hak (2013) investigated the mechanisms underlying the connection between stepping adaptability and biomechanical stability. Participants in Hak's (2013) study were asked to perform a gait adaptability task by targeting virtual light targets placed on the ground. Participants demonstrated increases in their typical step width, along with decreasing their typical step length, while maintaining the same margin of stability observed in normal walking.

However, within the framework of DST, the concepts of adaptability and stability appear to oppose one another. An entirely stable system (i.e., highly repeatable and therefore having a "low" amount of variance) is arguably unable to adjust from the typical pattern of behaviour, and becomes highly sensitive to perturbations (Figure 1-1). In contrast, an adaptable system has an optimal level of variability, which is not overly stable and is not unstable, such that adaptations can occur (Harbourne and Stergiou, 2009). The healthy gait system appears to resolve this apparent paradox by capturing the adaptability of the stepping pattern while maintaining biomechanical stability. Therefore, applying the DST framework to gait may capture a specific aspect of gait control, specifically adaptability.

1.2.1. Complexity as a biomarker of gait adaptability

Several biomechanical measures have been developed to assess walking adaptability in relation to a particular paradigm (e.g., obstacle crossing, target stepping, and fixed-interval timing imperative, to name a few). Some examples of such measures used in the literature include the temporal and spatial aspects of stepping error, obstacle clearance distance, trail-limb clearance distance, medial-lateral foot adjustment error, and the standard deviation of lower-limb gait parameters. (Perry et al., 2009; Roerdink et al., 2011; Hollands, et al., 2015). The coordination between an actor (i.e., an individual) and the environment (i.e., an external stimulus) can reveal aspects of adaptability.

Roerdink (2011) made use of a fixed-interval timing imperative to assess auditory-motor synchronization. At comfortable walking speeds, individuals synchronized with the timing imperative within six strides of onset. In Roerdink's (2011) study, synchronization was defined as the cumulative difference of three consecutive heel strikes that were within +/- 20 ms of the beats elicited from the timing imperative start. As expected, as the frequency of the timing imperative's beats were increased, the number of strides required for synchronization also increased. Furthermore, as the frequency of the timing imperative decreased below comfortable walking speed, the number of strides required for synchronization also increased. Overall demonstrating a non-linear relationship between the frequency of the timing imperative and the quickness of synchronization. Interestingly, a similar non-linear relationship between walking speed and the fractal scaling index has been observed (Jordan et al., 2007).

Timing steps to the beat of a fluctuating timing imperative (i.e., a metronome with fluctuating frequency) has demonstrated that healthy individuals show a variety of stepping strategies for matching gait complexity with the complexity of the timing imperative (Rhea et al., 2014). Interestingly, as participants time their steps to a fluctuating timing imperative, their gait complexity shifts from a baseline value towards the complexity of the fluctuating timing imperative, demonstrating an entrainment effect (Marmelat et al., 2012). Rhea (2014) demonstrated that once the fluctuating timing imperative is ceased, this complexity entrainment effect is retained within the gait pattern. This research methodology, which can entrain and retain gait complexity, has opened the possibility of experimentally testing how gait adaptations are related to gait complexity.

Currently, there is no robust measure of walking adaptability. However, based on theory and application from DST, complexity is understood to be a critical marker of gait control and may measure gait adaptability. An appropriate paradigm is needed to adequately test whether complexity is related to gait control. A paradigm that entrains a specific level of complexity, and tests the retained complexity on a stepping task, may reveal the connection between gait complexity and gait adaptability. This paradigm should be based on new methodology indicating that the entrainment effect of fluctuating timing imperatives can be retained.

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CHAPTER TWO

RESEARCH OBJECTIVES, QUESTIONS, AND HYPOTHESES

2.0. General Aims

The aims of this dissertation were to: (1) develop a paradigm to reliably entrain a change in the baseline level of gait complexity, and (2) evaluate how the level of retained complexity following entrainment is related to the process of adapting gait. To achieve these aims, the following objectives and questions set forth below were addressed:

2.1. Objectives

1) Assess the test-retest reliability of entraining gait complexity to several fluctuating timing imperative. (Aim 1)
2) Evaluate the duration of retention of complexity following entrainment to several fluctuating timing imperative. (Aim 1)
3) Understand whether attentional demands differ when timing between several different fluctuating timing imperatives. (Aim 2)
4) Assess temporal synchronization responses to following entrainment to a fluctuating timing imperative. (Aim 2)

2.2. Questions

1) What is the effect of timing ipsilateral heel contact to the beat of several different fluctuating timing imperatives (white noise, pink noise, and red noise) on stride interval complexity? (Objective 1)
2) What is the error (defined as the difference between inter-beat interval complexity and inter-stride interval complexity) of entraining stride interval complexity to several different fluctuating timing imperatives (white noise, pink noise, and red noise)? (Objective 1)
3) What is the consistency of entraining stride time complexity, with several different fluctuating timing imperatives (white noise, pink noise, and red noise) across three sessions? (Objective 1)
4) What is the effect of timing ipsilateral heel contact to the beat of several different fluctuating timing imperatives (white noise, pink noise, and red noise) on the duration of complexity retention following entrainment? (Objective 2)
5) Does probe reaction time differ when timing ipsilateral heel contact to the beat of several different fluctuating timing imperatives (white noise, pink noise, and red noise)? (Objective 3)
6) What is the relationship, between any retained complexity and stepping performance (i.e., synchronization measured by the error between heel contact and beat onset) on a fixed timing imperative? (Objective 4)

2.3. Hypotheses

I hypothesized that: (1) different fluctuating timing imperatives would alter the inter-stride interval complexity towards the direction of the stimulus complexity; (2) inter-stride interval complexity would match the complexity of the fluctuating timing imperative; (3) stride-interval complexity would consistently entrain to the stimulus complexity across three sessions; (4) entrainment of the complexity of the fluctuating timing imperative would be retained in the inter-stride interval for a minimum of 250 strides post-entrainment; (5) probe-reaction time would differ between fluctuating timing imperatives; (6) any retained complexity would alter the number of strides necessary for synchronization on a fixed timing imperative.

CHAPTER THREE

GENERAL METHODS

3.0. Methodological Consistencies

Aspects of the methodology of each study were common across the studies. These aspects are described in detail here and are referenced in the body of each chapter. Each study required participants to coordinate their gait with an audible timing imperative. Specifically, participants were asked to time the instant of heel contact with the instant of beat onset. This methodological approach was chosen to entrain the gait pattern to the complexity of the timing imperative. Several techniques to collect, analyze, and process data were used consistently across the studies.

The four studies were collected at two different locations. Study # 1 (Chapter Four) and Study # 2 (Chapter Five) were collected at York University, Toronto, Canada. Study # 3 and Study # 4 were collected at the University of Salford, Manchester, United Kingdom. Both studies used complimentary pieces of equipment (e.g., motorized treadmill and high resolution motion capture system). A description of the methods, which were consistent across all studies is provided below.

3.0.1. Participant Selection

All participants included in the proceeding studies were young healthy adults between the ages of 18-35 years old. The choice to include only young adults was made to avoid the potential confounding variable of age. Participants were excluded if they reported any history of neurological and musculoskeletal injury or disorder, auditory impairment, or significant pain or discomfort which limited walking in the past six months.

A total of 48 participants were recruited over the four studies (25 males; 23 females). Participants were recruited by word-of-mouth. The recruitment strategy and protocols were approved by York University's Research Ethics Board and the University of Salford's Health Research ethics panel. The same set of participants (n = 17, 11 females) are reported for the studies conducted at the University of Salford (Study #3 and Study #4).

3.0.2. Equipment

Kinematic data was collected for each study using high speed optoelectric motion cameras (Mx Series, Vicon, Oxford, United Kingdom or Oqus Series, Qualysis, Gothenburg, Sweden) to capture the timing of heel contact. Passive reflective markers were placed bilaterally on the heel [right (RHEEL) and left heel (LHEEL)] of each participant. All studies made use of a fixed-pace treadmill (Bodyguard Fitness, Quebec, Canada or C-Mill, Motek ForceLink, Amsterdam, Netherlands) in order to elicit steady-state gait at controlled walking speeds. Fixing gait speed allowed manipulation of the inter-stride interval with the auditory fluctuating timing imperative. Each timing imperative was elicited through speakers adjacent to the participant (MLi 699, MidLand, Germany or Sound Link Mini, Bose, USA).

3.0.3. Determination of preferred walking speed

The determination of preferred walking speed (PWS) was a two-part protocol (Figure 1-1). The first part began with participants walking at a slow belt speed (0.50 m/s); the speed of the treadmill belt was then systematically incremented in steps (0.10

m/s steps), until the participant verbally indicated their “comfortable walking speed”. The corresponding speed was noted as (PWS_L) and the number of increments were noted. The second part of the protocol began at a speed above the participants previously noted as $PWS_{L,}$ with approximately the same number of increments observed during the determination of PWS_L (PWS_L + (PWS_L - 0.5). The speed of the belt was progressively decreased in regular reductions (0.10 m/s) until a preferred walking speed (PWS_U) was identified by the participant. Each different walking speed was performed by the participants for a total of 15 seconds. PWS was calculated as the average between PWS_U and PWS_L (Dingwell & Marin, 2006).

The range of tested treadmill speeds and the magnitude of each increment was partly guided by previous reports in the literature, which suggest that average treadmill PWS is 1.3m/s ± 0.13 m/s during treadmill gait (Terrier & Deriaz, 2011).

3.0.4. Fluctuating timing imperative creation

White noise (WN), pink noise (PN), and red noise (RN) fluctuating timing imperatives were created in Matlab R2015b (The Mathworks, Natick, USA) by utilizing the wgn() function to create a participant-specific Gaussian white noise vector. The average and standard deviation of the white noise vector matched the individual participant’s baseline walking trial and included a minimum of 256 data points (Delignières et al, 2006; Marmelat et al, 2014).

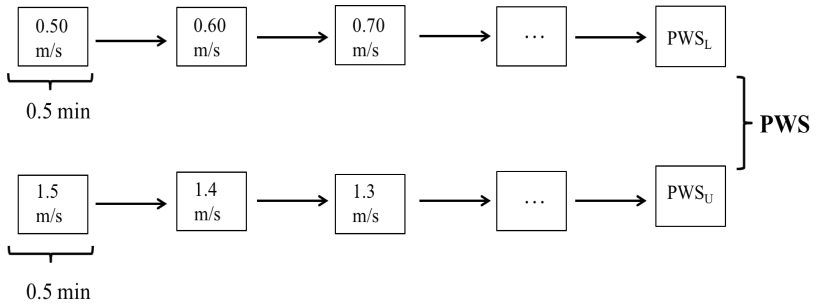

Figure 3-1: Protocol for determining preferred walking speed (PWS) on a motorized treadmill. Beginning at a slow speed (0.5 m/s), incremental changes in treadmill belt speed were made until participants identified their comfortable walking speed (PWS$_L$). An identical protocol was completed beginning at a fast walking speed (PWS$_L$ + (PWS$_L$ - 0.5). This was followed by fixed reductions in speed until the participants identified their comfortable walking speed (PSW$_U$). The average between PWS$_L$ and PSW$_U$ was taken as PWS for experimental trials.

The algorithm used to create pink noise and red noise signals is based on a method described in Kasdin (1995). To generate red noise and pink noise vectors, the original Guassian white noise vector was transformed into the frequency domain using a fast fourier transform (FFT). The sampling frequency that was used was determined by finding the sum of the inter-beat interval values, and dividing by the total number of samples (i.e., 256). Power was calculated by squaring the sine and cosine coefficients and then converted to decibels by multiplying by a factor of $10\log_{10}$. For the pink noise signal, the spectrum was divided by the square root of the amplitude of each frequency. Similarly, to generate a red noise signal, the spectrum was divided by the amplitude of each frequency (Figure 3-2). The subsequent red noise and pink noise vectors were transformed back into the time domain using an inverse fast Fourier transform (IFFT) function.

The respective WN, PN, and RN vectors were used to define the inter-beat interval (IBI) for each fluctuating timing imperative; the duration of each "beat" was 10 ms. Figure 3-3 below displays representative WN, RN, and PN IBI time-series that were used to entrain stride interval complexity (Figure 3-3). A triangle waveform with a period equal to the sum of the IBI and beat duration and amplitude set to the max volume of the system was created and converted to a sound file using the audiowrite() function.

All trials were initiated with the participants in steady-state walking. That is, the participants completed two-three strides at their pre-determined PWS prior to that start of the trial. Following the attainment of steady-state gait, the researcher initiated the start of the first beat with a three-count countdown ("three, two, one"). Each count approximately corresponded to the time of the participant's heel contact of the heel used time with the timing imperative, where "one" corresponded to the initiation of the first beat.

3.0.5. Post-processing

Raw kinematic signals were sampled at 100 Hz and filtered with a 4th order low-pass Butterworth filter with a frequency cutoff of 5 Hz. Detection of heel contact (HC) of the foot used to cue the stimulus beat was determined based on a zero-crossing of the velocity profile of the heel marker in the plane of progression (Figure 3-4) (Zeni Jr et al, 2009). The exact instant of event detection was taken as the instant prior to the change in direction of the heel marker. No interpolation was made to determine the instantaneous change in direction. The difference between successive HCs of the same foot was taken to determine the inter-stride interval (ISI) (Costa et al., 2003).

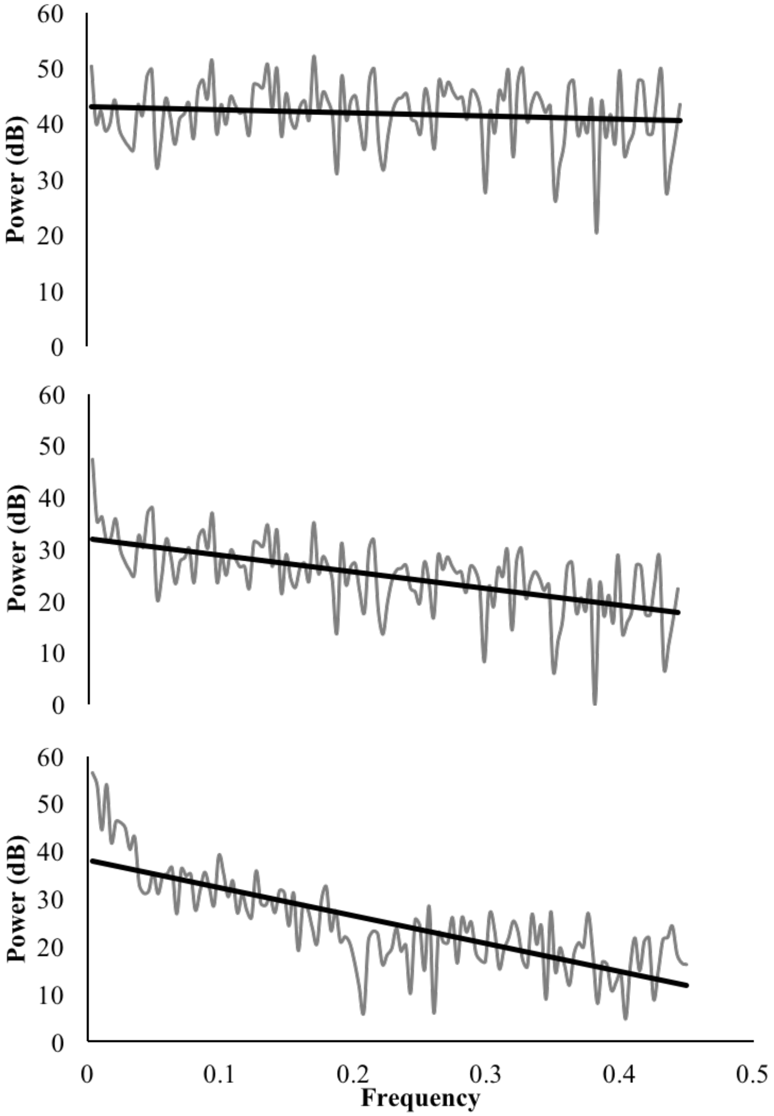

Figure 3-2: A representative plot of the frequency spectrum for three timing imperatives. Top: white noise shows approximately equal power in representative frequencies. Middle: pink noise demonstrates decay following multiplication by 1/√**f**. Bottom: red noise demonstrates sharper decay following multiplication by 1/f.

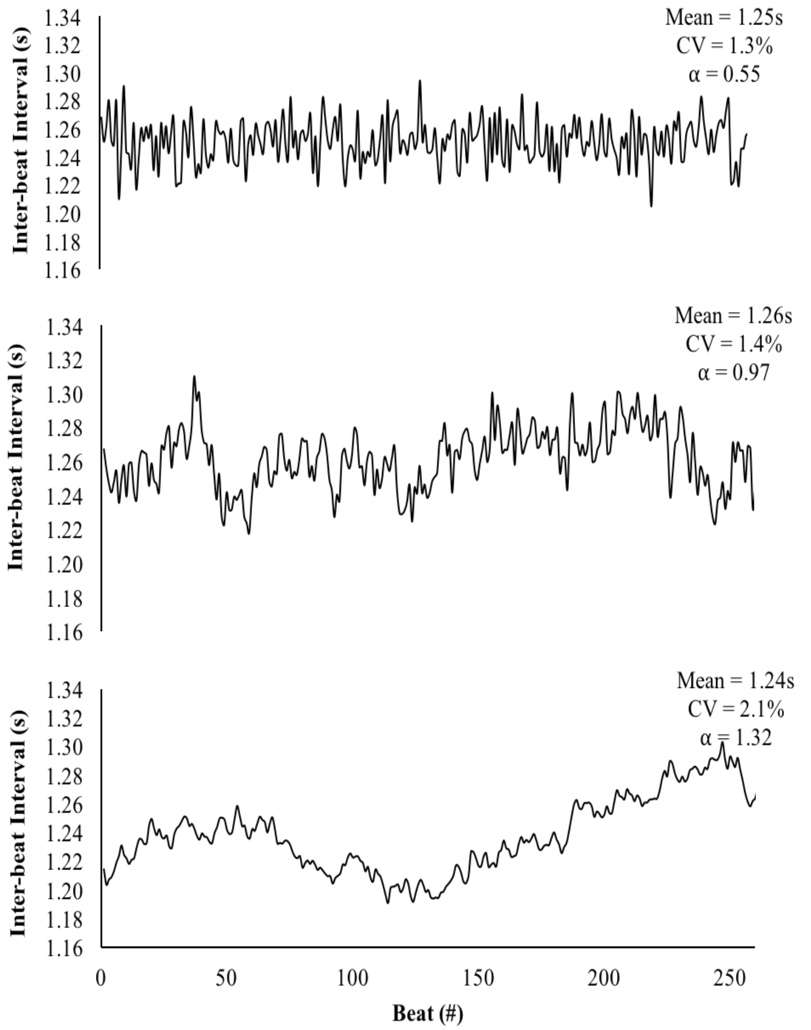

Figure 3-3: A representative plot of three fluctuating timing imperatives in the time domain, for a participant with a mean stride interval of 1.25 s and a standard deviation of 0.02s. Top: white noise inter-beat intervals (IBIs). Middle: pink noise IBIs. Bottom: red noise IBIs.

Analog signals (i.e., the timing imperative) were sampled at 1000 Hz at York University and 100 Hz at The University of Salford and were recorded with a custom-made cable. One end of the cable connected directly to the analog-to-digital processing unit. The opposite end of the cable was wired to an audio headphone jack. An audio splitter cable was connected to the laptop, and was also connected to the audio jack of the custom-made cable as well as the speaker audio jack (Figure 3-5). Post-processing of analog data was guided with the use of a probabilistic algorithm to confirm onset of the timing imperative beat (Chau and Rizvi, 2002).

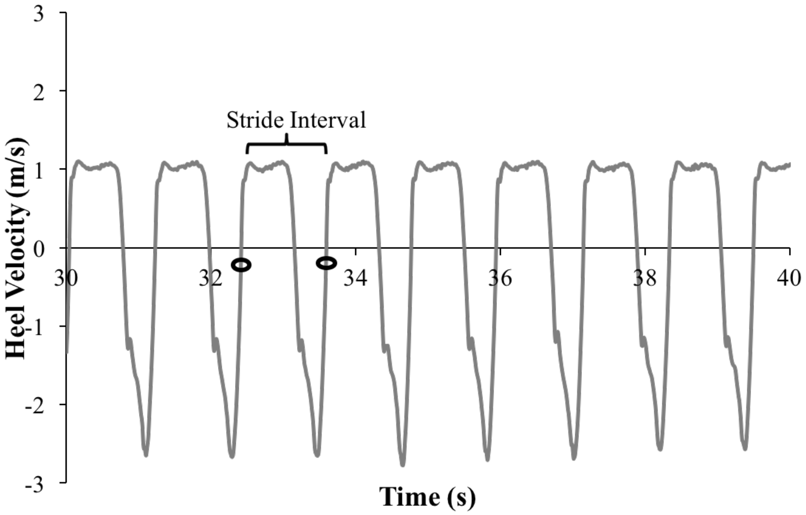

Figure 3-4: Representative heel marker velocity profile and detection of instantaneous heel contact during treadmill walking. Heel velocity was calculated based on a finite difference approach. Zero-crossings were approximated as change in direction of heel velocity, no interpolation was made. In this specific case, the orientation dictates that a change from negative to positive indicates instantaneous HC.

Gait complexity of ISI was calculated using a detrended fluctuation analysis (DFA) to generate a fractal scaling index (α) with a minimum of 255 strides of data for each trial. DFA is described as a modified random-walk approach to the analysis of a time-series (Hausdorff, 1995), which quantifies scale-invariant patterns within the signal at different time scales (e.g., milliseconds or seconds). The DFA approach is designed to have minimal sensitivity to non-stationary data (Myers, 2016). Quantifying the amount of variability at different time scales reveals an ordered relationship in the form of a power-law distribution (McGrath, 2016). Since the relationship between the magnitude of variability and the size of time scale follows the power-law, the scaling index (α) governing the strength of the power-law can be estimated by determining the slope of the log-transformed power-law distribution.

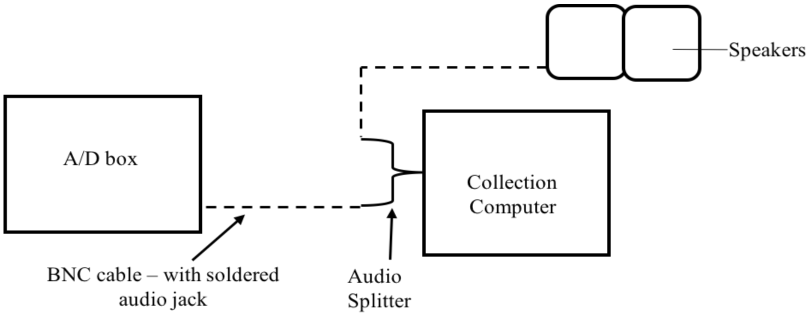

Figure 3-5: Flow diagram of analog signal recording method.

The fractal scaling index, α, ranges between $0 \lesssim \alpha \lesssim 2$. An $\alpha \approx 0$ - 0.49 represents anti-persistent fluctuations across time scales. An $\alpha \approx 0.5$ - 0.59 indicates that fluctuations across time scales are randomly ordered (white noise), and do not display statistical correlation between data points. An $\alpha \approx 0.6$ - 1.5 (pink noise) represents persistent fluctuations across time scales. An $\alpha > 1.5$ (red noise) represents fractional Brownian motion (also known as a random walk) (Hausdorff et al., 1995). The algorithm is as follows (Terrier and Deriaz, 2012):

1) Integrate the entire original time-series, $x(k)$, to create $\int y(k)$ using the rectangle method with the bias removed.
2) Divide the total time-series into non-overlapping boxes of equal length (n).

3) Quantify a line of best fit within each box using the least square method to obtain $y_n(k)$.
4) Detrend the integrated time-series, $\int y(k)$, by subtracting from the line of best from within each box $y_n(k)$; k = x-coordinate.
5) Calculate the average root mean square (RMS) (F(n)) for each box length (n).
6) Repeat steps one to five (1-5) with a variety of box length (n); n = 10-40.
7) Plot the distribution of RMS vs. box length (n) (power-law graph).
8) Apply a logarithmic transformation of the power-law graph created in step 7 to create a log-log plot.
9) Calculate slope of the log-log plot to obtain α scaling index (Figure 3-6).

The average fluctuation in for each box length (steps 1-5) can be generalized with the following equation (1):

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

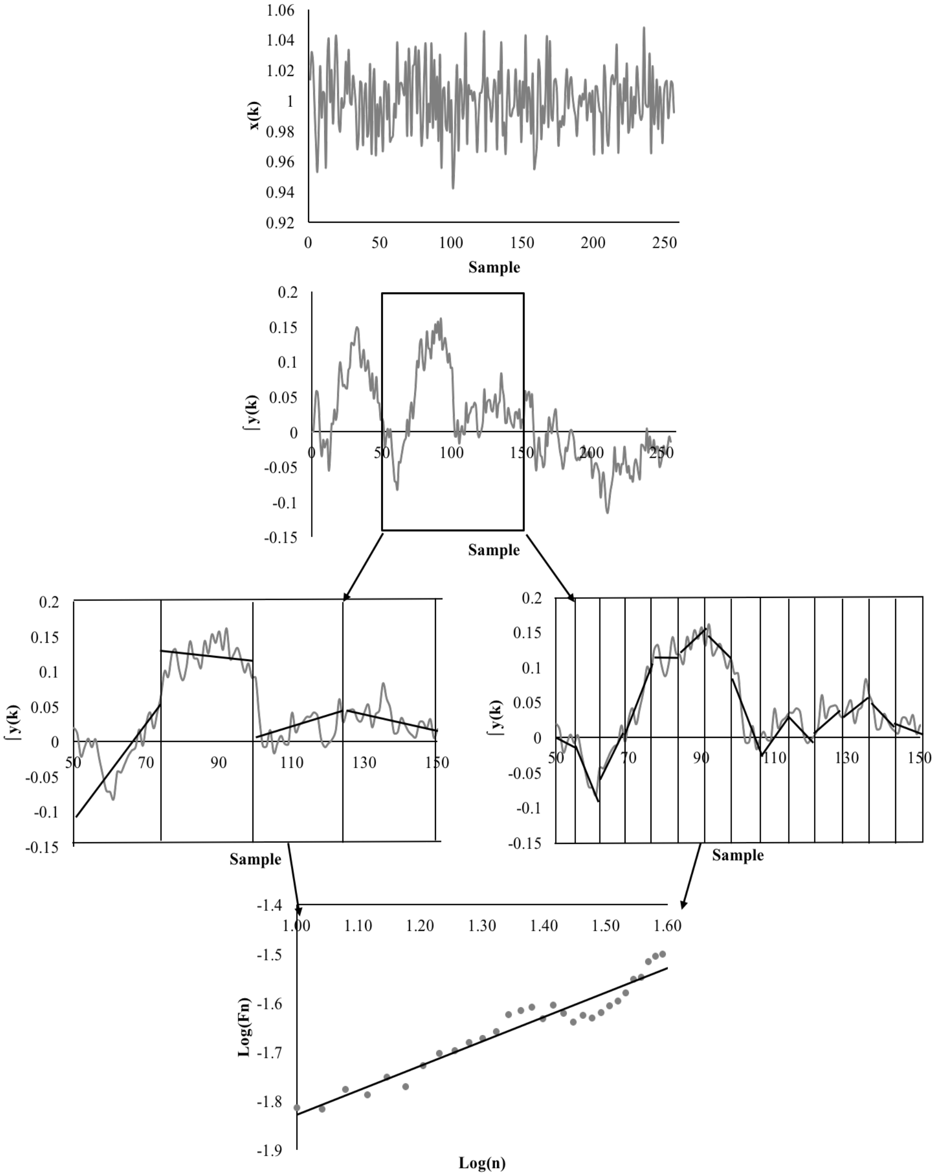

Figure 3-6: Visualization of the DFA algorithm. Top: represents the original white noise time series, $\mathbf{x(k)}$. Middle Top: represents the integrated time series, $\int \mathbf{y(k)}$. Middle Bottom: represents non-overlapping windows (10 and 40, respectively) over the integrated time series (samples 50-150) with line of best fit in each box. Bottom: represents log transform of all box lengths and corresponding RMS. The slope (black line) represents the fractal scaling index ($\alpha = 0.50$). Figure created by author and adapted from Rhea et al., (2014).

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SECTION TWO

EXPERIMENTAL STUDIES

CHAPTER FOUR

EVALUATING THE RELIABILITY AND ERROR OF ENTRAINING GAIT COMPLEXITY TO SEVERAL FLUCTUATING TIMING IMPERATIVES

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Preface

Healthy individuals have an ability to entrain gait complexity to the complexity of a fluctuating timing imperative within a single session of walking trials. Whether the prescription effect is robust and effective across a variety of fluctuating timing imperatives has not been studied. The purpose of this investigation is to assess whether auditory several fluctuating timing imperatives with various fractal characteristics can prescribe inter-stride interval (ISI) fractality consistently. In this study, 13 healthy young adults walked on a treadmill at a self-selected pace, synchronizing heel strike of their foot to an auditory fluctuating timing imperative. Four randomized trial walking conditions [Timing imperative (TI): uncued (UN), white noise (WN), pink noise (PN), and red noise (RN)] were administered over three sessions [Session (SES): session one (S1), session (S2), and session (S3)], which were each separated by a minimum of three days. There was a significant main effect ($p < 0.0001$) effect of TI on stride interval fractality. No main effect of SES ($p = 0.069$) was found. The results suggest that inter-stride interval fractality can be prescribed in a desired direction and with consistency across three (S1,

S2, S3) sessions for the WN, PN, and RN timing imperatives. A significant main effect of TI ($p < 0.0001$) was found for entrainment error. The results showed that entrainment error scaled with the fractal scaling index of the timing imperative. The results of this study suggest that with the use of an auditory fluctuating timing imperative, gait complexity can be prescribed in a desired direction and with consistency. Furthermore, the results suggest that entrainment error is dependent on fractal characteristics of timing imperative.

4.0. Introduction

Independent walking requires the ability to remain stable and flexibly adjust one's walking pattern while dynamically capturing environmental cues (Shumway-Cook and Wollocott, 2007). Despite the current wealth of knowledge on the mechanisms involved with walking control, there is limited insight into how to capture walking adaptability in dynamically changing environments. As such, there is no fulsome understanding of how to quantify gait control and specifically, adaptability (Balasubramanian et al., 2014).

Characterizing walking control requires an analysis of the time-varying changes in walking patterns. Advances in the understanding of time-varying characteristics necessitated a shift in the analytical frameworks of physiological systems (Harbourne and Stergiou, 2011). Dynamical Systems Theory (DST) is a framework that brings the pattern of variability to the forefront of understanding physiological dynamics (Decker et al., 2011). Furthermore, within the context of DST is a subset of systems known as complex systems, which views physiological systems as highly composite objects, where the behaviour of the whole is greater than the sum of each independent element (Bar

Yam, 2011). Conceptually, a complex system (e.g., the gait system) has many parts (e.g., mechanical, sensory, and cognitive parts) interacting on a variety of time scales (Rhea and Kiefer, 2016). The behaviour of a complex system remains stable on a single time scale, while also adapting to the time scales of each component, to absorb changes in a dynamically changing environment.

Viewing the gait system as a complex system has led to the development of metrics aimed at characterizing complex behaviour in gait. One such metric that has gained momentum in gait research is the fractal scaling index (FSI). Theoretically, the FSI captures the relationship between patterns in a time series across various time scales. FSI therefore characterizes scaling behaviour. More specifically, the FSI indicates where a time series pattern lies along the continuum between periodic, random, and chaotic patterns (Katz, 2015).

Hausdorff (1995) first presented the utility of the FSI in characterizing gait control by measuring the fractality of an inter-stride interval (ISI) time series. Hausdorff noted that the walking pattern has an inherent level of complexity that approaches 1/f scaling. A 1/f scaling pattern is a time series that is purely scale invariant, meaning that the spatio-temporal properties of the system are optimally correlated across all scales. A 1/f scaling process is characterized by a FSI = 1.0.

Several studies have confirmed that the natural fractal characteristics of gait during overground and treadmill walking range approximately between FSI = 0.70 – 0.80 (Hausdorff et al., 2007; Terrier and Deriaz, 2012; Maremelat et al., 2014). Additionally, the FSI measure appears to be sensitive to several disease states (e.g., aging, Parkinson's gait, and Huntington's disease), which is in line with the Dynamical Disease Theory and the Loss of Complexity hypothesis.

These theories assert that during steady-state situations, pathological cases demonstrate a decrease in complexity towards randomness that is indicative of the lack in adaptive capacity of the pathological gait system (Manor et al., 2013). This concept is intuitive, and is in line with evidence suggesting that healthy elderly and fall-prone individuals gait time series shift towards randomness (i.e., FSI = 0.5), as measured by the FSI (Hausdorff, 2007). However, these differences between populations, while promising, do not provide direct evidence that the FSI is an index of gait control or adaptability.

An underlying difficulty with utilizing FSI as a measure of gait control is the fact that the FSI is sensitive to task constraints. For example, when healthy individuals walk on a treadmill, there is a reduction in the FSI as compared to over-ground walking (Terrier and Deriaz, 2012). The FSI is also sensitive to the imposed treadmill speed, such that the FSI increases at speeds both slower and faster than the participants preferred walking speed (Jordan et al., 2007; Dingwell and Cusumano, 2010).

Furthermore, when healthy individuals cue their steps to the beat (i.e., time the moment of heel contact to beat onset) of a fixed interval timing imperative (i.e., a metronome with a fixed frequency), the FSI trends towards randomness (Hausdorff, 2007). What may show promise in deciphering the utility of the FSI in the control of gait behaviour is that cueing steps to a fluctuating timing imperative can lead to entrainment of the timing imperative's complexity (Hunt et al., 2014; Marmelat et al., 2014; Rhea et al., 2014). It has been suggested that the ability to synchronize the behaviour of a series of stride intervals to a fluctuating timing imperative is evidence of emergent behaviour, which is a characteristic of complex systems (Rhea et al., 2014).

The prospect of entraining and “prescribing” gait complexity by using a fluctuating timing imperative could lead to a paradigm aimed at revealing important aspects of gait adaptation to the environment, and could show promising applications in gait rehabilitation. However, before such applications can be explored, assessments of the entrainment consistency and level of error are warranted. The goals of the current study were three-fold: (1) assess the effectiveness of prescribing gait complexity to several fluctuating timing imperatives (e.g., white noise, pink noise and red noise); (2) evaluate the consistency of the prescription effect across several sessions, and (3) measure the error of entrainment. I hypothesized that the fractality of ISI would shift towards that of each timing imperative on a consistent basis across three sessions, with pink noise demonstrating the lowest entrainment error.

4.1. Methods and Protocol

4.1.1. Participants

Thirteen young, healthy, adult volunteers (n = 4 females, mean; age: 26 ± 3 years, height: 1.73 ± 0.10m) were recruited to participate in the study. Participants were provided with the details of the study, and signed an informed consent form prior to engaging in the experiment. Approval to conduct the study was granted by research ethics review board (REB) at York University. Exclusion criteria included: younger than 18 and older than 35 years; a self-reported history of neurological injury or disorder, musculoskeletal injury or disorder, auditory impairment, and pain or discomfort in the past six months that might affect walking and listening to an audible sound.

4.1.2. Equipment

A motorized, fixed-pace treadmill (Bodyguard Fitness, Quebec, Canada) was employed to evoke a steady-state gait. Kinematic data were captured using seven Vicon Mx series motion cameras (Vicon, Oxford, United Kingdom) surrounding the treadmill. Two reflective markers placed bilaterally on each heel (RHEEL and LHEEL) of the participant. Two speakers (MLi 699, MidiLand, Germany) were used to elicit the auditory fluctuating timing imperatives.

4.1.3. Pre-experimental protocol

The first testing session (i.e., session one) began with a treadmill habituation period, whereby preferred walk speed (PWS) was established for each participant. The process of determining PWS was completed in two steps. First, the speed of the treadmill belt was progressively increased in regular increments (0.10 m/s), beginning at a low speed (0.50 m/s), and the walking speed at each increment was maintained for 30 seconds. Speed was increased until the participants verbally communicated their "comfortable speed". The identified preferred walking speed (PWS_L) was noted by the research assistant.

The second step was identical to the first step, except that the treadmill belt began at a high-speed. The initial high-speed was based on the number of increments elicited during PWS_L. The speed of the treadmill was progressively decreased in regular reductions (0.10 m/s) until participants identified their preferred walking speed (PWS_U). The average between PWS_L and PWS_U (PWS: 1.0 ±0.10 m/s) was used as the speed of the treadmill for all experimental trials in all subsequent sessions (Dingwell & Marin, 2006).

Each session included a baseline walking trial, which involved six minutes of walking on the treadmill at PWS. Data recorded from the baseline walking trial were used to determine the average and standard deviation of the ISI for each participant. The average and standard deviation values were then used to create participant-specific timing imperatives used in the experimental trials.

White noise, pink noise, and red noise fluctuating timing imperatives were created in Matlab R2015b (The Mathworks, Natick, USA) (see Section One, Chapter Three, of this dissertation). First, a white noise vector of 256 data points (Delignières et al, 2006; Marmelat et al, 2014) was created. The average and standard deviation of the white noise vector matched the individual participant's baseline walking.

Next, to generate the pink noise and red noise vectors, the white noise vector was transformed into the frequency domain. For the pink noise vector, the components of the power spectrum were multiplied by $1/\sqrt{f}$. For the red noise vector, the components of the power spectrum were multiplied by $1/f$ (Kasdin, 1995). The subsequent pink noise and red noise vectors were transformed back into the time domain. The respective WN, PN, and RN vectors were used to define the inter-beat interval (IBI) sound files for each fluctuating timing imperative. The beat duration was 10 ms.

4.1.4. Experimental Trials

Participants were asked to attend three sessions, each separated by a minimum of 72 hours. During each session, participants completed two trials of each of four walking conditions in a randomized order: uncued (UN) walking, and white noise (WN), pink noise (PN), and red noise (RN) timing imperatives. Table 4-1 displays the average and standard deviation of FSI of each timing imperative used in the study.

A total of eight trials were performed within each session. Each trial entailed continuous walking for a total of 255 cued strides, which requires approximately five to six minutes to complete. Participants self-reported their foot of choice used to cue with the timing imperative. Trial initiation began with the participant in steady-state walking. Initiation of the beat sequence began with a countdown whereby the last count corresponded with the initiation of the first beat. Practice was provided prior to conducting experimental trials, in order for the participant to become familiar with the task of cueing their heel contact (HC) the beat onset. Rest was provided following the completion of each trial to avoid fatiguing. Participants verbally indicated to the research assistant when they felt comfortable to proceed to the next walking trial.

4.1.5. Data Processing and Analysis

Raw kinematic signals were sampled at 100 Hz and were filtered with a 4th order, low-pass Butterworth filter with a frequency cutoff of 5Hz. HC was determined by using the velocity profile to identify a zero-crossing in the plane of progression (Zeni Jr et al, 2009). The difference between successive HCs across the entire trial defined the ISI time series (Hausdorff et al., 1995; Costa et al., 2003). Figure 4-1 depicts a representative ISI time-series over 255 strides on a treadmill walking at PWS. Analog signals (i.e., the timing imperative) were sampled at 1000 Hz and captured with a custom-built cable. Beat onset was quantified as the instant at which the signal deflected away from zero (i.e., baseline).

The gait complexity of IBI and ISI time series was calculated using a detrended fluctuation analysis (DFA) approach. The DFA characterizes the scale-invariant features of a signal. More specifically the DFA calculates the fractal scaling index (α). The fractal scaling index (FSI) ranges between $0 \lesssim \alpha \lesssim 2$. An $\alpha \approx 0.5 - 0.59$ characterizes a white noise time series. An $\alpha = 1.0$ is characteristically a true scale invariant process (i.e., pink noise) time series. Lastly, an $\alpha > 1.5$ characterizes Brownian motion (i.e., red noise). The DFA approach is designed to have minimal sensitivity to non-stationary data (Terrier and Deriaz, 2012).

Table 4-1: Summary of fluctuating timing imperative fractality (mean ±SD) across TI and SES collapsed across all participants.

	Session 1 (S1)	**Session 2 (S2)**	**Session 3 (S3)**
White noise (WN)	0.52 ±0.02	0.53 ±0.02	0.52 ±0.02
Pink noise (PN)	0.86 ±0.05	0.83 ±0.05	0.85 ±0.06
Red noise (RN)	1.32 ±0.12	1.31 ±0.13	1.34 ±0.13

The mean and FSI of the ISI time series were estimated for each walking condition and session, across all participants. To assess the error of the complexity entrainment, the absolute difference between the FSI of the TI and ISI was quantified for each trial.

4.1.6. Statistical Analysis

All statistical analysis was performed in JMP (v.9.0 product of SAS). A two-way repeated measures design [timing imperative (TI: UN/WN/PN/RN) x session (SES: 1/2/3)] was used to assess the differences between the TIs and the consistency across sessions. Normality was assessed using a Shapiro-Wilk test. Skewed data was transformed by using a log transform for positively skewed data, or by using a square-root transform for negatively skewed data. Post-hoc comparisons were corrected for type-1 error with a Tukey-Kramer correction ($p < 0.05$).

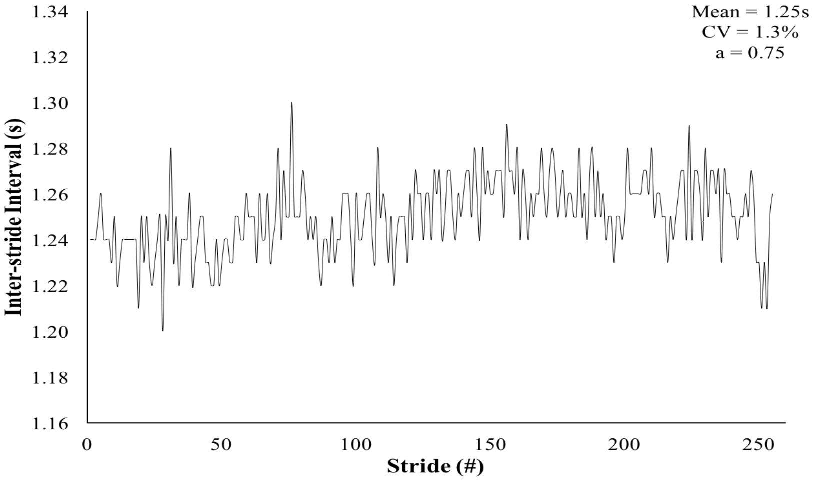

Figure 4-1: Representative ISI time-series over 255 successive strides of UN treadmill walking at PWS. Mean ISI was 1.25 ±0.02s and $\alpha = 0.75$.

4.2. Results

4.2.1. Inter-stride Interval gross parameters

Table 4-2 presents the results of all metrics. No significant interaction effect of TI and SES [F (6,72) = 1.04, p = 0.405] was found for mean ISI. A main effect of TI was found for mean ISI [F(3, 36) = 35.88, p = 0.0007]. Post-hoc analysis revealed that the mean ISI for UN was significantly less than WN, PN and RN; however, these differences were less than 1%. No main effect of SES [F(2,24) = 0.122, p = 0.886) was detected.

4.2.2. Group entrainment effect and consistency

Figure 4-2 displays the results of FSI entrainment. No significant interaction effect of TI and SES [F(6, 71) = 2.08, p = 0.067] was found for FSI. A main effect of TI was found [F(3, 35) = 56.71, p < 0.0001]for FSI. Post-hoc analysis revealed that the FSI was significantly different across all TI conditions (UN = 0.78 ±0.11; WN = 0.53 ±0.11; PN = 0.62 ±0.15; RN = 0.87 ±0.18). No main effect of SES [F(2, 24) = 3.00, p = 0.069] was revealed (Figure 4-2).

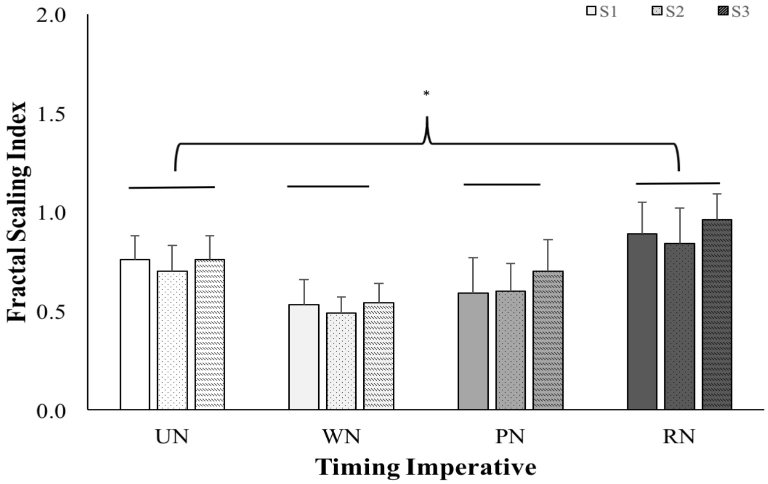

Figure 4-2: The mean ±SD of FSI with each TI separated across all sessions. Solid bars represent means for session 1 (S1). Dotted grey bars represent means for session 2 (S2). Dark striped bars represent means for session 3 (S3). TI was significantly different from each other. Error bars represent standard deviations. Asterisks represents significance at 0.05 level.

4.2.3. *Group entrainment error*

Table 4-2 displays the means and standard deviations across TI and SES. No significant interaction effect of TI and SES was found [F(4,42) = 1.87, p = 0.13] for entrainment error. A main effect of TI [F(2,25) = 59.02, p < 0.0001] was observed. Post-hoc analysis revealed that entrainment error was different between WN, PN, and RN (Figure 4-3). No main effect of SES [F(2,25) = 2.33, p = 0.118] was revealed.

Table 4-2: Summary of gait parameters (mean ±SD) across TI and SES collapsed across all participants.

TI	**UN**			**WN**			**PN**			**RN**		
SES	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Mean ISI (s)	1.16 ±0.07	1.15 ±0.07	1.16 ±0.07	1.16 ±0.07	1.17 ±0.07	1.17 ±0.08	1.17 ±0.06	1.17 ±0.07	1.17 ±0.08	1.17 ±0.06	1.17 ±0.07	1.17 ±0.06
FSI	0.76 ±0.12	0.70 ±0.13	0.76 ±0.12	0.53 ±0.13	0.49 ±0.08	0.54 ±0.1	0.59 ±0.18	0.60 ±0.14	0.70 ±0.16	0.89 ±0.11	0.84 ±0.18	0.96 ±0.13
FSI Error	N/A	N/A	N/A	0.15 ±0.08	0.10 ±0.08	0.12 ±0.11	0.30 ±0.14	0.24 ±0.12	0.18 ±0.09	0.45 ±0.21	0.50 ±0.19	0.37 ±0.10

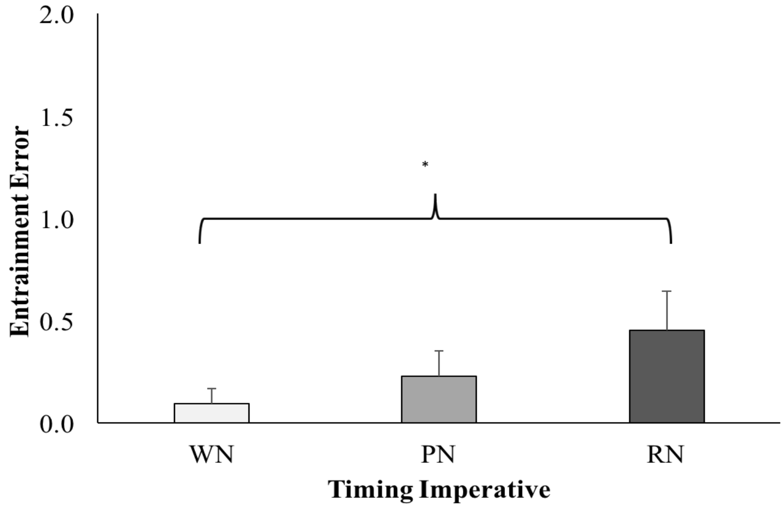

Figure 4-3: The mean ±SD entrainment error for each timing imperative collapsed across all sessions and participants. All conditions were significantly different from each other. Error bars represent standard deviations. Asterisks represents significance at 0.05 level.

4.3. Discussion

Complexity is becoming accepted as an inherent feature of the walking pattern (Rhea and Kiefer, 2016). Approaches to restoring "healthy" gait are being explored by using methods such as auditory fluctuating timing imperatives that entrain "healthy" complexities (Hunt et al., 2014, Marmelat et al., 2014). However, the effectiveness of such methods remains unclear. Furthermore, the function of complexity within the walking pattern is unknown, but it may relate to adaptability (Harbourne and Sterigou, 2011; van Emmerick et al., 2017). Therefore, the underlying goal of this study is to assess whether a paradigm for entraining complexity with consistency could be developed. Hence, the current study was conducted to assess the entrainment effect of cueing to several auditory fluctuating timing imperatives and to determine the consistency and error of FSI entrainment.

The results of the study suggest that stride interval complexity can be prescribed in a specified direction based on the fractal characteristics of the fluctuating timing imperative, with consistency across three sessions. Also, the participants demonstrated error when matching stride interval complexity to the complexity of the timing imperative, which was dependent on the fractal characteristics of the timing imperative.

4.3.1. Group prescription and ceiling effect

The primary objective of this study was to examine the effectiveness of entraining stride interval complexity with the use of a fluctuating timing imperatives. The results demonstrated a significant change in stride interval complexity with the use of a fluctuating timing imperative. UN walking was consistent with previous literature, which demonstrated a fractality of $\sim \alpha = 0.75$ (Hausdorff, 2007). The fluctuating timing imperatives (WN, PN, RN) elicited a deviation from observed UN fractality. This finding is consistent with previous literature, which has reported a prescription effect with the use of fluctuating timing imperatives (Hunt et al., 2014; Marmelat et al., 2014; Rhea et al., 2014).

Interestingly, on average, participants were unable to achieve $\alpha \geq 1.0$ when entraining to the RN imperative, though the FSI of the RN timing imperative ranged between $\alpha = 1.31$-1.34. Perhaps this result indicates a "ceiling" in the complexity observed in the healthy gait system. This ceiling is similar to findings presented in the literature, which have shown that participants have difficulty achieving a FSI above 1.0, despite entraining to a stimulus with an $\alpha \geq 1.0$ (Hunt et al., 2014). The underlying mechanism behind this effect is unknown, but may indicate that the gait system is not a true 1/f process ($\alpha = 1.0$), and is instead composed of a mix of deterministic and random components in order to remain adaptable (Rhea and Kiefer, 2016; van Emmerick et al., 2017).

4.3.2. Consistency across sessions

A second objective of the study was to assess the consistency of the entrainment effect. This study was the first to assess whether complexity can be consistently entrained across multiple sessions. No main effect of SES ($p = 0.069$) was found, which suggests that WN, PN and RN demonstrated entrainment consistency across all three sessions. This finding is important for future investigations that aim to test gait control with the use of auditory fluctuating timing imperatives. Also, the results indicate that auditory fluctuating timing imperatives that differ in their fractal characteristics can prescribe gait complexity consistently for at least three sessions. Overall, it appears that the prescription effect of the auditory stimuli represents a reliable method for entraining gait complexity.

4.3.3. FSI entrainment error

In the current study, the absolute difference between the ISI complexity and IBI complexity was quantified to assess the error of entrainment. This was done to interpret the participants' gait complexity relative to the auditory stimulus. Based on the collapsed results, it appears that the WN had the best results in terms of complexity entrainment error. However, this may be difficult to conclude, since as a combined group, the participants were 0.1 units away from the average fractality of the WN TI elicited in the study. This effectively entrained a fractality that is out of the range of $\alpha = 0.50\text{-}0.59$, and is no longer considered white noise.

In contrast, PN demonstrated that participants were considerably less accurate than with WN with entraining fractality of the TI (Table 4-2). Nonetheless the fractality remained within the bounds of pink noise (FSI = 0.6-1.5). RN was found to demonstrate the greatest error relative to the entrainment error of WN and PN timing imperatives. Perhaps the error with entrainment observed with PN and RN were due to the inability of participants to accurately time heel contact to the beat onset. However, this was out of the scope of the study, which was completed to assess the matching of FSI between stimulus and gait. Rhea (2014) did demonstrate that participants revealed a variety of strategies (e.g., reactive or proactive) when cueing a visual stimulus with FSI = 1.0, and participants were able to successfully match their gait complexity to the stimulus. Future investigations should assess the local performance (i.e., asynchrony between heel contact and beat onset) to discern whether the strategy of stepping relates to entrainment. Overall, it is difficult to assess, based on the FSI, the most effective TI in terms of entrainment error.

If error is assessed solely by the absolute difference between the stimulus complexity and gait complexity, then interestingly, the WN was best in terms of complexity entrainment. The authors believed that the PN would demonstrate the smallest error due to the similarity between PN fractality and the fractality observed in normal gait (Hausdorff, 2007). That hypothesis was based on the idea that information between two complex systems is maximal when the two systems have a similar complexity (West et al., 2008).

Previous literature has demonstrated that the effectiveness of auditory fluctuating timing imperative entrainment is greatest with a signal that is approximating a PN signal (Hunt et al., 2014). However, the methodology in our study was not entirely consistent with that of Hunt (2014), as that study infused a fractal stimulus approximating white noise, pink noise, and red noise into music, which was then used to entrain gait complexity. Furthermore, the length of the data trials in Hunt's study were double (512 strides) that of the current study (255 strides). Of note, Marmelat (2014) showed results that were consistent with the current study's findings, in that participants were able to match their gait complexity with that of a timing imperative approximating white noise. This may be due to similar methodologies, whereby the length of the auditory stimulus was 255 cued strides and was a simple beat (i.e., not infused into music).

4.4. Conclusions

The findings from the current study are the first to assess the effectiveness of auditory fluctuating timing imperatives in prescribing gait complexity accurately and consistently. Generally, the findings demonstrate the flexibility of the healthy gait system, albeit with an upper limit. This study specifically demonstrated that eliciting an auditory fluctuating stimulus can alter ISI complexity in a desired direction and consistently. However, entrainment error appears to be a function of the fractal characteristics of the timing imperative. More specifically, most participants were not able to achieve an FSI > 1.0.

A limitation in the study can be found in the duration between the sessions. As participation was voluntary, participants were asked to attend with a minimum time lapse of 72 hours between sessions. However, to truly test the consistency of the entrainment, it would be important for all participants to strictly adhere to a fixed time between each session, to rule out any carry-over effects of timing gait to a stimulus. Future studies should assess the local performance during entrainment to assess whether the coordination between gait complexity and stepping are linked. The results of this study are an initial step towards developing a paradigm aimed at prescribing complexity to assess gait adaptability and potentially as a tool for gait rehabilitation. Future studies should analyze the effects of complexity retention following entrainment.

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CHAPTER FIVE

ASSESSMENT OF SHORT-TERM RETENTION OF GAIT COMPLEXITY FOLLOWING ENTRAINMENT TO A FLUCTUATING TIMING IMPERATIVE

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Preface

Previous work has demonstrated that gait complexity can be entrained by to match the complexity of an auditory fluctuating timing imperative (i.e., a metronome with a fluctuating frequency). Yet, it is currently unknown whether these patterns of entrainment are retained and whether the fractal characteristics of the timing imperative influence retention. The purpose of this investigation was to assess the duration of retention following entrainment to three different fluctuating timing imperatives. 16 healthy young adults completed four randomized conditions [Timing Imperative (TI): baseline (UN), white noise (WN), pink noise (PN), red noise (RN)] to entrain the gait pattern, while walking on a treadmill at a self-selected pace. Each trial lasted for a total of 1024 strides (~20 continuous minutes), which was separated into four blocks (PHASE) of 255 strides. The first 255 strides (entrainment phase: ENT) consisted of timing steps to the beat of a fluctuating timing imperative. The last three phases (post-entrainment: POS1, POS2, POS3) consisted of normal walking without any stimulus to assess the retention duration. WN and RN elicited a significant change in inter-stride interval (ISI) fractality away from UN during ENT ($p = 0.004$). No differences were found during the

post-entrainment phases, despite an 19%, 23% and 6% change in FSI between ENT and POS1 for WN, PN and RN, respectively. A secondary analysis was performed to understand the immediate retention of FSI between ENT and POS1 using a sliding window approach. The FSI over three windows of POS1 (SHORT: 25 strides, INT: 50 strides, FULL: 256 strides) was calculated. The results indicate retention of FSI complexity was greater for the first 25 and 50 strides compared to the full 256 strides of POS1. The outcomes of this study suggest that the use of an auditory fluctuating timing imperative, regardless of the complexity, had immediate carry-over effects after the stimulus is turned off, which diminished towards baseline as the number of strides increased post-entrainment. Furthermore, the retention effect appears to be greatest during the first 50 strides post-entrainment. The implications of this study help provide evidence on the efficacy of auditory fluctuating timing imperatives for altering the gait pattern.

5.0. Introduction

Steady-state gait is a motor control task that appears periodic and fixed in the timing and position of steps. While it appears that gait is highly consistent, the gait system performs stride-to-stride behaviour with an optimal level of variation (Decker et al., 2010). This variation, once believed to be a result of error from physiological noise, is now thought of as functional for navigation of a complex environment. It is now known that the gait system produces stride-to-stride fluctuations that includes inherent complexities, which approach 1/f scaling (Hausdorff, 2007). More specifically, stride-to-stride fluctuations demonstrate long-term dependencies across time scales van Emmerick et al., 2017). This inherent complexity causes the gait system to be under-constrained and allows for adaptation (Harbourne and Stergiou, 2011). Specifically, any step that varies from the mean of the stepping pattern, is not likely to be corrected immediately (i.e., not likely to regress back to the mean). Instead deviations away from the mean are likely to continue for several additional steps before regressing towards the mean, which is known as statistical persistence. As follows, anti-persistence presents as an over-constrained (i.e., rigid) system, which corrects deviations immediately (Terrier, 2016).

Complex behaviour is characterized by scale-invariant patterns (Katz, 2016). Several metrics have been developed, and utilized in gait research, to capture complexity in gait dynamics. One such measure is the fractal scaling index (FSI) that is computed through a technique called detrended fluctuation analysis (DFA). The DFA approach captures the relationship in fluctuations across short and long time scales. FSI (α) is a metric describing the presence of long-range correlations in a fluctuating time series. An FSI value computed from the DFA that approximates $\alpha = 0.5$ denotes randomness (i.e., white noise). Specifically, $\alpha = 0.5$ is a time series wherein current fluctuations are not statistically connected to future and past fluctuations (i.e., are neither persistent nor anti-persistent). An FSI above $\alpha = 0.5$ indicates that fluctuations demonstrate connectedness across short and long scales (i.e., persistence), and approaches 1/f scaling ($\alpha = 1.0$). Conversely, an FSI value below $\alpha = 0.5$ demonstrates connectedness across short scales (i.e., over-constrained) (Terrier and Deriaz, 2012). The application of the DFA to gait analysis has shown its sensitivity to aging, disease, and task constraints (Hausdorff, 2007; Dingwell and Cusumano, 2015).

Advances in the understanding of gait complexity have led many researchers in search of a method for restoring or slowing the decline of “healthy complexity”. The use of a fixed interval auditory timing imperative (i.e., a metronome with a fixed frequency) to cue steps breaks down the natural complexity in the gait pattern from persistence towards randomness or anti-persistence (Hausdorff, 2007). This has also been confirmed in fixed interval visual timing imperatives, as well (Terrier, 2016). Recent literature has demonstrated that fractal patterns can be prescribed and entrained into a walking pattern with the use of auditory (Marmelat et al., 2014; Hunt et al., 2014) and visual (Rhea et al., 2014) fluctuating timing imperatives. “Fluctuating” implies that the time between beats is not fixed, but instead fluctuates in a complex pattern (e.g., random, fractal, or chaotic). When participants cue their steps to the beat of a fluctuating timing imperative the fractal characteristics of the timing imperative become entrained in the gait pattern. This entrainment effect is flexible in that a variety of fractal patterns can be entrained (Hunt et al., 2014). It remains unknown whether the pattern of entrainment is retained when cuing is stopped, and if so, for how long is entrainment retained. Several clinical studies have examined this effect in Parkinson’s patients and have demonstrated retention of fractal scaling in short trials (e.g., three minutes) (Hove et al., 2012; Uchitomi et al., 2013). Patients in these studies also reported “feelings of being more stable” (Hove et al., 2012), suggesting a healthy level of complexity is related to functional mobility. Rhea (2014) made use of a visual fluctuating timing imperative and demonstrated that fractal patterns are retained up to 15 minutes post-entrainment. However, the previously mentioned studies used a single fractal stimulus with an $\alpha = 0.98$. Understanding whether several different complex stimuli are entrained and retained, can aid in understanding the flexibility of the healthy gait system.

The purpose of this investigation was to determine whether fractal gait patterns are retained following entrainment to three different fluctuating timing imperatives. The objective of this study was to assess the duration of retention effects of three different fluctuating timing imperatives. I predicted that the entrainment effect would be retained in the immediate phase (~250 strides) post-entrainment and would eventually diminish towards baseline.

5.1. Methods and Protocol

5.1.1. Participants

Sixteen young healthy adult volunteers (n = 8 females, mean; age: 29 ±3 years, height: 1.71 ±0.08m), were recruited to participate in the study. Participants were provided details of the study and signed an informed consent prior to testing. Ethical approval to conduct the study was granted by Research Ethics Review Board (REB) at York University. Exclusion criteria included: younger than 18 and older than 35 years, and a self-reported history of neurological injury or disorder, musculoskeletal injury or disorder, auditory impairment, or pain and discomfort in the past six months that might affect walking and listening to an audible sound.

5.1.2. Equipment

A motorized fixed-pace treadmill (Bodyguard Fitness, Quebec, Canada) was utilized to elicit a steady-state gait at controlled walking speeds. All participants were asked to report if they had previous experience walking on a treadmill. Kinematic data was captured using seven Vicon Mx series motion cameras (Vicon, Oxford, United Kingdom) surrounding the treadmill. Heel markers (RHEEL and LHEEL) were landmarked on each participant corresponding calcanei. A set of two speakers (MLi 699, MidiLand, Germany) were used to administer the three different auditory beat sequences and were placed 1m adjacent to the right side of the treadmill and the participant.

5.1.3. Pre-experimental protocol

Testing sessions began with a two-part process for determining each participants preferred walking speed (PWS) on the treadmill (see Section one, Chapter three of this dissertation). To begin the treadmill belt began at a slow speed and was incremented in small amounts (0.10 m/s) until participants percieved their "comfortable walking speed". The same protocol was repeated with small reduction (0.10m/s) in speed until the participants again percieved their "comfortable walking speed". The average of the two speeds was used as the treadmill speed for all experimental trials (PWS: 1.08 ±0.20 m/s). A baseline walking trial for a total of six minutes was completed to capture the participants' average and the standard deviation of inter-stride interval (ISI) for at least 250 strides.

The creation of white noise, pink noise and red noise fluctuating timing imperatives is described in detail in a previous section (see Section one, Chapter three, of this dissertation). All signals were created in Matlab R2015b (The Mathworks, Natick, USA) using the function wgn() to create an initial white noise vector. The subsequent pink noise and red noise vectors were created by transforming a white noise vector into the power spectrum. Next, the pink noise vector was created by dividing the frequency components by $1/\sqrt{f}$. Similarly, to create the red noise vector the frequency components was divided by 1/f. All created signals contained 256 data points. Each of the white noise, pink noise, red noise signals were participant specific such that the mean and magnitude of variability of the inter-beat interval (IBI) matched the participants inter-stride interval (ISI) mean and magnitude of variability acquired from the baseline trial.

5.1.4. Experimental Trials

Participants completed four randomized trials: Uncued walking (UN), white noise (WN), pink noise (PN) and red noise (RN) timing imperatives. Each trial consisted of approximately 1024 strides. The first phase was the entrainment phase (ENT), which required participants to cue the moment of heel contact (HC) to the beat onset. To understand the carry-over effect of entrainment (if any) from cueing to the stimulus into the post-entrainment uncued phase (POS), each trial was divided into four sections, each consisting of 255-256 strides: entrainment (ENT), post-entrainment 1 (POS1), post-entrainment 2 (POS2), and post-entrainment 3 (POS3). The timing imperatives presented during the ENT phase were presented in a randomized order.

Each participant identified their foot of choice to cue to the beat of the timing imperative. Trials began with the participants in steady-state walking prior to the initiation of the first beat of the timing imperative. The first beat of the timing imperative was elicited approximately in time with heel contact of the participant. Practice was provided prior to conducting experimental trials, in order for the participant to become familiar with the task. Rest was provided after the completion of each trial to avoid fatiguing. Participants verbally indicated to the research assistant when they felt comfortable to proceed onto the next walking trial.

5.1.5. Data Processing and Analysis

Raw kinematic signals were sampled at 100 Hz and were filtered with a 4th order low-pass Butterworth filter with a frequency cutoff of 5Hz. Detection of heel-contact (HC) was based on a change in direction based on the velocity profile of the heel marker on the foot used to time the audible beat (Zeni Jr et al, 2009). ISI was defined as the time between successive HC of the ipsilateral foot (Hausdorff et al., 1995; Costa et al., 2003). Analog signals (i.e., the timing imperative) were sampled at 1000Hz using a custom built-cable. Post-processing included detection of beat onset, which was defined as a the first deviation in the signal away from baseline (i.e., zero).

The fractal scaling index of ISI was calculated using a detrended fluctuation analysis (DFA). The DFA quantifies the relationship between time scales (e.g., milliseconds or seconds) on the magnitude of variability. The approach is described in Section One, Chapter Three, of this dissertation and in the literature as well (Terrier and Deriaz, 2012; Rhea et al., 2014). Briefly, the ISI time series is integrated and then divided into nonoverlapping boxes of equal length. Next, the integrated signal within the box is detrended by subtracting the line of best fit to the signal from the integrated signal. The root mean square of the detrended signal is then calculated. This step is then repeated across a variety of window sizes (typically 10-40 non-overlapping windows). The average root mean square deviation across all windows is plotted against window size. Quantifying the amount of variability at different time scales reveals an ordered relationship in the form of a power-law distribution (McGrath, 2016). The plot of box length against the magnitude of variability is then converted using a logarithmic transform, to construct a log-log plot. Since the relationship between the magnitude of variability and the size of time scale follows power-law, the scaling index (α) governing the strength of the power-law can be estimated by determining the slope of the log-log plot. α ranges between $0 < \alpha < 2$.

Dependent measures included the mean ISI, coefficient of variation (COV) of ISI, and FSI of ISI for each TI and PHASE. More specifically, our primary objective was to determine how the number of strides post-entrainment influenced the FSI and whether this differed between timing imperatives.

A secondary analysis was conducted to assess the immediate retention effects following entrainment; the analysis focused on the first phase following post-entrainment (POS1). The secondary analysis aimed to determine whether the carry-over effect of entrained gait FSI was greater in the immediate 25 to 50 strides following the cessation of the timing imperative. Specifically, the DFA was applied over 256 data points to a time-series that overlapped ENT and POS1, capturing either the first 25 (SHORT) and 50 (INT) and 256 (FULL) data points of POS1 (Figure 5-1).

5.1.6. Experimental Design & Statistical Analysis

All statistical analysis was performed in JMP (v.9.0 product of SAS). A two-way repeated measures design (timing imperative [TI: UN/WN/ PN/RN] x block [PHASE: ENT/POS1/POS2/POS3]) was used to examine each mean, COV and FSI of the ISI. A second two-way repeated measures ANOVA (timing imperative [TI: WN, PN, RN] x window [WIN: ENT, SHORT, INT, FULL]) was performed on the FSI of ISI. Normality was assessed using a Shapiro-Wilk test. Skewed data were corrected using a log transform for positively skewed or with a square-root transform for negatively skewed data. Tukey-kramer post hoc comparisons were utilized where appropriate (alpha = 0.05).

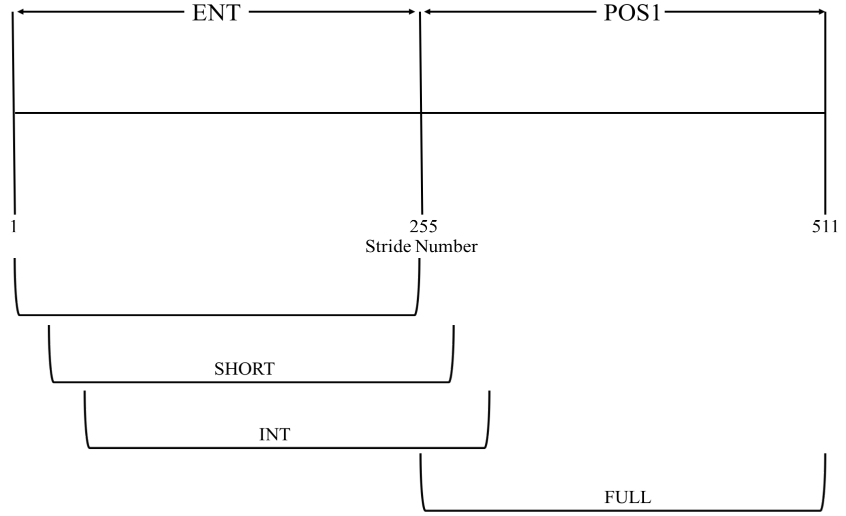

Figure 5-1: Schematic of the approach taken in the analysis of FSI consistency between ENT and POS1 windows. Brackets represent windows in which the DFA was applied. Each window is a total of 255-256 data points. SHORT captures the first 25 data points of POS1. INT captures the first 50 points of POS1. FULL captures the entire POS1 phase. The standard deviation between the ENT window and SHORT, INT and FULL was quantified as a measure of FSI retention.

5.2. Results

5.2.1. Inter-stride interval gross parameters

Table 5-1 presents the results all of metrics across timing imperatives and phases. No significant interaction effect of TI and PHASE [F(9,111) = 0.61, p = 0.79] was found for mean ISI. No main effect of TI [F(3,43) = 0.29, p = 0.60] or PHASE [F(3,45) = 0.67, p = 0.82] was revealed for mean ISI.

No significant interaction effect of TI and PHASE [F(9,107) = 1.39, p = 0.75] was detected for COV of ISI. No main effect of TI was found for (p = 0.07) COV of ISI. A main effect of PHASE was revealed [F(3, 35) = 4.79, p = 0.02] for COV. Post-hoc analysis found that COV was significantly greater in ENT than POS2.

5.2.2. Fractal entrainment and stride number effects on retention

Figure 5-2 is a representative trial of fractal entrainment followed by post-entrainment phases (POS1, POS2, POS3). Figure 5-3 displays group effects of TI and PHASE. A significant interaction effect of TI and PHASE [F(9, 134) = 2.85, p = 0.004] was found for FSI. Post-hoc analysis revealed that the FSI was significantly greater for RN compared to WN and PN during ENT. No other differences were detected. A main effect of TI [F(3, 44) = 3.83, p = 0.03] was detected for FSI. Post hoc-analysis showed that UN and WN were significantly less than RN. No main effect of PHASE [F(3,45) = 1.16, p = 0.34] was revealed for FSI.

5.2.3. Immediate FSI retention effects

Figure 5-4 displays the mean of FSI across windows ENT and SHORT, INT and FULL. A significant interaction effect of TI and WIN [F(6,84) = 5.32, p = 0.0001] was found for FSI. Post-hoc revealed that FSI was different between WN and RN for each corresponding WIN except FULL. A main effect of TI [F(2,30) = 8.31, p = 0.0014] was revealed. Post-hoc analysis detected greater FSI in RN compared to WN and PN. No main effect of WIN [F(3, 44) = 1.03, p < 0.0001] was detected for FSI.

Table 5-1: Summary of gait parameters (mean ±SEM) across TI and PHASE collapsed across all participants.

		PHASE			
	TI	**ENT**	**POS1**	**POS2**	**POS3**
MEAN ISI (s)	**UN**	1.18 ±0.03	1.18±0.03	1.18 ±0.02	1.19 ±0.02
	WN	1.19 ±0.03	1.18 ±0.02	1.17 ±0.02	1.18 ±0.02
	PN	1.19 ±0.02	1.18 ±0.03	1.19 ±0.03	1.19 ±0.03
	RN	1.19 ±0.02	1.19 ±0.03	1.18 ±0.02	1.18 ±0.03
COV ISI (%)	**UN**	1.89 ±0.21	1.65 ±0.21	1.58 ±0.17	1.70 ±0.24
	WN	1.83 ±0.16	1.54 ±0.20	1.67 ±0.21	1.71 ±0.22
	PN	2.11 ±0.16	1.88 ±0.24	1.68 ±0.27	1.76 ±0.20
	RN	2.29 ±0.14	1.81 ±0.24	1.71 ±0.19	1.91 ±0.38
FSI ISI	**UN**	0.68 ±0.05	0.67 ±0.04	0.72 ±0.03	0.73 ±0.04
	WN	0.61 ±0.04	0.73 ±0.04	0.73 ±0.04	0.74 ±0.04
	PN	0.68 ±0.04	0.77 ±0.05	0.73 ±0.04	0.71 ±0.03
	RN	0.82 ±0.05	0.77 ±0.04	0.76 ±0.04	0.73 ±0.04

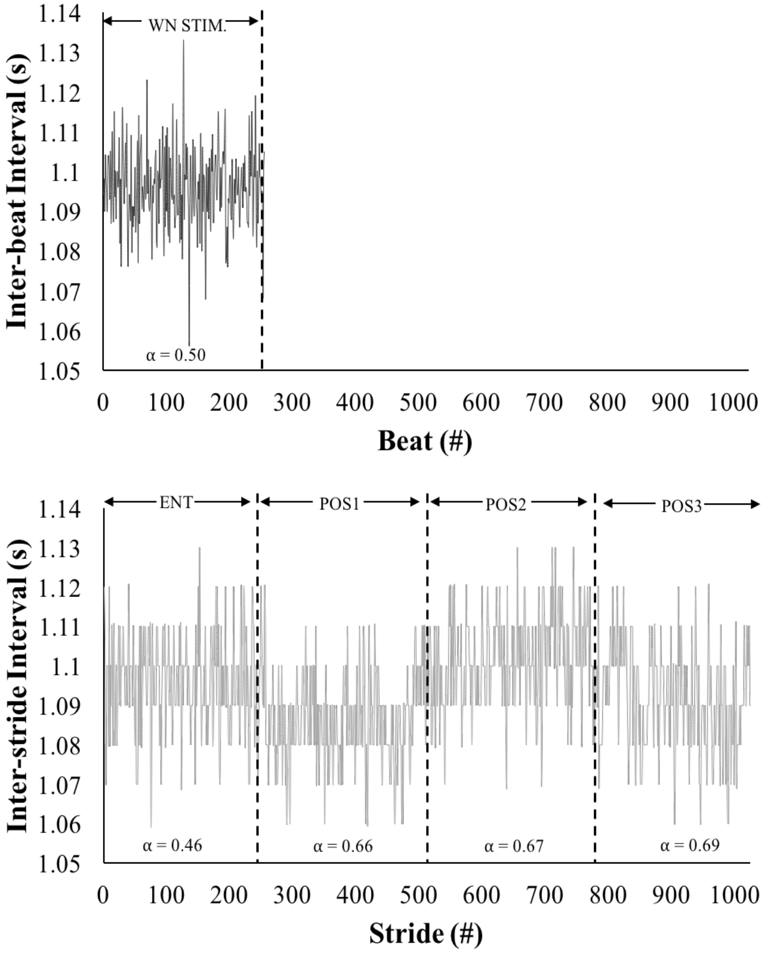

Figure 5-2: A representative trial of a single participant timing to a white noise timing imperative. Top: inter-beat interval (IBI) of white noise timing imperative. Bottom: the corresponding inter-stride interval (ISI). Participants completed three trials with an auditory timing imperative for the first 255 strides. ENT = entrainment phase, POS1 = post-entrainment phase 1, POS2 = post-entrainment phase 2, POS3 = post-entrainment phase 3. α = fractal scaling index (FSI).

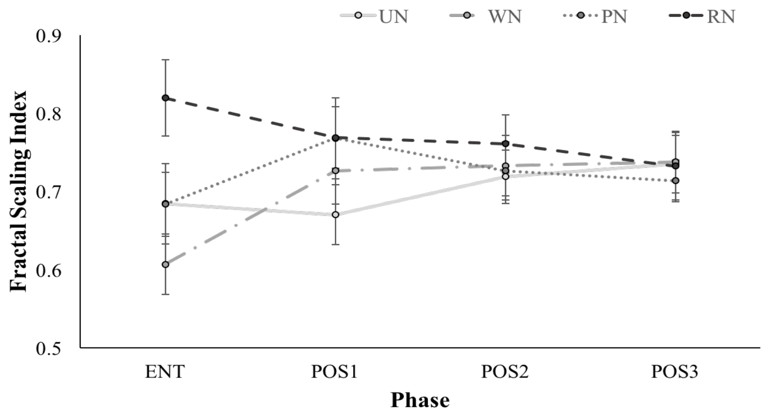

Figure 5-3: Mean ±SEM of FSI collapsed across all participants for each TI and PHASE. ENT = entrainment phase, POS1 = post-entrainment phase 1, POS2 = post-entrainment phase 2, POS3 = post-entrainment phase 3. A significant interaction effect (p = 0.004) was revealed. Post-hoc analysis indicated that RN (0.82 ±0.19) differed from WN (0.61 ±0.15) and PN (0.68 ±0.16) during ENT, indicative of an entrainment effect. A main effect of TI (p = 0.03) was found. Post-hoc analysis indicated that RN was different from UN and WN. No effect of PHASE (p = 0.34).

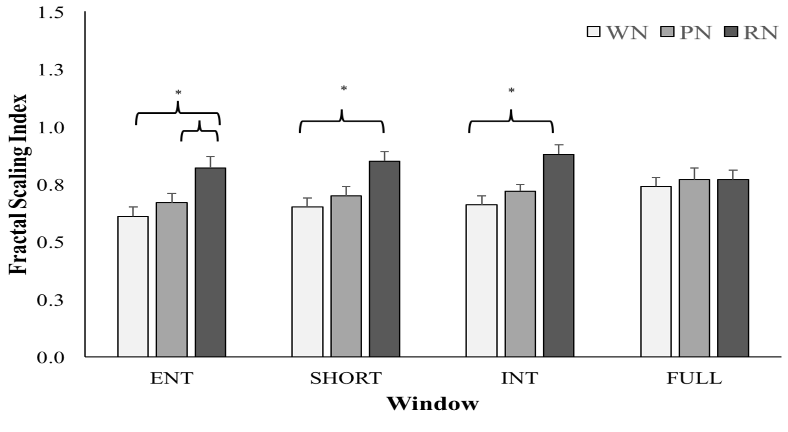

Figure 5-4: The mean ± SEM of FSI calculated across WIN. Asterisks indicates significance accepted at $p < 0.05$. ENT indicates the entrainment window of 255 data points. SHORT includes the first 25 data points of POS1. INT includes the first 25 data points of POS1. FULL is the entire 256 data points of POS1.

5.3. Discussion

Complexity is a considered an important marker of healthy gait, but the nature and role of complexity in gait is not well understood (Decker et al., 2010; Harbourne and Stergiou, 2011). Cueing to auditory and visual timing imperatives is a useful method for understanding motor behaviour in gait (Costa et al., 2003; Roerdink et al., 2011; Terrier and Deriaz, 2012). Retaining complexity of the gait pattern following entrainment to a fluctuating timing imperative is a promising method for testing the impact of complexity on gait control, and is also a potential rehabilitation tool designed to restore "healthy" levels of complexity (Hove et al., 2012). The purpose of this study was to assess the retention effects following entrainment to an auditory fluctuating timing imperative, as part of a continued effort to develop a paradigm for entraining and retaining complexity. As hypothesized, the findings suggest that the entrainment effect persists after the fluctuating timing imperative ceases, and that FSI converges towards uncued fractality in the first 256 strides post-entrainment, stabilizing at levels similar to baseline at approximately 512 strides post-entrainment. However, there is an immediate effect of entrainment carry-over that is evident in the first 50 strides post-entrainment.

5.3.1. Entrainment carry-over and trail-off

Figure 5-3 demonstrate that the entrainment carry-over virtually trails-off and converges towards the UN FSI values almost immediately in POS1. The FSI values observed in UN were similar to results presented in chapter one ($\alpha = 0.78$) of this dissertation and also published reports of FSI in normal healthy gait ($\alpha = 0.75$) (Hausdorff et al., 2007). A significant interaction effect was revealed and it was found that the type of timing imperative (i.e., WN, PN, RN) impacted the FSI during ENT, indicating an entrainment effect. However, considering the entrainment carry-over diminished in POS1 this would indicate that the timing imperatives entrainment effect was not sufficient to enable retention long enough to influence the FSI of the stride-interval in the subsequent three phases (i.e., 768 strides).

Rhea (2014) demonstrated that fractal characteristics using a visual fluctuating timing imperative, using a discrete stimulus that flashes in front of the participants, are retained with a high level of consistency between entrainment and post-synchronization for up to 15 minutes once the stimulus is ceased. Perhaps the different modalities employed (auditory versus visual) are the cause for the conflicting results regarding retention. However, it is clear from Figure 5-3 that a diminishment of the entrainment effect is observed as the number of strides post-entrainment increases.

5.3.2. Immediate entrainment carry-over

Our secondary analysis focused on the POS1 phase to assess the immediate impact of post-entrainment stride number on complexity retention. This was done due to the appearance of diminished retention in FSI after 256 strides (i.e., full POS1 phase) of walking once the stimulus ceased and the additional finding of no significant differences when the entire 256 strides of POS1 were considered (Figure 5-3). Hence, an additional analysis quantifying the FSI using a sliding window approach was undertaken (Figure 5-1). No effect of WIN was revealed, but FSI showed a 6%, 4%, 3% change between ENT and SHORT for WN, PN and RN respectively. In addition, an 8%, 7%, 7% change in FSI between ENT and INT. This analysis indicates that there was short period of strong complexity retention immediately following stimulus termination regardless of the timing imperatives' fractal characteristics.

It is important to note that the window length was identical in each FSI window (ENT, SHORT, INT and FULL). Specifically, the window length was 255-256 data points. The choice of the length of the window was attributed to the DFA algorithms need for a large number of data points. Calculation of the DFA has been suggested to include over 250 data points for consistent results (Delignières et al, 2006). Due to this computational necessity, an inherent limitation in the retention analysis was that the SHORT and INT windows included the majority of data points from the entrainment phase. This may not capture true retention considering that a major portion of the data in SHORT and INT included cued steps. Despite this limitation, the results indicate a potential immediate retention of the stimulus fractal characteristics.

5.3.3. Development of a framework for assessing gait

Previous work (see Section Two, Chapter Four of this dissertation) has shown that entrainment of a fluctuating timing imperative is consistent across three sessions separated by a minimum of three days. Previous research has demonstrated that the entrainment effect can be observed with the use of a visual fluctuating timing imperative (Rhea et al., 2014), as well. The results of the current study aimed to extend the aforementioned studies by estimating the retention effects of several different auditory fluctuating timing imperatives.

Despite the minimal retention following entrainment (Figure5-3), the secondary results provide encouraging evidence towards development of a paradigm for testing gait control. The use of fixed-interval timing imperatives has led to an understanding that normal walking complexities break down as a result of cueing (Hausdorff, 2007). Hausdorff and colleagues (2007) demonstrated that when walking to a fixed timing imperative, the inter-stride duration time series FSI shifted towards 0.50. Only in the past few years have fluctuating timing imperatives been used in gait research to better understand the nature of the healthy gait system (Marmelat et al., 2014; Hunt et al., 2014; Rhea et al. 201). These works have collectively demonstrated that gait complexity can be prescribed to "match" the complexity being imposed by the timing imperative. The results of the current study extend previous results such that the relationship between gait complexity and gait control (i.e., stability or adaptability) can be tested on the retained complexity in the immediate 50 strides post-entrainment.

Several limitations in the data collection and analysis may constrain the interpretations of the results. First, due to collection software limitations and the number of real-time data points being streamed into our dedicated collection desktop, the 20 minute trials required manual segmentation into phases. Therefore, each trial was not recorded continuously despite the participant walking for a continuous period. This may have led to a loss of 1-3 strides between each manual start (i.e., between each phase). However, I do not anticipate that this potential loss of strides would adversely affect the FSI values. Unpublished data from our laboratory suggest that the removal of more than 10 samples from the time series is required before a substantial change in the FSI is observed.

Second, the limitation in the DFA algorithm, previously mentioned, was the basis for long trials. Specifically, the DFA requires ~256 data points for computation consistency. This impacted the authors decision to conduct ~20 minute waking trials. Metrics such as the permutation entropy which, is noted to have consistency between short and long data sets (Leverick et al., 2014), may be a more effective tool for assessing short-term complexity retention and enable repeated trials, to get a true representation of entrainment-retention effects.

5.4. Conclusions

The current study was aimed at understanding the retention effects following entrainment to various auditory fluctuating timing imperatives which, differed in their fractal characteristics. The results indicate that entrainment may persist in the immediate 50 strides (~one to two minutes) post–entrainment but subsequently diminishes towards baseline. The fractal characteristics of the timing imperative do not impact the retention effects observed in the study. Future studies may find it necessary to assess complexity retention following entrainment with complexity metrics that do not require as many data points as the DFA approach. The immediate retention effects observed in this study can inform future studies aiming to investigate the impact of complexity on walking or studies analyzing the efficacy of complexity entrainment on retention.

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CHAPTER SIX

THE ATTENTIONAL DEMANDS ASSOCIATED WITH CUEING TO A FLUCTUATING TIMING IMPERATIVE

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Preface

Entraining to a fluctuating timing imperative (i.e., a metronome with a fluctuating frequency) is a promising method for assessing the flexibility of the gait system and slowing the decline of healthy complexity that is typically observed in the healthy walking pattern. Previous results in this dissertation, have shown that the error of entrainment matching depends on the complexity of the timing imperative, which could be a function of an attentional load associated with the cueing. Currently, it is unknown whether cueing steps to auditory fluctuating timing imperatives, with different complexities requires differences in attention, as compared to uncued walking. The goal of the current study is to understand the role attention plays when entraining gait complexity to a fluctuating timing imperative. Twelve healthy young adults participated in this study. Participants completed 12 walking trials: four in each of the three timing imperatives conditions [Timing Imperative (TI): uncued (UN), white noise (WN), and pink noise (PN)]. Of the 4 trials in each condition, 2 trials included a probe reaction time (PRT) task, which had a visual probe elicited during left-mid stance. The PRT task did not influence the fractality of gait ($p = 0.26$). Furthermore, no significant increase in PRT was found across TI ($p = 0.82$). The results of this study confirm that cueing to an auditory fluctuating timing imperative does not alter attentional demands associated with gait.

6.0. Introduction

Paying attention to cues in a changing environment is essential to remaining adaptable, and requires cognitive effort. An inadequate processing capacity can increase the likelihood of suffering a slip, a trip, or a misplaced step, and can eventually result in a fall. Complexity is now understood to be a fundamental component of the healthy gait pattern (Decker et al., 2011). Complexity is a marker of the gait system's proficiency, and may be related to adaptability (Harbourne and Stergiou, 2011).

A promising method for slowing the decline of healthy levels of complexity in clinical populations is the use of fluctuating timing imperatives (Hove et al., 2012; Uchitomi et al., 2013). The use of such methods requires sufficient attention to cue steps with an external cue. Assessing the processing capacity that is required to synchronize with complex stimuli can help uncover the attentional demands needed to navigate complex environments. Furthermore, this evidence can provide insight into the attentional capacity that is needed to elicit fluctuating timing imperatives during rehabilitation.

In this context attention is defined as an individual's cognitive processing capacity (Neumann, 1984). There are several methods to probe the requisite cognitive effort during the performance of gait tasks. For example, researchers have used a counting task, by either counting backwards or in multiples (Nacimbeni et al., 2015), or have used an auditory stroop task (Weerdesteyn et al., 2003; Mazaheri et al., 2015). Gait pattern complexity has shown sensitivity to walking tasks that include computer recognition task (Leverick et al., 2014). However, the previously mentioned dual-task paradigms may not be a true reflection of the attentional demands associated with walking (Teasdale et al., 1993).

Instead, many studies assessing cognitive load during walking have adopted a probe reaction time (PRT) paradigm to estimate the attention during gait (Gage et al., 2003; Peper et al., 2012; Mazaheri et al., 2014). It is well-established that attentional load increases during the performance of several gait tasks under postural threat (Gage et al., 2003), such as during obstacle crossing (Hawkins et al., 2011), or when attending to auditory (Peper et al., 2012) and visual cues (Mazaheri et al., 2014). Hawkins (2011) measured reaction time (RT) with an auditory probe, while participants crossed an obstacle and carried a load of different magnitude, and demonstrated that RTs increased with load magnitude. Dual-task investigations with a vibration probe have compared RTs, while walking normally (i.e., uncued) and while cueing steps to visual fixed interval timing imperatives and shown that RTs were longer during visual cueing (Mazaheri et al., 2014). When comparing auditory to visual fixed interval timing imperatives, visual cues demand greater attention and show longer RTs (Peper et al., 2012). While there is the potential to utilize fluctuating timing imperatives in rehabilitation, it remains unknown whether there is an attentional demand associated with cueing to such timing imperatives, and whether any such attentional demand would differ across different fluctuating timing imperatives.

To date, the attentional costs associated with cueing to several fluctuating timing imperatives are unknown. The purpose of the present study was two-fold: (1) to investigate the attentional demands associated with cueing steps to an auditory fluctuating timing imperative, and (2) to evaluate whether any differences exist in the attentional demands associated with the complexity of the timing imperative. Attention was assessed using a visual probe elicited during the left mid-stance gait event. It was hypothesized that RTs would be greater in dual-task conditions (i.e., cueing to white noise and pink noise timing imperatives) compared to uncued normal walking, and that there would be no difference in the RT between dual-task conditions.

6.1. Methods and Protocol

6.1.1. Participants

Twelve young, healthy, adult volunteers (n = 8 females, mean; age: 29 ±5 years, height: 1.71 ±0.08 m) were recruited to participate in the study. Participants were provided with the details of the study, and signed an informed consent form prior to engaging in the experiment. Approval to conduct the study was granted by the Health Research Ethics Board of the University of Salford. Exclusion criteria included: younger than 18 and older than 35 years, and a self-reported history of neurological injury or disorder, musculoskeletal injury or disorder, auditory impairment, or pain and discomfort in the past six months that might affect walking and listening to an audible sound.

6.1.2. Equipment

A fixed-pace, instrumented C-Mill treadmill (Motek ForceLink, Amsterdam, Netherlands) was used for the walking trials. The treadmill is equipped with a uniaxial force platform (70 x 300 cm), which records the magnitude and the position of the vertical force and provides gait event detection captured by CueFors software. The treadmill is also connected to a projection system on the left side of the belt, which displayed visual probes onto the treadmill belt (Figure 6-1).

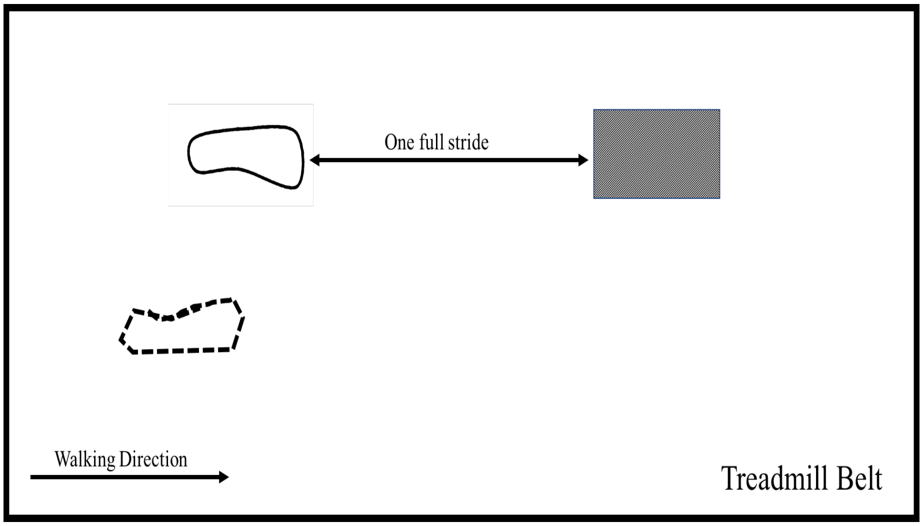

Figure 6-1: Transverse view of the participant's position on the treadmill belt relative to the appearance of the visual probe (grey rectangle) projected onto the belt. To dissociate the visual probes from interfering with the auditory timing task, all probes appeared on the contralateral side of the participant's cueing foot. This was to minimize the potential for desynchronizing with the timing imperative. The visual probe was presented at mid-stance, and approximately one full stride in front of the participant.

Analog data (i.e., switch response and timing imperative) were captured using a Qualysis track manager (v. 2.8), (Qualysis, Gothenburg, Sweden). The C-Mill and Qualysis systems were time-locked, and the trial initiation between both systems was synchronized. A single speaker (Sound Link Mini, Bose, USA) was used to administer the auditory fluctuating timing imperatives. This speaker was placed to the left side, approximately 100cm adjacent to the treadmill and the participant. The participants held a small hand trigger (Qualysis, Gothenburg, Sweden) in their dominant hand, which they pressed to record probe reaction times.

6.1.3. Pre-Experimental Protocol

Each testing session began with a two-step process to determine each participant's preferred walking speed (PWS). This method has been described in Section One, Chapter Three of this dissertation. As participants stood on the treadmill the speed of the belt was incremented in small amounts (0.10 m/s) until the participants percieved their "comfortable walking speed". The same protocol was repeated with small reductions (0.10m/s) in speed until the participants again percieved their "comfortable walking speed". The average of the two speeds was calculated and classified as the participants' preferred walking speed (PWS: 1.04 ±0.18 m/s) for all experimental trials. A three-minute baseline walking trial was completed to capture the participants' average inter-stride interval (ISI) and the standard deviation of ISI, which were used to create the inter-beat interval (IBI) of the timing imperative.

White noise (WN) and pink noise (PN) fluctuating timing imperatives were created in Matlab R2015b (The Mathworks, Natick, USA), based on a method described in Kasdin (1995). The procedure is as follows: a white noise vector of 256 data points was created using the Matlab function wgn(). The original white noise signal was transformed into the frequency domain with a Fast fourier transform (FFT), which was expected to show equal power amongst all frequencies in the signal. Transformation of the white noise signal enabled removal of the higher frequency components to generate the pink noise signal. This was done by multiplying the white noise signals' frequency spectrum by a factor of factor $1/\sqrt{f}$. The resulting signal was then transformed into the time domain with an inverse fast Fourier transform (IFFT). Each of the white noise and pink noise signals created were participant specific, such that the mean and magnitude of variability of the IBI matched the participants' ISI from the baseline trial.

6.1.4. Experimental Trials

Participants completed 12 randomized trials: Uncued walking (UN), white noise (WN), and pink noise (PN) timing imperatives. Four trials of each walking condition were performed by participants. During the WN and PN participants were asked to cue their foot at the time of heel strike to the beat of the timing imperative. Participants selected the foot they would perform the cueing task. Practice was provided prior to conducting experimental trials, in order for the participant to become familiar with the task. To synchronize participants immediately with the timing imperative, the trials began with a three-count countdown matched to the participants' heel contact, where the first beat of the timing imperative was elicited on the last count. This procedure was also conducted during UN, for consistency, though there was no timing imperative used in this condition.

Of the four trials in each condition, two included visual probes for 20% of the trial (50 per trial). The visual probe appeared approximately one stride in front of the participants' location on the treadmill belt. The choice of the location of the visual probe was two-fold: (1) to minimize the potential of desynchronizing the timing of the cueing foot with the auditory stimulus; and (2) to prevent the participant from looking directly down at their feet during the trial, thereby causing an unnatural gait.

Participants were asked to respond immediately to the sight of the visual probe by depressing the button on the handheld switch, and they were asked to give priority to the timing imperative task. Therefore, a total of six PRT trials each with a total of 300 visual probes were elicited for each participant. Due to the changes in attention across the gait cycle with younger adults (Gage et al., 2003), the presentation of the visual probe was consistently presented at the mid-stance. The visual probes were presented at random throughout the trial; on average, a visual probe appeared every five strides.

6.1.5. Data Processing and Analysis

Analog signals (i.e., the timing imperative and the hand switch) were sampled at 100Hz. C-Mill data was sampled at 500Hz. Due to the discrepancy in sampling rates between the collection systems (i.e., Qualysis and C-Mill), the analog data from the Qualysis system was up-sampled from 100Hz to 500Hz. This up-sampling procedure was done in Matlab, by using the resample() function and by specifying the resample parameter = 5. The resample() function interpolates additional samples and applies an antialiasing finite impulse response, low-pass filter, to the original data. This process was done to accurately match the onset times from the handheld switch signal (collected through the Qualysis system) and the visual probe signals (collected through the C-Mill system).

All signals from the switch trials were plotted individually to inspect the true signal relative to the noise. This was done to define a clear threshold value that indicated switch depression. Due to contamination from measurement noise, switch depressions were considered correct if they showed a sharp rise and decline from the baseline signal, and exceeded a pre-determined threshold of 0.1 volts (V). As such, all signal components below 0.1 V were set to zero, in order to clearly distinguish the true signal from noise. The onset times of switch depressions were then extracted from the filtered data. Visual probe onsets were recorded by the C-Mill system, and were extracted from the output data.

The fractal scaling index (FSI) of ISI was calculated using the DFA. DFA is a method used to analyze the scale-invariant pattern of a time-series (Hausdorff, 1995). Specifically, the algorithm quantifies the relationship between time scales (e.g., milliseconds or seconds) on the magnitude of variability. The algorithm is described in Section One, Chapter Three of this dissertation.

Generally, the ISI time series is integrated, and is then divided into non-overlapping boxes of equal length. Next, within each box, a line of best fit is calculated and is subtracted from the integrated series. The root mean square is calculated on the residuals between the integrated signal and the line of best fit. The last 3 steps are then repeated across a variety of non-overlapping box sizes (typically 10-40). The average root mean square deviation of each box length is plotted against the corresponding box length. The slope of the log-transformed plot represents the fractal scaling index (α).

Dependent measures from gait include the mean, coefficient of variation (COV), and FSI of ISI of all trials. Stimulus-response RT was taken as the difference between the onset of the visual probe and the onset of the switch pulse. RTs outside of the 120ms-1100ms range were considered erroneous, which is consistent with previous research suggesting that any value below that range is the result of anticipation and that any result above that range is due to loss of attention to the task (Mazaheri et al., 2014).

6.1.6. Statistical Analysis

All statistical analysis was performed in JMP (v.9.0 product of SAS). A two-way repeated measures ANOVA (timing imperative [TI: UN, WN, PN] x task [TASK: NRT, RT]) was used to examine the mean, COV and FSI of inter-stride interval (ISI). A one-way ANOVA (timing imperative [TI: UN/WN/ PN]) was used to examine probe reaction time (PRT) results. Normality was evaluated using a Shapiro-Wilk test. Skewed data were transformed by using a log transform for positively skewed data, and by using a square-root transform for negatively skewed data. Post-hoc comparisons were corrected for type-1 error with a Tukey-Kramer correction ($p < 0.05$).

6.2. Results

6.2.1. Gait parameters and fractality

Table 6-1 presents a summary of gait parameters. The mean and COV of the ISI distributions were not normally distributed, as indicated by a significant Shapiro-Wilk test (Mean: $W = 0.91$, $p < 0.001$; COV: $W = 0.92$, $p < 0.001$). Therefore, the data were log transformed prior to conducting the analysis of variance tests. Performance of the PRT task did not affect gait COV and FSI. A significant interaction effect of TI and TASK [$F(2, 22) = 7.74$, $p = 0.003$] was found for mean ISI. Post-hoc analysis revealed that the mean ISI differed between NRT and RT during UN, though this difference was less than 2%. No main effect of TI was found for the mean ISI [$F(2, 22) = 0.43$, $p = 0.654$]. A main effect of TASK [$F(1, 11) = 5.09$, $p = 0.045$] was revealed, which indicated that mean ISI was on average lower in the RT condition, though this difference was less than 0.5%.

No significant interaction effect of TI and TASK [$F(3, 21) = 1.13$, $p = 0.34$] was detected for the COV of ISI. A main effect of TI was revealed for [$F(3, 22) = 7.90$, p =

0.003]. Post-hoc analysis revealed that UN was significantly different than PN. No main effect of TASK [F(2, 11) = 0.88, p = 0.37] was detected.

No significant interaction effect of TI and TASK [F(2, 19) = 2.83, p = 0.08] was detected for FSI of ISI. A main effect of TI was revealed for FSI [F(2, 22) = 7.12, p = 0.004]. Post-hoc analysis indicated that WN was significantly lower than UN and PN FSI. No main effect of TASK [F(1, 11) = 1.38, p = 0.26] was revealed.

Table 6-1: Summary of gait parameters (mean ±SEM) across TI and TASK.

	No Reaction Time (NRT)			**Reaction Time (RT)**		
	UN	**WN**	**PN**	**UN**	**WN**	**PN**
Mean ISI (s)	1.16 ±0.02	1.15 ±0.02	1.15 ±0.02	1.14 ±0.02	1.16 ±0.02	1.15 ±0.02
COV ISI (%)	2.23 ±0.22	2.50 ±0.22	2.92 ±0.24	1.86 ±0.17	2.46 ±0.23	2.88 ±0.20
FSI ISI	0.80 ±0.03	0.66 ±0.03	0.79 ±0.02	0.76 ±0.04	0.69 ±0.04	0.84 ±0.02

6.2.2. Probe Reaction Time

Figure 6-2 displays the results of the probe reaction time task during all TI conditions. Several steps were taken to clean switch response signals and extract legitimate response times. However, only 4% of the total expected responses from the handheld switch were captured. PRT data were collected from 17 participants, but participants without at least 1 PRT response in each TI condition were removed from the analysis, leaving a total of 12 participants each having 3 PRTs (1 each for UN, WN, and PN).

The PRT data were not normally distributed, as revealed by a significant Shapiro-Wilk test (W= 0.93, p = 0.032). Therefore, a log transformation was applied to the PRT data. No significant effect of TI [F(2, 22) = 0.203, p = 0.82] was found for PRT results; PRT was not different between timing imperative conditions.

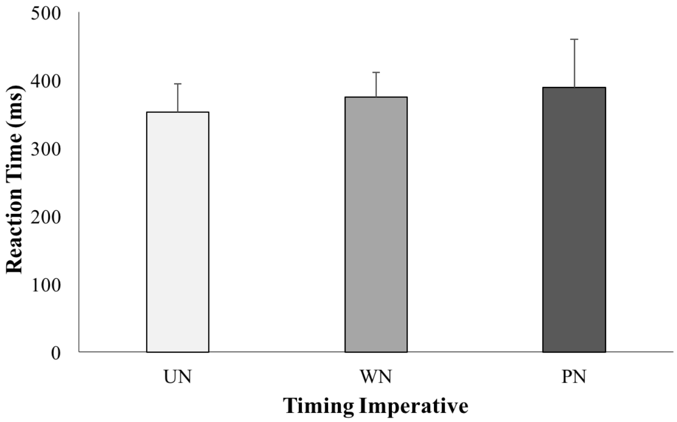

Figure 6-2: Mean ±SEM probe reaction time responses across each timing imperative (TI). UN = uncued, WN = white noise, and PN = pink noise. No significant ($p > 0.05$) differences in response latencies were found across conditions.

6.3. Discussion

The current study was the first to investigate the attentional costs associated with cueing to a fluctuating timing imperative. The use of such fluctuating timing imperatives has potential in the study of gait control, including rehabilitating deficits in walking proficiency (Rhea et al., 2014; Hove et al., 2011). As shown in previous works (Hawkins et al., 2011; Gage et al., 2003), the PRT task did not alter gross gait parameters. This study has highlighted that performance of the PRT task did not affect the FSI during the cueing conditions (WN and PN). This finding is important for evaluating the contribution of attention to the timing task.

The UN FSI (α = 0.78) results were consistent with previous reports measuring the fractal index during uncued (i.e., no stimulus) treadmill walking (Terrier and Deriaz, 2012). Performance of the PRT did not differ between the three tested walking conditions (UN, WN, PN); further, performance of the PRT task did not affect the FSI within either the WN or PN. These results indicate that tuning to the cues of a fluctuating timing imperative does not alter the typical attentional demands observed with uncued walking.

The mean PRT results in the current study are slightly greater to than those observed in other PRT gait studies (Hawkins et al., 2011; Peper et al., 2012). However, the modality (i.e., a visual probe) used in the current study was unlike the modalities of the probes used in previous works (e.g., auditory and tactile). In terms of information processing, vision is considered to be the slowest sensory system, followed by audition, and then followed by touch as the fastest system (Ng and Chan, 2012). When eliciting a tactile probe, Peper (2012) reported PRTs with averages of ~250ms during normal uncued walking, and ~260ms while cueing to a fixed interval timing imperative. Previous work in our lab reported PRTs of 260ms to 280ms when presented with an auditory cue (Hawkins et al., 2011). The average response time in our study during uncued walking was ~350ms. However, in a study of simple reaction time to visual, auditory, and tactile sensory modalities, Ng and Chan (2012), demonstrated that the visual processing delay in a single-choice RT task was 34% and 6%, longer than the tactile and auditory response, respectively. Therefore, the discrepancy in response times between prior studies and in our study might be attributed to the probe modality. Nonetheless, an important aspect of our findings is the relative difference between each condition, which was deemed not statistically different. This finding is important, as it suggests that entraining the gait complexity of different fractalities is not confounded by differences in attentional load.

Despite the inconsistency in PRTs across studies, the results of our study clearly indicate that performance of the probe RT task does not affect gait fractality. This can inform future studies which seek to assess the importance of gait complexity in the gait systems function. Gait research currently recognizes that complexity is an inherent feature of the gait pattern and as a critical marker of gait, but the extent of this remains unknown. Accordingly, in studies that employ a fluctuating timing imperative as a paradigm to entrain gait complexity, it should be noted that entraining to a complex stimulus does not change the cognitive demands associated with gait.

This study imposed an auditory timing imperative on the individual during complexity entrainment. Previous research has shown that complexity can also be entrained with a visual fluctuating timing imperative (Rhea et al., 2014). Therefore, the results of the current study, which used an auditory timing imperative, may not translate to a study using a visual timing imperative. Therefore, caution should be taken if extending the current study results to the use of a visual timing imperative to entrain gait complexity. This may be especially true if such paradigms for entraining gait are used with elderly adults (Peper et al., 2012). This is because elderly adults demonstrate age-related deficits in attention during gait, especially if the dual-task interferes with visual processing (Bock, 2008). Future studies should address this issue by considering the attentional load between auditory and visual timing imperatives, as well as between young and elderly adults.

Some limitations in this study may hinder the interpretation of the results. First, due to noise contamination in the switch signal, our study sample included a small portion of the total PRT responses. Thus, it can be argued that the results are not a true representation of the mean PRT during the performance of dual tasks. Also, while different sampling frequencies across platforms is not atypical practice, ideally when extracting timing data, the data is captured at identical sampling frequencies. As a result a potential aliasing (infusion of lower frequency components) effect of the digitally sampled signal may have occurred.

6.4. Conclusions

The results of the study suggest that the performance of cueing steps to a fluctuating timing imperative does not require additional attentional demands compared to uncued walking. The implications of these results indicate that employing such timing paradigms to entrain gait complexity is likely a function of the local stepping behaviour and not confounded by the attentional demands of the task. This evidence now opens the possibility of entraining gait complexity as a paradigm for testing the effect of entrained gait complexity on gait function (i.e., on stability and adaptability). Future studies should extend the current results with additional timing imperatives and populations.

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CHAPTER SEVEN

ASSESSMENT OF THE EFFECT OF GAIT COMPLEXITY ENTRAINMENT ON SYNCHRONIZATION TO A FIXED TIMING IMPERATIVE

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Preface

Complexity is considered a central marker of healthy gait. Presumably, complexity links the gait system's proficiency to its functionality. Fluctuating timing imperatives (i.e., a metronome with a fluctuating frequency) are a suitable method for entraining a desired level of complexity into the healthy gait pattern. However, the coupling between global gait dynamics (i.e., the complexity of a series of strides) and local gait (i.e., the stepping pattern) is not well understood in literature. The current study was designed to assess the effect of gait complexity on stepping performance. A total of 17 healthy young adults participated in this study. These participants were asked to complete an auditory-motor coordination task by timing their heel contact to an audible sound. The participants completed six total walking trials, which were split into two continuous phases. The first phase (entrainment) consisted of 255 cued strides and was used to entrain each participant's inter-stride interval to a specific level of complexity. Participants were presented with an auditory stimulus that contained a fluctuating frequency with specific fractal characteristics; white noise (WN) or pink noise (PN). Two trials were completed in each of three different walking conditions: [entrainment (ENT): Uncued (UN), WN, PN], during the first phase. The ENT phase was followed by the post-entrainment (POS) phase, which included 50 strides, during which participants cued their strides to a fixed interval timing imperative. The results indicate that participants can synchronize their fractality to the timing imperatives fractality ($p < 0.0001$) despite differences in the consistency of their stepping response ($p = 0.04$). Additionally, the results of the second phase indicate that after entraining to a WN timing imperative leads to synchronization within 3-5 strides, of fixed timing imperative onset. Additionally, after entraining to PN to fixed timing imperative compared to UN and PN. Together, these results demonstrate that synchronizing to the start of a stimulus may relate to global dynamics but entraining to the complexity of a complex stimulus can result from a variety of stepping strategies.

7.0. Introduction

Healthy individuals produce stride-to-stride fluctuations during gait, which have been shown to correlate across time scales. The correlation between time scales is known as scale-invariance (Hausdorff et al., 2007). The gait system is composed of many interacting components (e.g. neural, cognitive, and mechanical) that coordinate over multiple time scales in a non-linear manner. The gait system thereby produces a complex stepping pattern. Long-term correlations between stride-to-stride fluctuations, over different scales, are a function of the gait system's complexity. In gait, complexity results in a stride-to-stride pattern that remains consistent, but is also flexible to the environment (Rhea and Kiefer, 2014).

Currently, an adequate level of gait complexity is said to reflect a healthy gait system. More specifically, gait complexity may indicate adaptability (Harbourne and

Sterigou, 2009). However, the connection between gait complexity and adaptability is not clear. Adaptability can be defined as a process involving step adjustments (Balasubrimanian et al., 2014). Clinical assessments of gait adaptability often assess the error of stepping, and they increase difficulty by adding time constraints (Hollands et al., 2015).

Presently, it is unknown if global gait dynamics, characterized by complexity, influence local gait dynamics (such as stepping patterns or responses to localized stepping changes). Parkinson's patients entraining to an interactive rhythmic timing imperative, which provided a complex inter-beat interval that also adjusted the interval according to feedback based on the participants' heel contact, increased the complexity (e.g., fractal scaling index = 1.0) of their gait pattern, as compared to Parkinson's patients entraining to a fixed timing imperative (e.g., fractal scaling index = 0.9) (Hove et al., 2012). Those results suggest that there may be a direct relationship between global gait dynamics (e.g., complexity) and local gait dynamics (i.e., stepping pattern). This would be important to understanding gait control, and to assessing gait function in special (i.e., elderly) and pathological populations.

Previous work presented in this dissertation demonstrated adequate entrainment and retention (see Section Two, Chapters One and Two) of stimulus complexity following a trial of cueing. This paradigm may be an effective method for investigating the link between global and local gait processes. Here, "global" is described as the overall temporal structure (i.e., the fractal measure) of the entire inter-stride interval time series. "Local" is defined as the individual inter-stride interval (Rhea et al., 2014).

External cues place constraints on the gait system. Previous studies have suggested that cueing to a fractal stimulus results in the emergence of strong anticipation (Dubois, 2003). Specifically, cueing to a fractal stimulus and the emergence of strong anticipation involves synchronizing at the global level, as opposed to at the local level (Stepp and Turvey, 2010). “Strong” anticipation differs from “weak” anticipation, in that weak anticipation involves the development of an internal model (e.g., schemas) by the actor (i.e., gait system), which is used to predict future events based on past events. In contrast, strong anticipation does not require an internal model and rather occurs from spontaneous coupling between the environment and the actor, leading to coordination between the two systems (Stepp and Turvey, 2010). Strong anticipation does not rely on local coordination for synchronization at the global level. For example, recent gait research has shown that participants cueing to a fluctuating timing imperative demonstrate a combination of proactive (early), synchronized (on time), and reactive (late) local stepping strategies. However, the participants consistently entrained the global (i.e., fractal) dynamics of the stimulus (Marmelat et al., 2014; Rhea et al., 2014).

The present study aimed to investigate the relationship between complexity and adaptability. Specifically, the study aimed to: (1) entrain inter-stride interval with the complexity of a white noise and pink noise timing imperatives; and (2) assess the number of strides required to synchronize with a fixed interval timing imperative following entrainment. I hypothesized that: (1) participants would entrain their gait pattern complexity with the fluctuating timing imperative and demonstrate minimal error, and (2) that entrainment to white noise would increase the number of strides required to synchronize with a fixed interval timing imperative.

7.1. Methods and Protocol

7.1.1. Participants

Seventeen young, healthy, adult volunteers (n = 11 females, mean; age: 30 ±5 years, height: 1.70 ±0.08 m) were recruited to participate in the study. All participants were provided with the details of the study, and signed an informed consent form. Approval to conduct the study was granted by the Health Research Ethics Board of the University of Salford. Exclusion criteria included: younger than 18 and older than 35 years, and a self-reported history of a neurological injury or disorder, a musculoskeletal injury or disorder, auditory impairment, or pain and discomfort in the past six months that might affect walking and listening to an audible sound.

7.1.2. Equipment

A fixed-pace C-Mill treadmill (Motek ForceLink, Amsterdam, Netherlands) was used in the experiment. The treadmill is equipped with a uniaxial force platform (70 x 300 cm) that records the magnitude and the position of the vertical force, and provides gait event detection captured by CueFors software.

Kinematic data were captured using six Qualysis (Oqus series) motion cameras (Qualysis, Gothenburg, Sweden) that surrounded the treadmill. Two passive reflective markers were placed on the heels (RHEEL and LHEEL) of each individual. The treadmill and motion capture systems were time-locked; the initiation of the treadmill triggered the motion cameras to begin recording.

A single speaker (Sound Link Mini, Bose, USA) was used to administer the auditory beat sequences. This speaker was positioned 100 cm adjacent to the left of the treadmill. Analog data (i.e., the timing imperative) were captured using Qualysis track manager (v. 2.8), (Qualysis, Gothenburg, Sweden).

7.1.3. Pre-Experimental Protocol

Before the start of experimental trials, each participant underwent a treadmill familiarization period, wherein preferred walking speed was determined (see Section One, Chapter Three for full details). First, as the participant stood on the treadmill belt, the speed of the treadmill was incremented in small amounts (0.10 m/s) until the participants percieved their "comfortable walking speed". A similar protocol was repeated, but with small decrements (0.10m/s) in speed, until the participants again percieved their "comfortable walking speed". The average of the two speeds was calculated and classified as the participants' preferred walking speed for all experimental trials (PWS: 1.10 ±0.20 m/s). A three-minute baseline walking trial was completed to record the participants' average inter-stride interval (ISI) and the standard deviation of ISI. These were used to create the inter-beat interval (IBI) of the timing imperatives.

White noise (WN) and pink noise (PN) fluctuating timing imperatives were created to entrain the gait pattern complexity in a desired direction. The IBIs of each stimulus were generated in Matlab R2015b (The Mathworks, Natick, USA), based on a routine described in Kasdin (1995) using the wgn() function. The procedure begins with a white noise vector that is has a mean and standard deviation matched to the participants baseline ISI parameters. A Fast Fourier transform (FFT) is then used to transform the white noise vector into the frequency domain. To create the pink noise vector, the amplitudes of the power spectrum (i.e., the originally transformed white noise vector) were multiplied by factor $1/\sqrt{f}$ (see Section One, Chapter 3 for full details). The resulting signal was then transformed into the time domain with an inverse fast Fourier transform (IFFT).

7.1.4. Experimental Trials

Participants completed six randomized trials under three stimulus conditions [uncued walking (UN), white noise (WN), and pink noise (PN) timing imperatives] for the first 255 strides. Each participant performed two trials of each condition. During the WN and PN conditions, the participants were asked to match the time the moment of heel contact to the moment of beat onset. Participants decided on the foot of choice to cue to the timing imperative. Practice was provided in order to familiarize with the task of cueing. Each trial began with a countdown to synchronize participants with the first audible beat.

The entrainment phase (i.e., the first 256 timing imperative beats) was immediately followed by a post-entrainment phase. During the post-entrainment phase, participants continued cueing their heel contact to the timing imperative, however, the fluctuating timing imperative signal was followed by a fixed-interval, timing imperative (i.e., a metronome with a fixed frequency) for an additional 50 beats. The time between each beat of the post-entrainment stimulus was made equal to the mean of the participants' average ISI (captured during the baseline trial). Therefore, each trial consisted of a total of 306 beats (i.e., 305 strides) (Figure 7-1).

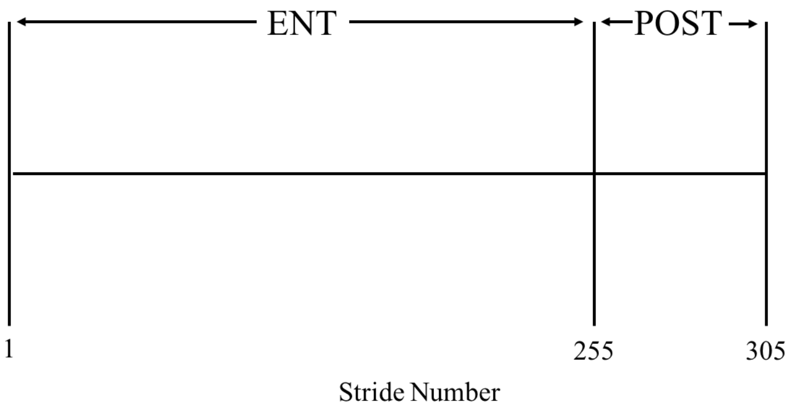

Figure 7-1: Schematic of the phases involved with each trial. The first phase included entraining (ENT) to either uncued (UN), white noise (WN), or pink noise (PN) over 255 strides. The second phase included a secondary stimulus (fixed interval timing imperative) for 50 strides.

7.1.5. Data Processing and Analysis

Both kinematic and analog signals were sampled at 100 Hz. Raw kinematic data were filtered with a 4th order low-pass Butterworth filter with a frequency cutoff of 5 Hz. The detection of heel contact (HC) was a similar approach used in previous studies which, made use of the heel marker velocity profile (See Section One, Chapter Three). ISI was defined as the time between successive HC of the ipsilateral foot (Hausdorff et al., 1995; Costa et al., 2003).

All analog signals (i.e., timing imperative signals) were plotted individually. After inspection of the raw data, it was apparent that each signal was consistently contaminated with measurement noise, which showed a peak at 0.01 volts (V) (Figure 7-2-Top and 7.2-Middle). Timing imperative beats were deemed correct if they displayed a sharp rise and decline from the raw signal, and exceeded a pre-determined threshold of 0.01 V. All signal values below the threshold were forced to zero (Figure 7-2-Bottom).

Forcing all values below the pre-determined threshold enabled the identification of beat onsets as the instant a deviation away from zero was detected.

The fractal scaling index (FSI) of ISI during the entrainment period (the first 255 strides) was calculated using the DFA algorithm. The algorithm quantifies the relationship between time scales (e.g., milliseconds or seconds) on the magnitude of variability. The DFA algorithm is described in detail in Section One, Chapter Three of this dissertation.

Dependent measures included the mean, coefficient of variation (COV), and the FSI of ISI during the ENT phase. Additionally, the time difference between the instant of heel contact and beat onset was quantified as a measure of local stepping asynchrony (ASYN) during the entrainment ($ASYN_E$) and post-entrainment ($ASYN_P$) phases, where positive values indicate that HC came before the stimulus onset (Figure 7-3). The mean and standard deviation of ASYN were quantified in order to obtain a measure of accuracy and consistency in ASYN.

A simple moving average approach was calculated to understand whether entrainment to the fluctuating timing imperatives (i.e., to WN and PN) affected the number of strides required for synchronization during post-entrainment to the fixed interval timing imperative. Synchronization was considered as the window where the average of three consecutive asynchronies fell within a specified threshold. Three different thresholds (±20ms, ±60ms, and ±100ms) were examined. More specifically, the synchronization window (SWIN) at which synchronization was considered with the secondary stimulus was when the average of three $ASYN_P$ was within ±100, 60, and 20 ms.

7.1.6. Statistical Analysis

All statistical analysis was performed in JMP (v.9.0 product of SAS). A one-way ANOVA [entrainment timing imperative (TI: UN/WN/PN)] was used to examine differences in mean stride time, COV, FSI, and SYN. A two-way ANOVA [entrainment timing imperative: (TI: WN/PN) x phase: (PHASE: ENT/POST)], was used to compare the mean and standard deviation of ASYN in WN and PN. Normality was evaluated using a Shapiro-Wilk test. Skewed data were transformed by using a cube root transform for positively skewed data, and by using a square root transform for negatively skewed data. Post-hoc comparisons were corrected for type-1 error with a Tukey-Kramer correction ($p < 0.05$).

7.2. Results

7.2.1. Gait parameters and fractality entrainment

Table 7-1 presents a summary of gait parameters across each TI during the ENT. Of the 102 trials collected (six trials per participant x 17 participants), the trials that demonstrated a stride interval FSI within a threshold of 0.15 of the stimulus FSI were considered for analysis. Specifically, the absolute difference between stride interval FSI and stimulus FSI during the ENT phase was calculated for PN and WN. All trials that fell within a threshold of 0.15 of the absolute difference of the stimulus were considered for analysis. For the UN condition, a previously reported and accepted value of uncued FSI (0.75) was used to determine which UN trials were in range of 0.15.

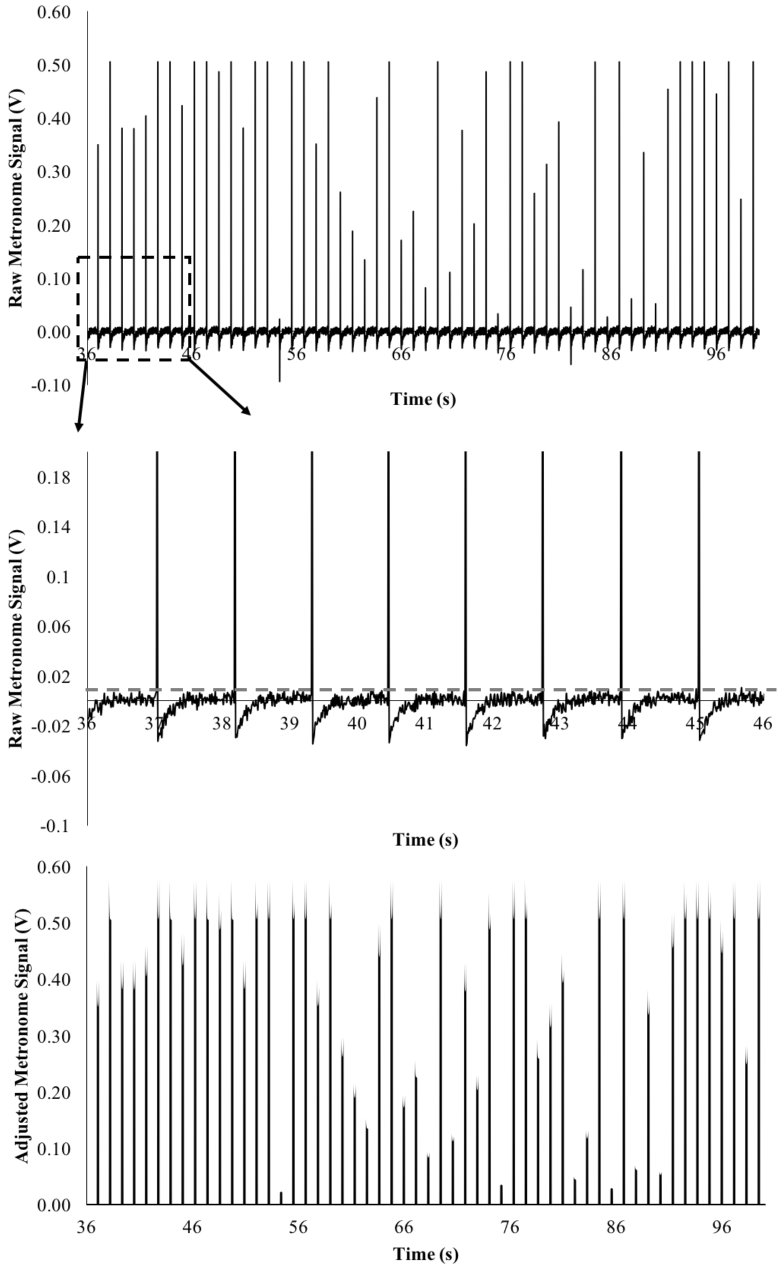

Figure 7-2: Representative plot of sound recording. Top: clipped raw timing imperative digitally sampled signal. Middle: 10 second magnified plot of raw signal. Closer inspection shows that measurement noise contaminated the signal and defined the threshold of 0.01 V (dashed line). Bottom: all values below the pre-determined threshold were made equal to zero for the estimation of beat onset.

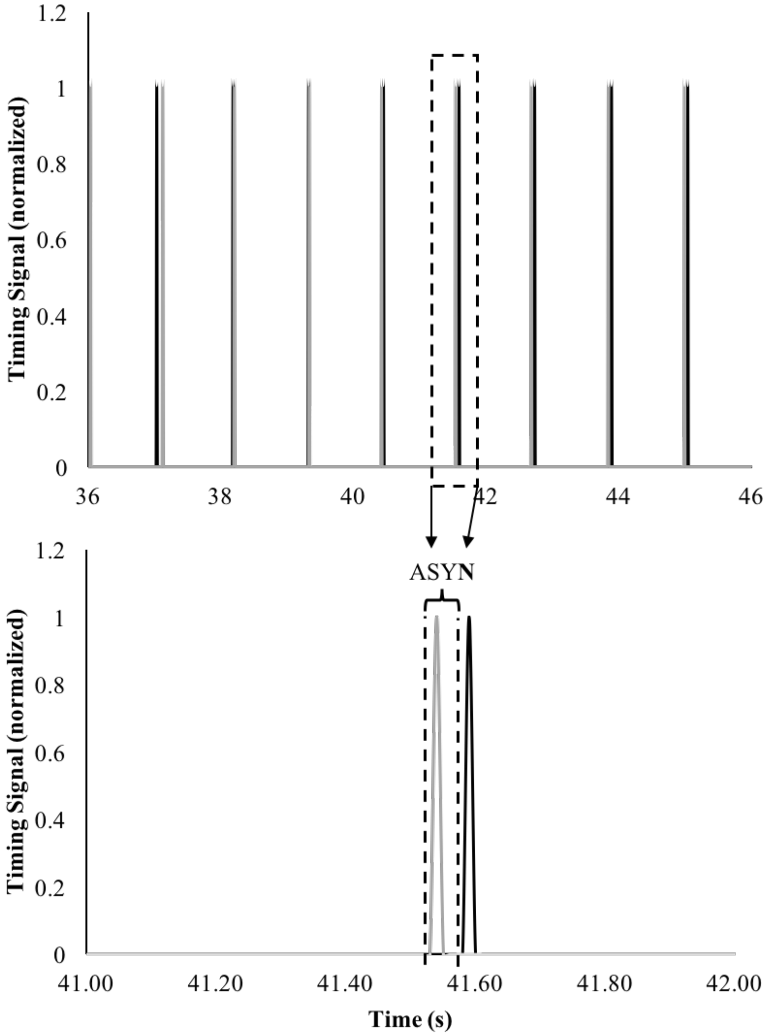

Figure 7-3: A representative plot of the method used to calculate asynchrony (ASYN), between beat onset and heel contact. Grey lines represent timing imperative beats and black lines represent heel contact. Top: normalized timing signal, where each deflection from zero represents the time of beat onset or heel contact. Bottom: magnified image of the ASYN in (top) between time points 41-42 seconds. The difference between the two signals represents the ASYN.

The decision to include trials within this pre-determined threshold of 0.15, was guided by findings presented in Chapter Four of this dissertation, and previous literature

(Terrier and Deriaz, 2012), which found during uncued treadmill walking the standard deviation of FSI was between 0.12-0.15. The justification for this approach was to confirm the effect of the ENT stimulus condition (i.e., UN, WN, and PN) on synchronization prior to the onset of the fixed interval timing imperative POS stimulus. Using these criteria, 56% of trials were found to elicit entrainment of FSI ISI within 0.15 and these trials were used for analysis.

Table 7-1: Summary of gait parameters (mean ±SEM) during ENT across TI.

	UN	**WN**	**PN**
TRIALS ANALYZED (#)	21	15	19
FSI TI	N/A	0.52 ±0.01	0.83 ±0.01
MEAN ISI (s)	1.14 ±0.02	1.15 ±0.02	1.14 ±0.01
COV ISI (%)	2.2 ±0.1	2.3 ±0.2	2.7 ±0.2
FSI ISI	0.76 ±0.02	0.53 ±0.02	0.81 ±0.02

No significant effect of TI [F(2, 21) = 0.245, p = 0.78] was found for mean ISI. Additionally, no significant effect of TI [F(2, 25) = 0.76, p = 0.48] was revealed for the COV of ISI. A significant effect of TI [F(2, 25) = 39.55, p < 0.0001] was detected for FSI. Post-hoc analysis indicated that WN was significantly lower than UN and PN. No difference was detected between UN and PN (Table 7-1).

7.2.2. Stepping (local) performance

Table 7-2 provides a summary of the ASYN data for both the mean and standard deviation during entrainment and post-entrainment phases. No significant interaction effect [F(1,8) = 7.95, p = 0.71] of mean ASYN was found. No main effect of TI [F(1,9) = 0.61, p = 0.66] or PHASE [F(1,9) = 1.34, p = 0.28] of mean ASYN was revealed.

Table 7-2: Summary of asynchrony (ASYN) during the entrainment and post-entrainment phases (mean ±SEM).

		UN	**WN**	**PN**
Entrainment	**MEAN $ASYN_E$ (s)**	N/A	0.04 ±0.01	0.05 ±0.01
	SD $ASYN_E$ (s)	N/A	0.06 ±0.01	0.04 ±0.01
Post-Entrainment	**MEAN $ASYN_P$ (s)**	0.05 ±0.01	0.03 ±0.01	0.04 ±0.01
	SD $ASYN_P$ (s)	0.04 ±0.01	0.03 ±0.01	0.03 ±0.01

A significant interaction effect of TI x PHASE [F(1,11) = 6.98, p = 0.02] was revealed for the standard deviation of ASYN. Post- hoc analysis revealed that PN during ENT was significantly greater than PN and WN during POS. WN during ENT was significantly greater than WN POS and PN ENT. No differences were revealed between PN POS and WN POST.

A significant main effect of TI [F(1,11) = 5.27, p = 0.04] for standard deviation ASYN was found. Post-hoc analysis revealed that PN was larger than WN. A significant effect of PHASE [F(1,11) = 53.46, p < 0.0001] was also revealed for standard deviation of ASYN. Post-hoc analysis revealed that ENT was greater than POS.

7.2.3. Percentage of trials in which synchronization in the POS phase was achieved

For the 100ms threshold, 100% (of the 56% considered) of the trials achieved synchronization with the fixed timing imperative within the 50 beats of the secondary stimulus. For the 60ms threshold, 98% of trials, demonstrated synchronization. For the 20ms threshold, 85% of trials showed frequency synchronization.

7.2.4. Number of strides prior to synchronization

As there is no accepted methodology in the literature for determining when synchronization with the secondary stimulus (i.e., the fixed timing imperative) occurred, three different thresholds were visually examined: 100ms, 60ms, and 20ms. Individual plots of $ASYN_P$ are included in Figure 7-4. It appears that some participants had difficulty achieving synchronization with the stimulus when transitioning from the uncued walking condition, and demonstrated fluctuations in synchronization throughout the remainder of the trial. In contrast, most participants achieved synchronization earlier when transitioning from the WN and PN conditions, and maintained synchronization throughout the remainder of the trial. Figure 7-5 displays the mean synchronization window for each threshold, for each TI.

The data for SWIN for 60ms and 100ms was not normally distributed as indicated by a significant Shapiro-Wilk test (60ms: $W = 0.57$, $p < 0.0001$; 100ms $W = 0.56$ $p < 0.0001$). Furthermore, transforming the data did not improve normality with both measures. Therefore, nonparametric comparisons were considered. For SWIN for the 60ms, Kurskall-Wallis H-test test ranks were statistically significant [$H(2) = 10.36$, $p = 0.001$] with a mean rank of 36, 19, and 27 for UN, WN and PN, respectively. Nonparametric multiple comparisons on each pair revealed that UN was significantly larger than WN ($p = 0.01$).

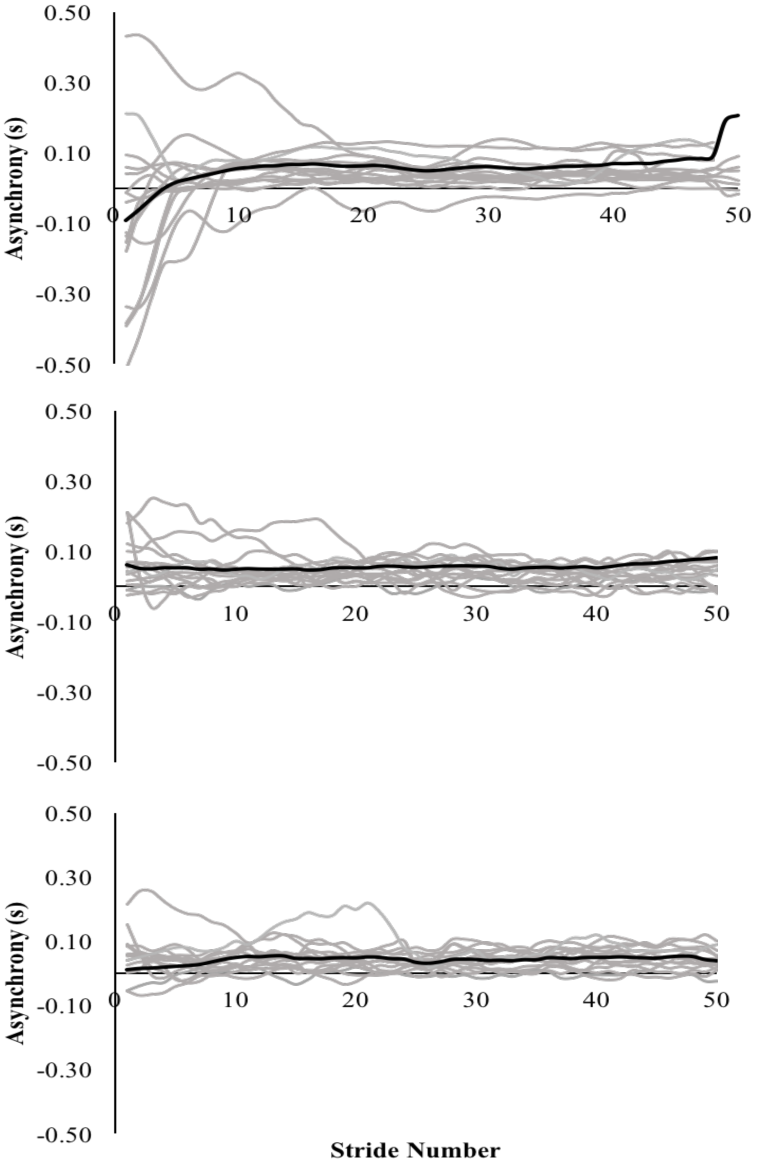

Figure 7-4: Individual (gray lines) and mean (black line) time series of asynchronies (relative time between heel contact and beat onset) during post-entrainment, when cueing to the fixed interval timing imperative. Top: uncued asynchronies. Middle: white noise asynchronies. Bottom: pink noise asynchronies.

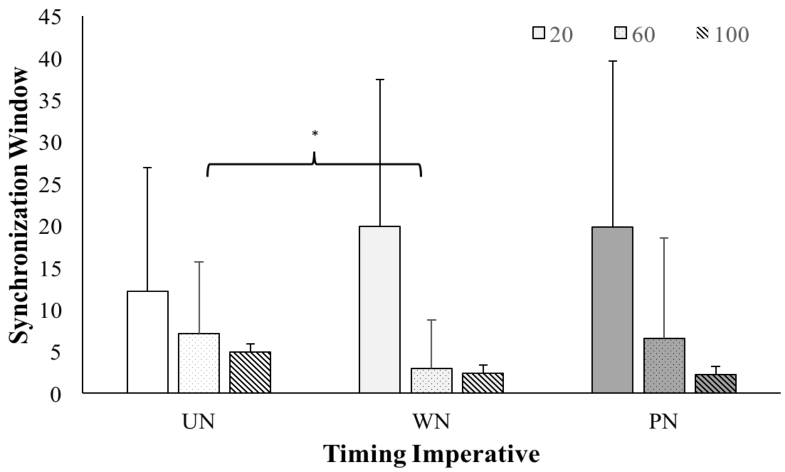

Figure 7-5: Mean ±SD of synchronization window for each threshold considered (20ms, 60ms, and 100ms) across TI.

7.3. Discussion

Complexity is a marker of healthy gait (Hausdorff, 2007). With the use of fluctuating timing imperatives, gait control is becoming better understood. Several studies, as well as previous work in this dissertation (Section Two, Chapter Four), have demonstrated the ability of young, healthy participants to entrain to the complexity of a fluctuating timing imperative within a reasonable error (Marmelat et al., 2014; Hunt et al., 2014; Rhea et al., 2014).

As such, there is a need to assess the impact that complexity has on stepping adaptability; that is, global and local processes in gait. In gait, the coupling between these two processes is not well understood. The results suggest that healthy individuals can entrain to complex stimuli by performing different stepping strategies. Specifically, participants demonstrated entrainment with the complexity of both white noise and pink noise timing imperatives, but also differed in their consistency of ASYN. Additionally, entraining to a white noise timing imperative appears to promote rapid local synchronization with a fixed timing imperative.

7.3.1. Global and Local Synchronization (entrainment)

This study aimed to investigate the relationship between global and local gait behaviour by using complex timing imperatives to entrain gait complexity. In doing so, I applied a systematic approach for selecting trials that demonstrated successful entrainment of the timing imperative. It was found that participants successfully entrained the stimulus complexity into their ISI, within 0.15 units, in 56% trials. Only these trials were used in subsequent analysis to ensure that any effect (if any) of adaptation to the secondary stimulus was a function of the ENT stimulus. In the selected set of trials, it was found in the selected set of trials that participants showed global entrainment (i.e., fractality within 0.15 units) with the white noise and pink noise stimulus, but they also elicited different local strategies (i.e., the consistency of stepping) to accomplish such global synchronization (Table 7-1 and 7-2).

The current results suggest that during WN and PN, participants $ASYN_E$ was on average +40 ms and +50 ms, respectively, with cueing HC to the beat onset (Table 7-2). This indicates that participants were typically anticipating (i.e., using a proactive strategy) throughout the duration of the entrainment to either stimulus. Additionally, this strategy was typically less accurate for the pink noise timing imperative (indicated by larger mean ASYN), despite consistently synchronizing at the global level. This may indicate that synchronization with the complexity of the pink noise stimulus does not require accurate synchronization between beat onset and HC.

The average strategy adopted by participants during ENT, in the current study contrasted with Rhea (2014), who demonstrated that on average the participants were reactive when timing to a fractal stimulus. However, Rhea (2014) cites that the collection of the timing imperative and the kinematics was unsynchronized in time. This may have caused a three to four stride interval (i.e., approximately four to five seconds) offset between heel contact and beat onset. Additionally, all the participants in Rhea (2014) were asked to walk at the same walking speed (1.3 m/s), which may have influenced their ability to accurately time HC to the stimulus. Therefore, the previous limitations may have cause the discrepancy in the typical strategy (i.e., reactive versus proactive) observed in the two studies. The results from the current study of the mean $ASYN_E$ are in line with the results of Marmelat (2014), who mentioned that participants were proactively timing to several different fluctuating timing imperatives.

Despite the typical response to the white noise and pink noise stimulus suggesting a proactive strategy, the standard deviation of $ASYN_E$ provides evidence that the local strategy also included negative (i.e., reactive) values, particularly during entrainment to the white noise stimulus. Therefore, the results of the current study appear to support evidence that local stepping behaviour during entrainment to a white noise and pink noise stimulus includes a mix of timing strategies (Stephen et al., 2008). Additionally, the results indicate that changing between a complex timing imperative to a fixed timing imperative elicits a change in local stepping behaviour that is more consistent. This is likely due to the consistent IBI that is elicited compared to the fluctuating IBI during entrainment.

7.3.2. Adaptation to fixed interval timing imperative

The second objective of this study was to assess whether cueing to a fluctuating timing imperative affected the adaptation response to a secondary stimulus, which in this case was a fixed-interval timing imperative. This objective was specifically designed to test whether entraining to a specific fractality alters the number of strides needed for subsequent synchronization. This is the first study to assess the adaptation response following a period of entrainment. Previous work presented in this dissertation suggested that following entrainment to a fluctuating timing imperative, once the timing imperative ceased, the fractality of the timing imperative would be retained in the walking pattern (see Section Two, Chapter Five for full details). Therefore, the current study sought to utilize the retention effect, and elicit a secondary stimulus to test the relationship between complexity and adaptability.

The results of this study showed a significant difference between UN and WN for SWIN when considering a 60ms synchronization threshold. Specifically, WN demonstrated synchronization within the third window (i.e., three to five strides) on average across participants (Figure 7-3). This result contrasts with the author's hypothesis, based on previous reports which suggested that a 'loss of complexity' is related to poor adaptability (Lipitz, 1992; Manor et al., 2013). However, previous research has demonstrated that timing to a fixed timing imperative leads to a breakdown of one's natural complexity (Hausdorff et al., 2007). Furthermore, the fractality of a periodic stimulus (e.g., a fixed timing imperative) is below 0.5. It has been suggested that information exchange is maximized between two systems sharing similar global dynamics (West et al, 2008). As a result, the finding that entraining to a white noise stimulus leads to hastier synchronization with the secondary stimulus may be due to similarity in the global dynamics between the timing imperative and the participant. Additionally, considering that the FSI was not significantly different between UN and PN and both conditions did not lead to a significant difference in SWIN, there may be a link between how quickly one can adapt to an external timing stimulus with similar complexity.

7.4. Conclusions

The current study aimed to understand the coupling between gait complexity and stepping adaptability. The results indicate that the local stepping consistency differs while cueing gait to a white noise or pink noise stimulus, despite successful global entrainment to both stimuli. Furthermore, the results suggest that entrainment to a white noise stimulus can lead to quicker synchronization with a fixed interval timing imperative. Taken together it appears that adjusting to the beginning of a timing imperative may depend on similar global dynamics between two systems. However, entraining to the complexity of a timing imperative can result from a variety of stepping strategies.

Limitations in the current study may hinder the interpretation of the results. First, the kinematic and timing imperative data were sampled at 100 Hz, providing resolution to every hundredth of a second. Thus, error due to rounding, may have lost part of the resolution of the ASYN data. Also, no interpolation of the true heel contact was made. Additionally, due to the low sampling rate there may have been aliasing of the digital recording of the timing imperatives. Combined, this may have caused an error approximately of 20- 40ms in the calculation of asynchronies. Future studies should seek to assess the capture data at higher sampling frequencies. Furthermore, to adequately assess the impact of complexity on adaptability, future research should assess the effect of entrainment on several different secondary tasks, such as visually guided cueing and a broader range of complex stimuli. Future research may also seek to extend such assessments to over-ground walking, in order to provide ecological validity to the results.

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SECTION THREE

GENERAL DISCUSSION AND FINAL CONCLUSIONS

CHAPTER EIGHT

DISCUSSION AND CONCLUSIONS

8.0. Objectives Revisited

The objectives of this dissertation were to: 1) assess the test-retest reliability of entraining gait complexity with a fluctuating timing imperative; 2) assess whether entrained complexity is retained; 3) determine the attentional demands associated with entrainment, and 4) assess the effect of retained complexity on an adaptation task.

The first study (Chapter Four) demonstrated that the entrainment of complexity is reliable across three sessions of entraining. However, the error of matching complexity to the timing imperative depends on the fractal characteristics of the timing imperatives. Additionally, the second study (Chapter Five) revealed that once the timing imperative has ceased, a brief period of retention occurs (i.e., the complexity from entraining to the timing imperative is carried over). The third study (Chapter Six) showed that the act of cueing to the timing imperative does not reflect a change in attentional demands. Finally, the fourth study (Chapter Seven) demonstrated that similar complexity between the gait pattern and timing imperative results in quicker adaptation at the local level (i.e., local synchronization), but also may reveal that entraining complexity is involved with adopting a variety of local stepping strategies.

8.1. Discussion

Our understanding of gait control is currently guided by theories and methods rooted in DST and Complexity Science. Despite the number of studies (Sterigou et al., 2006; Harbourne and Sterigou, 2009; Decker et al., 2010; Bruijn et al, 2013) advocating the application of concepts from Complexity Science to gait analysis, our understanding of the relationship between these notions and the applications to gait function is limited.

Complexity is currently viewed as an important marker of gait control. The literature and the current dissertation (see Section Two) have revealed that during steady-state walking (both over-ground and on a treadmill), the gait complexity of healthy individuals approaches a 1/f process (Hausdorff et al., 1995; Dingwell and Cusumano, 2010; Terrier and Deriaz, 2012). This finding is coupled with evidence that in pathological populations, gait complexity shifts towards a random process (Hausdorff et al., 2007). It has been suggested that the complexity observed in healthy individuals allows gait to be adaptive to the environment (Rhea and Kiefer, 2014, van Emmerick, 2017).

The recent use of fluctuating timing imperatives as a method to cue stepping has shed light on the flexibility of the gait pattern. Furthermore, this methodology has demonstrated the potential to extend our current understanding of gait control by specifically identifying what aspects of gait function are related to complexity. Accordingly, the purpose of this dissertation was to systematically assess the use of fluctuating timing imperatives, to entrain gait complexity and to evaluate the impact of entrainment on a subsequent adaptation task.

8.1.1. A paradigm for testing gait control

Gait control was previously described using a three-pronged model consisting of forward progression, stability, and adaptability (Shumway-Cook and Wollocott, 2007). While a paradigm for assessing gait control has not been developed, such a paradigm would be valuable in clinical settings to identify individuals at risk for falling (Balasubramanian et al., 2014). An ideal method would systematically probe all three components of the three-pronged model.

Complexity measures are promising tools for identifying individuals who are at risk for falling (Bruijn et al., 2013). The work in this dissertation is built on the framework of recent studies, which have demonstrated that the healthy gait pattern can entrain a particular level of complexity that is elicited by a fluctuating timing imperative (Marmelat et al., 2014; Hunt et al., 2014, Rhea et al., 2014). This framework was extended to show that several fluctuating timing imperatives, which differ in fractality (i.e., white noise, pink noise, and red noise), can consistently prescribe gait pattern complexity in a desired direction and with a reasonable level of entrainment error (see Section Two, Chapter Four). The culmination of this dissertation is a proposed paradigm that is reliable within a single session and in line with DST.

The proposed paradigm for assessing gait control includes a single walking session that entails entrainment to a fluctuating timing imperative for 255 strides. This proposed paradigm shows malleability, in that the entrainment stimulus can be modified by changing the complexity of the stimulus, or by changing the modality (i.e., auditory, visual, or tactile) by which the stimulus is delivered. Furthermore, evidence presented in

Chapter Six indicated that the proposed paradigm, as compared to uncued walking, does not alter attentional demands.

The work from this dissertation demonstrated that the consistency of timing heel contact with beat onset was significantly reduced during entrainment to a white noise stimulus, as compared to a pink noise stimulus (Section Two, Chapter Seven). However, the white noise stimulus elicited greater accuracy compared to the pink noise (not significant). As such, this proposed paradigm may be most suited to assessing gait adaptability by testing the accuracy and consistency of the foot adjustments (i.e., local gait dynamics) made in response to entrainment to several fluctuating timing imperatives.

8.1.2 Linking complexity and adaptability

Adaptability is the least understood component of this three-pronged model of gait control (Balasubramanian et al., 2014). Several studies support the connection between complexity and adaptability (Harbourne and Sterigou, 2009, Manor et al., 2013). However, to date, there is only a single known biomechanical clinical assessment of walking adaptability (Hollands et al., 2015).

This dissertation was the first to systematically investigate the effect of complexity on adaptability. Firstly, it was found that during entrainment to a fluctuating timing imperative, participants demonstrate lower accuracy (approximately 10ms) with a pink noise stimulus as compared to a white noise stimulus (although not significant) (see Section Two, Chapter Seven). In conjunction with this finding, participants also demonstrated different stepping consistencies across both conditions. More specifically, these findings implied that participants may have adopted a combination of reactive, synchronous, and proactive strategies when timing to a white noise stimulus. This contrasted with the pink noise stimulus, which mainly elicited a proactive strategy. Therefore, healthy individuals may adopt fundamentally different strategies when synchronizing to stimuli with differing fractal characteristics. This evidence may shed insight into how healthy individuals adapt their stepping to a fluctuating frequency.

Secondly, it was demonstrated that entrainment to a fluctuating timing imperative leads to a carry-over effect of the entrained complexity (see Section Two, Chapter Five). This carry-over effect was exploited to test the effect of complexity on a secondary timing task. It was found that entraining to a complex stimulus did not affect the overall adaptive response to a secondary timing stimulus. Specifically, the number of strides needed to synchronize to the secondary stimulus (i.e., the fixed timing imperative) was lower following entrainment to a white noise stimulus, as compared to entrainment to a pink noise stimulus.

These results indicate that synchronizing the local process of stepping to the beat of a fixed interval stimulus might depend on similar global dynamics between stride interval (the actor – individual cueing steps to external stimulus) and the timing imperative (the environment – the external stimulus). However, entraining to the stimulus complexity (global synchronization) can occur with a variety of stepping strategies (local synchronization). This may shed light on how differences between gait patterns which approach randomness or 1/f noise are related to gait function, and specifically are related to adaptability.

8.1.3. Fluctuating timing imperatives as a potential rehabilitation tool

The Loss of Complexity hypothesis claims that complexity is inherent to healthy biological systems (Lipitz, 1992). However, in pathological gait cases (e.g., fall-risk, Parkinson’s disease, and Huntington’s disease), natural complexity is diminished. Much of the sensorimotor synchronization literature on gait has focused on the use of fixed timing imperatives to restore gait rhythm. However, the use of fixed timing imperatives has shown to break down the natural complexity observed in healthy individuals (Hausdorff et al., 2007). Recent efforts have advocated the use of fluctuating timing imperatives in gait rehabilitation models to restore or limit the shift in gait complexity observed in healthy gait (Hove et al., 2012; Uchitomi et al., 2013).

The third study (Chapter Five) demonstrated that there is a brief period of entrainment carry-over in the walking pattern. This result mirrored investigations by Rhea (2014), which suggested entrainment carry-over, but with the use of a visual fluctuating timing imperatives. However, Rhea’s (2014) duration of carry-over (~15 minutes) was comparatively longer than the duration of carry-over observed in the current dissertation (approximately one to five minutes).

The discrepancy may be related to the modality of choice used for entrainment. A single study by Sedjic (2013), has examined the differences between administering a pink noise fluctuating timing imperative with different modalities. Specifically, this study compared auditory, tactile. and visual stimuli, and found that visual and tactile cueing maintained the natural gait dynamics (i.e., approaching 1/f process) observed in the gait pattern. In contrast, auditory cueing shifted gait dynamics towards anti-persistence (Sedjic et al., 2013).

This is a stark contrast to the findings presented in Chapter Four of this dissertation, and the findings of other studies (Marmelat et al., 2014; Hunt et al., 2014), which demonstrated the efficacy of auditory fluctuating timing imperatives. More specifically, in these studies, participants consistently entrained their gait pattern towards the complexity of an auditory fluctuating timing imperatives tested (See Section Two, Chapter Four). However, before extending these findings to a clinical setting, future investigations should determine the most appropriate modality for the entrainment and retention of healthy complexity levels.

8.1.4. Extension to complexity science and sensorimotor synchronization literature

The synchronization between two systems exhibiting fractal dynamics is thought to result from strong anticipation (Stephen et al., 2008). The theory of strong anticipation asserts that anticipatory behaviour is the result of one system embedding itself within another system (actor-environment coupling). Anticipation means that there is a time lag between the two systems (Stepp and Turvey, 2010). "Strong" anticipation differs from "weak" anticipation, in that weak anticipation involves the development of an internal model (e.g., schemas) by the actor, which is able to predict future events based on past events. In contrast, "strong" anticipation does not rely on an internal model, but the embodiment of an actor with the environment creates a new, dynamic relationship between the actor and environment, which leads to the emergence of anticipation (Stepp and Turvey, 2010).

Synchronization shows emergence at the global level, wherein the actor synchronizes to the dynamics of the environment (Stephen, et al., 2008). Furthermore, local synchronization exhibits a mix of strategies (i.e., reactive, synchrony and proactive), because when cueing to an individual event in the environment, the actor does not depend on being "early" or "late". This was shown in Chapter Seven, where participants adopted a mean anticipatory response to the white noise and pink noise timing imperatives, but also demonstrated a standard deviation that captures a variety of stepping strategies.

Additionally, evidence from the first study (Chapter Four) indicated that the healthy gait system's complexity can be prescribed towards the complexity of a fluctuating timing imperatives, which provides evidence of actor-environment synchronization at the global level (i.e., long-term). However, there may be a limit to the complexity of the gait systems' synchronization with its environment, as evidence from the first study (Chapter Four) suggested that cueing to a red noise timing imperative did not entrain a fractality of the inter-stride interval above one.

8.1.5. Limitations and Future Work

There are limitations in the work presented throughout this dissertation that must be acknowledged. First, the determination of heel contact and beat onsets may have underestimated the true event by a single frame (10ms) for each event. This is due to the algorithm used to determine the first change in direction of the heel marker and the first deflection from zero of the timing imperative.

Next, the work throughout this dissertation used the FSI as a measure of complexity by applying the DFA algorithm to a gait time series. This algorithm requires a large number of data points for a reliable calculation of the FSI (Delignéres et al., 2006). Therefore, to use the algorithm and achieve reliable computation of the FSI, study participants are limited to individuals who could perform at least 250 strides. The number of trials was accordingly limited, and therefore may not be a true representation of each participant's performance. Specifically, in the second study (Chapter Five), the choice to complete four trials (as opposed to eight or more) was attributed to the length of the trials, which was guided by the number of data points needed to compute the FSI.

Additionally, considering the long trials of the second study (Chapter Five), the effect of the FSI may have been confounded by fatigue, though the good health and relative youth of the participants may have mitigated this particular risk. Future work that utilizes measures that are more reliable in computing complexity with short data sets, such as permutation entropy (Riedl et al., 2013; Leverick et al., 2014), may be more appropriate for assessing complexity entrainment and retention, particularly with pathological populations.

Lastly, when extending this work to clinical settings, it is critical to extend the work of this dissertation to over-ground examinations while employing a fluctuating timing imperative. The FSI levels found in this dissertation (during uncued walking) were similar to the values reported in Hausdorff (2007), who conducted over-ground walking trials. However, in a comparison study between treadmill and over-ground walking, it has also been shown that treadmill walking may shift the FSI below levels measured during over ground walking (Terrier and Deriaz et al., 2012). Nonetheless, in order to extend these efforts outside of the laboratory setting, over-ground examinations that employ the proposed entrainment paradigm are required.

Future investigations may scrutinize the red noise timing imperative presented in the first and second studies (Chapter Four and Chapter Five, respectively). It was found that the red noise timing imperative demonstrates the largest entrainment error, when compared to pink noise and white noise timing imperative. Perhaps a closer examination of the effect of this specific timing imperative may provide insights into gait control and its utility in clinical settings.

Additional efforts may find it useful to employ a cross-sectional analysis of the proposed paradigm on different populations to assess gait control and adaptability. Some populations of interest may include dancers and healthy, elderly individuals. Dancers have received training in matching body movements to various tempos, and may accordingly shed light on the entrainment effect. Healthy elderly individuals may also be a group of interest because of their age-related risk of falling. Therefore, assessing whether the proposed paradigm is feasible with a group of elderly individuals is important in extending this work outside of the laboratory.

Furthermore, as previously mentioned, there should be additional efforts to investigate the efficacy of different modalities with entraining gait complexity. These combined efforts will help refine the proposed paradigm developed in this dissertation, to assess gait control and the intersection between complexity and adaptability.

8.2. Concluding Remarks

The current series of studies took steps towards systematically revealing the link between complexity and adaptability. This dissertation thereby provided a foundation for testing gait control in healthy individuals. Entraining to auditory fluctuating timing imperatives can reveal important aspects of stepping adaptability, and can begin to explain the relationship between complexity and adaptability.

To further investigate how adaptability is related to complexity, future efforts need to test different populations and utilize a broader range of fluctuating timing imperatives. The current set of investigations suggests that complexity entrainment is a feasible method of assessing gait control and probing adaptability. The investigations also suggest that entrainment shows carry-over into the uncued gait pattern, and does not demand a large attentional load. This may have potential as a rehabilitation tool for deterring the impact of natural aging on the shift in gait complexity. Lastly, this dissertation suggests that similar complexity between two systems may allow for rapid synchronization.

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