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## QUANTIFYING GAIT ADAPTABILITY: FRACTALITY, COMPLEXITY, AND STABILITY DURING ASYMMETRIC WALKING

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**QUANTIFYING GAIT ADAPTABILITY:  
FRACTALITY, COMPLEXITY, AND STABILITY DURING  
ASYMMETRIC WALKING**

A Dissertation Presented

By

SCOTT W. DUCHARME

Submitted to the Graduate School of the  
University of Massachusetts Amherst in partial fulfillment  
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

September 2017

Department of Kinesiology

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## **DEDICATION**

To my children, Adele and Max, who are my perpetual sources of inspiration, motivation, and distraction. I love you both more than the world.

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## **ABSTRACT**

### **QUANTIFYING GAIT ADAPTABILITY: FRACTALITY, COMPLEXITY, AND STABILITY DURING ASYMMETRIC WALKING**

SEPTEMBER 2017

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Successful walking necessitates modifying locomotor patterns when encountering organism, task, or environmental constraints. The structure of stride-to-stride variance (fractal dynamics) may represent the adaptive capacity of the locomotor system. To date, however, fractal dynamics have been assessed during unperturbed walking. Quantifying gait adaptability requires tasks that compel locomotor patterns to adapt. The purpose of this dissertation was to determine the potential relationship between fractal dynamics and gait adaptability. The studies presented herein represent a necessary endeavor to incorporate both an analysis of gait fractal dynamics and a task requiring adaptation of locomotor patterns. The adaptation task involved walking asymmetrically on a split-belt treadmill, whereby individuals adapted the relative phasing between legs. This experimental design provided a better understanding of the prospective relationship between fractal dynamics and adaptive capacity. Results from the first study indicated there was no association between unperturbed walking fractal dynamics and gait

adaptability in young, healthy adults. However, there was an emergent relationship between asymmetric walking fractal dynamics and gait adaptability. Moreover, fractal dynamics increased during asymmetric walking. The second study investigated fractal dynamics and gait adaptability in healthy, active young and older adults. The findings from study 2 showed no differences between young and older adults regarding unperturbed or asymmetric walking fractal dynamics, or gait adaptability performance. The second study provided further evidence for the lack of association between unperturbed fractal dynamics and gait adaptability. Furthermore, study 2 delivered additional support that asymmetric walking not only yields increased fractal scaling values, but also associates with adaptive gait performance in older adults. Finally, while the first two studies explored stride time monofractality during various walking tasks, the third study aimed to understand the potential multifractality, i.e. temporal evolution of fractal dynamics, of unperturbed and asymmetric walking. The results suggest that unperturbed walking is monofractal in nature, while more challenging asymmetric walking reveals multifractal characteristics, and that multifractality does not associate with adaptive gait performance. This dissertation provides preliminary evidence for the lack of relationship between gait adaptability and unperturbed fractal dynamics, and the emergent association between adaptive gait and asymmetric walking fractality.

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## GLOSSARY OF TERMS

**Attractor State:** Term that describes a coordinative pattern or behavior towards which a dynamical system tends to evolve. This state is characterized by maximal stability, and minimal variability and metabolic cost.

**Base of Support (BOS):** An area that encompasses all parts of the body in direct contact with the surface of support. This may also include external devices such as canes that act as ‘extensions’ to the base of support.

**Center of Mass (COM):** A theoretical point around which the body’s mass is equally balanced.

**Complexity:** The degree of uncertainty of a behavior or signal, that is, how well system dynamics or emergent behaviors can be predicted. A complex behavior is non-random and structured, with processes interacting within and between spatio-temporal scales. Statistically, a signal exhibiting  $1/f$  long-range correlations is maximally complex. That is, when a signal exhibits  $1/f$  relationship, the power of the signal at any given frequency is inversely related to that frequency.

**Fractality / Fractal Dynamics:** Behavior exhibiting self-similarity, in which small spatial or time scales are statistically correlated to larger spatial or time scales. In human locomotion, fractal dynamics are present when small fluctuations in a gait variable (stride time, step length, etc.) at short time scales are dependent upon or correlated with larger fluctuations at longer time scales.

**Gait Adaptability:** The locomotor system’s ability to respond to changing environmental or task demands. Adaptability may refer to the capacity to adapt gait, or the speed by which these changes occur.

**Gait Stability:** General term referring to the locomotor system’s resistance to imbalances following internal, external, or self generated perturbations. Gait stability is comprised of global stability and local stability.

**Global Stability:** The capacity of the locomotor system to maintain upright equilibrium following exposures to large external perturbations, such as tripping over an obstacle or slipping on a low-friction surface.

**Local Stability:** The locomotor system’s resilience to infinitesimally small perturbations, such as those naturally produced by the system during locomotion.

**State Space:** Geometrical representation of time series data in which a minimal number of state variables are used to define the system. The state space displays the configuration of the attractor.

# CHAPTER 1

## INTRODUCTION

Bipedal locomotion in humans is a common yet inherently complex activity. Successful walking demands that upright equilibrium be maintained in the face of constantly changing foot placement through various environmental terrains. With every swing phase of walking, only one foot is contacting the ground and there is a corresponding transient period of instability. This unstable phase must be followed immediately by recovery via subsequent steps. The challenge of this task is amplified with the addition of the natural aging-related degeneration of the visual, vestibular, somatosensory, muscular, and neural systems (Maki et al., 2008). Perhaps expectedly, older adults experience a high rate of falls, which are a primary cause of injury-based deaths and hospitalization in this population (CDC, 2011, 2012). Falls most often occur while walking at normal or hurried walking speeds (Berg, Alessio, Mills, & Tong, 1997). When individuals do experience falls, they may be negatively affected physically, psychologically, emotionally, and financially. Economically, fall-related incidents accounted for ~ \$18.6 billion in health care costs in 2005 (CDC, 2005a, 2005b, 2005c). These expenses are estimated to rise to nearly \$60 billion by 2020.

Considering the high prevalence and associated costs of falls and the multifaceted complexity of locomotion, a multitude of interventions have been developed in an attempt to reduce these fall occurrences. Interventions typically entail strength, cardiovascular, or balance training (Cadore, Rodriguez-Manas, Sinclair, & Izquierdo, 2013; Lord et al., 2005), as well as fall prevention education, modifications to medication

causing dizziness, or improvements to eyewear prescriptions (M. Choi & Hector, 2012; Lord et al., 2005). While some reports indicate that multi-faceted intervention programs significantly reduce fall rates (Cadore et al., 2013; Gillespie et al., 2004), others suggest little or no benefits (M. Choi & Hector, 2012; S. Gates, Lamb, Fisher, Cooke, & Carter, 2008; Hill-Westmoreland, Soeken, & Spellbring, 2002; Lord et al., 2005; Vind, Andersen, Pedersen, Jorgensen, & Schwarz, 2009). One meta-analysis concluded that multi-factorial interventions effectively reduced rates of falls by 4% on average (Hill-Westmoreland et al., 2002). As fall prevention paradigms have yielded few positive results, two concepts in the study of gait biomechanics have emerged as highly important to first define and second quantify: gait adaptability and gait stability.

## **1.1 Gait Adaptability**

The term ‘adaptability’ can be defined as the locomotor system’s ability to adjust to changing task and environmental demands (Kelso, 1995). Moreover, adaptability may refer to the speed by which these changes occur. For example, a more rapid (and correct) adjustment in locomotor patterns indicates a more adaptable system. Considering the constantly changing terrains while walking (e.g., pavement vs. grass, steps, curbs), gait patterns must be able to aptly adapt to new constraints. With aging and disease, the ability to adapt gait patterns may be reduced as the locomotor system becomes more constrained (Lipsitz & Goldberger, 1992).

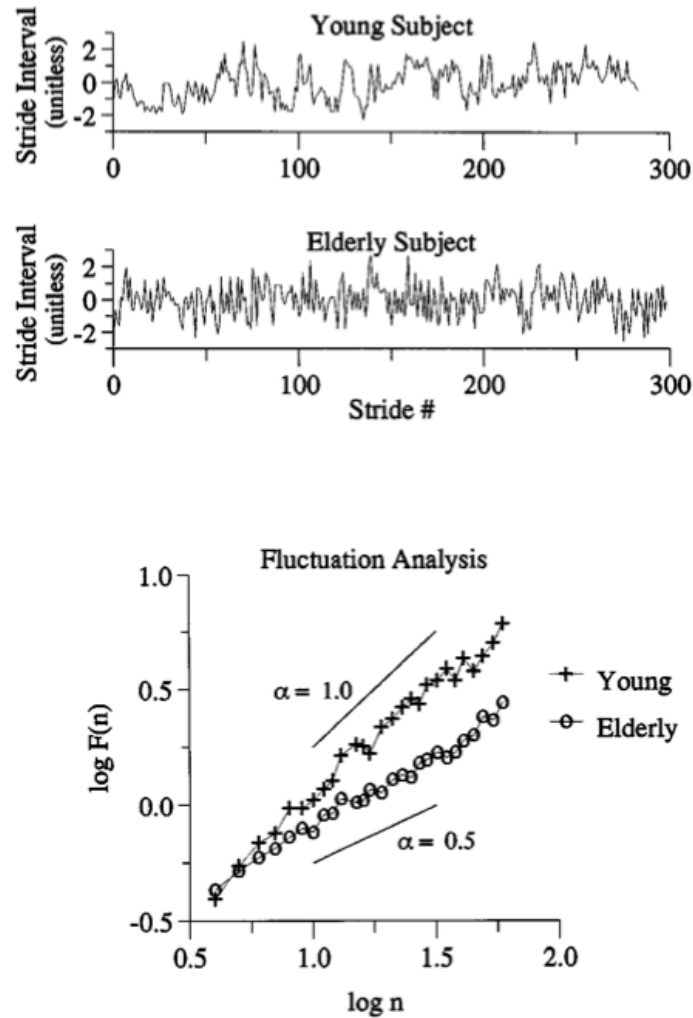
### **1.1.1 Fractal Dynamics**

Statistical analyses based on dynamical systems theory have been developed to describe the locomotor system’s adaptability. For example, stride time variability was

once considered to be unwanted random noise that the locomotor system attempts to minimize. However, deeper inspection has indicated that this variability is, in fact, patterned and complex.

#### **1.1.1.1 Monofractals**

The development of the detrended fluctuation analysis (DFA) technique (among others) has provided quantification of these variability patterns (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Peng, Havlin, Stanley, & Goldberger, 1995). Small fluctuations at short time scales (e.g., across 5-10 strides) are correlated to larger fluctuations at longer time scales (e.g., across 50-100 strides). These long-range correlations are known as ‘fractal dynamics’. When these fluctuations are plotted on a double logarithmic graph, the fluctuations increase linearly as a function of scale size, indicating a power-law scaling relationship (Figure 1.1). The slope of the regression line, known as the scaling exponent or  $\alpha$ , indicates the strength of fractal dynamics. A scaling exponent or slope of 1 is indicative of pink noise, or the so-called ‘1/f’ phenomenon, whereby the power in the signal at any given frequency is inversely proportional to that frequency (Keshner, 1982; West & Shlesinger, 1990). Pink noise is considered to have optimal fractality. Fractal dynamics have been shown to reveal differences in cohorts. Figure 1.1 illustrates stride times of young (top) and older (middle) adults. These stride times are normalized by subtracting the mean and dividing by the standard deviation.



**Figure 1.1: Detrended fluctuation analysis of stride intervals.** Top) Normalized stride times across several hundred strides for a young and elderly participant. Bottom) DFA results. From Hausdorff et al, (1997).

Fractal analysis of these stride times reveal that young healthy adults display an  $\alpha$  of  $\sim 0.75$ , while older adults and individuals with neurological disease display a decreased  $\alpha$  closer to  $\sim 0.5-0.6$  (Hausdorff et al., 1997). Fractal dynamics are thought to represent adaptable gait because the correlations across temporal scales may indicate interactivity among subsystems that are observed in healthy functioning organisms (Lipsitz & Goldberger, 1992).

### **1.1.1.2 Multifractals**

Monofractal analyses have been advantageous in distinguishing age and disease cohorts. However, a single scaling exponent cannot precisely describe some behaviors or signals. That is, transient periods of high or low variability indicate locally changing scaling exponents and, thus, fractal strength. An assumption of the monofractal DFA algorithm is that a single scaling exponent describes the entire system. To avoid this assumption, multifractal analyses have been developed to determine the local evolution of fractal dynamics across a time series. This provides a series of local scaling exponents, and the range of exponents reveal the extent of multifractality. Multifractal analysis of heart beat intervals has provided insights regarding healthy individuals versus those with heart disease (Ivanov et al., 1999). Those with healthy functioning hearts exhibited a wide range of scaling exponents, while those with heart pathologies exhibited a reduced range. This reduced range of exponents indicates overall systemic constraints.

While a wider range of scaling exponents indicates healthy heart activity, a reduced range may be indicative of a healthy locomotor system. To be clear, there is a general gap in the literature exploring multifractality in human gait dynamics. However, the few studies that have assessed gait multifractality have indicated young healthy adults display nearly monofractal behavior, while children, elderly, and those with neurological diseases exhibit greater multifractality (Muñoz-Diosdado, 2005; Munoz-Diosdado, del Rio Correa, & Brown, 2003). Additional experiments are needed to verify or refute these findings. Moreover, while most of the aforementioned gait studies evaluating fractality have analyzed stride time intervals, examining other gait parameters (e.g., step length,

step width, marker trajectory) may provide supplemental or opposing insights into the organization of the locomotor system.

### **1.1.2 Complexity Analyses**

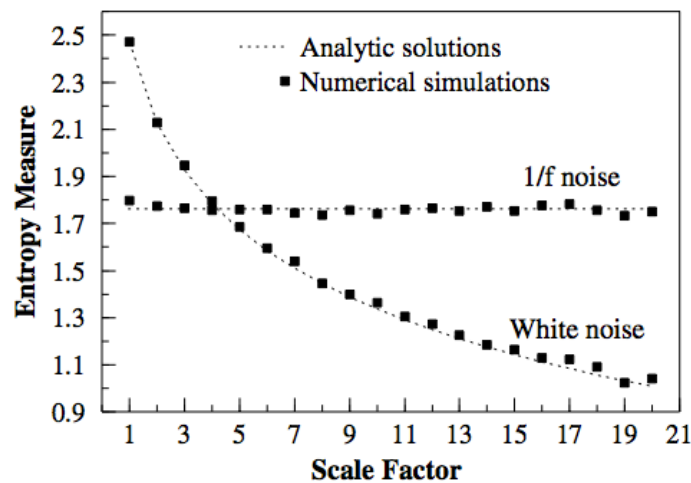
In addition to fractal dynamics, mathematical analyses of complexity have been developed to describe gait adaptability. The term ‘complexity’ has several definitions, conceptualizations, and quantifications. Complexity can be defined as the degree of uncertainty of a behavior or signal. In other words, complexity describes how well system dynamics or emergent behaviors can be predicted (Burggren & Monticino, 2005). A similar way to define complexity based on entropy analysis is the amount of information required to predict future system dynamics (Lipsitz & Goldberger, 1992). If little information is needed to predict future conditions (e.g., a sine wave), the system is not complex. A complex behavior is non-random and structured, with processes interacting within and between spatio-temporal scales (van Emmerik, Ducharme, Amado, & Hamill, 2016). Relatedly, complexity may be quantified by the dimensionality of a system, that is, the number of independent dynamic variables that are needed to generate the output of the system (Lipsitz & Goldberger, 1992). In general, the higher the number of dimensions (or variables) required to describe the system, the more complex it is. Complexity can also be described as a system exhibiting fractal-like behavior or long-range correlations, whereby a signal exhibiting the aforementioned  $1/f$  behavior is considered optimally complex (Lipsitz, 2002). Finally, and generically speaking, complexity can be considered the amount of ‘meaningful structural richness’ (Costa, Goldberger, & Peng, 2005) of a behavior or biophysical signal.

In general, a predictable, deterministic behavior has little complexity. A highly complex system is not only unpredictable (Lipsitz & Goldberger, 1992), but is also considered to be highly adaptive to changing environmental demands (Costa, Goldberger, & Peng, 2002; Costa et al., 2005; Costa, Peng, Goldberger, & Hausdorff, 2003; Gruber et al., 2011). As previously mentioned, however, the many descriptions of complexity correspond with various quantifications. For example, dimensionality can be determined via a state space or fractal dimension analysis (Lipsitz & Goldberger, 1992), while long-range correlations can be determined with fractal analysis (Hausdorff et al., 1995). Finally, in order to evaluate the degree of uncertainty of a signal, entropy measures are commonly implemented (Costa et al., 2002; Lake, Richman, Griffin, & Moorman, 2002; Richman & Moorman, 2000). Sample Entropy (SampEn), for example, evaluates the degree of uncertainty of a signal by evaluating how close a signal at time point  $i + 1$  is in relation to the signal at  $i$ . This algorithm also searches for repeated strings of data points, such as the number of times the relationship at  $i : i + 1 : i + 2$  is repeated throughout a time series (Lake et al., 2002; Richman & Moorman, 2000).

The shortcoming of SampEn is that a random signal will yield high entropy values. That is, there will be a low probability of a signal being stationary from point to point, as well as low probability of repeating patterns within the signal. As mentioned, the goal of measuring complexity is to determine the degree of ‘meaningful structural richness’ of a signal (Costa et al., 2005). One drawback of SampEn is that it identifies a system’s entropy at one only time scale. Multiscale entropy (MSE) analysis evaluates complexity using SampEn, but across multiple scales (Busa & van Emmerik, 2016; Costa et al., 2002, 2005; Costa et al., 2003; Manor et al., 2010; van Emmerik et al., 2016).



Greater complexity across scales indicates greater adaptation of the system in standing or walking (Costa et al., 2002; Costa et al., 2003; Lipsitz & Goldberger, 1992). Figure 1.2 illustrates the benefits of MSE over SampEn. Note that a white noise signal has higher entropy than a 1/f signal at a single scale factor, but across multiple scales, white noise presents with less and less complexity, while the 1/f signal remains complex. Determining the area under each curve, the so-called ‘complexity index’, reveals the 1/f signal is indeed more complex than the random signal (Busa & van Emmerik, 2016; Costa et al., 2007).



**Figure 1.2: Multiscale entropy analysis of 1/f pink noise and white noise.** From Costa et al, (2003).

The MSE analysis has been shown to differentiate healthy versus neurologically impaired participants in standing posture. For example, healthy controls displayed a higher complexity index compared to individuals with idiopathic scoliosis when analyzing center of pressure signals in both the AP and ML directions (Gruber et al., 2011). Healthy controls also exhibited higher complexity indices compared to individuals

with visual and somatosensory impairments (Manor et al., 2010). The extent to which MSE can discern young versus older adult cohorts in walking is currently unknown.

### **1.1.3 Split-Belt Treadmill Paradigm**

A relatively new experimental paradigm that evaluates gait adaptability is the split-belt treadmill paradigm (Bruijn, Van Impe, Duysens, & Swinnen, 2012; J. T. Choi & Bastian, 2007; Dietz, Zijlstra, & Duysens, 1994). This treadmill has two independently controlled motorized belts that can produce various task constraints, such as one leg moving twice as fast as the other leg, or the two limbs moving in opposite directions. Essentially, participants are exposed to an environment that promotes novel asymmetric gait patterns, and the locomotor system attempts to reconcile these asymmetries. That is, gait patterns attempt to return to a preferred state of symmetry or, from the contra-lateral limb coordinative perspective, pure anti-phase. For this reason, adaptability can be quantified by measures of gait symmetry, such as leg angle (J. T. Choi & Bastian, 2007), step length, stride length, or swing time (Bruijn et al., 2012). In a healthy, adapted system, gait patterns between legs are symmetrical, i.e., a 1:1 ratio. Spatial-temporal patterns, such as joint angles, settle into anti-phase ( $180^\circ$  or  $\pm\pi$  radians). Deviation from this symmetrical state is indicative of a maladapted system, that is, a system that sub-optimally changes locomotor patterns in response to changing task constraints.

In addition to evaluating gait pattern adaptation, the split-belt paradigm provides analysis of gait *re*-adaptation (Bruijn et al., 2012; J. T. Choi & Bastian, 2007). After adapting to asymmetrically constrained gait, as displayed by improved symmetry measures, participants show aftereffects when the asymmetry is removed. That is, when participants are exposed once more to standard treadmill walking, they exhibit

asymmetries in the opposite order. Specifically, the leg that lagged in the asymmetric condition begins to lead in the subsequent symmetric condition. This aftereffect phenomenon is a clear indicator of the level of adaptation that had occurred, and can also be used as an additional measure of adaptability, i.e., the ability to re-adapt or the speed by which re-adaptation occurs.

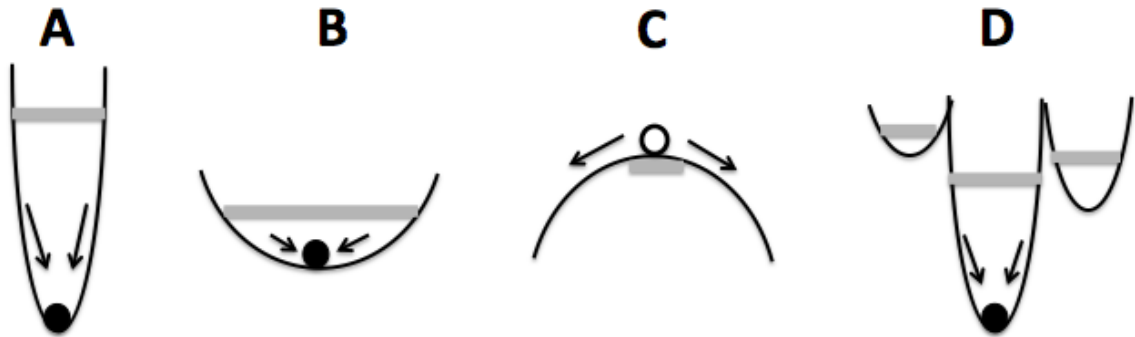
## **1.2 Gait Stability**

Stability is a term that generally refers to resilience to change. In upright posture, stability may refer to the ability to resist perturbations by maintaining foot placement, that is, not having to step to change the base of support (BOS), or to generally be able to maintain upright stance. In locomotion, the BOS is not static. Thus, gait stability can be defined as the locomotor system's ability to maintain upright equilibrium following exposures to external or self-generated perturbations. Gait stability can be subcategorized into one of two terms: global stability and local stability.

### **1.2.1 Global Stability**

Global stability refers to the capacity of the locomotor system to resist external finite or large perturbations, such as tripping over an obstacle or slipping on a low-friction surface (Dingwell, Cusumano, Cavanagh, & Sternad, 2001). In dynamical systems, a system is globally stable if it tends to move toward the attractor irrespective of the initial conditions (Kaplan & Glass, 1995; Strogatz, 1994). An 'attractor' is a coordinative pattern or behavior towards which a dynamical system tends to evolve (Figure 1.3). An attractor is characterized by maximal stability (Van Emmerik, Miller, &

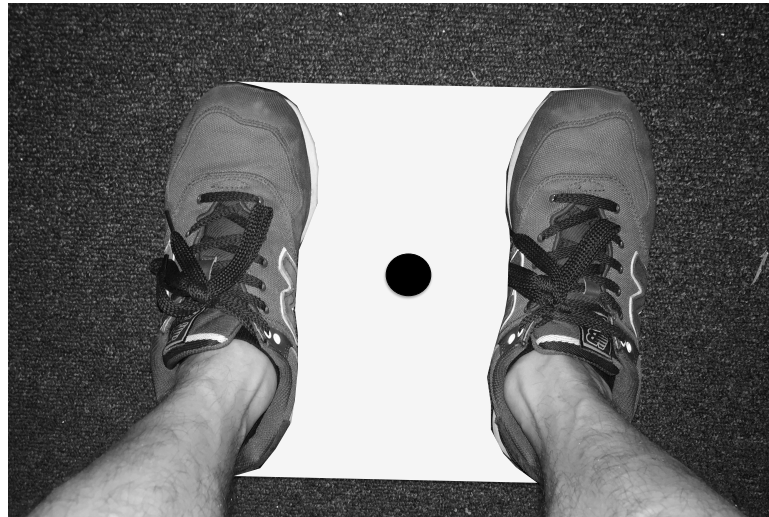
Hamill, 2013) and minimal variability (Mpitsos & Soinila, 1993) and metabolic cost (Holt, Hamill, & Andres, 1991).



**Figure 1.3: Current and attractor states represented by a ball and a well, respectively.** A) A deeper well indicates a more stable system. B) A shallower (less stable) well. C) Unstable or transitory states. D), bi- or meta-stability states. A, B, and C adapted from Kelso, (1995).

From the perspective of human bipedal locomotion, the state of locomotion is considered the global attractor state. That is, the preferred state is the rhythmic phenomenon of gait; the ‘gait state’. If gait persists following a perturbation, the locomotor system can be considered globally stable. If the perturbation leads to a different state, such as falling, the system can be considered globally unstable. As such, global stability is the simplest stability measure to conceptualize because, at its core, it can be reduced to binary terms. That is, when exposed to finite external perturbations, if a person can maintain upright stance, he or she is stable. Conversely, if a fall occurs following a perturbation, he or she is unstable. However, understanding the *degree* of global stability provides valuable information. For example, knowing how close one is to falling (or shifting into a different state) may provide insights into the magnitude of

perturbation one can withstand. Thus, global stability is often quantified by evaluating the relationship between the Center of Mass (COM) and BOS (Figure



**Figure 1.4: Representation of the center of mass (COM) relative to the base of support (BOS) during postural stance.** COM vertical projection to the ground labeled as filled circle; BOS is the surface area of the feet and the white shaded area between the feet.

1.4). The COM is a theoretical point around which the body's mass is equally balanced (Hall, 2012). The vertical projection of the COM to the floor is sometimes called the center of gravity (Winter, 1995), but for the purpose of this document we use the term 'COM' to refer to this vertical projection to the support surface. The BOS is the area that encompasses all parts of the body that are in direct contact with the surface of support (Hall, 2012). For postural control, the COM must remain within the BOS. During locomotion, the COM extends beyond the BOS during the single support phase. The COM and BOS provide a wealth of information regarding global stability, and various measures have been developed to quantify this information. For example, margin of stability (MOS) evaluates the extrapolated COM (position adjusted based on velocity)

compared to the anterior-most BOS (Barrett, Cronin, Lichtwark, Mills, & Carty, 2012; Hof, 2008). Time to Contact (TTC) determines the instantaneous COM position, velocity, and acceleration in reference to the BOS boundaries to predict future conditions (Remelius & van Emmerik, 2015; Slobounov, Slobounova, & Newell, 1997). These measures provide information regarding the *extent* of global stability by specifying how close a system is to transitioning into an unstable state.

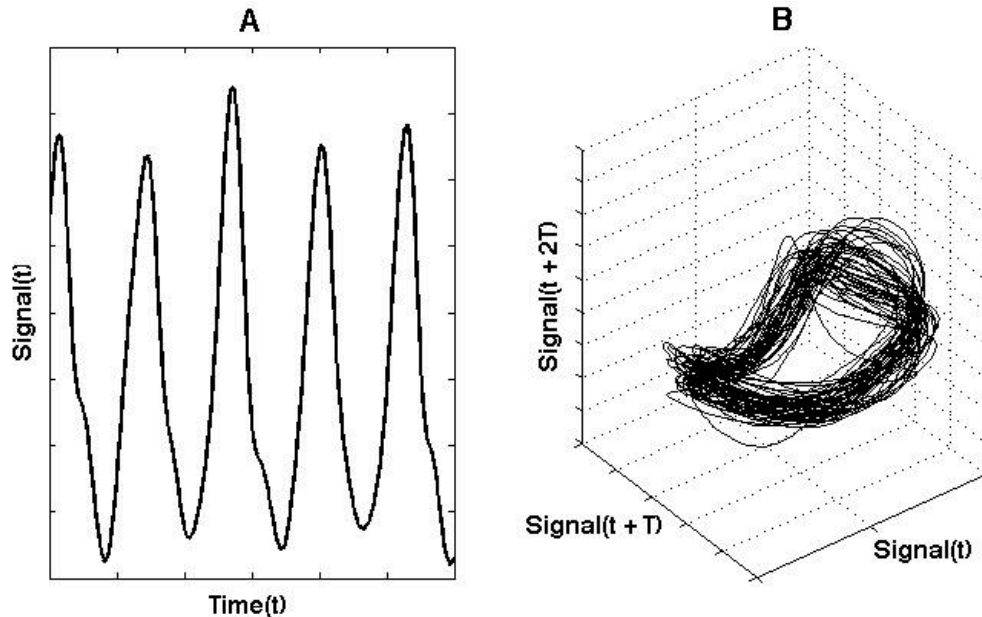
### **1.2.2 Local Stability**

Local stability refers to the locomotor system's resilience to infinitesimally small perturbations, such as those naturally produced by the system during steady state locomotion (Dingwell et al., 2001). In dynamical systems, a system is locally stable if it evolves toward the attractor when its initial conditions are close to the attractor, but does not move toward it if initial conditions are not close to it (Kaplan & Glass, 1995). In the latter case, over time small disturbances grow rather than dampen out (Strogatz, 1994).

#### **1.2.2.1 Lyapunov Analysis**

To determine local stability, non-linear methods have been developed. The maximal finite-time Lyapunov exponent ( $FT\lambda_{MAX}$ ), for example, evaluates a signal's resistance to very small perturbations that naturally occur during locomotion (Dingwell, Cusumano, Sternad, & Cavanagh, 2000). Though these perturbations are not large, they must still be attenuated before they grow larger and stability is lost. Analysis of local stability first requires that a time series is transformed into its 'state space' (Figure 1.5). A state space is a geometrical representation of time series data where a minimal number

of state variables is used to define the system. The state variables here are time-delayed versions of the signal, known as ‘delay embedding’ (D. H. Gates & Dingwell, 2009).



**Figure 1.5: State space reconstruction.** A time series signal (A) is transformed into its state space (B) by embedding a time delay ( $T$ ). The number of delays indicates the dimension of the state space; here illustrated as a 3-Dimensional space, with two embedded delays ( $\text{Signal}(t + T)$ ,  $\text{Signal}(t + 2T)$ ).

This delay can be applied to the original time series multiple times (e.g.,  $N$  number of times), where  $N$  defines the number of dimensions of the state space (dimension =  $N+1$ ).

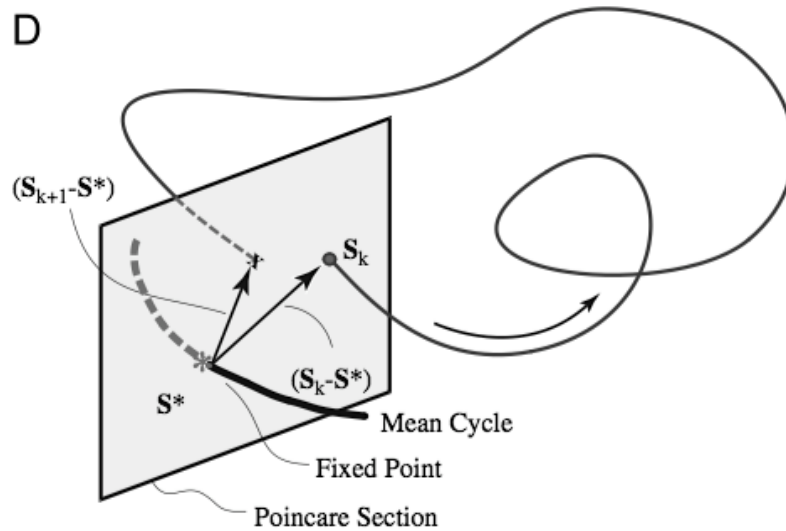
The  $FT\lambda_{\text{MAX}}$  evaluates the rate of divergence of nearby trajectories within the state space.

A larger  $FT\lambda_{\text{MAX}}$  indicates a greater rate of divergence and, thus, a less stable system.

### 1.2.2.2 Floquet Theory

Similar to analysis of the  $FT\lambda_{\text{MAX}}$ , Floquet multipliers evaluate the orbital stability of a cyclic trajectory (Granata & Lockhart, 2008), such as those observed

during steady state walking. Orbital stability analysis uses a Poincare section (grey box in



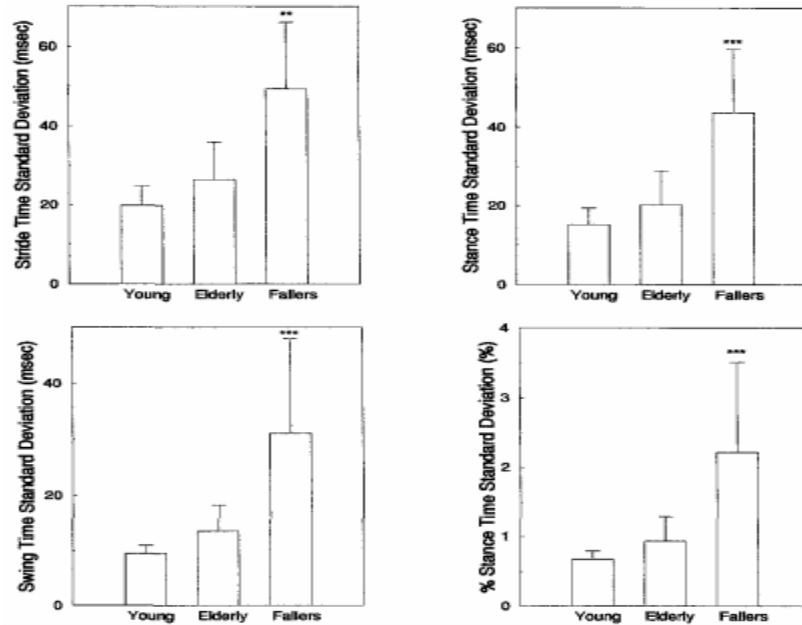
**Figure 1.6: Example of orbital stability analysis using a Poincaré section and Floquet Multipliers.** From Kang & Dingwell, (2008).

Figure 1.6) to evaluate convergence or divergence of trajectories. The Poincaré section is a plane that is orthogonal to the mean ( $S^*$ ) of the cycles in the state space, whereby each trajectory passes through this plane. The distance from the mean ( $S^*$ ) is subtracted from the signal at cycle ( $k$ ) and subsequent cycle ( $k + 1$ ). If  $S_{k+1} > S_k$ , the trajectory is diverging and the system is considered unstable (Figure 1.6).

### 1.2.3 Scalar Variability-Based Stability Measures

Finally, numerous variability-based measures of stability have emerged in the literature, such as step width variability (Brach, Berlin, VanSwearingen, Newman, & Studenski, 2005; Dean, Alexander, & Kuo, 2007), stride length variability (Maki, 1997; Vergheze, Holtzer, Lipton, & Wang, 2009), and stride time variability (Hausdorff, Rios, & Edelberg, 2001), as well as other gait parameters such as gait speed (Van Kan et al., 2009; Vergheze et al., 2009). These measures are associated with fall risk, and are classified as scalar measures of variability because they assess the overall magnitude of





**Figure 1.7: Differences in variability between young, elderly, and elderly with a history of falls.** From Hausdorff et al, (1997).

variance without regard for the structure of variability. These biomechanical analyses of human gait have provided valuable information regarding differences in various gait parameters in young healthy adults versus older healthy adults, or older healthy adults versus older adults with a history of falls. For example, greater stride-time variability is correlated with a higher risk of falling (Hausdorff, 2007; Hausdorff et al., 2001) (Figure 1.7). Additionally, the preferred speed of walking slows with aging (Himann, Cunningham, Rechnitzer, & Paterson, 1988), and slower speeds are associated with greater risk of falls (Van Kan et al., 2009; Verghese et al., 2009) and mortality (Van Kan et al., 2009).

#### **1.2.4 Dynamical Systems' Attractor State**

Figure 1.3 displays states of varying stability levels. The attractor is represented by a well, and the basin of attraction (grey lines) indicate the area within the space that all initial conditions will eventually converge (Van Emmerik, Rosenstein, McDermott, & Hamill, 2004). A ball in the well represents the system's current state, and a deeper well (A) specifies a more globally stable system. Small or large perturbations will not kick the ball out of the well (i.e., larger basin of attraction). Any disturbances to the stronger attractor will be followed by a rapid return to the nadir. A shallower well (B) cannot withstand the same perturbation magnitude and remain in the same state. Disturbances will require more time for the ball to return to its original state. Figure 1.3 B may represent a system that is locally but not globally stable. It is locally stable because the ball will remain within the well if it is close to the nadir and not sizably disturbed. If a perturbation, however, will kick the ball out of the well, the system can be considered globally unstable. In unstable or transitory states (C), the ball will be displaced by small perturbations. There are often two (bi-stability) or more (meta-stability) attractor states in competition (D), and the most stable state will have a higher probability of persisting. Arrows represent the direction the ball is 'attracted' to (or repelled from in C). Black and white balls indicate stable and unstable states, respectively.

#### **1.3 Statement of the Problem**

The term 'gait adaptability' has often been discussed in posture and locomotion studies, yet it has rarely been evaluated. Adaptability has been used to describe healthy gait that can functionally adjust to changing environmental or task demands (Rhea &

Kiefer, 2013). Some studies have evaluated gait adaptability by measuring the system's capacity to return to a symmetric walking state when exposed to an asymmetric environment (Bruijn et al., 2012; J. T. Choi & Bastian, 2007; Dietz et al., 1994). Although many studies have noted that an individual's adaptive capacity may be described by measures of complexity (Costa et al., 2002, 2005; Gruber et al., 2011; Manor et al., 2010), fractal dynamics (Jordan, Challis, & Newell, 2007b) and local stability (Dingwell et al., 2001), these analyses were performed on steady state walking, i.e., absent of any necessity to adapt gait patterns. The associations between gait adaptability and fractality and complexity need to be assessed within the context of constrained gait, such as during split-belt walking. Does an individual's fractal dynamics or complexity profiles determine, explain, or associate with gait adaptability? For example, are fractal dynamic or complexity measures during steady state associated with gait adaptability during an asymmetric gait paradigm? One could argue that, because older adults exhibit weaker fractal dynamics (scaling exponents closer to  $\alpha = 0.5$  or uncorrelated) compared to young adults (Hausdorff et al., 1997), and because older adults' gait is widely considered less adaptive than young adults (Barrett et al., 2012; Bruijn et al., 2012), weaker fractal dynamics may indicate less adaptability. Clearly, this must be empirically evaluated.

While gait adaptability has received little empirical attention, attempts to quantify gait stability have been numerous and diverse. However, the predominant shortcoming of studies evaluating gait stability is a lack of perturbation elicited (i.e., steady state gait analysis). Note that in steady state gait stability analysis, 'perturbations' are in fact still present in the form of small, internally generated disturbances. Although several direct

and indirect measures of gait stability have been studied extensively in a variety of cohorts, the functional consequences of these stability parameters are currently unknown or, at best, speculative. For example, older adults exhibit greater stride time variability (Maki, 1997). Does this parameter indicate a less stable locomotor system? Additionally, no study has yet evaluated the *global* stability of perturbed gait in individuals who naturally walk at differing levels of *local* stability (as measured by the  $FT\lambda_{MAX}$ ) during unperturbed gait. That is, is local stability associated with or a descriptor of global stability? It has been argued that the global outcomes of localized behavior are in fact, unpredictable (Mpitsos & Soinila, 1993). Indeed, the relationship between local and global stability requires empirical scrutiny.

Finally, evaluating system dynamics that exhibit multiple interactions across temporal scales is challenging. Monofractal analysis may not sufficiently describe the system in its entirety. Thus, a multifractal analysis may better describe the complex interactions occurring between temporal scales. To date, however, few studies have evaluated the potential for multifractality in gait parameters of young or older adults. Do young adults exhibit more or less multifractality in steady state walking compared to older adults? Moreover, what is the response to asymmetric gait exposure, and is this response different in young and older adults?

#### **1.4 Significance of this Dissertation**

Determining which measures of gait adaptability or stability correctly describe the locomotor system allows for two main outcomes. First, researchers can better determine the odds of a future fall on an individual basis. Particularly, those individuals already at

higher risk of a future fall (e.g., older adults, adults with neurological disorders) may benefit from the knowledge of their relative risk of a future fall. If risk is high, interventions could be incorporated to reduce this risk. Second, training studies could utilize these measures to determine the efficacy of the intervention. In other words, does the training intervention actually improve the adaptability or stability of gait?

Alternatively, in the event that no measures accurately describe adaptability, new measurement techniques must be developed. Fully understanding what a measurement is revealing about the system will only serve to improve experimental validity.

## **1.5 Proposed Experimental Designs**

### **1.5.1 Study 1 - Gait Adaptability in Young Adults**

Nonlinear gait parameters such as fractal dynamics and complexity have been associated with adaptability (Costa et al., 2002; Jordan et al., 2007b). However, specific evaluation of gait adaptability has yet to be explored in reference to these measures. That is, complexity and fractality are determined during steady state walking. The extent to which steady state analyses predict constrained gait behavior is not established. Therefore, this first study will expose participants to a task that requires the locomotor system to adapt. Specifically, the constraint will consist of asymmetric walking that requires participants to attempt to adapt leg symmetry.

The purpose of this study is to evaluate if nonlinear measures of adaptive capacity are associated with gait adaptability performance. The first aim of this study is to determine the capacity for young, healthy adults to adapt their gait in response to asymmetric task constraints. The second aim is to assess the relationship between

indicators of adaptability under steady state conditions and gait adaptability performance. The goal is to better understand what information the proposed nonlinear analyses are revealing about the locomotor system. If fractal dynamics during steady state walking describe locomotor adaptability, gait symmetry performance during asymmetric walking and steady state fractal dynamic measures should be correlated. And if so, could interventions focused on improving adaptability use fractal or complexity measures as an assessment of efficacy? For this study, participants will first walk at their preferred walking speed, as well as at half of their preferred speed. Participants will then be exposed to asymmetric walking trials, whereby one belt of the treadmill will move at the participant's preferred walking speed, and the other at half of the preferred speed. Leg symmetry relative phasing will determine the extent and rate of gait adaptability. For steady state measures of adaptability, DFA will determine the strength of fractal dynamics, and MSE will determine complexity.

Study 1 will test the following hypotheses:

**H1.1:** Asymmetric walking will initially break down fractal dynamics to values closer to  $\alpha = 0.5$ , followed by a return to standard fractal values observed in unperturbed walking ( $\alpha \sim 0.75$ ). This hypothesis is based on the observed break down of long-range correlations in older adults and adults with neurological disorders (Hausdorff et al., 1997). When the system is constrained via aging or disease, interactions across spatio-temporal scales are reduced. In this paradigm, the asymmetric split-belt walking condition is expected to serve as a task constraint that will manifest as reduced fractal dynamics. With more experience, participants

are hypothesized to adapt to this constraint and fractal dynamics will therefore increase.

**H1.2:** Fractal dynamics during steady state walking will be correlated with gait adaptability. Specifically, individuals with low fractal scaling indices (i.e.,  $\alpha$  closer to 0.5) will display poorer gait adaptability. This will be exhibited by larger deviations from intended leg phasing (anti-phase), i.e., greater gait asymmetry. The rationale here is that older adults have been shown to demonstrate lower fractal scaling exponents (Hausdorff, Mitchell, et al., 1997), as well as reduced ability to adapt their gait to symmetric walking (Bruijn et al., 2012). Thus, if fractal dynamics are associated with gait adaptability, fractality closer to  $\alpha = .05$  should yield poorer gait performance. While young, healthy adults exhibit  $\alpha$ 's  $\sim 0.75$  on average, the range within this cohort is often large. The data from Hausdorff et al. (1995), for example, displayed a range from  $\alpha = 0.56 - 0.91$ . Thus, even within a younger age group, low fractal dynamics are hypothesized to be correlated with reduced gait adaptability.

**H1.3:** Complexity during steady state walking will be correlated with gait adaptability.

Specifically, higher complexity indices, as measured by MSE analysis, will be associated with greater gait adaptability. This will be displayed by smaller deviations from intended leg phasing (anti-phase). The rationale is that a complex behavior is considered to be highly adaptive to environmental changes (Costa et al., 2002; Costa et al., 2003). Few studies have investigated participant-specific differences between complexity measures during walking, and therefore it is difficult to determine expected ranges. Regardless (and assuming there will

*some* degree of heterogeneity), greater complexity should manifest as greater gait adaptability.

**H1.4:** Gait adaptability will be associated with stride time variability, step length variability, and step width variability. Specifically, greater variability will be associated with poorer gait adaptability. This hypothesis is based on the common observation that greater variability in various gait parameters is associated with greater fall risk in older adults. This association suggests greater variability is indicative of less controllability of the locomotor system. A highly constrained system may display very little variability, though this generally occurs with aging or disease states (Brach et al., 2005). For this young, healthy cohort, however, if a participant has high gait parameter variability (e.g., stride time, step length, step width), it may be inferred that less control is evident, and manifest as reduced ability to symmetrize gait.

**Exploratory Analysis 1.1:** Two variables (fractal dynamics (DFA) and complexity (MSE)) will predict gait adaptability more accurately than either single variable alone, based on a multiple regression analysis. Fractality and complexity analyses of the same data set have been shown to be uncorrelated (Costa et al., 2003), indicating that each of these are autonomous measures with respect to the other. While these are two independent terms, both are considered indicators of the locomotor system's adaptability. This leads to two important questions: 1) is one analysis a better predictor of gait adaptability than the other, and 2) If both predict adaptability, will the combined regression analysis yield a stronger (or more robust) model to predict adaptability? The working hypothesis is that,



because fractal dynamics evaluate interactions between temporal scales, and complexity evaluates interactions within and across scales, these two variables combined should describe system dynamics better than either one individually.

**Exploratory Analysis 1.2:** As an alternative to combining fractal dynamics and complexity, this exploratory analysis will determine if stride time variability and fractal dynamics can predict gait adaptability more accurately when combined. This notion is based on the concept of gait dynamics, which refer to evaluation of gait variability via: 1) fractal dynamics and 2) variability magnitude (Hausdorff, 2007). The relationship between variability and fractality also appears to be independent (Hausdorff et al., 1996). Combining these two variables into a regression model may also provide a better model for predicting gait adaptability performance.

### **1.5.2 Study 2 - Gait Adaptation and Re-Adaptation in Young and Older Adults**

The split-belt training paradigm has been shown to differentiate young versus older adults, whereby older adults are less successful in adapting gait patterns (Bruijn et al., 2012). The first study will explore gait adaptability in young, healthy adults within this split-belt paradigm. The logical next step is to determine if there is, in fact, an age effect of gait adaptability or fractal or complexity measures, as older adults are at the highest risk of falling and are more likely to have more severe consequences in the event of a fall. Moreover, determining if gait stability measures are associated with the responses to an unexpected change in gait symmetry would provide support for or dispute against the utility of such measures. That is, while all measures of gait stability (e.g.,

local, global) are thought to describe the overall stability of the system, limited research has empirically evaluated this notion.

Clinically, if one or more of the previously mentioned measures (fractality, complexity) in older adults is associated with gait adaptability, interventions could be designed around improving these measures and, thus, gait adaptability. For example, it has been shown that the strength of fractal dynamics increases when young, healthy adults adhere their foot strike timing to that of a metronome with intervals of fractal-like behavior (Rhea, Kiefer, D'Andrea, Warren, & Aaron, 2014). If fractal dynamics are a quantification of gait adaptability in older adults, does changing one's fractal dynamics change one's gait adaptability? If so, metronome-training gait interventions might help improve gait adaptability in this cohort. Moreover, interventions aimed at improving adaptability could utilize these nonlinear techniques to determine whether or not the intervention is successful.

This protocol will be similar to study 1, but will occur over the course of two sessions. Two healthy, active cohorts will be recruited: young and older adults. On the first session, participants will stand quietly with eyes open and closed, and walk at their preferred walking speed and at half their preferred walking speed. On the second session, participants will repeat the quiet standing and PWS walking trials, as well as perform three split-belt conditions in which one treadmill belt travels at their preferred speed, and the other at half their preferred speed. A final condition will consist of having the treadmill belts moving at the same speed once more, as is the case in preferred and half preferred conditions. This will provide a measure of adaptation that occurred, as well as an ability to re-adapt gait patterns.

The purpose of this study is to better understand the connection between gait adaptability and nonlinear measures of adaptive capacity in young and older adults. The aims of this study are fivefold. First, this paradigm will address whether older adults' gait is in fact less adaptable, as was previously reported (Bruijn et al., 2012). Second, this study will determine if indicators of gait adaptability (i.e., fractal dynamics and complexity) during steady state correlate with observed adaptation performance. That is, are fractality or complexity values during steady state walking associated with gait symmetry differences during asymmetrically constrained walking? Third, this paradigm will evaluate if fractal dynamics or complexity measures correlate with re-adaptation. Fourth, this study will establish if there is an age effect of re-adaptation. Finally, analysis of the initial shift from 1:1 to 2:1 asymmetric walking will provide quantification of gait stability that can be compared to those measures determined during steady state, unperturbed walking. Do unperturbed walking stability measures predict the responses to a transient perturbation?

Study 2 will test the following hypotheses:

**H2.1:** Older adults will have an overall reduced ability to adapt to asymmetric gait, compared to younger adults. This will be displayed by larger deviations from intended leg phasing (more asymmetric). Bruijn and colleagues (2012) demonstrated that older adults adapted to asymmetric walking less and at a slower rate when analyzing relative timing in swing phase, and stride and step length symmetry.

**H2.2:** Older adults will require more time to adapt their gait, compared to young adults.

This hypothesis is also based on reported results from Bruijn et al. (2012),

whereby the older adult group adapted their gait at a slower rate than young adults.

**H2.3:** Older adults will display decreased aftereffects in the re-adaptation condition compared to young adults. This will be a result of reduced adaptation during the asymmetric conditions. Bruijn and colleagues (2012) did not observe this effect in older adults. However, their protocol only exposed participants to 10 minutes of asymmetric walking, compared to this proposed protocol of 36 minutes.

**H2.4:** Fractal dynamics will be lower in older adults compared to young adults during preferred speed walking. This premise is based on earlier studies that have indicated older adults and those with Huntington's disease generate lower fractal scaling indices, compared to young adults Hausdorff et al. (1997).

**H2.5:** Complexity will be lower in older compared to young adults. Although there is empirical data that suggests postural complexity is not different between young and older adults (Duarte & Sternad, 2008), walking is a more challenging task. This hypothesis is based on the loss of complexity hypothesis (Lipsitz & Goldberger, 1992), which would predict an age-related difference, whereby aging and disease reduces systemic complexity.

**H2.6:** While fractal dynamics on average will be lower ( $\alpha$  closer to 0.5) in older adults compared to young, fractal dynamics will still be associated with gait adaptability within each group. That is, irrespective of age cohort, lower fractal values during steady state walking will be associated with poorer gait adaptability during asymmetric walking in both groups. The argument is that older adults may exhibit poorer overall gait adaptability as well as lower fractal

dynamics, but within each cohort, there will be a range of adaptability performances and a range of fractal scaling. Hausdorff et al. (1997) observed fractal scaling exponents of  $0.68 \pm 0.14$  in older adults (range was not reported). The range of adaptability performances results will correlate to fractal scaling.

**H2.7:** There will be a U-shaped relationship between gait adaptability and step width variability during steady state walking in older adults. Specifically, very high or very low variability will be associated with poorer gait adaptability. The basis for this hypothesis is similar to hypothesis 1.4, in which a high degree of gait parameter variability is associated with a higher risk of falling. This increased risk may suggest that variability is a manifestation of less systemic controllability. Conversely, when a system is naturally constrained, as is the case with aging and disease, it may also display little variability. This has been displayed in prior studies of ideal step width variability magnitudes (Brach et al., 2005), in which very high or very low variability was associated with greater fall risk. Thus, older adults with very high or very low step width variability are expected to yield poorer gait adaptability.

**H2.8:** Gait stability measures (minimal TTC, MOS during stance phase) during steady state walking will be associated with stability measures immediately following the perturbation (belt speed change). This hypothesis is based on the general idea that greater steady state gait stability should yield greater transient stability following locomotor perturbations.

**H2.9:** Older adults will exhibit reduced gait stability measures (smaller minimum TTC and MOS) during steady state walking. Older adults are generally considered less stable with higher incidents of falls; if this is the case, the older cohort should display lower overall gait stability measures during unperturbed, steady state walking.

**H2.10:** Older adults will exhibit lower gait stability measures (smaller minimum TTC and MOS) in response to the altered belt speed. Similar to the rationale for hypothesis 2.9, if older adults are generally less stable, the rapid change in belt speed should perturb this cohort more so than the younger group.

### **1.5.3 Study 3 – Multifractal Analysis of Asymmetric Walking in Young and Older Adults**

While monofractal analysis (e.g., DFA) may provide insights regarding locomotor organization and response to constraints, a multifractal analysis will allow for a more comprehensive assessment of subsystem autonomy or dependence. That is, there may exist more than one subsystem at a particular time scale interacting with other subsystems at other time scales. One major assumption of the DFA algorithm is that a single scaling exponent can faithfully describe the overall fractality of a signal or behavior. However, transient periods of very high or very low variability would produce local scaling exponents that are closer to  $\alpha = 0.5$  and  $\alpha = 1.5$ , respectively. By evaluating fractality from a local perspective, the evolution of the signal can be determined. Few studies have explored the degree of multifractality in young and older adults, and of those studies, unanticipated results have been reported. Specifically, Munoz-Diosdado and colleagues (2005; Munoz-Diosdado et al., 2003) reported that young healthy adults exhibit nearly

monofractal behavior in gait, while children, elderly, and those with neurological disease display greater multifractality. The phenomena from these studies require further empirical scrutiny.

Study 3 will test the following hypotheses:

- H3.1:** Young adults will display less multifractality compared to older adults. This hypothesis is based on earlier studies evaluating multifractality across the lifespan and found that the width of the multifractal spectrum was larger in children and older adults compared to their younger counterparts (Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003).
- H3.2:** Young adults will exhibit greater multifractality in response to asymmetric walking compared to older adults. The asymmetric gait is expected to perturb participants, and therefore intermittent corrections to locomotor patterns (e.g., brief periods of high or low variability) may be beneficial in maintaining the overall goal of continued locomotion. If young, healthy adults possess a greater capacity to adapt their gait patterns, this may be achieved via these intermittent corrections, while older adults may exhibit less ability to make these intermittent modifications.
- H3.3:** Young adults will display reduced multifractality during the 2<sup>nd</sup> and 3<sup>rd</sup> split-belt trials, compared to older adults. This hypothesis is based on the assumption that young, healthy adults will quickly adapt their gait to the asymmetric walking pattern and no longer require intermittent corrections by the 2<sup>nd</sup> and 3<sup>rd</sup> split-belt conditions. Older adults may require more time to adapt gait,

and thus exhibit greater multifractality compared to young adults in the 2<sup>nd</sup> and 3<sup>rd</sup> split-belt conditions.

## **1.6 Summary**

Fall events present a significant danger for the aging population. While several steady state gait parameters are known to have moderate associations with fall risk, precise measures of gait adaptability and stability have not been fully scrutinized. The first aim of this dissertation is to determine if measures of complexity and fractality during steady state align with observed gait adaptability performances. The second aim will address if fractality, complexity, and gait adaptability and stability are irrespective of or dependent upon age. The final aim of this dissertation is to determine if multifractal analysis reveals important information supplemental to or separate from the more common monofractal analysis. Determining precise quantifications of gait stability and adaptability allow practitioners to: 1) categorize an individual's risk of future falls and provide appropriate recommendations for gait training, and 2) determine efficacy of fall prevention interventions.



## **CHAPTER II**

### **LITERATURE REVIEW**

Walking is a common activity or task performed by most individuals for most of the lifespan. Upright, bipedal locomotion is a highly beneficial form of gait, providing advantages over quadrupedal locomotion. It has afforded humans the ability to perform ancillary activities with their upper limbs (dual or multitask). In addition, arm motion during walking and running provides an axial torque to counteract the torque generated by the legs (Chapman, 2008). However, freeing of the upper limbs comes at the cost of transient instabilities during walking. During every single-support phase, the COM often extends beyond the BOS, and the swing leg must catch up to prevent a fall. As we age, diminished vision, somatosensory information, and muscular strength further complicate the act of locomotion. As a result, older adults fall often, and the consequences can be physically or emotionally severe. While several interventions and gait parameters have been associated with fall risk, the quantification of adaptable and stable gait is still evolving.

#### **2.1 Falls During Locomotion**

##### **2.1.1 Overview**

Falls occur frequently in older adults. Approximately one-third of all individuals aged 65 years or older experience a fall every year. These fall events are the leading cause of hospitalization and injury-related deaths in this population (CDC, 2011, 2012). Falls most often occur while walking at normal or hurried walking speeds (Berg et al.,

1997). A 'fall' can be defined as an unintentional decent under the acceleration of gravity from upright standing or walking, resulting in undesired contact with the support surface. There are many potential intrinsic, extrinsic, or behavioral factors that may result in a fall. Intrinsic factors include changes in physiology due to aging or disease, such as visual impairments, muscular weakness, reduced cognitive function, or general postural instability. Extrinsic factors involve contact with external perturbations, such as slipping on a slick surface or tripping on an obstacle. Finally, behavioral factors that may contribute to falls include lifestyle decisions in which activities undertaken ultimately increase overall fall risk, such as walking in a poorly lit area containing various obstacles (Greany & Di Fabio, 2010). Although many possible mechanisms for falls exist, Troy and Grabiner (2006) indicated that up to 50% of all falls are due to slipping accidents.

The consequences of falls present not only a significant physical and psychological affliction in older adults, but also a substantial economic burden. The Centers for Disease Control and Prevention estimate falls accounted for ~ \$18.6 billion in health care costs in 2005 (CDC, 2005a, 2005b, 2005c), and this number is estimated to rise to \$59.6 billion by 2020.

### **2.1.2 Fall Prevention Interventions**

With the prevalence of falls increasing, many interventions have been developed to reduce fall rates. These interventions typically involve strength, cardiovascular, or balance training, or some combination therein (Cadore et al., 2013; Lord et al., 2005). Other interventions involve fall prevention education, medication adjustments, or eyewear prescription updates (M. Choi & Hector, 2012; Lord et al., 2005). Studies typically explore the efficacy of single or multifactorial fall prevention interventions by

determining rates of falls in an intervened versus controlled group. Results from individual studies, as well as review papers and meta-analyses, have been mixed.

One large study using data from the Cochrane Review (Gillespie et al., 2004) determined that multi-faceted fall prevention programs significantly reduce the occurrence of falls. A study by Tinetti et al. (1994) found that a 3-month multifactorial intervention reduced the occurrence of falls, as 35% of the intervened group reported a fall at a 1-year follow up, compared to 47% of the control group. Another review reported overall improvements in balance, strength, and fall risk following various interventions (balance, strength, cardiovascular training (Cadore et al., 2013).

While some literature reports benefits from these interventions in the form of reduced fall events following the intervention, others report little or no benefits achieved (M. Choi & Hector, 2012; S. Gates et al., 2008; Lord et al., 2005; Vind et al., 2009). Studies developed as a follow-up to the Cochrane review have expressed findings that contradict the originally published results (S. Gates et al., 2008; Vind et al., 2009). Vind and colleagues (2009) compared a individual-specific intervention group (based on an individual's risk factors) to a control group, and determined there were no fall-reducing effects from the intervention. In a review and meta-analysis of 19 randomized and quasi-randomized controlled fall-intervention studies, Gates et al. (2008) concluded that there was little or no evidence to support the notion that interventions reduced the number of falls (risk ratio 0.91). In a meta-analysis, Choi and Hector (2012) determined multi-factorial interventions reduced the rate of falls by only 10% on average. Additionally, Hill-Westmoreland and colleagues (2002) concluded in a 12-study meta-analysis that various interventions reduced the rates of falls by only 4%. Lord et al. (2005) concluded

after a 6-month individualized fall prevention intervention that, while the intervened group improved fall risk scores (as measured by the Physiological Profile Assessment) compared to a control group, the actual rate of falls were not different. Lightbody and colleagues (2002) conducted a similar experiment, and results revealed the intervened group did not improve fall rates compared to the control group, even though scores of physical function were increased.

Clearly, the efficacy of fall prevention programs requires further evaluation. Many of the aforementioned interventions have focused on general intrinsic and behavioral issues associated with falls. However, determining relationships between falls and risk factors such as static balance provide indirect associations, as opposed to cause-and-effect information. That is, risk factors cannot directly explain why a person may fall; they can only offer the statistical ‘odds’ or likelihood of a future fall. In order to understand physiologically and biomechanically why a person falls (or recovers), kinematic and kinetic analyses must be performed. Thus, many researchers have developed biomechanically analytic paradigms that evaluate parameters of steady state or perturbed gait (i.e., elicit a perturbation) to evaluate gait parameters that may distinguish successful versus failed recoveries.

### **2.1.3. Predictors of Future Falls**

#### **2.1.3.1. Unperturbed Gait Parameters**

Efforts to attenuate the burden falls place on older adults have led researchers to search for gait variables that distinguish fallers from non-fallers. That is, the goal of these studies has been to identify individuals at a high risk of falling by determining

characteristics of walking gait that may predict the likelihood of a future fall. These attempts have led to analysis of various parameters during unperturbed walking gait including: step length (Lockhart & Liu, 2008; Lockhart, Smith, & Woldstad, 2005), stride time variability (Hausdorff, 2007; Maki & McIlroy, 1997), stride length variability (Dean et al., 2007; Maki & McIlroy, 1997; Verghese et al., 2009), step width (Dean et al., 2007), step width variability (Dean et al., 2007), fractal dynamics (Hausdorff, 2007; Hausdorff et al., 1997; Hausdorff et al., 1996; Jordan et al., 2007b; Rhea, Kiefer, D'Andrea, et al., 2014), local dynamic stability using the Lyapunov exponent (Dingwell & Cusumano, 2000; Dingwell et al., 2001; Dingwell et al., 2000; Dingwell & Marin, 2006; England & Granata, 2007; Kang & Dingwell, 2008a; Lockhart & Liu, 2008), Poincare analysis (Granata & Lockhart, 2008), and limit cycle attractor analysis (Vieten, Sehle, & Jensen, 2013). In addition, preferred walking speed, or the speed at which an individual tends to walk under normal conditions, has been assessed (Himann et al., 1988). These above-mentioned variables have been shown to differentiate cohorts and fall risk. For example, shorter step lengths (Lockhart & Liu, 2008; Lockhart et al., 2005), longer step widths (Dean et al., 2007), and greater step width variability (Dean et al., 2007) and stride time variability (Hausdorff, 2007) have been associated with increased risks of falling.

#### **2.1.3.2. Perturbed Gait Parameters**

While some of these variables are associated with relative fall risk, directly determining fall resistance capability in the absence of a slip perturbation is difficult. For this reason, some studies have attempted to distinguish fallers from non-fallers by eliciting a slip and evaluating characteristics during the slip that differentiate between the

groups. These gait characteristics include: slip foot displacement (Brady, Pavol, Owings, & Grabiner, 2000; Lockhart & Kim, 2006; Lockhart et al., 2005; Troy, Donovan, Marone, Bareither, & Grabiner, 2008), slip foot velocity (Brady et al., 2000; Chambers & Cham, 2007; Chambers, Margerum, Redfern, & Cham, 2003; Lockhart & Kim, 2006; Lockhart et al., 2005; Troy et al., 2008), slip foot acceleration (Lockhart et al., 2005; Troy et al., 2008), foot angle at heel strike (Brady et al., 2000), ankle, knee, and hip moments (Cham & Redfern, 2001), arm displacements (Marigold, Bethune, & Patla, 2002; Tang & Woollacott, 1998), center of mass (COM) displacement (You, Chou, Lin, & Su, 2001), and COM motion state (position and velocity) (Espy, Yang, Bhatt, & Pai, 2010; Espy, Yang, & Pai, 2010; Yang, Bhatt, & Pai, 2011). Others have used surface electromyography to evaluate muscular activation patterns such as: onset timing (Chambers & Cham, 2007; Tang & Woollacott, 1998), activation rate (Lockhart & Kim, 2006), burst magnitude duration (Tang & Woollacott, 1998), and co-activation duration (Chambers & Cham, 2007; Tang & Woollacott, 1998). While all of these parameters have shown some capacity to differentiate fall outcomes, two (slip displacement (Brady et al., 2000) and velocity (Troy et al., 2008)) have exhibited particular effectiveness at discriminating between fallers and non-fallers. For example, slip foot displacement correctly classified 70% of the perturbation outcomes as either fall or recovery (Brady et al., 2000). However, the methodological challenge to this paradigm is that a slip must be initiated before the classification can be predicted (or verified), whereas other measures (e.g., foot angle at heel strike and COM motion state) are determined at the onset of the slip or during unperturbed gait.

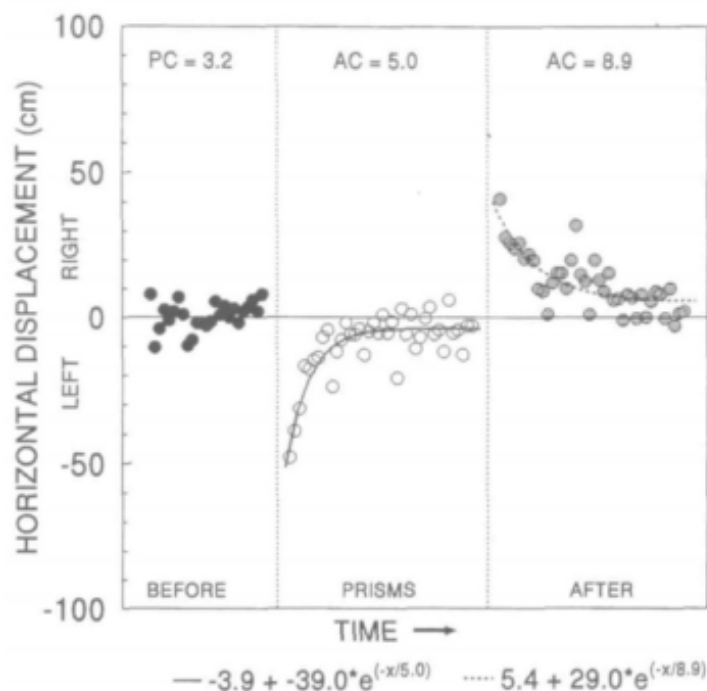
### **2.1.3.3. Cautious Gait**

Finally, when an individual anticipates a slippery floor while walking, a different gait pattern often emerges, including: slower gait speeds (Fong, Mao, Li, & Hong, 2008), shorter step lengths (Bhatt, Wang, Yang, & Pai, 2013; Cham & Redfern, 2002), more anterior COM position (Bhatt et al., 2013), flatter lead foot at heel strike (Cham & Redfern, 2002; Heiden, Sanderson, Inglis, & Siegmund, 2006; Marigold & Patla, 2002), slower velocity of ankle plantar flexion following heel strike (Cham & Redfern, 2002), greater shank angle at heel strike (Brady et al., 2000), reduced peak joint moments (Cham & Redfern, 2002), and increased muscular activity (Heiden et al., 2006). Taken together, individuals adopt a more cautious gait pattern that minimizes foot displacements in the event of a slip.

To summarize, falls occur frequently within the aging population. Most often, these falls occur during walking, and because of this fact, various interventions have been developed. The primary outcome goal of each intervention is usually a reduced number of falls. While some interventions have provided evidence of their efficacy to reduce falls, others have not. From a macroscopic perspective, reviews and meta-analyses on fall prevention interventions have indicated that, at best, results vary. At worst, interventions do little or nothing to reduce the rate of falls. Alternatively, biomechanical analyses have provided gait parameters during steady state and perturbed gait that are associated with fall risk. While these various parameters are promising, they currently serve as a moderate or weak predictor of future fall risk.

## 2.2 Gait Adaptability

The word ‘adaptability’ generally refers to the capacity to successfully respond to changing demands. ‘Changing demands’ usually refer to changes to environmental or task constraints. For example, Martin and colleagues (1996) instructed participants with neurological deficits and healthy controls to throw a



**Figure 2.1: Prism goggle adaptation paradigm.** Adaptation to prism goggles that shift the visual field (center cluster, white circles), and re-adaptation after removal of the goggles (right cluster, grey circles). From Martin et al, (1996).

clay ball several times at a target 2 meters away, attempting to hit the center of the target. They then performed the activity while wearing prism goggles, which shifted the entire visual field 17° to the left. While this initially and expectedly increased lateral error to the left, this error no longer occurred after an average of 8.5 throws (Figure 2.1 middle, white circles). Following the prism adaptation trial, participants performed a final condition



without the goggles. The researchers observed lateral errors in the opposite direction (right) that lasted for the first 6.5 throws, on average, before a return to generally successful attempts (Figure 2.1 right, grey circles). Essentially, when exposed to altered visual information, individuals show the capacity to adapt visual-haptic multi-sensory integration to successfully complete a task. When the altered environment is removed, individuals must re-adapt their multimodal integration.

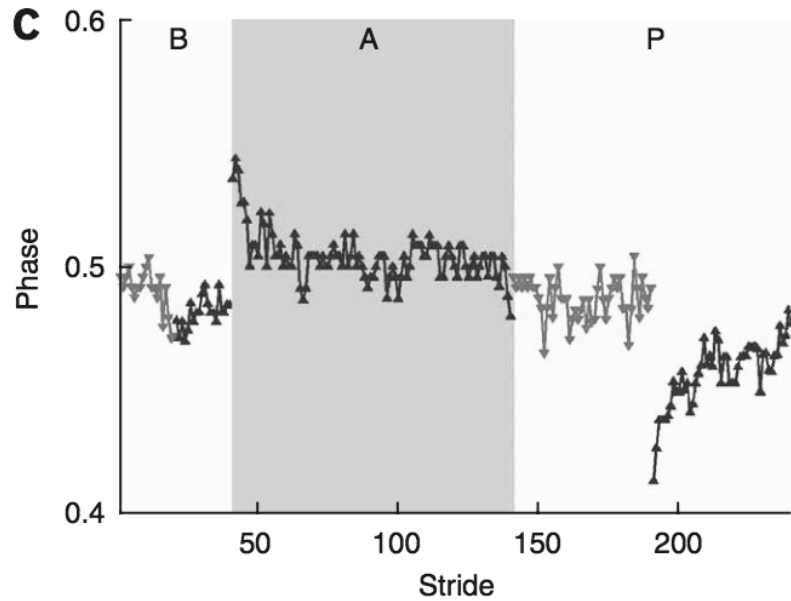
In reference to walking, the locomotor system has the ability to change if needed. Specifically, gait adaptability can be defined as the locomotor system's ability to respond to changing demands within the environment or task. Some researchers alternatively refer to this ability or skill as 'flexibility' (Wagenaar, Holt, Kubo, & Ho, 2002). Few studies have directly evaluated this notion of adaptability by quantifying a system's ability to modify gait patterns, or the speed by which desired locomotor patterns are achieved.

### **2.2.1 Split-Belt Treadmill Paradigm**

An excellent paradigm to assess adaptability is the split-belt treadmill. This treadmill has two adjacent belts arranged so that each foot is on a separate belt. These two belts have separate motors, and as such are independently controlled. This allows the programmer to move one belt faster than the other, or in a different direction. Essentially, this apparatus allows researchers to expose participants to asymmetric gait constraints in order to determine how (and how well) they can adapt their gait patterns.

### 2.2.1.1 Split-Belt Adaptation and Re-Adaptation

The general phenomenon with the split-belt treadmill is that, when exposed to an asymmetric task constraint, individuals attempt to regain symmetry rather than remain asymmetric. This attempt to re-symmetrize may represent the system being pulled into a more stable attractor state. Bruijn and colleagues (2012) compared older and young adults in their ability to achieve symmetry in step length, stride length, swing speed, and percentage swing time when exposed to asymmetric gait conditions. Older adults were slower in adapting their gait patterns and illustrated fewer aftereffects, indicating poorer capacity to adapt their gait. Choi and Bastian (2007) provided evidence that participants could rapidly adapt to not only different forward walking speeds for each leg (2:1 ratio), but also alternating directions (one leg forward and the other backward). Similar to the findings of Martin et al., (1996), Choi and Bastian (2007) also noticed a required re-adaptation period. That is, there was an initial adaptation from asymmetry to symmetry during the asymmetric (2:1 forward walking) condition. This adaptation is illustrated in Figure 2.2. The forward walking (dark grey triangles) baseline (B) phase is characterized by anti-phase motion (phase  $\sim 0.5$ ). Note that a phasing of 0.5 indicates perfect anti-phase, which corresponds to symmetrical gait. The adaptation (A) phase changes from initially  $> 0.5$  towards 0.5. When the split-belt asymmetry was removed (post-adaptation (P)), the adaptation resulted in asymmetry in the opposite direction (Figure 2.2 P, phase change from  $< 0.5$  towards 0.5 (dark grey triangles)) That is, when the belts moved at the same speed, the leg phase that lagged during the split-belt condition initially led. The re-adaptation phenomenon is illustrated by the return to 0.5 phasing. Note that the backward



**Figure 2.2. Symmetry measures during split-belt walking.** B = baseline, A = adaptation, and P = post-adaptation trials. Forward and backward walking represented by dark grey and light grey triangles, respectively. Anti-phase = 0.5. From Choi & Bastian, (2007).

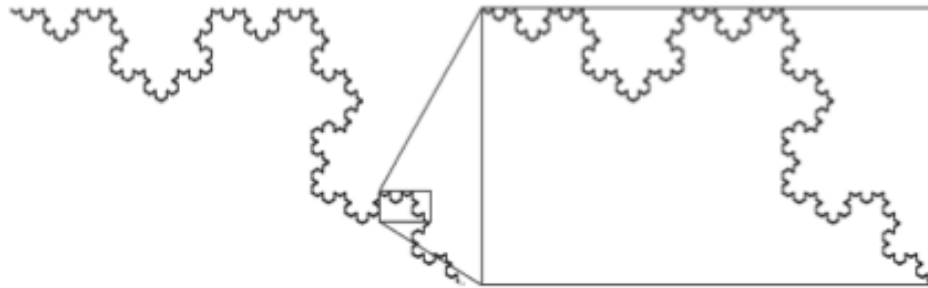
walking trials (light grey inverted triangles) did not cause an adaptation to the subsequent forward walking trials (Figure 2.2 P). Finally, Dietz et al. (1994) provided further evidence that individuals have the capacity to rapidly adapt their gait patterns (within 15-20 strides), even when gait speeds were considerably different (2.0 m/s and 0.5 m/s) during asymmetric split-belt conditions.

### 2.2.2 Fractal Analysis

In 1922, Lewis Fry Richardson, in describing his observations of the interactions across spatial scales in the atmosphere, remarked:

“Big whirls have little whirls that feed on their velocity; and little whirls have lesser whirls, and so on to viscosity.” (Richardson, 1922)

It would not be until 1975 that mathematician Benoit Mandelbrot would first coin the term ‘fractal’, which was based on the latin word *fractus*, meaning fractured (Mandelbrot, 1977). A fractal is essentially an infinitely repeating pattern that is self-similar across multiple scales. A fractal may possess geometric self-similarity, as is the case in, for example, the Koch snowflake (Figure 2.3) or the



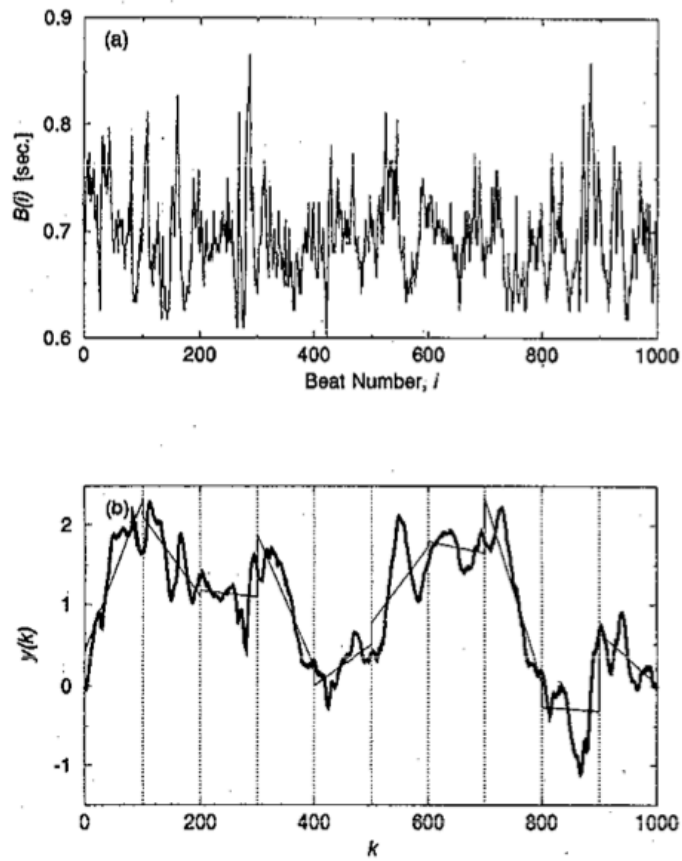
**Figure 2.3: Koch snowflake as an example of a geometric fractal object.** The object is self-similar in that smaller pieces are copies of the entire piece. Here the small box is enlarged to reveal more details about its structure (large box). From Liebovitch & Shehadeh, (2003).

Sierpinski triangle (Liebovitch & Shehadeh, 2003), or it may possess statistical self-similarity. A statistically self-similar object or signal is one whereby smaller pieces (or time scales) resemble the entire piece (or time series) (Liebovitch & Shehadeh, 2003). Although not precisely the same, the small pieces/time scales are similar to the larger ones based on a power-law distribution. That is, when plotted on a log-log graph, the probability density function (PDF) and scale size are linearly related. While many structures in natural phenomena (trees, lightning) and human physiology (nerves, blood vessels) exhibit a fractal nature, it was not until 1995 that Peng and colleagues determined biophysical signals may also display fractal behavior (Peng et al., 1995). Peng et al. (1995) developed a modified root-mean-square analysis of a random walk,

termed detrended fluctuation analysis (DFA, Equation 2.1). The DFA algorithm evaluates the degree of variability of a signal at different time scales, or window sizes. In order to accomplish this, a biophysical signal is first integrated, then sectioned into non-overlapping boxes or windows ( $n$ ). In each window, a least-squares linear fit line is applied to the signal (Figure 2.4). A root-mean-square analysis is then performed on the data, subtracting the local trend line's y-coordinate from the integrated signal's fluctuations. This process is performed and averaged across all windows of a given window size ( $n$ ), as shown in Equation (2.1).

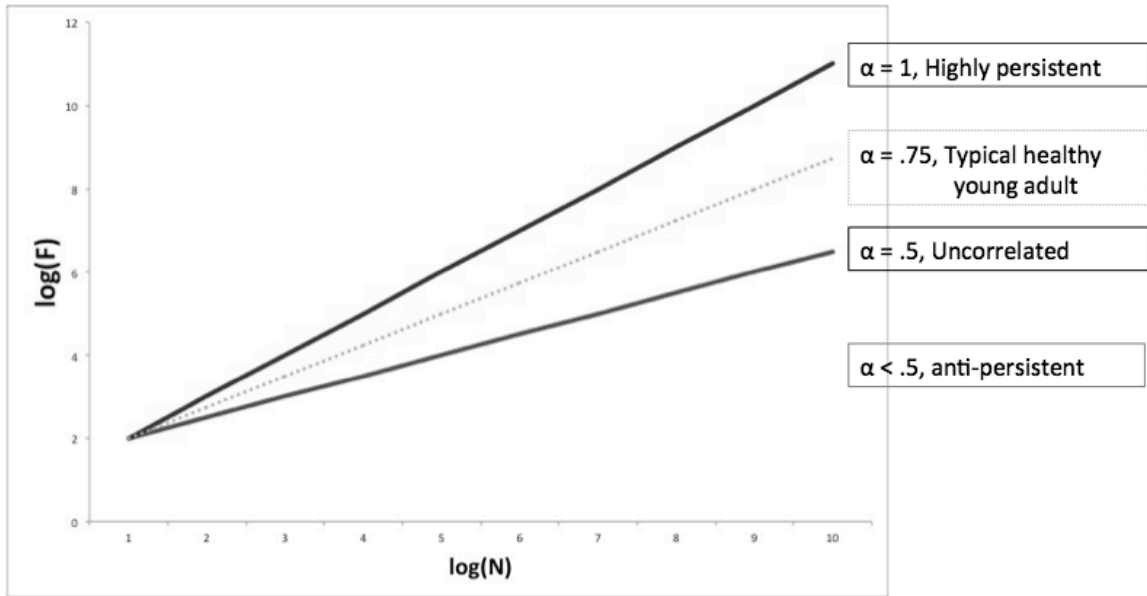
$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^N [y(k) - y_n(k)]^2} \quad \text{Equation 2.1}$$

where  $F(n)$  is the average fluctuation in a given window ( $n$ ),  $N$  is the total number of windows of size  $n$ ,  $y(k)$  is the integrated signal, and  $y_n(k)$  is the y-coordinate of the local trend line. The average fluctuation ( $F$ ) at a given window size ( $n$ ) is then



**Figure 2.4: Illustration of detrended fluctuation analysis (DFA) method on a biophysical signal.** A time series (top) is integrated and sectioned into non-overlapping windows (bottom). Within each window, a linear fit line is applied, and a root-mean-square analysis of fluctuations from the fit line is performed. From Peng et al, (1995).

plotted in a log-log graph against the window size ( $n$ ). A linear relationship on this double-log graph indicates the existence of power law scaling (Peng et al., 1995).



**Figure 2.5: Different scaling exponents and their meanings.** When the log of fluctuations ( $\log(F)$ ) is plotted against the log of the scale size ( $\log(N)$ ), a linear relationship indicates power-law scaling. The slope, or  $\alpha$ , of the linear fit line indicates the presence or absence of fractality.

The slope of the linear fit on the log-log graph is called the scaling exponent, singularity exponent, or  $\alpha$  (Figure 2.5). The DFA algorithm is highly advantageous in biological signals because the local detrending avoids issues related to signal non-stationarity. A scaling exponent of 1 indicates  $1/f$  phenomena, whereby the power of the signal is inversely related to the frequency (West & Shlesinger, 1990). A scaling exponent of  $\alpha = 0.5$  indicates a completely uncorrelated signal, equivalent to white noise. A scaling exponent of  $0.5 < \alpha \leq 1.0$  indicates long-range persistence, whereby small or large fluctuations are likely to be followed by small or large fluctuations, respectively. In contrast, a scaling exponent of  $0 < \alpha < 0.5$  indicates long-range anti-persistence, whereby small fluctuations are likely to be followed by large fluctuations, and vice versa. Finally, a scaling exponent  $> 1.0$  no longer signifies a power-law relationship, and a scaling exponent of 1.5 indicates Brown noise (i.e., the integration of white noise) (Peng et al.,

1995). Brown noise is characterized by nonstationary random drifts, whereby it is partially dependent upon its previous conditions, and partially random. That is, it exhibits random steps at short time scales, yet the overall distance traveled is dependent upon the number of steps taken. This is in contrast to white noise ( $\alpha = 0.5$ ), which is absent of dependence upon previous or future states. Peng et al. (1995) applied the DFA algorithm to the heart-beat interval timing of healthy adults with no history of heart disease, and compared it to heartbeat intervals of individuals with severe heart failure. The DFA algorithm determined that the healthy individuals exhibited a scaling exponent of  $1.00 \pm .11$ , indicating long-range correlations and, more specifically,  $1/f$  behavior. The individuals with severe heart disease, on the other hand, exhibited scaling exponents of  $1.24 \pm .22$ , a behavior that approached brown noise ( $\alpha = 1.5$ ). This indicates these heartbeat intervals were no longer a power-law relationship, and they more closely resembled a random walk.

#### **2.2.2.1 Monofractals in Human Gait**

In a series of follow-up experiments, and the first of their kind to evaluate the potential fractal-like nature of human locomotion, Hausdorff and colleagues (Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996) utilized the DFA algorithm on stride-time variability. A stride time or stride interval is the amount of time from heel strike of one foot to the subsequent heel strike of the same foot. Although appearing relatively random, deeper inspection of stride times over a multitude of strides provides evidence of patterns. Gait studies employing the DFA algorithm have provided an indication that young, healthy adults exhibit persistent long-range correlations, that is,



scaling exponents of  $0.5 < \alpha \leq 1.0$ . The exact scaling exponent varies by study. For example, young healthy adults walking at their preferred speed have reported scaling exponents of  $\alpha = .76 \pm .11$  (Hausdorff et al., 1995) and .84 (Hausdorff et al., 1996). The discrepancies in precise scaling exponent values can likely be explained by differences in experimental design or parameterization. For example, greater trial lengths create a larger number of stride times, which will impact the DFA algorithm. Additionally, determination of minimum and maximum window sizes have been debated, and while specific guidelines have been suggested (Damouras, Chang, Sejdic, & Chau, 2010), a clear consensus has not been agreed upon. Finally, treadmill versus overground walking has displayed differences in scaling exponents, as treadmill walking generally reduces the scaling exponent (Terrier & Deriaz, 2011).

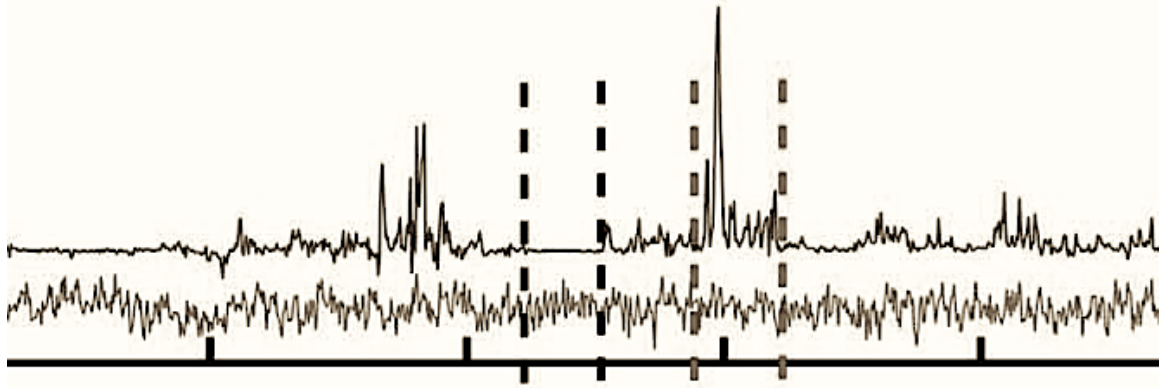
In addition to preferred walking trials, long-range correlations in young adults were observed at faster or slower walking speeds. In fact, walking slower or faster than preferred resulted in *greater* scaling exponents of  $\alpha = 0.9$  and  $1.0$ , respectively (Hausdorff et al., 1996). This phenomenon has been repeated in subsequent studies on walking (Jordan et al., 2007b) and running (Jordan, Challis, & Newell, 2007a). On the other hand, walking while keeping pace with a metronome yields uncorrelated scaling exponents ( $\alpha \sim 0.5$ ) (Hausdorff et al., 1996).

In contrast to young healthy adults, older adults were shown to walk with scaling exponents of  $\alpha \sim 0.68$ , and individuals with Huntington's disease walked with scaling exponents of  $\alpha \sim 0.6$ . Both of these cohorts displayed a breakdown of long-range correlations, with scaling exponents closer to uncorrelated random fluctuations (Hausdorff et al., 1997). Additionally, the scaling exponent was linearly associated with

the disease severity ( $r = .78$ ), whereby greater disease severity displayed scaling exponents closer to 0.5 (Hausdorff et al., 1997). Based on the breakdown of long-range correlations with aging, Huntington's disease, and metronome, the authors speculated that supraspinal processes are responsible for the fractal behavior in gait. These higher order centers are either diminished with age or disease, or can override the natural behavior when keeping with a metronome.

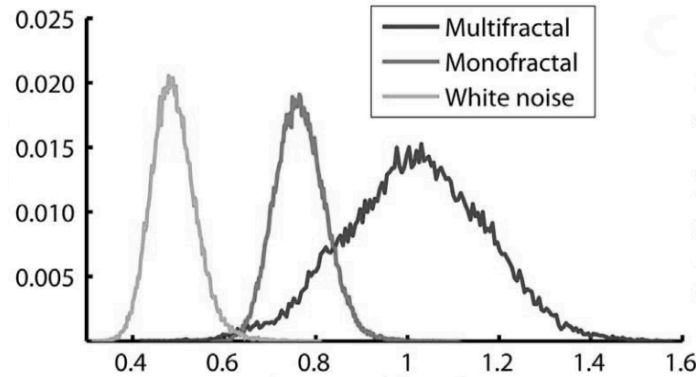
#### **2.2.2.2 Multifractals in Human Gait**

One major assumption with the DFA measure is that one scaling exponent sufficiently describes the entire biophysical signal. Qualitative inspections of some signals, however, reveal intermittent periods of very high variability (lower  $\alpha$  values) and periods of very low variability (higher  $\alpha$  values, Figure 2.6). Thus, multifractal analysis was developed to describe signals that cannot be expressed using a single scaling exponent. Several methods have been developed to evaluate the multifractal nature of a signal. One common method involves systematically amplifying large or small fluctuations via a parameter known as a  $q$ -order or  $q$  moment (Ivanov et al., 1999; Kelty-Stephen, Palatinus, Saltzman, & Dixon, 2013; Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003). This parameter implements weighting to different characteristics. For example, as  $q$  increases, the scaling exponent decreases, and vice versa. Thus, a monofractal signal will not be affected by this parameter, while a multifractal signal will.



**Figure 2.6: Illustration of the difference between a monofractal and multifractal signal.** The monofractal (bottom) is absent of periods of large variability or small variability. The multifractal (top), conversely, exhibits periods of very little variability (between black dashed lines) and periods of very large variability (between grey dashed lines). From Ihlen & Vereijken, (2013).

An alternative method that appropriately assesses small data sets, such as the stride time variability of a finite walk, was introduced by Ihlen and colleagues (Ihlen, 2012; 2013a, 2013b). This analysis evaluates the scaling exponent in a time series by performing a DFA using a moving window. The benefit of this analysis is that it displays the evolution of the *local* scaling exponent across a trial. The end result is a spectrum of scaling exponents (Figure 2.7). The final step of this multifractal analysis is to place all of the scaling exponents into a probability distribution graph. This provides information regarding: 1) the mode, which is analogous to the results of a monofractal analysis, and 2) the width of the spectrum. A wider spectrum indicates a more ‘multifractal’ signal. Figure 2.7 displays the results of a multifractal analysis of a known multifractal (black), monofractal (dark grey), and white noise (light grey) signal (Ihlen, 2012). The multifractal signal has the largest range width, while the white noise signal has the smallest.



**Figure 2.7: Multifractal analysis using the probability distribution method of local scaling exponents.** The x-axis displays the local scaling exponent, and the y-axis is the probability distribution. From Ihlen, (2012).

Evaluation of heartbeat intervals using multifractal analysis has revealed differences in healthy and diseased individuals (Ivanov et al., 1999). Specifically, young, healthy individuals display a multifractal spectrum that includes smaller and larger scaling exponents, while individuals with heart failure exhibit a drastically reduced spectrum width. These findings indicate a loss of adaptability of the system.

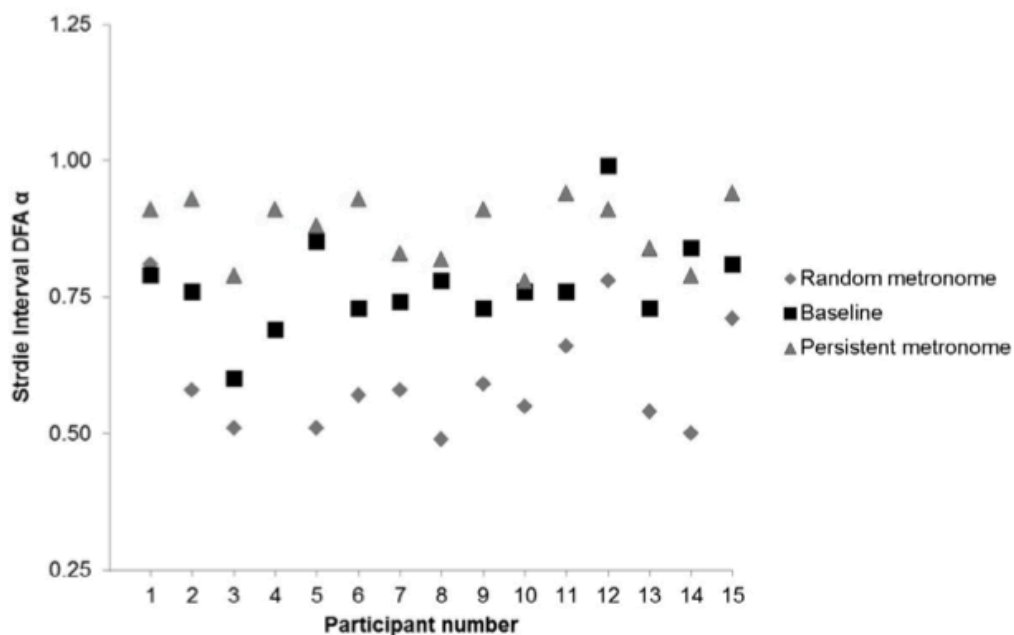
Analysis of stride intervals under steady state conditions, however, have expressed opposite findings. To be clear, few studies have evaluated stride time fluctuations, or any gait parameter for that matter, for multifractal characteristics. Thus far, though, healthy young adults appear to display nearly monofractal fluctuations, while older adults and adults with neurological disorders (Parkinson's, Huntington's, ALS) display a greater width of the multifractal spectrum (Muñoz-Diosdado, 2005; Muñoz-Diosdado et al., 2003). Additionally, children exhibit greater multifractality that progressively narrows with age until it appears similar to that of a young healthy adult (Munoz-Diosdado et al., 2003). The explanation for the apparent differences between heart rate and stride time dynamics may be methodological. For example, in the study on multifractal analysis of heartbeat intervals, as well as the study of gait dynamics, the

researchers used the q-order method in determining the scaling exponent spectrum. The study by Munoz-Diosdado et al. (2003) used prior gait data from 4 distinct databases. The data lengths for each of these databases were not reported. Considering three of the cohorts had neurological diseases, and the fourth were older adults, the trial lengths were most likely limited. For this reason, determining the multifractal spectrum using q-order statistics may not be appropriate. Rather, determination of the probability distribution of local scaling exponents should have been employed. Beyond potential data length discrepancies, gait speed differences between groups may have skewed the data, considering monofractal analyses are sensitive to gait speed (Hausdorff et al., 1996; Jordan et al., 2007b), and these data were collected from various databases. Finally, an alternative explanation for these findings are that, under steady state conditions, young healthy adults do in fact produce a monofractal signal that is void of periods of small or large fluctuations. Certainly, the extent to which constraints upon the individual, task, or environment affect the multifractal spectrum remains unknown.

### **2.2.2.3 Fractal Entrainment**

Finally, while attempting to adhere to a metronome removes naturally occurring long-range correlations (Hausdorff et al., 1996), adhering to an auditory or visual stimulus that exhibits fractal-like behavior has been shown to increase the strength of long-range correlations (Hove, Suzuki, Uchitomi, Orimo, & Miyake, 2012; Kaipust, McGrath, Mukherjee, & Stergiou, 2013; Rhea, Kiefer, D'Andrea, et al., 2014; Rhea, Kiefer, Wittstein, et al., 2014; Stephen, Stepp, Dixon, & Turvey, 2008). Gait training using auditory stimuli has been used in clinical settings to evaluate changes in standard gait parameters (Thaut et al., 1996) and more recently fractal dynamics (Hove et al.,

2012). Specifically, Hove (2012) noted a shift in the fractal dynamics of patients with Parkinson’s disease closer to  $1/f$ . Rhea and colleagues (2014) presented a visual stimulus that exhibited long-range correlated intervals ( $\alpha = .98$ ), and instructed participants to match the timing of their heel strikes to the stimulus. Participants’ scaling exponents increased from baseline ( $\alpha = .77 \pm .09$ ) to more persistent values ( $\alpha = .87 + .06$ , Figure 2.8). In a follow-up study, participants followed a fractal-like visual stimulus for 15 minutes, and then walked without a stimulus for an additional 15 minutes. The pattern of fluctuations remained persistent (i.e., higher scaling exponent compared to baseline).



**Figure 2.8: Effects of fractal entrainment on stride interval scaling exponent.** There was an overall increase in fractal scaling during entrainment to the metronome (triangles) compared to baseline (squares), and reduction in fractal scaling during metronomic walking (diamonds). From Rhea et al, (2014).

### 2.2.3 Complexity Analysis

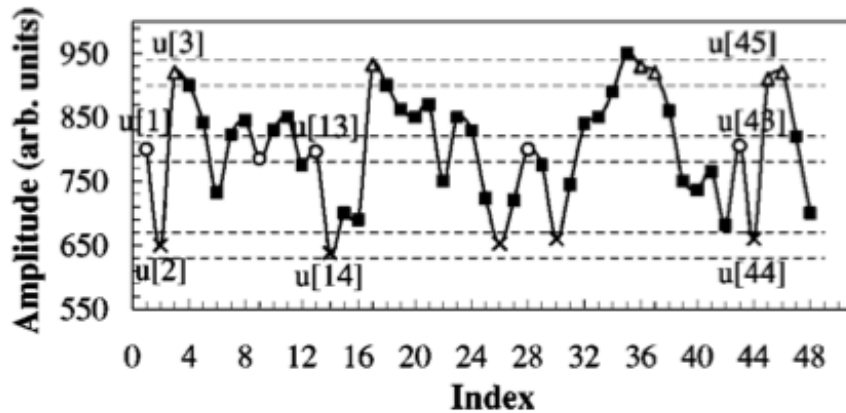
In addition to fractal dynamics, measures of complexity have been used to evaluate a locomotor system's adaptability. At its root, a complex behavior is non-random with interactions within and between spatio-temporal scales (van Emmerik et al., 2016). However, complexity is an often cited and disparately defined concept. Complexity can be defined as the amount of uncertainty in a behavior. It can relatedly be defined by the amount of information required to predict the future conditions of a system (Lipsitz & Goldberger, 1992). A more complex system requires more information to determine its dynamic evolution. In other words, complexity describes how well a system's evolving behaviors can be predicted (Burggren & Monticino, 2005). A signal such as a sine wave is highly deterministic, and therefore represents a system of low complexity. In contrast, a system that exhibits long-range correlations across spatio-temporal scales is thought to represent a highly complex behavior.

Complex behaviors are considered to be well adapted to changing environmental conditions. Predictable behaviors, on the other hand, are less complex and may lack the capacity to adapt to changing conditions. However, similar to the various definitions of complexity, numerous algorithms exist that quantify a system's or behavior's complexity. Fractal analyses quantify the extent of long-range correlations, whereby a signal with a scaling exponent of  $\alpha = 1.0$  or  $1/f$  indicates optimal complexity (Lipsitz, 2002). The fractal dimension or state space analysis evaluates the dimensionality of a signal. The more dimensions or independent variables needed to define a system, the more complex it is. Finally, various entropy measures have been developed. Based on Kolmogorov entropy, which determines the rate of new information that is generated, approximate

entropy was developed for shorter time series (Richman & Moorman, 2000). If there is a high probability of repeating sequences, and thus a high degree of regularity, approximate entropy is low. This algorithm has been deemed biased due to its self-matching nature; that is, sequences match themselves. This bias manifests as high dependency on the length of the data set, as shorter data sets are consistently lower in entropy. To account for this issue, a newer algorithm was developed that does not self-match, known as sample entropy (SampEn, Equation 2.2, Figure 2.9) (Lake et al., 2002; Richman & Moorman, 2000).

$$SampEn(m, r, N) = -\ln \frac{\phi^{m+1}(r)}{\phi^m(r)} \quad \text{Equation 2.2}$$

where  $N$  is the length of the data set,  $r$  is a tolerance level known as the radius of similarity,  $m$  is the distance between points being compared, and  $\phi$  is the



**Figure 2.9: Illustration of sample entropy algorithm.** The signal at  $u[1]$  is bounded by dotted lines whose values are  $\pm r$ , where  $r$  is a criterion threshold. Two data points are considered a ‘match’ if they fall within the  $\pm r$  boundary. Additionally, consecutive data points can be linked as a pattern. From Costa et al, (2003).



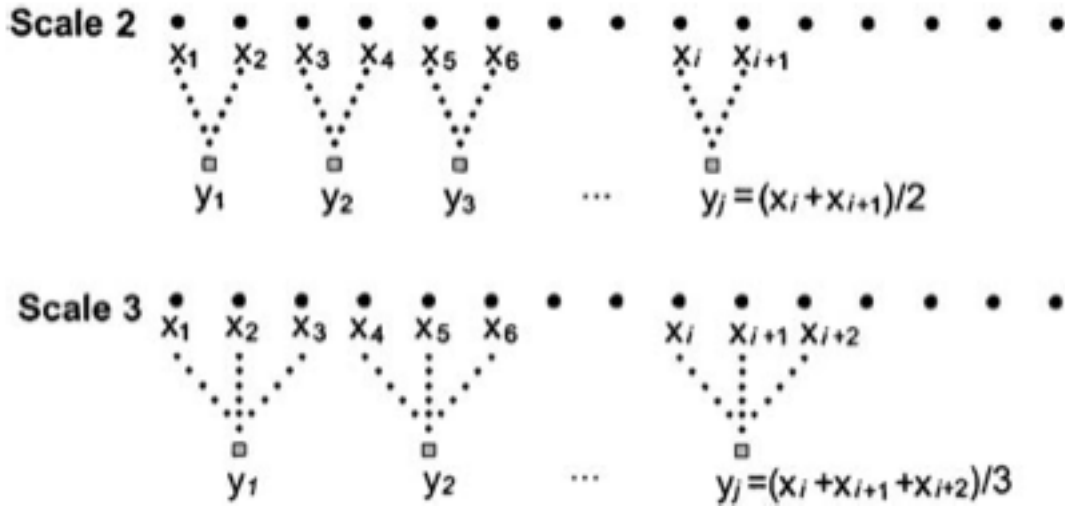
probability that two points that are distance  $m$  apart will be within the radius of similarity ( $r$ ) (Busa & van Emmerik, 2016). The  $r$  parameter is usually set at a percentage of standard deviation, such as  $.15 * SD$ , while the  $m$  parameter is often set to the minimum of 2. Essentially, sample entropy is the negative natural logarithm of the probability that two sequences will remain similar at the next iteration (Richman & Moorman, 2000). The algorithm determines if a signal at  $i$  is within a radial boundary ( $r$ ) at the next iteration ( $i+1$ ). A regular signal will often yield  $i+1$  within the bounds of  $i$ , indicating the signal at  $i+1$  is predictable given information about the signal at  $i$ . In the case of Figure 2.9, a data point is a match to  $u[1]$  if it lies within the dotted lines that bound  $u[1]$ , such as those labeled as open circles.  $Xs$  and  $\Delta s$  represent parts of the signal that are matches to  $u[2]$  and  $u[3]$ , respectively. The algorithm also searches for sequential patterns, such that a signal from  $(i)$  to  $(i + 1)$  to  $(i + 2)$  will repeat throughout a time series. In Figure 2.9,  $u[1]-u[2]-u[3]$  is later repeated at  $u[43]-u[44]-u[45]$ .

The shortcoming of the SampEn measure is that random signals will yield high complexity values. That is, the algorithm is sensitive to noise, and random signals will yield higher complexity values than a signal of known high complexity. The most likely reason for this issue is that SampEn evaluates a signal at one scale. The purpose of complexity measures are to determine the degree of ‘meaningful structural richness’ of a signal (Costa et al., 2005). Physiological behaviors are occurring across multiple temporal and spatial scales, and thus a true description of the behavior requires a multi-scaled approach. For this reason, Costa and colleagues (2002) developed the multiscale entropy (MSE) technique. This analysis uses the SampEn algorithm, yet does so across

multiple scales. The scaling is achieved by coarse-graining the data; that is, averaging together non-overlapping data points (Figure 2.10, Equation 2.3).

$$y_j^\tau = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \leq y_j \leq N/\tau \quad \text{Equation 2.3}$$

where  $y_j$  is the new data point at timescale  $\tau$ , and  $x_i$  is the original time series (Busa & van Emmerik, 2016). By utilizing the SampEn algorithm across various



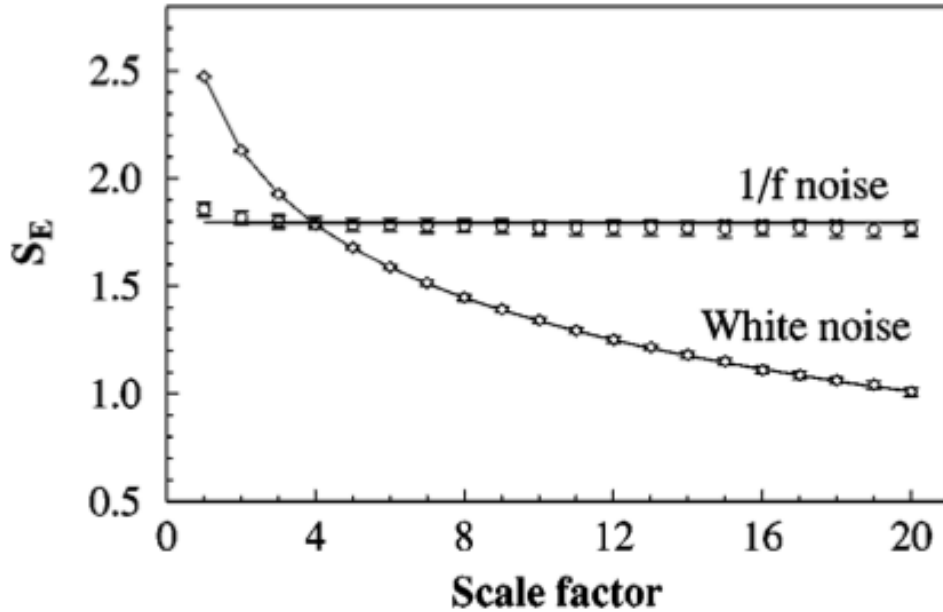
**Figure 2.10: Developing scale factors from physiological signals for MSE analysis.** Non-overlapping data points are averaged together across the entire data set (e.g., Scale 2 above,  $x_1$  is averaged with  $x_2$  to produce  $Y_1$ ). Higher scales will average more data points. From Costa et al, (2005).

scales, a more complete profile of the signal is attained. The final step in quantifying the complexity of the signal is to assess the overall entropy values across the various scales.

This is achieved by integrating the area under the SampEn curve:

$$CI = \sum_{i=1}^N SampEn(i) \quad \text{Equation 2.4}$$

The benefits of the MSE technique over SampEn can be illustrated when comparing a random white noise signal with a 1/f complex signal (Figure 2.11). If

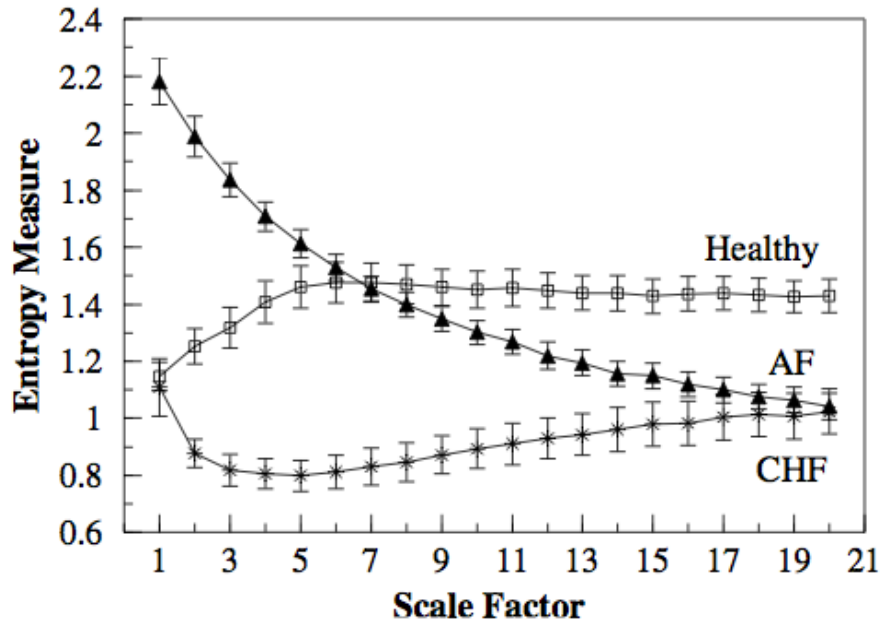


**Figure 2.11: MSE analysis of white noise versus 1/f noise.** From Costa et al, (2005).

complexity were evaluated based on SampEn of the raw data (scale factor = 1), white noise would appear more complex than 1/f noise. If, however, one were to evaluate the Complexity Index (Equation 2.4) based on the results of the MSE analysis in Figure 2.11, the 1/f signal would be significantly higher than the white noise signal. Thus, MSE analysis evaluates the ‘non-random yet seemingly randomness’ of a signal.

### 2.2.3.1 Multiscale Entropy in Physiological Signals

Costa evaluated the differences in heart rate inter-beat intervals of healthy individuals compared to two heart diseased groups: those with congestive heart



**Figure 2.12: MSE analysis of healthy and diseased states.** This plot represents entropy across various scale factors for healthy (squares) heart function versus those with congestive heart failure (CHF, stars) and atrial fibrillation (AF, triangles). From Costa et al, (2002).

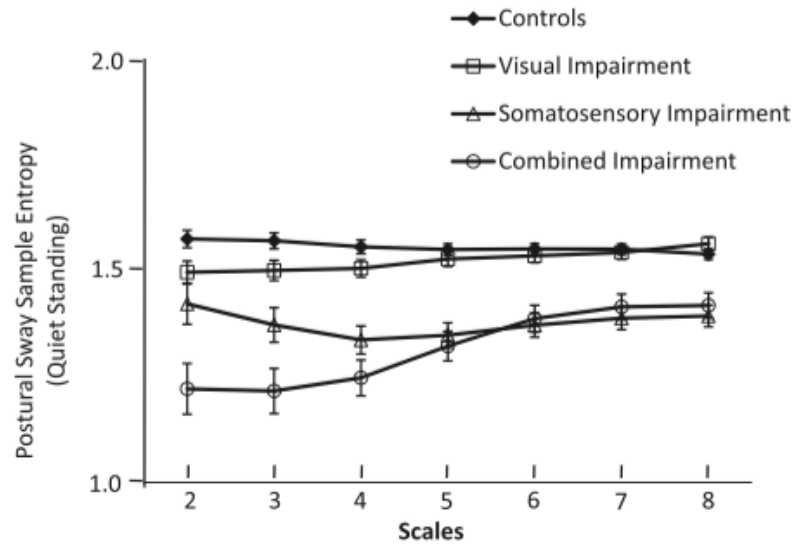
failure and atrial fibrillation (Figure 2.12). If only SampEn was analyzed, it would appear that individuals with atrial fibrillation had the most complex heart rate dynamics. However, across varying scales using the MSE technique, it becomes clear that the heart rate dynamics of healthy individuals are most complex. In addition, MSE analysis also revealed that older adults' heart rate entropy measures were lower than young adults across all scales (Costa et al., 2002). The authors concluded that diseased states and aging leads to a loss of the integration of information across scales that manifests as a more predictable (and less complex) behavior.

### 2.2.3.2 Multiscale Entropy in Posture

MSE has also been used to evaluate postural dynamics during quiet standing. Gruber and colleagues (2011) compared the center of pressure (COP) dynamics of

individuals with scoliosis with healthy controls. MSE analysis revealed the control group had a significantly higher Complexity Index compared to the scoliosis group in both the ML and AP directions (Gruber et al., 2011). Manor et al. (2010) compared the postural complexity of healthy controls with those with visual impairments, somatosensory impairments, and both visual and somatosensory impairments using MSE analysis on the COP profiles. The control group had the highest complexity across scales (1-8 scales), followed by a systematic decrease in complexity in the visually impaired, somatosensory impaired, and finally both visual and somatosensory impaired (Figure 2.13). The somatosensory impaired and combined impairment groups exhibited greater COP area and speed compared to the control and visually impaired groups. Finally, addition of a secondary task (dual task) reduced complexity and increased COP area and speed in all groups. However, dual tasking increased postural sway speed more so in the somatosensory and combined-impaired groups compared to the control and visually impaired groups (Manor et al., 2010).

Finally, comparing MSE analyses of healthy young versus older adults during quiet standing has revealed interesting findings. Older adults exhibited greater complexity at and across all scale factors (Duarte & Sternad, 2008). These results suggest the age-related deterioration in somatosensation may not reduce but rather *increase* complexity. However, these findings may be a result of recruiting relatively young older adults (mean age = 68) that were enrolled in a physical activity program.



**Figure 2.13: MSE analysis across varying levels of impairment.** Controls (diamonds); visually impaired (squares); somatosensory impaired (triangles); combined impaired (circles). From Manor et al, (2010).

### 2.2.3.3 Multiscale Entropy in Locomotion

To date, studies evaluating complexity using MSE have almost entirely focused on heart rate dynamics or postural tasks. One study, however evaluated the complexity of stride interval times in young, healthy men while walking at different speeds, as well as with and without adherence to a metronome (Costa et al., 2003). When analyzing stride times during unconstrained walking, normal (preferred) paced walking resulted in the highest entropy measures across scales, followed by faster walking, and finally slower walking. All of the walking conditions displayed significantly higher entropy values than randomly shuffled surrogate data, which indicates the presence of complexity was not simply due to randomness in the signals. In addition, metronome paced walking resulted in entropy measures that were not different from surrogate data at all walking speeds. That is, walking while adhering to a metronome resulted in a random stride interval time series. These findings suggest unconstrained self-paced walking yields the greatest

physiologic complexity. The authors also concluded that MSE analysis compliments DFA analysis in evaluating interactions. The authors compared DFA analyses and MSE results at scale 4 from the same data set and found correlations  $< .46$ , indicating these two techniques are independent. This is probably because the DFA and MSE analyses quantify different components of a signal or behavior. That is, while both DFA and MSE evaluate systemic adaptive capacity, DFA assesses correlations between time scales, while MSE estimates complexity within and across time scales. Thus, while DFA may be interpreted as calculating the interactivity between different components of the locomotor system, MSE can be interpreted as analyzing the complexity of a specific component, as well as across various components, of the system.

In a recent study, MSE was applied to trunk acceleration data of children, young adults, and older adults during gait (Bisi & Stagni, 2016). The results revealed an overall age effect, whereby children exhibited greater entropy values in the anterior-posterior and vertical directions. These results were surprising, considering higher entropy is generally associated with better health. Using sample entropy, Tochigi and colleagues (2012) observed higher entropy values during walking in healthy adults compared to those with osteoarthritis. The overall discrepancies in results are likely an artifact of different entropy measures used, as well as methodological differences (e.g., placement of the accelerometer).

In summary, gait adaptability is a broad term that refers to the ability of the locomotor system to change gait patterns as needed, based on the changes in the environment. One approach to assess gait adaptability is to expose participants to an asymmetric environment. This can be achieved in several ways, and one common method

is to use a split-belt treadmill, whereby each belt moves at independent speeds or directions. This mechanically produced asymmetry requires participants to adapt their gait patterns accordingly to successfully continue to locomote. In addition to gait adaptations to imposed treadmill asymmetries, nonlinear analyses of steady state (symmetric) gait have been employed in order to quantify locomotor adaptability. DFA evaluates the extent of statistical dependence of gait parameter variability that is present across various time scales. MSE calculates the complexity of a gait parameter signal, that is, the amount of information required to predict future states. While DFA and MSE techniques have been able to discriminate healthy versus diseased cohorts, these analyses have not been evaluated with respect to asymmetric gait constraints.

## **2.3. Gait Stability**

### **2.3.1. Overview**

The term ‘stability’ is commonly used in a variety of settings, and as such holds many context-specific definitions. A general definition of stability is resistance to change, which may refer to chemical, physical, or psychological maintenance of equilibrium. In motor behavior, static stability or postural stability commonly refers to an individual’s ability to maintain upright stance in the face of external or internal perturbations. Internal perturbations can refer to forces produced by the system, such as voluntary or involuntary muscle activation (e.g., movement of limbs) or motion due to vital functions (e.g., respiration or heart beating). External perturbations refer to disturbances from outside the system, such as slipping on a low-friction surface, tripping over an obstacle or uneven terrain, or being physically contacted by external forces (e.g., struck by a wall, car,



human, breeze, etc.). The process of maintaining upright stance involves generating resistive forces and moments that counteract any disturbances.

Activities that entail whole body displacement, however, require a dynamical component in the evaluation of stability. For example, cyclic motion such as human walking or running gait demands gross body displacement that can only be achieved by a constantly evolving level of instantaneous stability. That is, at certain points of each cycle, the instant stability may be low, but overall stability is sufficient. This is in contrast to standing posture, whereby a high degree of stability can continuously be maintained without transient periods of low stability or instability.

In order to evaluate and interpret an individual's level of stability, a clear definition must first be attained, followed by appropriate measures of assessment. If an individual falls following an external perturbation, he or she can be considered unstable. Likewise, if an individual is able to resist the perturbation and maintain upright stance, he or she could be considered stable. The shortcoming of defining stability in binary terms, however is that the magnitude of perturbation is not considered. For example, if the external perturbation is small in magnitude, successful recovery of balance does not necessarily indicate high stability. Similarly, a large perturbation (for example, being struck by a moving train) that yields a fall does not indicate an individual is unstable. Thus, two potential paradigms arise to counteract this shortcoming; 1) disturb individuals using various perturbation magnitudes, or 2) determine computations that quantify stability as a result of a perturbation that does not lead to a fall. The gait stability literature indicates that researchers often opt for the latter.

### **2.3.2. Global Stability**

Global stability can be defined as a system's ability to resist large external perturbations, such as slipping on a low-friction surface, or tripping over an obstacle (Dingwell et al., 2000). In dynamical systems, a system or behavior is considered globally stable if it tends toward the attractor, even if its initial conditions are not close to the attractor (Kaplan & Glass, 1995; Strogatz, 1994). Gait, for example, can be considered the global attractor state, as the overall goal of gait is to remain upright and continue locomoting. Thus, a system that can retain the action of gait following a perturbation can be considered globally stable. If perturbed, the system may be displaced from this attractor transiently, yet is able to return to the preferred state or gait state. The global concept of stability is arguably the best understood notion because stability can be considered in simplified binary terms. That is, an upright system that is perturbed is stable if able to maintain upright locomotion, or unstable if unable to resist the disturbance. As mentioned earlier, however, defining stability solely via binary measures may result in misinterpretations. That is, a large perturbation that destabilizes a system does not clearly indicate the system is unstable, but rather unstable in relation to that specific perturbation. Likewise, a system that can handle minute disturbances can only be considered stable in terms of these small perturbations.

#### **2.3.2.1. Margin of Stability**

Gait stability cannot be computed in the same manner as postural stability. Both the COM and BOS are constantly in motion, and as such they also possess instantaneous velocities that have a large impact on overall stability. Hof and colleagues (2005) developed a measure of dynamic stability by modeling a simple inverse pendulum model,

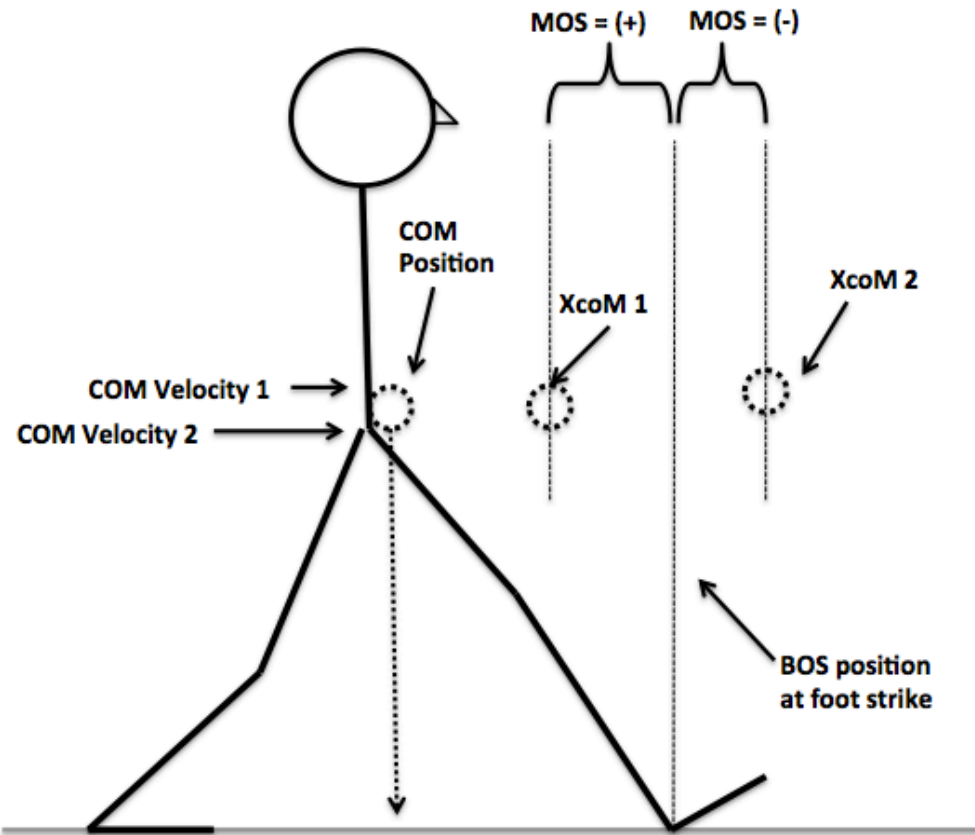
similar to those used to model postural control. Hof's model, however, takes into account both the COM's position and its velocity. Hof used the term 'extrapolated COM', or XcoM, to refer to the COM's instantaneous conditions based on position and velocity. The XcoM is a virtual location of the velocity-adjusted COM. For example, if velocity is large in the anterior direction, the XcoM is displaced farther in the anterior position. The XcoM would be anterior to the COM. The XcoM measure is evaluated in comparison to the anterior-most point of the BOS. The term 'margin-of-stability' (MOS) refers to the difference between the XcoM and the BOS (Hof, 2008; Hof et al., 2005). Using Equation (2.5) from Carty et al. (2011), the XcoM can be quantified as:

$$XcoM = P_{COM} + \frac{V_{COM}}{\sqrt{g/l}} \quad \text{Equation 2.5}$$

where  $P_{COM}$  is the position of the COM,  $V_{COM}$  is the velocity of the COM,  $g$  is the acceleration due to gravity, and  $l$  is the length of the leg. The MOS can be evaluated in relation to the BOS using Equation (2.6):

$$MOS = BOS - XcoM \quad \text{Equation 2.6}$$

Essentially, Hof's model states that, for a stable system, the XcoM should fall within the BOS. If the MOS is positive, the BOS is anterior to the XcoM, and the system is stable. If the MOS is negative, though, XcoM is anterior to the BOS, and the system is unstable. In these instances, the system either falls or requires a rapid change in BOS by stepping



**Figure 2.14: Margin of stability illustration.** To obtain the extrapolated COM (XcoM), the COM position is adjusted based on COM velocity. Margin of stability (MOS) and XcoM concepts adapted from Hof et al, (2005).

forward. Figure 2.14 illustrates two possibilities for XcoM that will have varying effects on the MOS. In the case of COM velocity 1 (small velocity, represented by short arrow), the XcoM 1 will be posterior to the BOS at foot strike. This will result in a positive MOS, indicating stability. That is, an additional step is not required to maintain upright stance. In the case of COM velocity 2 (larger velocity represented by a longer arrow), The XcoM at foot strike is beyond the BOS. In this event, the MOS is negative and the system is transiently unstable, whereby an additional forward step is required to maintain upright balance.

The MOS calculation is of particular importance because it is proportional to the impulse required to unbalance the system (Hof, 2008). Therefore, this measure specifies the quantitative *degree* of stability of a system. This indicates that MOS can discriminate between different ‘stable’ systems regarding the extent of stability, assuming the task goal is to maximize stability. If two individuals respond to an external perturbation successfully (i.e., maintain upright stance), the individual with a larger MOS can theoretically withstand a larger perturbation than the other.

### 2.3.2.2. Time to Contact

Similar to MOS, another assessment of global stability is time-to-contact (TtC). Originally developed by Riccio (1993), TtC takes into account the instantaneous position of the BOS and position and velocity of the COM or Center-of-pressure (COP). Additionally, the method used by Slobounov and colleagues (1997) incorporates the COM or COP acceleration. The instantaneous COM position, velocity, and acceleration are used to extrapolate a predicted time element that the COM will reach the BOS, given its current conditions. Haddad and colleagues (2006) determined addition of acceleration yielded a more robust measure of the information the postural control system uses under static conditions (compared to only using position and velocity) . TtC can be attained by first determining the position vector ( $p_i$ ) of the COM or COP using a time variable ( $\tau$ ) in Equation (2.7):

$$p_i(\tau) = r_x(t_i) + v_x(t_i) * \tau + \frac{a_x(t_i)\tau^2}{2} \quad \text{Equation 2.7}$$

where  $r_x$ ,  $v_x$ , and  $a_x$  are the instantaneous position, velocity, and acceleration at an instant in time ( $t_i$ ) (Haddad et al., 2006; Slobounov et al., 1997). Hasson and colleagues used the TtC measure based on the methods of Slobounov et al. (1997) using Equation 2.8:

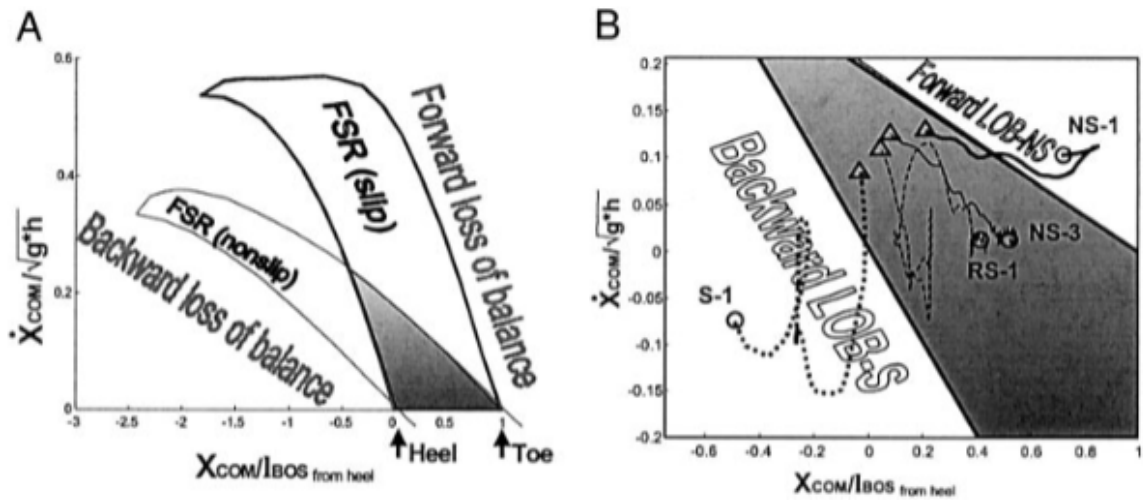
$$TtC = -v \pm \frac{\sqrt{v^2 - 2a(p_{max} - p)}}{a} \quad \text{Equation 2.8}$$

where  $p$ ,  $v$ , and  $a$  are the COM instantaneous anterior-posterior positions, velocities, and accelerations, respectively, and  $p_{max}$  is the position of the BOS (toe or heel). Smaller TtC values (shorter times) indicate transient periods where the COM is rapidly approaching the BOS, and therefore considered either less stable or close to a transition phase. Hasson et al. (2008) evaluated TtC with and without acceleration information, as well as TtC of the XcoM, during a full-body postural perturbation via a pendulum. The authors concluded that TtC (including acceleration) may be used as a control parameter in determining when to step following a perturbation. That is, individuals may opt to maintain postural control without moving foot position for low-intensity disturbances, but when the disturbance is large enough that the local minima of the TtC reaches a threshold, the decision to step occurs.

### 2.3.2.3. COM Motion State

Another elaboration of dynamic stability that incorporates COM velocity in addition to position is the COM motion state. Pai and Patton (1997) first developed the COM motion state, which refers to the COM's position as a function of its velocity (Figure 2.15). This can also be considered the COM's phase plane. Similar to Hof's

MOS, Pai and Patton (1997) developed a model based on an inverse pendulum. An optimization algorithm was created and applied to a two segment (foot, inverted pendulum) model to determine the so-called feasibility region, which refers to a region on the phase plane that



**Figure 2.15: COM motion state evaluation during a sit-to-stand task.** A) The feasible stability region for conditions in which a slip is (thick line) and is not (thin line) initiated, and an overlapping area (shaded area) in which stability is reached irrespective of condition. B) Examples of COM motion state trajectories during a slip condition (S-1) and non-slip condition (NS-1). Position is normalized by foot length, and velocity by body height. From Pai et al, (2003).

encompasses all of the possible combinations of COM positions and velocities that yield a stable system. Essentially, for a given COM position, the algorithm determined the largest allowable COM velocity that could still return to zero prior to reaching the anterior BOS, and the smallest required velocity to allow the COM to reach the anterior BOS. If the system's COM motion state (position and velocity combination) falls within the upper or lower limits of the feasibility region, the system is stable. Forward and backward losses of balance are initiated if the COM motion state exceeds the upper and lower boundaries, respectively. For example, the condition producing a slip (S-1) in Figure 2.15 B resulted in a backward loss of balance, while the condition without a slip

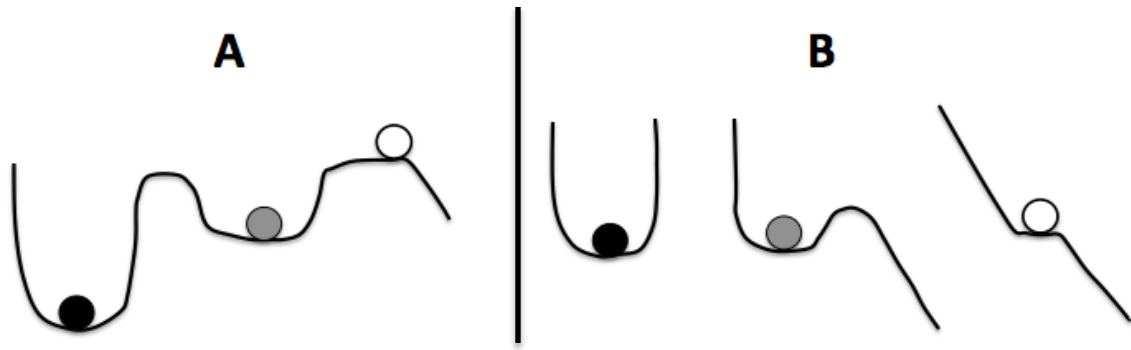
(NS-1) resulted in a forward loss of balance. These scenarios require a forward or backward step, respectively, that extends the BOS to avoid a fall.

The COM Motion State parameter has been used to identify changes in stability following repeated slip exposures during gait using a passive moveable platform. Pai and colleagues (Bhatt & Pai, 2005; Bhatt, Wening, & Pai, 2005; Pai, Wening, Runtz, Iqbal, & Pavol, 2003) evaluated the COM motion state relative to the BOS at slip onset and mapped these conditions onto the aforementioned feasible stability regions (Pai & Iqbal, 1999). Specifically, stability was defined as the distance from the predicted threshold/boundary for balance loss and the instantaneous COM motion state. The results of one study (Pai et al., 2003) indicated the COM motion state's predicted balance loss coincided with actual percentages of losses of balance ( $r^2 = 0.957$ ,  $p < 0.01$ ).

### **2.3.3. Dynamical Systems' Stability**

Mathematically, dynamical stability is determined within a trajectory's state space. A stable state without motion, or an unchanging state relative to two oscillating components, may be considered a fixed-point attractor. That is, the system dynamics tend to converge to a single point (Van Emmerik, Miller, et al., 2013). If the system evolves cyclically, the mean position of these cycles is considered the attractor state, or preferred state. Specifically, a cyclic attractor state is a limit cycle attractor. The attractor state is the behavior that the system will eventually evolve into. Figure 2.16 demonstrates an attractor state as a well, and a ball in the well represents the current state of the system. A system may





**Figure 2.16: Dynamical systems' attractor states.** The attractor is represented by a well, and the strength (stability) of attractor is represented by the well's depth. Adapted from Kelso, (1995).

be in a strong stable (black ball), weak stable (grey ball), or unstable (white ball) state depending on the attractor strength. A deeper well (e.g., Figure 2.16 A, left versus middle versus right) is more resilient to disturbances; small or large perturbations will not kick the ball out of the well. The same magnitude of perturbations may kick a less stable attractor (grey ball) into a different well (i.e., different attractor state). At moments of transition (Figure 2.16 B), the attractor becomes systematically less stable (i.e., critical slowing down) and more variable (i.e., critical fluctuations). The originally stable state (B, left) becomes less stable (center) and eventually is annihilated (right) to allow for a transition to another state.

The general shape of the attractor state is considered the order parameter, or collective variable (Van Emmerik, Miller, et al., 2013). The order parameter is the observed behavior of the system. Observation and quantification of an order parameter can be achieved, for example, by a participant's thigh segment position relative to its velocity. The position-velocity combination is analogous to the COM motion state mentioned earlier (Figure 2.15). In contrast to the order parameter, the control parameter

is a variable independent of the system's behavior that is used to determine the 'control' of the system. In other words, the control parameter is an external input that probes the stability of the system's behavior (order parameter) (Rickles, Hawe, & Shiell, 2007). A common control parameter used in locomotion studies is speed, as manipulating speed tests and exploits the relative ability of the system to maintain its behavior.

Irrespective of control parameter manipulation, determining the degree of stability of the attractor state involves quantifying one of two variables, 1) the variance of individual cycles from the attractor state, or 2) the time to recover from a disturbance and return to the attractor state, i.e., the relaxation time (Kelso & Ding, 1993). During phase transitions, the cycle variance increases, as does the relaxation time (i.e., critical slowing down, Figure 2.16 B). To be clear, variance or fluctuations are not considered 'unwanted noise' but rather a beneficial source of information that allows discovery of and transition to new patterns (Kelso, 1995). Thus, a stable system would not be invariant but instead possess variability and the capacity to attenuate any fluctuations that lead to deviations from the attractor state.

#### **2.3.4. Nonlinear Stability Measures**

Beyond exploration of the relationship between the COM and the BOS, several nonlinear mathematical/statistical measures have been developed to determine gait stability. These analyses are derived from the study of nonlinear dynamical systems. In general, the analyses listed in this section reflect examination of a behavior's evolution in time and space.

#### **2.3.4.1. Local Stability**

One common nonlinear analysis of stability is determination of local stability. Local stability can be described as the locomotor system's resilience to infinitesimally small perturbations (Dingwell & Cusumano, 2000). These perturbations are thought to arise as a result of the internal fluctuations of the movements producing locomotion. If these perturbations, albeit small, are not attenuated, the system is considered unstable. From a dynamical systems' perspective, a system is locally stable if it tends to move toward the attractor when its initial conditions are close to the attractor, but tends to move away from the attractor when its initial conditions are not close to the attractor (Kaplan & Glass, 1995; Strogatz, 1994). Thus, in order to be considered locally stable, it must be able to resist infinitesimally small perturbations by not allowing these small disturbances from causing excessive divergence away from the attractor state.

Mathematicians have long evaluated the stability of a dynamical system by quantifying the rate of divergence of nearby trajectories within its state space. A state space is a geometrical representation of time series data, whereby there are  $n$  number of variables that define the system. The most common calculation for determining this rate of divergence is the Lyapunov exponent. However, as convergence and divergence can occur in multiple dimensions, exploration of the spectrum of maximal Lyapunov exponents allows a more robust analysis (Kantz & Schreiber, 2004). Considering this analysis is performed on a microscopic scale of convergence and divergence of neighboring trajectories, it provides a measure of the aforementioned 'local stability'. Theoretically, if a system is highly stable, its ability to resist minute perturbations is also high. Thus, the maximal rate of divergence of neighboring trajectories should be low. In

mathematics, this analysis has been predominately used to decipher the degree of chaos versus noise within a system (Rosenstein, Collins, & De Luca, 1993).

In order to determine the maximal Lyapunov exponent, a raw time series data set must first be reconstructed into its state space (Equation 2.9). There are several methods that can be used to define the state space, but of the most commonly used method for local stability analysis is known as delay-embedding (D. H. Gates & Dingwell, 2009). This process entails graphing the original time series against a time-delayed version of it several times:

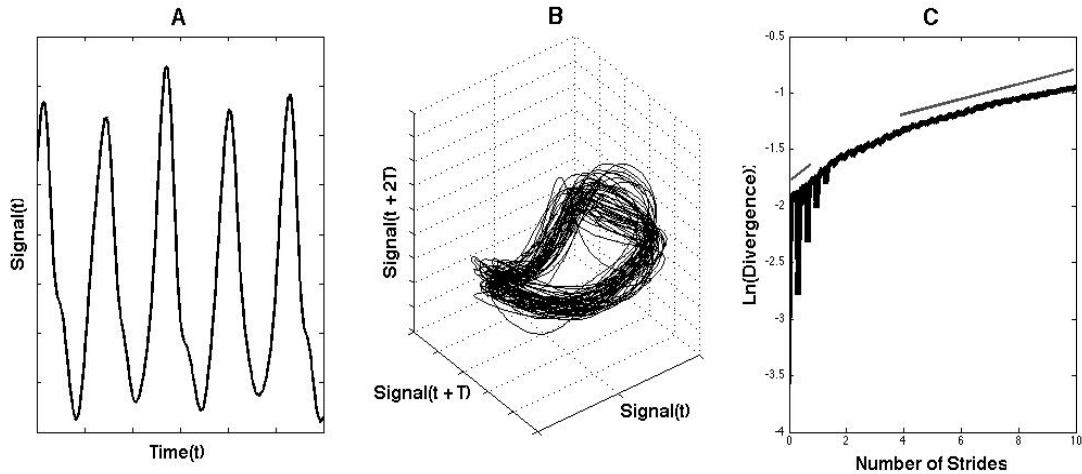
$$X(t) = [x(t), x(t + T), \dots, x(t + (d_E - 1)T)] \quad \text{Equation 2.9}$$

where  $X$  is the state space vector of dimension ( $d_E$ ) at time ( $t$ ),  $x$  is the original time series data at time ( $t$ ), and  $T$  is the time delay (Dingwell & Cusumano, 2000)(Figure 2.17). The time delay can be obtained in several different ways, including determining the first zero-crossing of an autocorrelation function, or determining the first local minimum using an average mutual information (AMI) algorithm (Fraser & Swinney, 1986). The AMI function is essentially a non-linear version of the (linear) autocorrelation function, as it determines the amount of information that is shared between two signals over a multitude of time delays. The next step entails determining the number of dimensions required to faithfully describe the state space by using a global false-nearest-neighbor analysis (GFNN) (Kennel, Brown, & Abarbanel, 1992). This concept is based on the fact that a system may appear to have two trajectories that are close in an  $n$ -dimensional space, but adding an additional dimension ( $n+1$ ) reveals distance between the trajectories. The

GFNN procedure involves systematically increasing the number of dimensions until a further increase in the dimensions no longer reveals ‘false neighbors’. Finally, once the appropriate embedding dimension is determined, the maximum Lyapunov exponent ( $\lambda_{\max}$ ) can be evaluated (Equation 2.10). Nearest neighbors are determined as the closest Euclidean distance between neighbors (data points). These nearest neighbors are tracked across the state space, and the rate of change in the distance between the two neighbors is quantified by the  $\lambda_{\max}$  (England & Granata, 2007):

$$d(t) = D_0 e^{\lambda_{\max} t} \quad \text{Equation 2.10}$$

where  $d(t)$  is the average displacement between the two neighbors, and  $D_0$  is the initial displacement (Dingwell & Cusumano, 2000).



**Figure 2.17: State space reconstruction and Lyapunov exponent analysis.** A time series signal (A) is converted into an  $N^{\text{th}}$  dimension state space (B, here illustrated as 3-Dimensions) by adding a time delay ( $T$ ) to the original time series. C) The logarithmic rate of divergence of neighboring trajectories is plotted across strides, and the FT $\lambda_{\text{MAX}}$  evaluates the short-term (0-.5 or 0-1 stride) or long-term (4-10 strides) rate of divergence (grey lines above divergence plot). From Van Emmerik et al, (2016).

The major shortcomings with these methods are that 1) the system assessed needs to be deterministic in nature, and 2) the calculation requires an infinite number of data points. These issues are problematic in evaluating biophysical signals because physiological signals are generally not considered deterministic (but rather stochastic in nature (Riley & Turvey, 2002)), and only a finite number of data points can feasibly be collected and analyzed. Therefore, in order to determine the finite-time Lyapunov exponent ( $FT\lambda_{MAX}$ ), Rosenstein et al.'s (1993) algorithm can be employed (Equation 2.11, Figure 2.17):

$$\ln[d_j(i)] \approx (FT\lambda_{MAX})(i\Delta t) + \ln [d_{oj}] \quad \text{Equation 2.11}$$

where  $d_j(i)$  is the distance between the  $j$ th pair of nearest neighbors after  $i$  number of iterations, and is averaged across all nearest neighbors.  $FT\lambda_{MAX}$  is then projected based on the slope (Equation 2.12; Figure 2.17C) of a linear fit of the curve:

$$y(i) = \frac{1}{\Delta t} \langle \ln [d_j(i)] \rangle \quad \text{Equation 2.12}$$

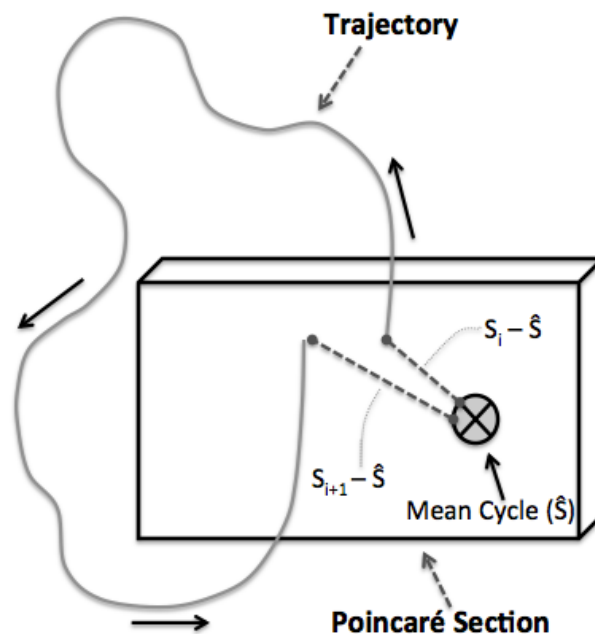
Where  $y(i)$  is the slope of linear fit, and  $\langle \rangle$  indicate the average across all  $j$  pairs of nearest neighbors (Dingwell & Cusumano, 2000).

This algorithm (Rosenstein et al., 1993) is well suited for human movement studies using relatively small data sets. The first studies to evaluate local dynamic stability on human movement data using the  $FT\lambda_{MAX}$  were by Dingwell & colleagues (Dingwell & Cusumano, 2000; Dingwell et al., 2001; 2000). In these studies, tri-axial

accelerometers were attached to each participant's sternum so that acceleration signals could be converted into the state space and stability assessed via the  $FT\lambda_{MAX}$ . In two studies, both gait speed and  $FT\lambda_{MAX}$  were lower in patients with diabetic neuropathy, indicating these patients reduced gait speed in order to increase local stability, even though they also displayed greater kinematic variability (Dingwell & Cusumano, 2000; Dingwell et al., 2000). Furthermore, a follow-up study indicated that local dynamic stability was not correlated to kinematic variability (Dingwell et al., 2001).

### 2.3.4.2 Orbital Stability

Similar to local stability analysis, Floquet multipliers evaluate the degree of orbital stability of a cyclic trajectory. In order to determine if a system is



**Figure 2.18. Poincaré Section and evolution of a trajectory in its state space.** The location of the mean of the signal ( $\hat{S}$ ) on the Poincaré Section is subtracted from the location of the signal  $S$  at cycle  $i$ . Adapted from Dingwell & Kang, (2007).

converging upon or diverging from the attractor, the time series signal is transformed into its state space, and a Poincaré section is created (Figure 2.18). The Poincaré section is a plane that is orthogonal to the mean of the signal's trajectory, such that the signal at every cycle transects this plane. The distance from the mean cycle location on the Poincaré section is subtracted from the distance at cycle  $i$ . If the subsequent distance ( $S_{i+1}$ ) increases (i.e., if  $S_{i+1} - \hat{S} > S_i - \hat{S}$ ), the system is diverging and (relatively) unstable. Alternatively, if the distance decreases, the system is converging and is (relatively) stable.

Dingwell & Kang (2007) noted that in previous studies (Dingwell & Cusumano, 2000; Dingwell et al., 2001; Dingwell & Marin, 2006) participants exhibited periods of high local instability, yet were able to continue upright walking (i.e., did not fall). They hypothesized that, although local instabilities may exist as a result of inherent noise in the system, participants may still be stable from cycle to cycle (i.e., orbital stability). By comparing local dynamic stability and orbital stability analysis, they concluded that participants were indeed orbitally stable, even though periods of local instability existed. This occurred during both overground and treadmill walking (Dingwell & Kang, 2007). This means participants may exhibit instabilities at infinitely small scales, yet can still exhibit cyclic stability from stride to stride. The small perturbations that are observed in periods of local instability may propagate and manifest as lower orbital stability, but for individuals who do not fall, the degree of orbital stability is still sufficient to maintain locomotion.

Granata and Lockhart (2008) evaluated the orbital stability of the COM relative to the COP at heel strike. The COP is thought to reflect the body's attempts to resist



external forces and maintain the COM position. While no differences were observed between healthy young and healthy older adults, older adults with a history of falls had significantly greater average and maximal Floquet multipliers, indicating that older fall-prone adults were less orbitally stable.

### **2.3.5 Scalar Variability-Based Stability Measures**

Finally, numerous variables within the motor behavior literature are known to be associated with fall risk. These associations are based on correlational data, whereby changes to one or more variables are accompanied by, and sometimes predict, changes in fall occurrences. Greater stride time variability, for example, represents a parameter that is correlated to greater fall risk within large datasets. These measures are called ‘scalar’ because they describe the magnitude of variance over the course of a stride, trial, etc., but do not evaluate the structure of variability in the way that other measures (e.g., fractality) do.

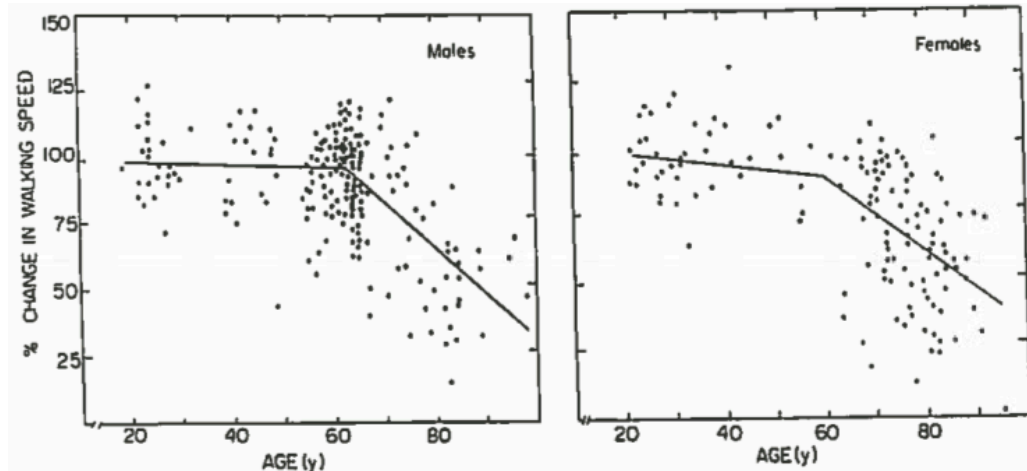
Variability in temporal or spatial parameters during gait have been often cited as indicators of gait stability. In general, greater variability is associated with lesser stability. Stride time variability, for example, is associated with fall risk, whereby greater variability is correlated to greater risks of falling (Hausdorff, 2007). In addition, greater step width variability (Maki, 1997; Owings & Grabiner, 2004) and stride length variability (Maki, 1997) are also associated with greater fall risk. These relationships are however not always linearly correlated. That is, too *little* step width variability has been shown to be as detrimental to postural and gait stability as too *much* variability (Brach et al., 2005; Van Emmerik, Jones, Busa, & Baird, 2013). One possible reason for this phenomenon is based on the loss of complexity hypothesis (Lipsitz & Goldberger, 1992),

whereby aging and disease reduces the available degrees of freedom to perform a task. This constraint manifests as reduced variability. Scientists studying dynamical systems have reported the benefits of variability in transitioning to new states, and that variance should not solely be considered unwanted noise (Kelso, 1995; Kelso & Ding, 1993; Riley & Turvey, 2002; Van Emmerik, Miller, et al., 2013).

One important point of discussion regarding variability measures is the location or level of variability. That is, variability can occur at the level of task performance or at the level of coordinative dynamics. Traditionally, variability has been considered unwanted noise in the physiological system. However, variability could also be considered ‘dynamical noise’, referring to fluctuations that are inherent to and crucial for the dynamical system of interest (van Emmerik et al., 2016). In pistol shooting, for example, fluctuations at the level of the gun barrel motion is defined as end-point variability, while fluctuations at the level of the joints (e.g., shoulder, elbow, wrist) can be defined as coordinative variability. In this task, expert marksmen exhibit low end-point variability and high coordinative variability, relative to novices (van Emmerik et al., 2016). Therefore, the location or level of variability should be considered when determining if more or less variability is desired.

Another commonly observed phenomenon in lifespan motor development is that the speed by which individuals prefer to walk slows down with aging. This slowing is gradual throughout adulthood, but accelerates beginning in the 7<sup>th</sup> decade of life (Himann et al., 1988). Figure 2.19 illustrates the age-speed relationship. A bi-linear regression model was fit for both genders with an inflection point at 62 years. Note that following this breakpoint the slope is steeper for males, indicating this cohort slows their preferred

walking speed faster. Slower preferred walking speeds are associated with greater risk of falls (Van Kan et al., 2009; Verghese et al., 2009) and mortality (Van Kan et al., 2009) in older adults. The primary reason for this slowing of preferred speed has been disputed, but may be an attempt to optimize stability or metabolic cost.



**Figure 2.19. Changes in preferred walking speed across the adult lifespan.** Males = left plot; Females = right plot. A bi-linear regression line is fit to both genders at age 62. From Himaan et al, (1988).

These measures of variability and gait speed have proven to be a valuable approach to categorize fall risk. To be clear, however, none of the aforementioned variables have been shown to *cause* a fall. These variables simply provide a correlation, and certainly warrant deeper inspection.

To summarize, gait stability is a term that refers to the ability of the locomotor system to resist perturbations. Gait stability has been quantified using numerous methods, including MOS, TTC, COM motion state, dynamical systems' approach,  $FT\lambda_{MAX}$ , Floquet multipliers, and gait parameters such as preferred walking speed and variability measures. The most common practice thus far has been to calculate stability during

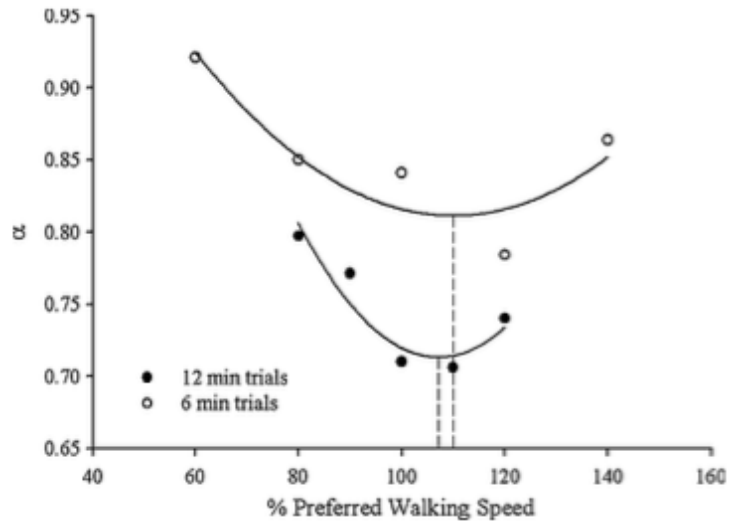
steady state (i.e., unperturbed) gait. A limitation to this approach is that it is difficult to determine stability or instability that may lead to a future fall. Indeed, the locomotor system must be perturbed in order to fully assess stability.

#### **2.4. Effects of Gait Speed on Adaptability and Stability**

The most heavily scrutinized variable in the gait literature has been gait speed. As mentioned earlier, aging is associated with slower preferred walking speeds (Himann et al., 1988), and these slower speeds in older adults are associated with more fall incidents (Greany & Di Fabio, 2010; Verghese et al., 2009) and a higher risk of mortality (Van Kan et al., 2009). The potential mechanisms for slower preferred walking speeds with aging are disputed by researchers, but may include: reduced muscular strength or power (Reid & Fielding, 2012), greater metabolic cost of walking (Mian, Thom, Ardigo, Narici, & Minetti, 2006), higher fatigability (Eldadah, 2010), increased agonist-antagonist co-activation to counteract decreased joint stability (Mian et al., 2006), or to optimize gait stability (Hak, Houdijk, Beek, & van Dieen, 2013).

##### **2.4.1 Speed Effects on Gait Adaptability**

Few studies have evaluated gait speed's effects on gait adaptability. However, both fractal dynamics and complexity analyses have been shown to be sensitive to gait speed. For example, studies on fractal dynamics have indicated that walking at speeds faster or slower than preferred increases fractal scaling

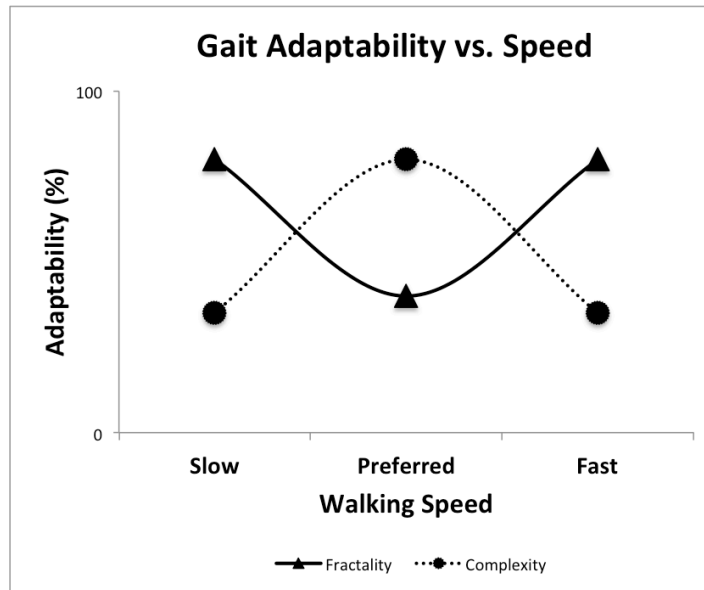


**Figure 2.20: Influence of walking speed on fractal scaling.** The scaling exponent ( $\alpha$ ) minima occur close to preferred walking speed (100%) for both 6-minute (white circles) and 12-minute (black circles). From Jordan et al, (2007).

closer to  $\alpha = 1.0$ , or 1/f noise (Hausdorff et al., 1996; Jordan et al., 2007b)(Figure 1.8C, 2.20). When a system exhibits 1/f behavior, it is considered optimally complex (Lipsitz & Goldberger, 1992). Although paradoxical, this may indicate that walking faster or slower than preferred walking speed yields more adaptable gait. The effects of varying fractal dynamics on gait adaptability, however, have not yet been examined empirically.

Conversely, complexity analyses have provided evidence for an inverse U-shaped relationship between complexity indices and gait speed. Costa and colleagues (2003) manipulated gait speed and evaluated complexity using the MSE algorithm; they observed the highest complexity index during preferred speed walking, followed by fast walking, and finally slow walking. These results suggest preferred walking speed optimizes gait adaptability, as complexity is linked to a locomotor system's adaptive capacity. Figure 2.21 displays the speed effects of two different gait adaptability measures. As the graph illustrates, walking faster or slower than preferred speed increases

fractality yet decreases complexity. The effects of gait speed on gait adaptability remain unknown.



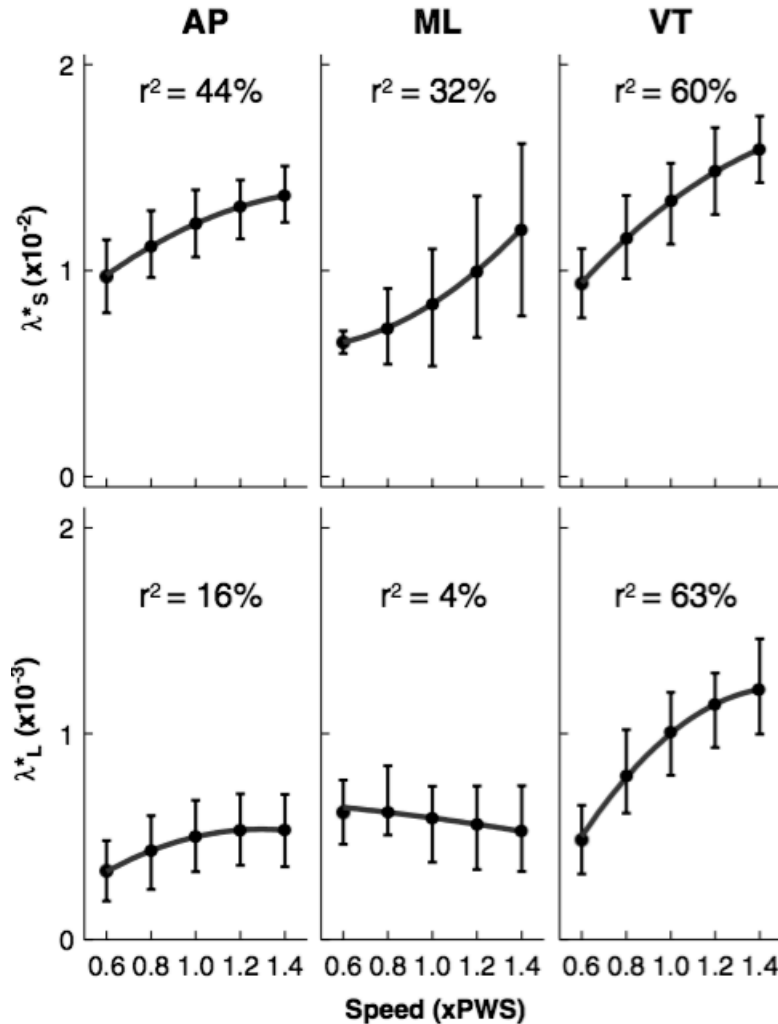
**Figure 2.21: Effects of gait speed on measures of gait adaptability.** Adaptability (y-axis) is an arbitrary value between 0-100, whereby 100 = optimal adaptability. Complexity measures adapted from Costa et al., 2003. Fractality measures adapted from Hausdorff et al, (1996).

### 2.4.2 Speed Effects on Gait Stability

The relationship between gait speed and gait stability is not well understood (Figure 1.8, 1.9). Various measures of gait stability have been examined in attempts to determine speed effects, yet the results are often conflicting. The most probable reason for mixed findings is that each stability measure is quantifying a different component of the locomotor system. Nevertheless, differing interpretations of gait speed's effects on stability lead to differing recommendations to optimize gait stability.

When local dynamic stability is measured via the  $FT\lambda_{MAX}$ , various effects of gait speed have been reported. Many studies have concluded that there is an inverse

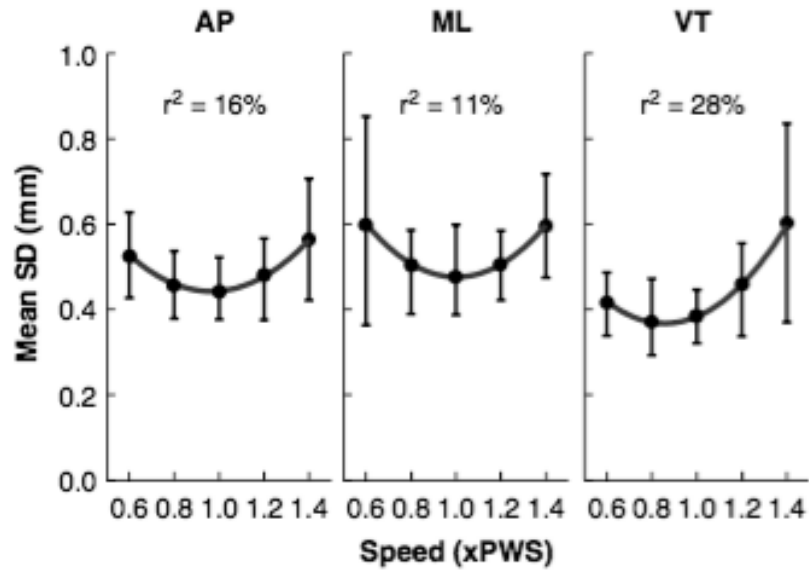
relationship between gait speed and local stability (Figure 1.8A). That is, as gait speed increases, local stability decreases (Dingwell & Cusumano, 2000; Dingwell et al., 2000; England & Granata, 2007; Manor, Wolenski, & Li, 2008). For example, Kang and Dingwell (2008a) found that local dynamic stability decreases linearly with increasing speeds. Dingwell and Marin (2006) compared kinematic variability to local dynamic stability using velocity profiles of tri-directional kinematics of a trajectory located on the first thoracic vertebrae, and again showed that local stability was reduced with increased speeds (Figure 2.22). This occurred in all three directions for the short-term  $FT\lambda_{\max}$  ( $\lambda^*_s$ , representing maximal divergence between 0 and 1 stride), and in the anterior-posterior and vertical directions for the long-term  $FT\lambda_{\max}$  ( $\lambda^*_L$ , representing maximal divergence between 4 and 10 strides). However, between-cycle variability across the entire gait cycle in all three directions increased at slower and faster speeds (Figure 2.23). That is, the kinematic variability of the marker (representing the dynamics of the entire system) displayed a U-shaped relationship with gait speed. Increased variability is associated with greater instability, yet the  $FT\lambda_{\max}$  results suggest slower walking, even with greater variability, is still more stable than preferred or faster walking (Figure 2.22). In a separate study, Bruijn and colleagues (2009) observed a direction effect of short-term local stability, whereby faster walking yielded greater local stability in the AP direction. Additionally, local stability in the ML direction displayed an inverse U-shaped relationship, whereby the most stability occurred at faster and slower walking speeds. For the long-term local stability analysis, the ML direction exhibited a linear relationship with walking speed, whereby greater walking speeds resulted in *increased* local stability (Bruijn et al., 2009).



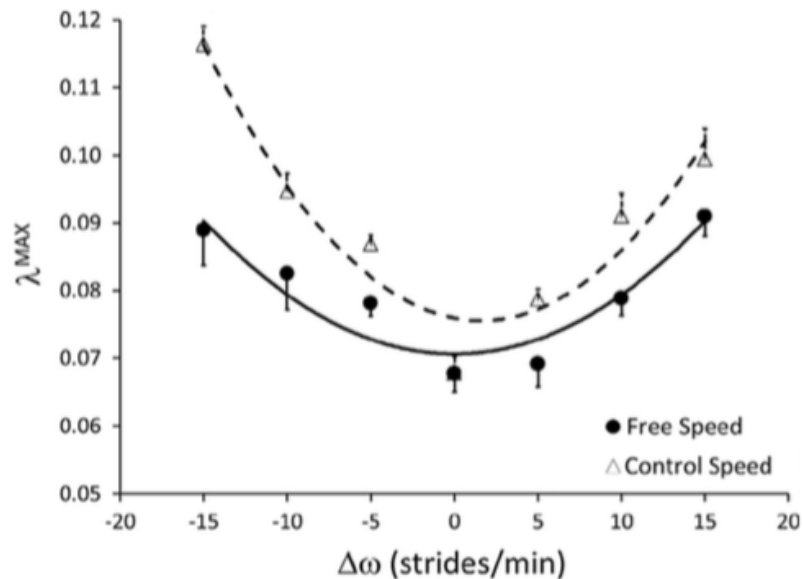
**Figure 2.22: Walking velocity's effects on local stability.** Local stability ( $FT\lambda_{MAX}$ ) shown in three directions for short-term ( $\lambda^*_S$ ) and long-term ( $\lambda^*_L$ ) divergence. Velocity is presented as a product of preferred walking speed (PWS). As walking velocity increased,  $FT\lambda_{max}$  increased, indicating less local stability at faster walking speeds. From Dingwell & Marin, (2006).

Finally, Russell & Haworth (2014) manipulated stride frequency and evaluated local stability, and observed a U-shaped relationship, in which the greatest local stability was observed during preferred stride frequency, and local stability decreased at faster or slower stride frequencies (Figure 2.24). It should be noted, however, that these conflicting reports of the effects of walking speed on local stability might be explained



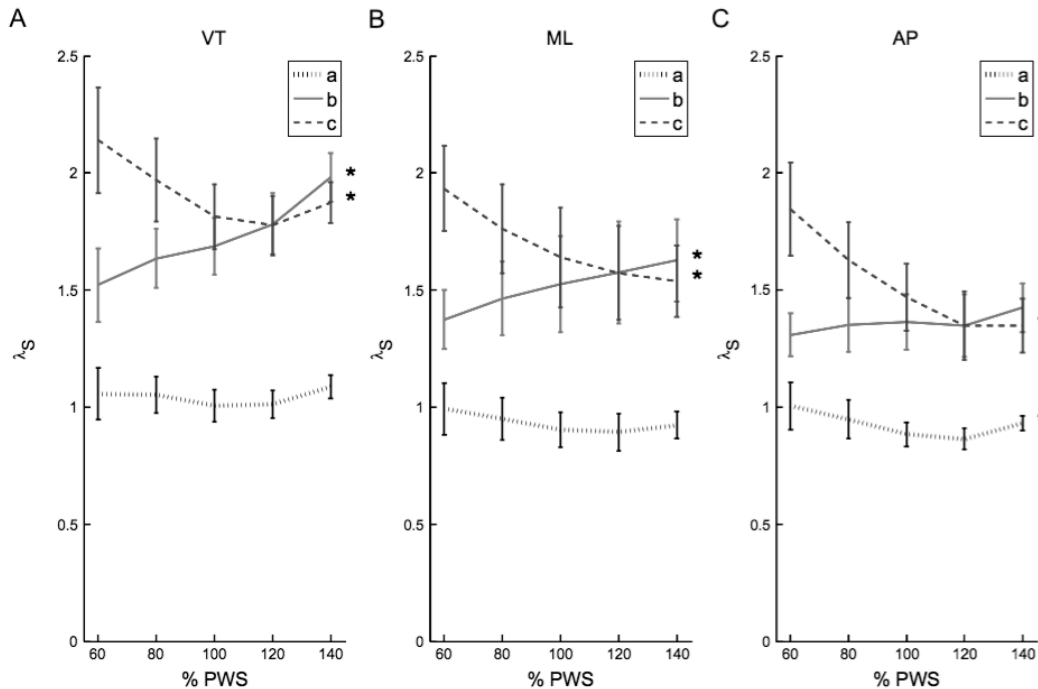


**Figure 2.23: Relationship between gait speed and variability.** In all three directions, variability is lowest at or near preferred walking speed (1.0 on x-axis). From Dingwell & Marin, (2006).



**Figure 2.24: Effects of stride frequency on local stability.** Local stability =  $FT\lambda_{MAX}$ . The '0' on the x-axis indicates preferred stride frequency. Conditions in which speed was constant (white triangles) or able to change based on participant (black circles) both yielded the lowest  $FT\lambda_{MAX}$  (highest stability) close to preferred stride frequency. From Russell & Haworth, (2014).

(at least in part) by methodological differences in determining  $FT\lambda_{MAX}$  (Stenum, Bruijn, & Jensen, 2014). In fact, Stenum et al. (2014) performed  $FT\lambda_{MAX}$  in three directions using three different methods. The first method expressed  $FT\lambda_{MAX}$  per stride time (i.e., acceleration per stride). Each stride was normalized to 100 data points (Figure 2.25 A). This method introduced stride number bias, as local stability was assessed by more cycles in faster walking than slower. The second normalized to a number of total



**Figure 2.25: Effects of walking speed and method type on local dynamic stability.** Local stability =  $FT\lambda_{MAX}$ .  $FT\lambda_{MAX}$  evaluated (A) per stride time and varying number of strides, (B) per second, and (C) per stride time with a fixed number of strides. From Stenum et al, (2014).

data points (number of strides \* 100) and expressed  $FT\lambda_{MAX}$  as the logarithmic rate of divergence per time (i.e., acceleration per second, Figure 2.25 B), which introduces a dependency on stride duration. The third method also time normalized the data to a total number of data points, but the number of strides evaluated was kept constant and

expressed  $FT\lambda_{MAX}$  per stride (i.e., acceleration per stride, Figure 2.25 C). The authors discovered that, depending on which method was used,  $FT\lambda_{MAX}$  either increased, decreased, or remained constant as a function of gait speed.

While most of the local stability experiments suggest slower walking speeds are more stable, other studies indicate faster walking speeds maximize stability. Using the COM motion state as the measure of stability, Bhatt and colleagues (2005) determined there was a positive linear relationship between gait speed and gait stability (i.e., faster speeds are more stable, Figure 1.8 B). Espy et al. (2010) concluded that faster walking speeds and shorter step lengths improved gait stability. Moreover, as mentioned earlier, Bruijn et al. (2009) manipulated gait speed and evaluated stability using the long-term  $FT\lambda_{MAX}$  and found increased stability with increased speeds in the ML direction. This concept can be likened to bicycle dynamics (Jones, 1970), whereby faster speeds increase internal stability.

Finally, from a dynamical system's perspective, preferred walking speed represents the preferred state, or attractor state, whereby stability is maximized (Kelso & Ding, 1993). Deviation from this attractor state yields reduced systemic stability (i.e., greater sensitivity to perturbations). The attractor state is the collective variable, or order parameter. In locomotion, the actual act of walking upright can be considered the preferred state, or the aforementioned 'gait state'. In order to test the stability of the attractor, a control parameter is typically introduced. The control parameter is the variable that is systematically manipulated to probe the attractor. Often in dynamical systems, the control parameter is speed. The variability of various gait parameters has been shown to be sensitive to gait speed. Specifically, variability is minimized during

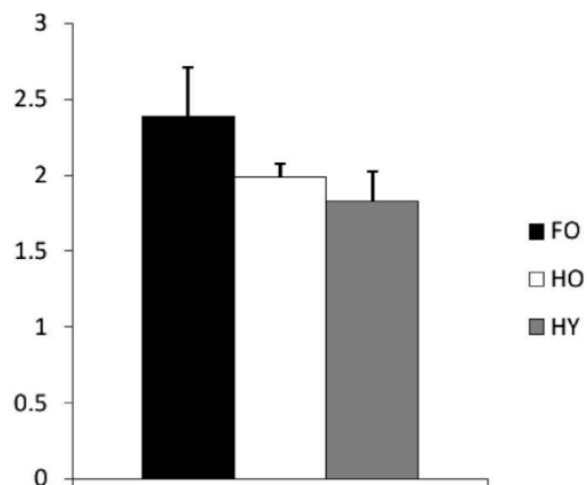
preferred walking speed, and increases during slower and faster than preferred walking (Dingwell & Marin, 2006; Kang & Dingwell, 2008b). While increased variability may represent an upcoming behavior shift (i.e., critical fluctuation (Kelso & Ding, 1993)), in this paradigm participants are performing steady state gait. Therefore, slow or fast walking should be predicted to reduce gait stability.

#### **2.4.3. Speed Effects of Perturbed Gait Outcomes**

Surprisingly few studies have evaluated gait speeds effects on gait stability by evoking a perturbation during walking. Bhatt, Wening, and Pai (2005) perturbed participants in the AP direction using a passive sliding platform, and found that faster gait speeds increased global stability by providing momentum for the COM to ‘catch up’ to the anteriorly-sliding foot. Espy and colleagues (2010) cleverly decoupled gait speed from step length and found that one standard deviation decrease in gait speed yielded over 4-times greater odds of falling. Moreover, one standard deviation increase in step length resulted in over 6-times greater odds of falling. The authors concluded the most globally stable gait involves walking fast while taking shorter steps. The studies by Bhatt et al. and Espy et al. were unique in that they were the only two that explicitly evaluated fall resistance by implementing a slip perturbation at differing speeds (Bhatt et al., 2005; Espy, Yang, Bhatt, et al., 2010). It should be noted, though, that these studies utilized a passive slip platform perturbation, and that the observed strategies may (at least, initially) reduce stability if the perturbation is a trip (Bhatt et al., 2013).

Alternatively, two separate studies found that local dynamic stability was lower in fall-prone older adults compared to healthy older adults and young adults, even though walking speeds were slower and step lengths were smaller (Granata & Lockhart, 2008;

Lockhart & Liu, 2008). Lockhart and Liu (2008) compared local dynamic stability measures of healthy young, healthy older, and fall-prone older adults. Adults were considered ‘fall-prone’ based on an earlier study in which participants were perturbed and unable to maintain upright stance, in addition to reporting at least one fall in the previous six months. The results indicated the older fall-prone adults were the least locally stable,



**Figure 2.26: Local stability analysis of healthy young and older adults, and older adults with a fall history.** Local stability determined using the maximal finite-time Lyapunov exponent ( $FT\lambda_{MAX}$ ). Local stability is lowest (highest  $FT\lambda_{MAX}$ ) in older fall-prone adults (FO) compared to healthy older (HO) and healthy young (HY) adults. From Lockhart & Liu, ((2008).

even though their gait speeds were slower and step lengths shorter (Figure 2.26). The findings of Granata and Lockhart (2008) and England and Granata (2007) either support the research that indicates faster gait speeds are more dynamically stable, or suggest older adults are less stable irrespective of step length and walking speed.

Finally, Hak and colleagues (2012) explored the notion that individuals slow gait speed to increase stability when exposed to perturbations. To test this, they allowed participants to regulate their gait speed while ML visual perturbations were applied. This

was achieved by using an interactive treadmill that would speed up or slow down based on the participants AP displacement. That is, if a participant slowed down, the treadmill belt would concomitantly slow down. The results indicated that participants did not change gait speed, but rather increased their step width and step frequency while decreasing step length. Moreover, local dynamic stability decreased in response to perturbations, yet MOS increased in both the ML and AP directions. The authors concluded the changes in gait parameters (e.g., step length, step width, step frequency) optimized global stability, even though local stability was reduced.

In summary, walking speed's effects on gait stability has been debated empirically. While some research suggests slower walking is more stable, other studies propose that faster walking is more stable. Furthermore, some research indicates that preferred walking speed is the most stable, and that deviation from preferred speeds (faster or slower) reduces gait stability. The main reason for these discrepancies is that 'stability' is quantified differently, and the paradigms vary considerably.

## **CHAPTER III**

### **PROPOSED METHODS**

#### **3.1 Overview**

The principal objective of this dissertation is to better understand and quantify gait adaptability and stability in young and older adults. Various mathematical measures have been developed to quantify the locomotor system's ability to adapt gait or resist internal or externally generated perturbations. Most of these measures, though, are assessed during steady state, unperturbed walking. In order to accurately quantify someone's locomotor capacity during walking, he or she must be exposed to an environment that compels the person to respond meaningfully and substantially, with the goal being continued locomotion. This perturbation paradigm will allow for comparison between mathematical quantifications of adaptability or stability during steady state conditions and a tested evaluation of such skills.

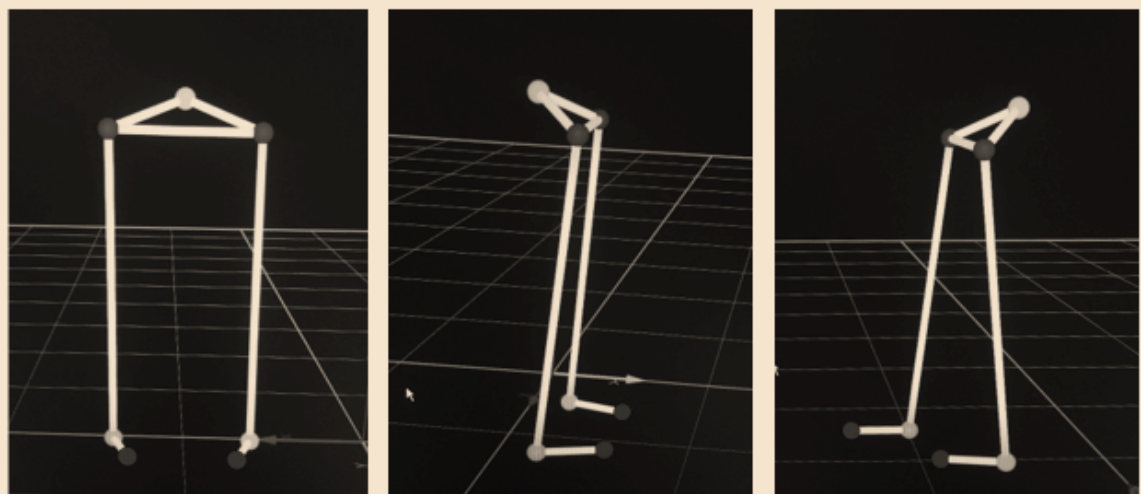
##### **3.1.1 Data Collection**

All three studies will be collected in the Locomotion Neuromechanics Laboratory (NeuroLab). This lab houses a force plate-instrumented split-belt treadmill. Each belt is capable of being independently controlled such that the belts can move at different speeds or directions, or one (or both) belt can be rapidly accelerated or decelerated for brief or prolonged periods of time. In addition to the treadmill, the NeuroLab also is instrumented with four high-speed cameras capable of collecting kinematic data at up to 500 Hz (Oqus, Qualisys, Gothenburg, Sweden). The cameras and force plates are synced together via Qualisys software, and the treadmill can be controlled via software provided by the manufacturer (Bertec Corporation, Columbus, OH, USA). For all of the proposed studies,

kinematics will provide most of the data. Kinematics will be collected at 100 Hz for all three studies, while force plate data will be collected at 1000 Hz. The force plate data will be used to confirm timing of gait events obtained by kinematic motion data.

### 3.1.2 Kinematic Model

Study 1 will use a 5-segment kinematic model composed of a pelvis and bilateral leg and foot (Figure 3.1). The pelvis will be constructed using markers on the greater trochanters and 2<sup>nd</sup> sacrum. The leg segment will be constructed using markers on the greater trochanters and ipsilateral heels. The foot will be constructed using markers on the toes and heels. Finally, Center of Mass (COM) will be estimated based on the location of the 2<sup>nd</sup> sacrum, which has been shown to correlate highly with kinematic full

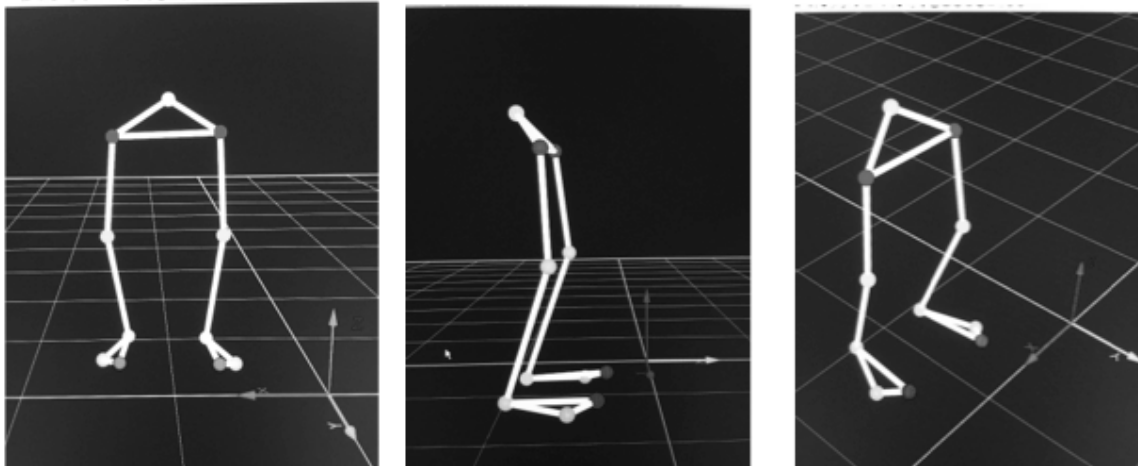


**Figure 3.1. Illustration of the proposed 5-segment lower body model.** Illustrated here from the sagittal (left), frontal (middle), and diagonal (right) plane perspectives.

body (13-segment) COM estimations during steady state and perturbed walking (Yang & Pai, 2014). However, some gait stability calculations require a precise COM position. For these analyses, a virtual COM will be constructed based on the vertical height and



medial-lateral position of the sacral marker, and the average anterior-posterior position of the greater trochanters.



**Figure 3.2. Illustration of the proposed 7-segment lower body model.** Illustrated here from the sagittal (left) and frontal (middle) plane perspectives, as well as a diagonal (right) view.

Study 2 will use a 7-segment kinematic model composed of a pelvis and bilateral thigh, shank, and foot (Figure 3.2). The pelvis and foot segments will be constructed using the same markers as in study 1. The thigh will be constructed using markers on the greater trochanters and ipsilateral lateral femoral epicondyles, while the shank segment will be constructed using markers on the lateral femoral epicondyles and ipsilateral heels.

### 3.1.3 Data Handling

All markers will be identified, labeled, and (if needed) interpolated within Qualisys Track Manager (QTM, Gothenburg, Sweden). Data will then be exported to MatLAB (The MathWorks, Natick, MA, USA) for data reduction and analysis. Finally, statistical analyses will be performed using R-Studio version 3.0.2 (R-Studio Inc., Boston, MA, USA). Whenever possible, data will be graphically represented as mean  $\pm$

95% Confidence Intervals. For all statistics, significance will be set at an alpha = 0.05. Additionally, Cohen's d effect sizes will be computed for all analyses, with 0.2, 0.5, and 0.8 indicating a small, moderate, and large effect, respectively (Vincent & Weir, 2012). For Pearson's product moment correlation modeling, a very strong positive and negative association will be accepted when  $.8 \leq r \leq 1$  and  $-.8 \geq r \geq -1$ , respectively, where r is the correlation coefficient. A strong positive and negative association will be accepted when  $.6 \leq r < .8$  and  $-.6 \geq r > -.8$ , respectively. Moderate positive and negative associations will be accepted when  $.4 \leq r < .6$  and  $-.6 > r \geq -.4$ , respectively. Finally, weak positive and negative associations will be accepted when  $.2 \leq r < .4$  and  $-.4 > r \geq -.2$ , respectively (Divaris, Vann Jr, Baker, & Lee, 2012).

### **3.1.4 Sample Size Estimates**

Table 3.1 provides the rationale for sample size estimates for each study. For study 1, sample size estimates are based on two dependent variables, fractal dynamics and split-belt gait symmetry measures. Data from the study by Choi and colleagues (2009) indicated a sample size of 10 would differentiate gait parameter symmetry between the first and last 5 strides in an asymmetric split-belt condition. Data from the study by Hausdorff et al. (1996) provided a sample size estimate of 8 in evaluating changes in fractal dynamics at different walking speeds. Because the proposed nonlinear techniques require long, continuous data sets, an additional 5 participants will be recruited to account for potential marker dropout, for a total of 15 participants.

Sample size estimates for study 2 again utilized the data from Choi et al. (2009) to determine adaptation to asymmetric split-belt conditions. Additionally, data from the study by Hausdorff et al. (1997) indicate a sample size of 11 is sufficient to determine

differences in fractal dynamics between young and older adults. Again, to account for potential marker dropout that deems the continuous data unusable, an additional 4 participants will be recruited, totaling 15. Finally, study 3 will utilize the data from studies 1 and 2.

**Table 3.1: Estimates of sample sizes based on reference data.** The ‘Pad’ column indicates the increased sample sizes based on the potential for data corruption (e.g., marker dropout).

Study		Reference 1	Reference 2	Pad	Final <i>n</i>
1	Reference	Choi et al., 2009	Hausdorff et al., 1996	5	15
	Power ( $\beta$ )	80%	95%		
	Sample Size	10	8		
	Variable	Leg angle symmetry	Fractal dynamics at different walking speeds		
2	Reference	Hausdorff et al., 1997	Choi et al., 2009	4	15 / group
	Power ( $\beta$ )	90%	80%		
	Sample Size	11	10		
	Variable	Fractal dynamics: young versus older adults	Leg angle symmetry		

### 3.2 Study 1: Gait Adaptability in Young Adults

In order to fully assess a locomotor system’s ability to adapt gait, participants will be exposed to task constraints that promote asymmetric walking. Earlier studies using the split-belt treadmill paradigm have indicated that participants exposed to asymmetrically moving treadmill belts attempt to regain leg symmetry (Bruijn et al., 2012; J. T. Choi &

Bastian, 2007; Dietz et al., 1994). This leg symmetry may be in the form of symmetric step lengths, or anti-phase leg angle motion. Evaluating individual-specific responses to this environment provides a precise quantification of gait adaptability.

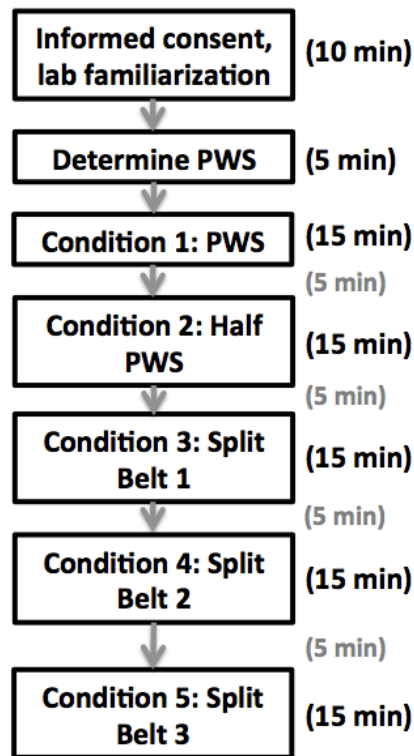
### **3.2.1 Participants**

This first study will consist of young, healthy adults aged 21-45. Recruitment will include a similar number of males and females (e.g., 8 of one gender, 7 of the other). These participants will have experienced walking on a treadmill, and be free from any injuries that may adversely affect walking gait. Additionally, participants will be free of general health risk factors (report ‘NO’ for all Physical Activity Readiness-Questionnaire (PAR-Q) questions, or obtain physician’s consent if answer ‘YES’ to one question). Because this will be the first study to evaluate fractal dynamics during asymmetric gait, and because many of these nonlinear measures require a large, continuous data set (i.e., no lost data within trial), a total of 15 participants will be recruited, which represents 150% of estimated sample size of 10 (Table 3.1) to account for potential data issues.

### **3.2.2 Protocol**

Participants will first read and sign an informed consent document, as well as a standard PAR-Q questionnaire. Once deemed eligible, participants will change into appropriate clothing attire and height and mass will be obtained. Retro-reflective markers will then be placed bilaterally on each participant’s greater trochanter of the femur, heel, and 2<sup>nd</sup> toe. In addition, a marker will be placed near the 2<sup>nd</sup> sacrum. The markers will be used to create a 5-segment model for kinematic data collection and analysis (Figure 3.1).

The next phase will entail familiarization with the treadmill and determination of preferred walking speed (PWS). To determine PWS, participants will be told that the treadmill will begin moving slowly and increase incrementally,



**Figure 3.3: Schematic of the protocol design for study 1.** Grey arrows and parentheses indicate rest time.

and instructed to verbally indicate when walking at ‘preferred’ or ‘comfortable’ walking speed. That is, the speed at which one would walk if neither rushing nor taking a leisurely stroll. The treadmill will begin moving at 0.5 m/s for 10 s, and increased by 0.1 m/s every 5-10 s thereafter until the participant verbally declares the current speed to be his or her PWS. This process will be repeated, only the treadmill will begin at their stated PWS plus 0.3 m/s, and incrementally decreased by 0.1 m/s every 5-10 s until the participant verbally declares the speed to be their PWS. The average of the two speeds will be

considered their PWS. If there is a discrepancy between the two values of  $> 0.1$  m/s, the protocol will be repeated until a consistent speed is determined.

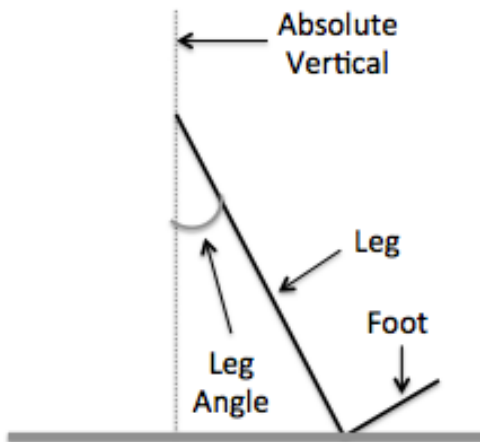
After obtaining PWS, participants will be told that the belt will move at their PWS for 15 minutes. After the trial is complete, they will be instructed to stay on the treadmill, and a chair will be placed on the treadmill for the 5-minute rest. The next trial will involve participants walking at half of their preferred walking speed ( $\frac{1}{2}$  PWS) for 15 minutes. Finally, participants will be exposed to three identical asymmetric split-belt (SB) trials. The SB trials will consist of the right belt traveling at the determined PWS and the left at  $\frac{1}{2}$  PWS. Participants will be instructed to use the handrails initially if compelled, but to attempt to minimize their use. Data recording will begin immediately, that is, there will not be an acclimation period, as the first strides represent the initial response to the asymmetric belt. Each SB trial will again last for 15 minutes, with a 5-minute break in between (Figure 3.3). The reason for placing the chair on the treadmill immediately following trials is to minimize any re-adaptation to the asymmetric belt exposure. Previous studies have suggested that adaptation and re-adaptation (or relearning) occurs rapidly with this split-belt paradigm (J. T. Choi & Bastian, 2007; Dietz et al., 1994).

### **3.2.3 Dependent Variables**

#### **3.2.3.1 Gait Parameters**

All of the ensuing gait parameters will be determined bilaterally. Stride time will be defined as the time from heel strike to subsequent heel strike of the same heel. Step length will be the anterior-posterior distance of the position of the heel marker at heel

strike to the position of the contralateral limb's heel marker at heel strike. Step width will be defined as the medial-lateral distance from the position of the heel marker of one leg at heel strike to the position of the heel marker of the other leg at subsequent heel strike. Stance time will be the



**Figure 3.4: Calculation of the sagittal plane leg angle.** The leg angle will be based on deviation of the leg segment from absolute vertical.

percentage of the gait cycle (stride time) in which the foot is in contact with the ground. Swing time will be the stride time minus the stance time. For stride time, step length, and step width variability, the standard deviation across strides will be obtained. Leg angle will be calculated as the angle in degrees of the leg segment from absolute vertical (Figure 3.4).

### 3.2.3.2 Performance Variables

Gait adaptability will be quantified based on symmetry measures, or more specifically, deviation from symmetry. Phase deviation of the leg angles ( $\text{Phase}_{\text{dev}}$ ) will be considered the average deviation from perfect anti-phase for each stride. Each stride

will be normalized to 100 points, and the cross correlation function will be calculated between leg angles for the right and left leg. The number of frame lags to maximal negative correlation (anti-phase motion) minus 0.5 (perfect anti-phase) will quantify  $Phase_{dev}$ , with greater number of lags indicating greater deviation (J. T. Choi & Bastian, 2007). In addition to  $Phase_{dev}$ , symmetry will be calculated for several gait parameters. For all measures of gait parameter symmetry, a general formula for symmetry index (Equation 3.1) will be employed (J. T. Choi et al., 2009):

$$Symmetry\ Index = \frac{Fast\ Leg - Slow\ Leg}{Fast\ Leg + Slow\ Leg} \quad \text{Equation 3.1}$$

where Fast Leg and Slow Leg are the legs moving at PWS and half PWS, respectively. A symmetry index = 0 indicates perfect symmetry. Greater deviation from 0 indicates greater asymmetry. Positive and negative values indicate the fast leg is taking a longer or shorter step, respectively (J. T. Choi et al., 2009). Based on the symmetry index, for step length symmetry ( $Sym_{length}$ ), the following calculation will be used:

$$Sym_{length} = \frac{SL_{fast} - SL_{slow}}{SL_{fast} + SL_{slow}} \quad \text{Equation 3.2}$$

where  $Sym_{length}$  is the symmetry of step length, SL is step length, and fast and slow represent the faster and slower moving legs, respectively. For step width symmetry, the following equation will be used:



$$Sym_{width} = \frac{SW_{RL} - SW_{LR}}{SW_{RL} + SW_{LR}} \quad \text{Equation 3.3}$$

where  $Sym_{width}$  is the step width symmetry, SW is step width, and RL and LR indicate the step width from right to left foot and left to subsequent right foot, respectively. To establish percentage of swing phase, the following calculation will be used) (Bruijn et al., 2012):

$$\%swing(i) = \frac{t_{heelstrike(i)} - t_{toeof(i-1)}}{t_{heelstrike(i)} - t_{heelstrike(i-1)}} * 100 \quad \text{Equation 3.4}$$

where t corresponds to timing of events, and  $i$  represents the stride index. The symmetry index will then be calculated as:

$$Sym_{swing} = \frac{\%Swing_{Fast} - \%Swing_{Slow}}{\%Swing_{Fast} + \%Swing_{Slow}} \quad \text{Equation 3.5}$$

Stride time symmetry will be determined using the following calculation:

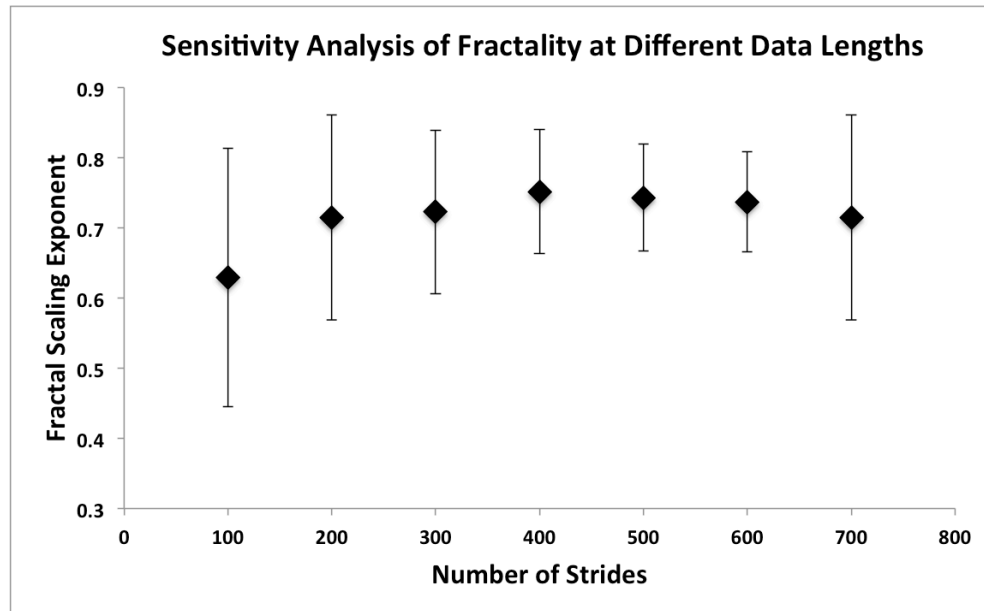
$$Sym_{stride} = \frac{ST_{Fast} - ST_{Slow}}{ST_{Fast} + ST_{Slow}} \quad \text{Equation 3.6}$$

where  $Sym_{stride}$  is stride time symmetry and ST is the stride time. All symmetry measures ( $Phase_{dev}$ ,  $Sym_{stride}$ ,  $Sym_{length}$ ,  $Sym_{width}$ , and  $Sym_{swing}$ ) will be calculated for the first and last 5 strides of each condition to provide comparisons with earlier studies (J. T. Choi & Bastian, 2007; J. T. Choi et al., 2009). Additionally, the absolute magnitude of phase and

symmetry deviation for non-overlapping windows of 50 strides will be quantified to assess the extent of deviation at the evolution of temporal scales (Bruijn et al., 2012). This analysis may also allow for a timing component of adaptation (e.g., deviation that is not different from 0 occurring at window 1 versus 2 indicates faster adaptation).

### **3.2.3.3 Nonlinear Gait Adaptability Variables**

Fractal dynamics will be determined using Detrended Fluctuation Analysis (DFA) of the first 500 strides. Although the PWS and SB trials will yield stride time data of length  $\sim 700$  or greater, the  $\frac{1}{2}$  PWS trial will only yield  $\sim 550$ . Sensitivity analyses conducted with pilot data (Figure 3.5) have suggested the DFA algorithm is sensitive to data length. Generally, greater data length is considered more appropriate for nonlinear techniques. While this sensitivity analysis does not provide evidence for conclusive recommendations, trial length will be held constant for all participants across all conditions. That is, rather than keeping trial time constant (i.e., 15 minutes), each trial will be truncated to the shortest data length for all subjects, which will likely be between 500-600 data points. A linear fit line will be used for detrending and fluctuation summation. The minimal and maximal window sizes will be 5 and 50, respectively.



**Figure 3.5: Sensitivity analysis of the effects of data length on fractal scaling exponent.** Data presented as median  $\pm$  SD for eleven participants' left leg stride times.

Complexity analyses will be evaluated using Multiscale entropy (MSE) of the sacral marker trajectory in three directions: vertical, AP, and ML. The  $m$  and  $r$  parameters will be set at 2 and .15, respectively (see section 2.2.3), based on previous work (Costa et al., 2003). Finally, summation of the area under the MSE-scale factor curve will define the Complexity Index (CI, equation 2.4), whereby greater CI indicates greater complexity.

### 3.2.4. Statistical Analyses

To test hypothesis 1.1 that asymmetric walking will initially break down fractal dynamics to values closer to  $\alpha = 0.5$ , followed by a return to standard fractal values observed in unperturbed walking ( $\alpha \sim 0.75$ ), a within-subject repeated-measures analysis of variance (ANOVA) will be performed, followed by post hoc adjustments using Tukey's Honestly Significant Difference (HSD) testing. Hypothesis 1.1 will be accepted

if stride time fractal dynamics during the first SB trial are significantly lower than during the PWS trial, and if there is no difference between fractal dynamics in the PWS versus the third SB trial.

Hypotheses 1.2 and 1.3 state that fractal dynamics and complexity, respectively, during steady state walking will be correlated with gait adaptability. To test these hypotheses, associations will be assessed via linear regression analyses. Specifically, two separate linear regressions will determine if gait adaptability (phase deviation as dependent variable) is associated with fractal dynamics (DFA scaling exponent as independent variable for first regression model) or complexity (MSE complexity index as independent variable for second regression model). Gait adaptability will be defined as the average magnitude of deviation from intended anti-phasing of the leg angles for the first 50 strides. Additionally, linear regression models will test hypothesis 1.4 that gait adaptability (phase deviation as dependent variable) will be associated with stride time variability, step length variability, and step width variability (separate independent variables).

Exploratory analysis 1.1 investigates whether fractal dynamics and complexity analyses together will better predict gait adaptability than either one algorithm alone. To test this, results from the fractal dynamics and complexity analyses will be submitted to a multiple regression analysis as independent variables, with gait adaptability treated as the dependent variable.

Finally, exploratory analysis 1.2 investigates whether stride time variability and fractal dynamics will predict gait adaptability more accurately combined than separate. A multiple regression analysis will again be used, with stride time variability and fractal

dynamics as independent variables, and gait adaptability as the dependent variable. For both exploratory analyses, gait adaptability will again be quantified as the mean amplitude of deviation from intended anti-phasing of the leg angles for the first 50 strides.

For all statistical analyses pertaining to gait adaptability, all of the proposed measures of gait symmetry ( $\text{Phase}_{\text{dev}}$ ,  $\text{Sym}_{\text{stride}}$ ,  $\text{Sym}_{\text{length}}$ ,  $\text{Sym}_{\text{width}}$ , and  $\text{Sym}_{\text{swing}}$ ) will be evaluated. However,  $\text{Phase}_{\text{dev}}$  will be the primary measure of symmetry and adaptability and tested to accept or reject the hypotheses, as this parameter has been shown to represent adaptation of gait (Bruijn et al., 2012; J. T. Choi & Bastian, 2007; Dietz et al., 1994) and distinguish cohorts (Bruijn et al., 2012).

### **3.3 Study 2: Gait Adaptation and Re-Adaptation in Young and Older Adults**

While identifying young adults' capacity to adapt gait is of interest and importance, what may be of greater significance is evaluating those individuals at highest risk of falling. Specifically, older adults represent a cohort that is at high risk for falling, and this risk increases with increasing age. Moreover, this cohort historically has been the most adversely affected by falls (CDC, 2011, 2012), as these incidences lead to bone fractures, concussions, long-term disability, and, at worst, death.

Determining an individual's capacity to successfully respond to a discrete gait perturbation will provide a more complete story of the capacity of the locomotor system. That is, can individuals respond to transient, as well as prolonged, alterations in locomotor demands? Furthermore, do measures of gait stability predict the ability to successfully respond to a discrete gait perturbation?

### **3.3.1 Participants**

For this study, two cohorts will be recruited. The first group will consist of healthy, active older adults (aged 60-70) with no history of falls. The second group will consist of healthy, active young adults aged 21-40. For both cohorts, fifteen participants per group (both evenly distributed for gender) will be recruited to allow for potential data issues (Table 3.1). All participants will either 1) answer 'NO' to each PAR-Q question, or 2) obtain physician's consent to participate in moderate-intensity physical activity. Participants will be free from any conditions that affect balance or locomotion (visual, vestibular, somatosensory deficits, musculoskeletal injuries, medications causing dizziness), and have experience walking on a treadmill. In addition, both groups will be matched for physical activity based on a questionnaire (Godin Leisure-Time Exercise Questionnaire) prior to data collection (i.e., during phone screen). Participants will declare that they participate in at least 150 minutes per week of moderate or 75 minutes per week of vigorous physical activity (2008). This criterion will ensure those recruited are self-reported as physically active. Recruiting physically active young and older adults will reduce potential fatigue effects and provide more homogenous groups. Once deemed as qualified for the study, participants will be instructed to wear an accelerometer for 7 days so that a precise quantification of physical activity can be attained.

### **3.3.2 Protocol**

This protocol will require two sessions (Figure 3.6). On session 1, participants will read and sign the informed consent and PAR-Q, complete a physical activity questionnaire (long form Godin Questionnaire), change into appropriate attire, and determine height and mass. Marker locations will be identical to study 1, except for the

addition of markers on the lateral epicondyles of the femur. This will allow for thigh and shank segment construction, and thus intra- and inter-limb coordination analyses (Figure 3.2). Participants will first be instructed to stand on a force plate and minimize motion (quiet standing) for 30 seconds. Participants will then be instructed to stand quietly for an additional 30 seconds, but with eyes closed. After determining each participant's individual PWS (see study 1 protocol), each participant will then experience the PWS walking trial for 15-minutes, followed by the half PWS trial for 20 minutes. Finally, participants will be provided with waist-worn accelerometers and detailed instructions as to its use over the next 7 days.

The second session will occur at least 7 days following the first (7-14 day range). Session 2 will begin with collection of the accelerometer, followed by a repeat trial of quiet standing eyes open and eyes closed for 30 seconds each. The next condition will be PWS for 10 minutes. The PWS trial will serve as the warm-up, and both the postural and PWS walking conditions will allow day-to-day reliability assessment. After the PWS trial, participants will perform three 2:1 asymmetric split-belt trials, each for 12 minutes. For each trial, the treadmill belts will first move at the same speed for an undisclosed number of strides (10-15). Following these initial strides, the belt of the non-dominant leg will rapidly ( $25 \text{ m/s}^2$ ) decelerate to half PWS while the left foot is in swing phase (i.e., not in contact with the treadmill). This rapid change in belt speed will serve two purposes: 1) provide a quantification of gait stability (TTC, MOS) at the onset of altered gait, that is, when the left foot touches down on the slower moving belt, and 2) mark the start of the asymmetric 2:1 split-belt condition. Following completion of the three split-

belt trials, participants will perform a re-adaptation trial, whereby both treadmill belts will move at PWS, which will last for 5 minutes (Figure 3.6).

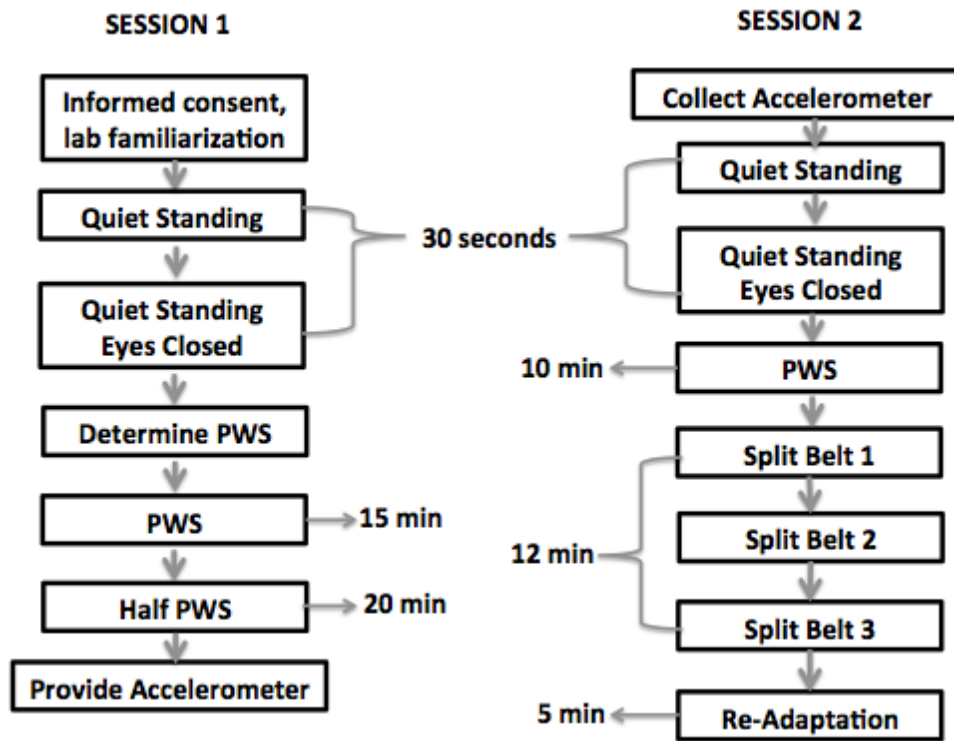


Figure 3.6: Schematic of the protocol design for study 2.

Rating of Perceived Exertion (RPE) values will be collected at the beginning, middle, and end of each walking trial. Five minutes of rest will be provided following each walking trial. However, more rest time will be provided if needed or requested by a participant to minimize fatigue.

### 3.3.3 Dependent Variables

#### 3.3.3.1 Gait Parameters

The same gait parameters obtained in study 1 will be determined in this study. These include: stride time, step length, step width, stance time, swing time, and variability of stride time, step length and width, and stance and swing time. Leg angles



will be calculated in the same manner as study 1, which will allow for comparison with study 1 and earlier studies (J. T. Choi & Bastian, 2007; J. T. Choi et al., 2009). In addition, leg angles will be calculated using the ‘thigh segment’ to determine if this method provides a better estimate of the interactions between legs.

### **3.3.3.2 Performance Variables**

Gait adaptability will again be quantified based on deviation of symmetry of phase measures using the same equations (3.1-3.6). Phase deviation of the legs ( $\text{Phase}_{\text{dev}}$ ) will be considered the average deviation from perfect anti-phase for each stride. Symmetry parameters ( $\text{Sym}_{\text{stride}}$ ,  $\text{Sym}_{\text{length}}$ ,  $\text{Sym}_{\text{width}}$ , and  $\text{Sym}_{\text{swing}}$ ) will be evaluated based on deviation from perfect symmetry (symmetry index = 0). All  $\text{Phase}_{\text{dev}}$  and symmetry performance variables will be calculated for the first and last 5 strides, as well as absolute magnitude of deviation in non-overlapping windows of 50 strides.

### **3.3.3.3 Nonlinear Gait Adaptability Variables**

Fractal dynamics will be determined using DFA. The DFA algorithm will be conducted on the shortest data length for all subjects for half PWS, PWS, and SB. That is, data length will again be held constant. A linear fit line will be used for detrending and fluctuation summation. The minimal and maximal window sizes will be 5 and 50, respectively.

Complexity analyses will be evaluated using Multiscale entropy (MSE). The  $m$  and  $r$  parameters will again be set at 2 and .15, respectively, based on earlier studies (Costa et al., 2003). MSE will be performed on the sacral marker trajectory in three

directions. Summation of the area under the MSE-scale factor curve will define the Complexity Index (CI), whereby greater CI indicates greater complexity.

#### **3.3.3.4 Gait Stability Measures**

Gait stability measures will be determined during unperturbed walking and at the onset and immediately following each perturbation (i.e., belt speed change during split-belt conditions). Minimal and average measures of margin of stability (MOS, equation 2.5, 2.6) and time to contact (TTC, equation 2.7, 2.8) of the COM during the stance phase to the lateral and anterior boundaries will be evaluated during unperturbed walking (PWS and half PWS). The lateral boundary ( $BOS_{ML}$ ) will be based on the 5<sup>th</sup> metatarsal marker of the stance foot. The anterior boundary ( $BOS_{AP}$ ) will be the stance foot's toe marker. The two derived variables will be the mean and minimal MOS and TTC. When perturbations are elicited, the minimal MOS/TTC and MOS/TTC at instance of perturbation and during recovery step will be computed for both anterior and lateral directions. The  $BOS_{ML}$  boundaries will again be based on the 5<sup>th</sup> metatarsal markers of each foot, while the  $BOS_{AP}$  boundaries will be based on the anterior-most and posterior-most foot marker in contact with the ground.

Local stability will be evaluated using the maximal finite-time Lyapunov exponent ( $FT\lambda_{MAX}$ , equation 2.11, 2.12) of the sacral marker during unperturbed walking. Orbital stability of the sacral marker and heel marker will be assessed via Floquet multipliers at each percentage of normalized stride in unperturbed walking, in addition to a discrete measure immediately prior to, during, and immediately following each perturbation.

Finally, scalar variability measures will be assessed for associations with gait stability. These measures include the variability of stride time, step length, and step width.

### **3.3.4 Statistical Analyses**

The hypotheses that older adults will have a reduced ability to adapt gait (2.1), as well as require more time to adapt gait (2.2), will be evaluated via independent samples t-tests. Specifically, the average magnitude of deviation from intended phasing (anti-phase, 0.5) of the leg angles for the first 50 strides will be assessed for young versus older adults.

To test the hypothesis that older adults will exhibit reduced aftereffects in the re-adaptation condition (2.3), independent samples t-tests of the average magnitude of leg angle phase deviation from anti-phase for the first 50 strides will be conducted for young versus older adults.

To test hypotheses 2.4 that fractal dynamics will be lower in older adults compared to young adults during preferred speed walking, independent samples t-test will be performed on fractal scaling exponents during preferred speed walking.

To test hypotheses 2.5 that complexity will be lower in older adults compared to young adults during preferred speed walking, independent samples t-tests will be performed on the complexity indices during preferred speed walking.

Hypothesis 2.6 states that fractal dynamics will be associated with gait adaptability. To test this, separate linear regression models will be fit to the data for each group, with gait adaptability measures (magnitude of phase deviation of leg angles) as dependent variables and fractal dynamics (scaling exponent) as the independent variable.

Hypothesis 2.7 predicts a U-shaped relationship between gait adaptability and step width variability in older adults. This will be evaluated by submitting the data (step width variability as the independent variable and gait adaptability (phase deviation) parameters as the dependent variable) to a quadratic regression analysis.

Hypothesis 2.8 predicts that there will be a relationship between gait stability measures during steady state and in response to the perturbation (initial change in belt speed). To test this, a linear correlation model will be applied to the gait stability measures (minimal TTC, MOS) during steady state walking at PWS and immediately following the belt speed change during the first split-belt condition.

The hypotheses that older adults will exhibit reduced gait stability during steady state (2.9) and following the perturbation (2.10) will be tested via separate independent samples t-tests of minimal TTC and MOS.

Once again, all measures of gait symmetry will be evaluated when testing gait adaptability versus other parameters.  $\text{Phase}_{\text{dev}}$  will again be the primary measure of symmetry and adaptability, as this has been shown to not only represent gait adaptation (Bruijn et al., 2012; J. T. Choi & Bastian, 2007; Dietz et al., 1994), but also and distinguish young versus older adult cohorts (Bruijn et al., 2012).

### **3.4 Study 3: Multifractal Analysis of Asymmetric Walking in Young and Older Adults**

While monofractal analysis (DFA) may provide insights regarding locomotor organization and response to constraints, some behaviors or signals may not be fully represented by one scaling exponent (Figure 2.6, 2.7). Signals that exhibit periods of high or low variability require a continuum of scaling exponents to accurately detect local

changes to the coupling of fluctuations across temporal scales. If there is more than a single physiological process at a given temporal scale interacting (or, at the least, statistically correlated) with processes at longer temporal scales, a multifractal analysis is required. As mentioned earlier, at this time only a few studies have attempted to determine the multifractality of walking gait parameters. Of those studies that have analyzed multifractality of gait, surprising and disputable findings were reported. More studies are needed to provide evidence of the presence or absence of multifractality in gait parameters of young and older healthy adults. If multifractality is present, the standard monofractal DFA algorithm should be replaced by a multifractal analysis.

#### **3.4.1 Participants**

The participants' data from studies 1 and 2 will be used to analyze multifractality. This will provide two young healthy cohorts and an older healthy and active cohort. Each group will consist of 15 participants. Analyzing two separate young, healthy groups from data collected at different times will allow for a reliability test of the multifractal algorithm. Analyzing young versus older groups will allow for an evaluation of potential age effects of multifractality in locomotion.

#### **3.4.2 Protocol**

Participants will experience the various conditions described in sections 3.2 and 3.3 for studies 1 and 2, respectively. Data from each of these study's conditions (quiet standing, quiet standing eyes closed, preferred speed walking, half preferred speed walking, asymmetric split-belt) will be used to determine the extent of multifractality.

### **3.4.3 Dependent Variables**

#### **3.4.3.1 Multifractality Measure**

Multifractal Detrended Fluctuation Analysis (MFDFA) will be employed to determine the extent of multifractality of a signal. The scaling exponents will be determined ‘locally’ by performing the traditional DFA algorithm on a moving-window across the time series (Ihlen, 2012, 2013; Ihlen & Vereijken, 2013b). This method provides a spectrum of scaling exponents that are then arranged in a probability distribution function (PDF). The range of the PDF scaling exponents (absolute range, interquartile range) provides a quantification of the degree of multifractality. A greater range indicates greater presence of multifractality.

This study will primarily evaluate the multifractality of stride times. As secondary measures, the multifractality of step length, step width, and sacral marker trajectory will also be determined.

#### **3.4.4. Statistical Analyses**

Hypothesis 3.1 states that the young cohort will display less multifractality compared to older adults. To test this, an independent samples t-test of the MFDFA results during PWS will be compared. A smaller multifractal spectrum width will indicate less multifractality.

While walking at slower than preferred walking speeds has been shown to increase fractal scaling closer to  $\alpha = 1.0$  (Hausdorff et al., 1996; Jordan et al., 2007a), no study has yet explored the effects of gait speed on multifractality. Thus, an exploratory

analysis will determine the effects of gait speed on the width of the multifractal spectrum, as well as if there is an age effect.

To test the 2<sup>nd</sup> hypothesis that young adults will display greater multifractality in response to the asymmetric walking condition (3.2), an independent samples t-test will be performed on the MFDFA results for the first split-belt condition. This hypothesis will be accepted if the multifractal spectrum width is greater in young versus older adults.

Finally, to test the hypothesis that young adults will exhibit reduced multifractality in the 2<sup>nd</sup> and 3<sup>rd</sup> split-belt conditions compared to older adults (3.3), a between-subject repeated measures ANOVA will be performed on the MFDFA results during PWS and three split-belt conditions. Tukey's HSD post hoc analysis will be performed between groups for the 2<sup>nd</sup> and 3<sup>rd</sup> split-belt trials.

#### **3.4.5. Potential Problems and Alternative Approaches**

The proposed 7-segment kinematic model (Figure 3.2) for study 2 (and partially study 3) will allow for inter- and intra-limb coordinative analyses. However, because the laboratory is currently limited to 4 cameras, adding more marker trajectories (and, thus, segments) may not be possible. The current camera set up may allow for the proposed kinematic model. Alternatively, it may be possible to temporarily acquire additional cameras. Pilot testing will confirm if this model can be used, and in the event it cannot, the proposed 5-segment model (Figure 3.1) from study 1 will be used.

An additional problem that may arise entails fatigue from the split-belt treadmill trials. Pilot testing has indicated that some participants report localized fatigue (e.g., hip flexor muscle) during the 15-minute trials but no global fatigue. To minimize the risk of fatigue, several considerations have been established. First, study 2 will now take place

over the course of two sessions. The first session will not involve asymmetric walking trials. On the second session, only two 30-s standing trials and a 10-min preferred walking speed warm-up trial will be performed prior to the asymmetric trials. In addition, trial length has been reduced from 15 to 12 minutes, thus reducing the overall asymmetric walking time from 45 to 36 minutes. Regarding trial number, while an argument could be made that performing three split-belt trials is insufficient in capturing full adaptation, pilot testing has indicated adaptation and changes to nonlinear measures are established by the end of the third trial. Additional trials would further increase the risk of fatigue. Moreover, while a minimum of 5 minutes of rest will be provided prior to each asymmetric trial, more rest time will be granted at any participant's request. Furthermore, physically active adults will be recruited, as those who qualify will report participating in at least 150 minutes of moderate or 75 minutes of vigorous physical activity per week. Finally, while several precautions will be taken, we will collect RPE values at 0, 4, 8, and 12 minutes for each split-belt trial. In the event of reported fatigue (or more accurately, increased exertion), the RPE data can be used as a covariate.



## CHAPTER IV

### AMMENDMENTS TO THE PROPOSED EXPERIMENTS

This chapter describes the changes made between the proposed studies and the subsequent chapters. The studies have maintained nearly all of the originally proposed outlines. The main modification is that some of the proposed analyses (with corresponding hypotheses) will not be reported in this document. Namely, certain measures of complexity (i.e., multiscale entropy), stability (i.e., time-to-contact, margin-of-stability) and gait adaptability (symmetry indices) are not included. Most of these analyses were still, in fact, executed. However, including all of these findings would likely distract from the primary aims of the dissertation, which are to determine the potential relationship between gait adaptability and fractality.

Studies 1 and 2 will not report on measures of complexity, and therefore not include hypothesis 1.3, 2.5, or exploratory analysis 1.1. In addition, these studies will focus on stride time variability magnitude and structure, and not on other measures of variability. Therefore, the subsequent chapters will not include hypotheses 1.4, 2.7, or exploratory analysis 1.2. Moreover, study 2 will not report on measures of gait stability (i.e., time-to-contact or margin-of-stability), and therefore hypotheses 2.8, 2.9, and 2.10 will not be presented.

Study 3 initially aimed to determine stride time multifractality in young and older adults, and thus we proposed to analyze data from study 2. However, evaluation of the potential multifractality of unperturbed walking is understudied, and assessing multifractality of asymmetric walking has not yet been investigated. Therefore, we decided to instead analyze data from study 1 that included only young, healthy adults.

With this change, hypotheses 3.1, 3.2, and 3.3 required updating, as all hypotheses were initially based on age group differences. Based on previous research, we now hypothesize that unperturbed walking will exhibit monofractality (H3.1), asymmetric walking will exhibit multifractality (H3.2), and that the extent of multifractality will associate with gait adaptability performance (H3.3).

## CHAPTER V

### ASSOCIATION BETWEEN STRIDE TIME FRACTALITY AND GAIT ADAPTABILITY DURING UNPERTURBED AND ASYMMETRIC WALKING

#### 5.1 Abstract

Human locomotion is an inherently complex activity that requires numerous processes at various spatiotemporal scales. Locomotor patterns must constantly be altered in the face of changing environmental or task demands, such as heterogenous terrains or obstacles. The variability in stride time occurring at short time scales (e.g., 5-10 strides) is statistically correlated to larger fluctuations occurring over longer time scales (e.g., 50-100 strides). This relationship is known as fractal dynamics, and optimal fractality exhibits a 1:1 proportional relationship and is thought to represent the adaptive capacity of the locomotor system. However, this has not been tested empirically. Thus, the purpose of this study was to determine if steady state stride time fractality could predict the ability for individuals to adapt their gait patterns when necessitated by the demands of the locomotor task. Participants were exposed to walking on a split-belt treadmill that induced an asymmetry that required adaptation of locomotor patterns. Fifteen healthy adults walked at their preferred speed, at half of their preferred speed, and with one leg at their preferred speed and the other at half speed (2:1 ratio asymmetric walking). The slow speed manipulation was chosen in order to determine slow walking fractal dynamics. Detrended fluctuation analysis was used to quantify the presence of fractality in stride times, and cross correlation analysis was used to measure the deviation from intended anti-phasing between legs as a measure of gait adaptation. Results revealed no

association between unperturbed walking fractal dynamics and gait adaptability performance. However, there was a quadratic relationship between perturbed, asymmetric walking fractal dynamics and adaptive performance during split-belt walking, whereby individuals who exhibited extreme fractal scaling values performed the poorest. Compared to steady state preferred walking speed, fractal dynamics increased closer to  $\alpha = 1.0$  when participants were exposed to asymmetric walking. These findings suggest there may not be a relationship between unperturbed preferred or slow speed walking fractal dynamics and gait adaptability. However, the emergent relationship between asymmetric walking fractal dynamics and gait adaptability may represent a functional reorganization of the locomotor system (i.e., improved interactivity between degrees of freedom within the system) to be better suited to attenuate externally generated perturbations at various spatiotemporal scales.

## 5.2 Introduction

Human locomotion is an inherently complex activity that requires the control and coordination of many neurophysiological and biomechanical degrees of freedom. To achieve locomotion, the body utilizes various physiological systems that are organized hierarchically at different spatiotemporal scales. That is, nested within larger structures (e.g., inter-limb dynamics) are subsystems (e.g., control of joints) that are at progressively smaller scales but no less important. For example, achieving a single step requires a network of neurons that innervate numerous muscles to activate in order to generate force so that the limbs are displaced. At larger scales, modifying joint angles via activation of these neurons occurs at higher order centers (e.g., motor cortex). At smaller scales, production of force in a muscle requires dynamics between calcium and filament components (e.g., actin, myosin) at the level of a single sarcomere. To further complicate matters, walking rarely occurs in the absence of endogenous or exogenous disturbances. Successful locomotion therefore requires the integration of sensorimotor processes (i.e., information from the periphery, vestibular system, visual system, brainstem, spinal reflex system, cerebellum or basal ganglia) across various spatiotemporal scales to attenuate these disturbances. From a system's perspective, locomotor adaptability (sometimes referred to as flexibility) and stability emerge as a result of the interactions among these processes (Goldberger, 1996; Ivanov et al., 2009; Manor & Lipsitz, 2013).

While a healthy system can attenuate perturbations and maintain locomotion, less adaptable systems may experience falls. Given the abundance of fall-related complications reported (CDC, 2011, 2012), numerous researchers have attempted to identify gait characteristics that predict future falls; a question that Hausdorff (2005)

labels as “one of the ‘holy grails’ of geriatric and rehabilitation research.” Within the locomotion literature, gait parameter variance has consistently been associated with fall risk, whereby higher variability has often been linked to reduced stability and system control. For example, greater stride time variability (Hausdorff, 2005; Maki, 1997) and step width variability (Dean et al., 2007; Owings & Grabiner, 2004) are associated with increased fall risk in older adults. However, variability magnitude only provides one piece of information about the locomotor system. Over the past two decades, researchers have begun to look beyond the magnitude of variability, and instead evaluate its *temporal structure* (Hausdorff et al., 1995; Hausdorff et al., 1996; Lipsitz & Goldberger, 1992; Peng et al., 1995). Nearly all physical and biological systems exhibit variable behavior. Understanding the nature of these fluctuations can provide important information about the system. When the behavior at small temporal or spatial scales resembles behavior at larger scales, it is considered self-similar or scale-invariant (Liebovitch & Shehadeh, 2003; Mandelbrot, 1977). Scale invariance indicates structural or behavioral complexity, and is a hallmark of healthy, adaptable systems. For example, scale invariance has been observed in biological systems both structurally (e.g., nucleotide sequences (Peng et al., 1992), vascular system (Guidolin, Crivellato, & Ribatti, 2011)) and temporally (e.g., heart rate variability (Peng et al., 1995), respiration (Peng et al., 2002)). It has also been observed in various motor behaviors, such as finger tapping (Chen, Ding, & Kelso, 1997; Gilden, Thornton, & Mallon, 1995; Torre & Delignieres, 2008), serial force production (Wing, Daffertshofer, & Pressing, 2004), and reaction time (Van Orden, Holden, & Turvey, 2003). Finally, the ubiquity of scale invariance extends beyond biological systems, as it is observed in various aspects of nature, such as the structure of lightning

(Liebovitch & Shehadeh, 2003), tree and root branching (Liebovitch & Shehadeh, 2003), coastlines (Mandelbrot, 1967), and the organization of traffic flow on an expressway (Musha & Higuchi, 1976).

Self-similar behavior is ‘persistent’ in nature. That is, statistically persistent processes are positively correlated such that successive deviations are statistically more likely to occur in the same direction. Persistent processes can be classified as either short- or long-term correlated. Short-term correlated processes are characterized by a rapidly decaying autocorrelation (e.g., first- or second-order autoregressive processes). Long-term correlated processes, on the other hand, are characterized by an autocorrelation function that does not decay rapidly but rather in a power-law fashion. These processes exhibit multiscale dependence on previous behavioral states and lack a characteristic timescale. Thus, the fluctuations occurring over short timescales are statistically correlated to fluctuations occurring over longer time scales. Long-range correlated processes are often referred to as ‘fractal’ behavior because of their scale-invariant nature, and are considered adaptive based on their dissipative characteristics.

Statistically persistent behavior has also been observed in human locomotion. There is substantial evidence demonstrating that the temporal structure of gait variability is not random, as previously believed, but exhibits statistically persistent fluctuations (Bollens, Crevecoeur, Nguyen, Detrembleur, & Lejeune, 2010; Hausdorff, 2007; Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996; Hausdorff, Zeman, Peng, & Goldberger, 1999; Ihlen & Vereijken, 2014; Jordan et al., 2007b; Marmelat, Torre, Beek, & Daffertshofer, 2014; Rhea & Kiefer, 2013; Terrier & Deriaz, 2011, 2012). For example, long or short stride times are likely to be followed by subsequent long or

short stride times, respectively. Statistical persistence may represent adaptive gait behavior. That is, a fractal signal exhibits power at every frequency that is proportional to the period of oscillation. If the power of the signal is dispersed in a manner that allow perturbations at any given scale to be attenuated, the system overall is more adaptable (Delignieres et al., 2006). Thus, the fractal properties observed in walking appear to represent gait adaptability, defined as the capacity to change locomotor patterns in response to imposed constraints (Balasubramanian, Clark, & Fox, 2014), because these correlations may indicate interactivity among biological processes that help to attenuate perturbations (Delignieres & Marmelat, 2012; Delignieres et al., 2006; Rhea & Kiefer, 2013; Stergiou & Decker, 2011). Fractal gait dynamics decrease in healthy older adults (Hausdorff et al., 1997) and those with neurological disorders, such as Parkinson's (Hausdorff, 2009) and Huntington's (Hausdorff et al., 1997) disease. Moreover, older adults with a fall history display lower fractality than healthy older adults (Herman, Giladi, Gurevich, & Hausdorff, 2005). These observations further suggest a connection between fractal dynamics and locomotor adaptive capabilities. However, this potential relationship has not yet been tested empirically.

While fractal analysis is a theoretical representation of adaptive gait, various paradigms have been developed to directly test locomotor adaptability. Empirically, gait adaptability can be evaluated by requiring an individual to change locomotor patterns to successfully continue walking. For example, obstacle clearance tasks (Heijnen, Muir, & Rietdyk, 2012) require increased toe height during the swing phase, while stepping onto specific locations on the floor (J. T. Choi, Jensen, & Nielsen, 2016) constrains spatial stepping parameters. However, these paradigms involve discrete locomotor pattern



changes (e.g., for a single step or stride), whereas real-world gait adaptations may often include chronic alterations. From an ecological perspective, perhaps a more appropriate paradigm assesses long-term locomotor adaptations while individuals walk on a split-belt treadmill. This treadmill has separate belts whose speeds can be independently controlled, allowing for exposure to asymmetric walking patterns (i.e., legs travel at different speeds during stance phase of walking). Generally, participants are able to adapt to asymmetric belt speeds by rapidly improving symmetry of leg relative phasing (J. T. Choi & Bastian, 2007), step length symmetry (Bruijn et al., 2012), or stance and swing time (Dietz et al., 1994).

Fractal dynamics are thought to represent the adaptive capacity of the locomotor system, yet this notion has not been testing empirically. The split-belt treadmill offers an ideal paradigm to evaluate long-term adaptive changes to asymmetries. Moreover, while organismic (e.g., age and disease) and task-level (e.g., gait speed (Hausdorff et al., 1996; Jordan et al., 2007b)) constraints alter fractal dynamics, it is unclear how asymmetric walking might affect fractality. Thus, the purpose of this study was to determine if stride time fractality during unperturbed and asymmetric walking in young, healthy adults predicts an individual's ability to successfully adapt locomotor patterns when exposed to gait asymmetries. We exposed participants to asymmetric split-belt walking and compared both steady state unperturbed (symmetric belt speeds) and perturbed (asymmetric belt speeds) walking fractality to their adaptive gait capacity. We hypothesized that 1) fractality while walking unperturbed at preferred walking speed would be associated with gait adaptability, whereby less persistent stride time fractal dynamics would associate with poorer gait performance. We also hypothesized that 2)

asymmetric walking fractal dynamics would associate with adaptive gait performance, again with less correlated behaviors aligning with poorer gait performance. Third, we hypothesized that 3) stride time fractality would break down (i.e., resemble more random structure) during the more challenging asymmetric walking condition. In addition, given that individuals appear able to adapt rapidly to imposed gait asymmetries (J. T. Choi & Bastian, 2007; Dietz et al., 1994), we hypothesized that 4) repeated exposure to asymmetric constraints would yield more fractal-like structured variability. Finally, because previous research provides evidence that slower walking increases fractal dynamics (Hausdorff et al., 1996; Jordan et al., 2007b), we hypothesized that 5) during asymmetric walking, the slower moving leg would exhibit greater fractal scaling values compared to the faster moving leg.

## **5.3 Methods**

### **5.3.1 Participants**

Fifteen healthy adults (8 male; age:  $28.5 \pm 4.7$  years; height:  $169.4 \pm 8.2$  centimeters; mass:  $75.7 \pm 15.8$  kilograms) participated in this study. All participants were free of neurological, visual, or vestibular impairments that might affect walking. In addition, all participants reported being right leg dominant, based on the question of which leg they would likely use to kick a ball. All participants completed a PAR-Q document and informed consent. The local Institutional Review Board approved this study.

### **5.3.2 Experimental Setup and Apparatus**

Participants wore tight fitting athletic shorts and shirt. Retroreflective markers were placed bilaterally at the toe (5<sup>th</sup> metatarsal), heel (3 cm inferior to the lateral malleolus), greater trochanter, and near the 1<sup>st</sup> sacral vertebrae. Kinematic data were collected using four high-speed Oqus cameras (Qualisys, Gothenburg, Sweden) at 120 Hz. Data were collected as participants walked on a Bertec split-belt treadmill (Bertec Corporation, Columbus, OH, USA).

### **5.3.3 Experimental Protocol**

To obtain a standing calibration, participants stood on the treadmill with arms crossed and attempted to minimize movement for ten seconds. Next, preferred walking speed (PWS) was determined using a protocol similar to Jordan et al. (2007b). The treadmill belt speed started at 0.5 m\*s<sup>-1</sup>, and increased by 0.1 m\*s<sup>-1</sup> every five to ten seconds. Participants informed the experimenter when ‘preferred’ or ‘comfortable’ walking speed was achieved. This speed was identified as the pace they would walk if they were not rushing, nor taking a leisurely stroll. The belt speed was further increased 0.3 m\*s<sup>-1</sup>, and decreased in 0.1 m\*s<sup>-1</sup> decrements until participants again declared PWS. Two values of PWS within 0.1 m\*s<sup>-1</sup> were determined for each participant. PWS was computed as the mean of the self-selected speeds.

Once PWS was obtained, participants performed five walking trials. For each trial, participants were instructed to walk normally, to avoid touching the handrails as much as possible, and to generally remain in the center of the treadmill. The first trial consisted of walking at PWS. The second trial consisted of walking at half of their PWS (Half-PWS). The PWS and Half-PWS conditions served as symmetric steady state

baseline measures. During trials three to five, participants walked with the right (dominant limb) treadmill belt traveling at PWS and the left (non-dominant limb) belt at Half-PWS (i.e., 2:1 ratio asymmetric ‘split-belt’ walking; Split 1, Split 2, Split 3, respectively). Each trial lasted 15 minutes and was followed by a 5-minute seated rest. The 15-minute trial lengths ensured that enough strides were obtained for analysis.

### **5.3.4 Experimental Analysis**

Kinematic data were filtered at 8 Hz using a low-pass, 4<sup>th</sup> order Butterworth filter. Data were collected and labeled using Qualisys Track manager, and custom MATLAB (The MathWorks, Natick, MA, USA) scripts were used for all analyses. Heel strike timing was determined based on the peak anterior position of the heel marker. Stride timing was defined as the temporal interval from heel strike to subsequent heel strike.

#### **5.3.4.1 Determination of Fractal Structure**

To determine the potential presence and structure of long-range correlated behavior, detrended fluctuation analysis (DFA) was performed on the first 512 stride times. DFA estimates the average correlation structure by quantifying the magnitude of variability of a signal across various temporal scales (Hausdorff et al., 1995; Hausdorff et al., 1996; Peng et al., 1995). This analysis is a modified random walk analysis that takes advantage of the fact that the extent of self-similarity (i.e., resemblance across scales) of a time series exhibiting long-range correlations can be quantified via simple integration of the signal (Hausdorff, Peng, Wei, & Goldberger, 2000). After the signal is integrated, it is sectioned into non-overlapping windows of size  $n$ . In each window, a least-squares linear fit line is applied to the signal. A root-mean-square analysis is then performed

within the window, subtracting the local trend line's y-coordinate from the integrated signal. This process is performed and averaged across all windows of a given size ( $n$ ):

$$F(n) = \sqrt{\frac{1}{\lfloor N/n \rfloor} \sum_{j=1}^{\lfloor N/n \rfloor} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_i)^2} \quad \text{Equation 5.1}$$

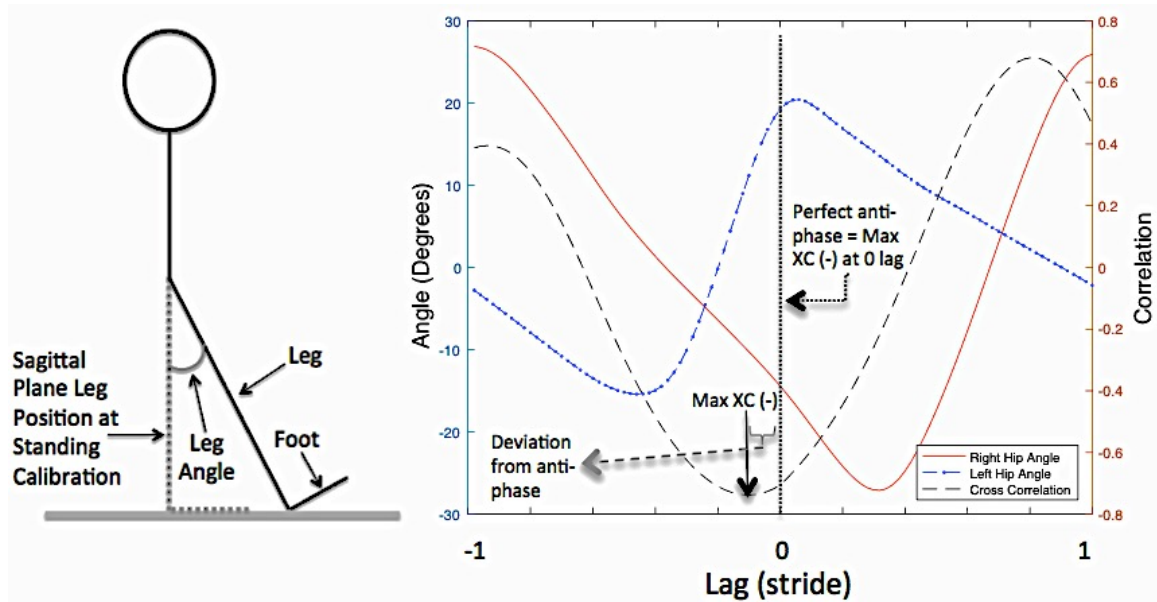
Where  $F(n)$  is the fluctuation magnitude at window  $n$ ,  $N$  is the total number of strides in the time series,  $X_i$  is the integrated signal at stride interval  $i$ , and  $\bar{X}_i$  is the y-coordinate location of the local trend within window  $n$ . This process is averaged across all non-overlapping windows ( $j$ ) of size  $n$  (total number of windows =  $N/n$ ). This procedure was performed on window sizes ranging from 4 to 50 ( $\sim N/10$ ) strides, providing  $F(n)$  for each window size. The choice to include maximal window sizes of  $N/10$  was made because larger maximal window sizes (e.g.,  $N/4$ ) may be considered under sampled (Hu, Ivanov, Chen, Carpena, & Stanley, 2001; Paterson, Hill, & Lythgo, 2011). When  $F(n)$  and  $n$  are plotted on a double logarithmic graph, a linear relationship indicates the presence of scale invariant self-similarity (Hausdorff et al., 2000). The slope of the line of best fit on the double-log plot represents the scaling exponent ( $\alpha$ ), where:  $F(n) \propto n^\alpha$ . A signal is considered to exhibit fractal-like persistent structure when  $0.5 < \alpha \leq 1.0$  (Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996), with  $\alpha = 1.0$  representing  $1/f$  behavior, whereby the power of the signal at a given frequency is inversely proportional to the frequency (Diniz et al., 2011; Keshner, 1982; West & Shlesinger, 1990).  $\alpha = 0.5$  indicates the absence of long-range correlations, equivalent to random white noise. When  $\alpha > 1.0$ , the signal becomes nonstationary and approaches

Brownian motion ( $\alpha = 1.5$ ) or the integration of white noise, whereby the signal is random from point to point, yet its magnitude of temporal evolution is bound by the number of data points. While Brown noise is persistent, it can be considered overly structured and therefore too regular or constrained. This behavior is characterized by minimal fluctuations from stride to stride, and a slow drift of increasing or decreasing stride times.

#### **5.3.4.2 Gait Adaptability Performance**

Relative phasing in the sagittal plane between the right and left legs was used to determine the adaptive capacity of the locomotor system (J. T. Choi & Bastian, 2007). Each 'leg' was defined as a segment from the greater trochanter to the lateral malleolus on the ipsilateral side (Figure 5.1). The angle of each leg was computed relative to the orientation of the leg during the standing calibration. Each stride was normalized to 100 data points, and a cross correlation function was performed between the right and left leg for each stride. The cross correlation function evaluates correlation strengths while systematically shifting one signal (leg angle) by one data frame bi-directionally. The result is a series of correlation values across a range of lags from -1 to 1 stride cycles. Once normalized to the length of correlation data, if maximal negative correlation occurs at -1 or 1 (i.e., maximum number of lags in either direction), the signals are perfectly in-phase, whereby the legs are moving in the same direction. When the maximal negative correlation occurs at zero lag, the signals are perfectly anti-phase, whereby the legs are moving in opposite directions. Gait performance was calculated based on the difference (in lags) from peak negative correlation to that of intended phasing (anti-phase) for each stride (Figure 5.1). A greater number of lags to reach peak negative correlation indicates

greater deviation from anti-phase. Two variables were calculated from these data. First, the summed absolute magnitude of deviation from intended phasing ( $\text{Phase}_{\text{DEV}}$ ) (J. T. Choi & Bastian, 2007) across the first 50 strides represented error magnitude. Second,



**Figure 5.1: Determination of leg relative phasing.** Left) determination of leg angle in the sagittal plane. The leg segment is created as a straight line from the greater trochanter to the ipsilateral heel. The leg angle is the angular displacement of the leg segment from its position during the standing calibration. Right) Determining deviation from intended anti-phase of the right (red solid line) and left (blue dashed-dotted line) hip angles via cross-correlation (grey dotted line) analysis. Phase Deviation was calculated as the shift (in lags) of the maximal negative correlation (Max XC (-)) to optimal anti-phasing (i.e., at 0-lag).

time-to-adaptation (TtA, representing the rate of temporal adaptation, Figure 5.2) was acquired by fitting an exponential decay model to the first 400 strides of the deviation data (Equation 5.2).

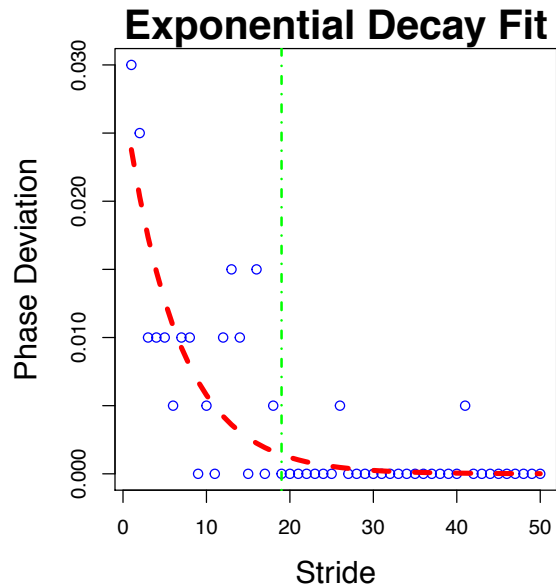
$$Y(x) = \exp(a - bx)$$

Equation 5.2

The variable  $Y$  represents the model fit at stride  $x$ ,  $a$  is the initial value, and  $b$  is the rate of decay. TtA was then determined based on the conventions employed by Rabuffetti et al. (2011) to find ‘time to stabilize’ in postural data:

$$TtA = \frac{1}{b*3} \quad \text{Equation 5.3}$$

This method is considered a reasonable estimation of settling time, i.e., the moment at which 95% of the initial disturbance is dissipated, or the instant the model will shift from its initial value,  $a$ , to infinity (Rabuffetti et al., 2011).



**Figure 5.2: Exemplar of the application of an exponential decay model.** Model (red dashed line) shown here relative to the phase deviation data (y-axis) and used to determine time-to-adaptation (shown here at 19 strides, green dash-dotted vertical line). Each blue circle represents the extent of deviation (in lags) from intended anti-phase between right and left legs for a given stride. Perfect anti-phase shown here as 0.0. Time-to-adaptation based on the inverse of  $3 * \beta$  coefficient, which represents the time taken to dissipate 95% of the initial disturbance (i.e., area under the model curve).



### 5.3.5 Statistical Analysis

To distinguish fractal scaling data from non-correlated random processes, surrogate data sets were created by shuffling the original time series stride times for each subject and condition, and submitting the data to the DFA algorithm. Paired t-tests were used to compare surrogate data sets to the original time series fractal scaling. If the observed data's fractal scaling values were statistically greater than the surrogate data's scaling values, the original data were considered to exhibit long-range correlated behavior. Stride time fractal scaling exponents across gait conditions (PWS, half-PWS, Split 1, Split 2, Split 3) were assessed using separate one-way repeated measures analyses of variance (ANOVAs) for the right and left legs. When significant main effects of condition were observed, two-tailed, paired samples t-tests were used to compare fractal scaling exponents across conditions for each leg. In addition, paired samples t-tests were used to evaluate fractal scaling differences between the right and left leg within each condition. Results were accepted when  $p \leq 0.05$ . The relationship between gait performance (Phase<sub>DEV</sub> and TtA) and fractal scaling at PWS, Half-PWS, and during asymmetric trials was determined by fitting both simple linear and quadratic regression equations. All statistics were performed using R-studio software (Version 1.0.136, R Foundation for Statistical Computing, Vienna, Austria).

## 5.4 Results

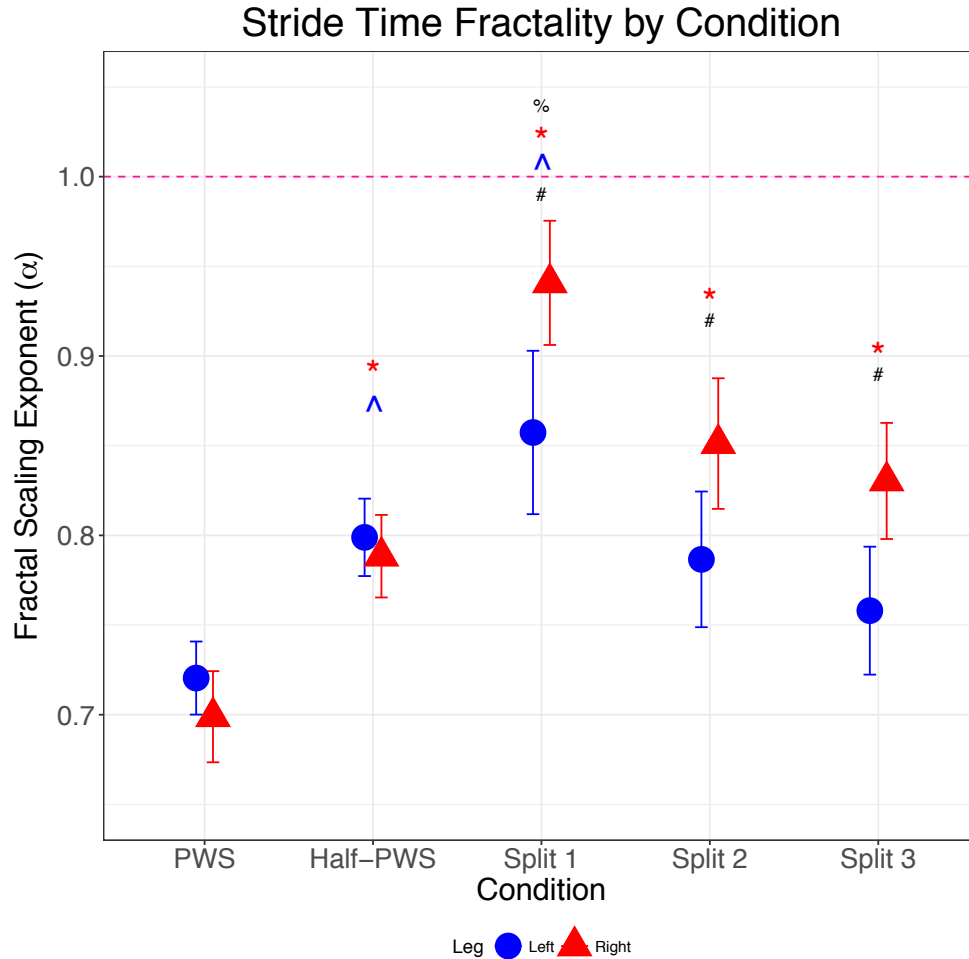
Paired t-tests between fractal scaling exponents of the observed versus surrogate data provided evidence for long-range correlations during all walking conditions for both

the right and left legs (Table 5.1, all  $p$ 's < .001). Surrogate data set  $\alpha$  values were less than the empirically derived data.

**Table 5.1: Original and surrogate data scaling exponents across conditions.** Statistical results of the separate repeated measures ANOVAs for the scaling exponent of the right and left legs.  $\alpha$  = scaling exponent; PWS = preferred walking speed; Split = split-belt asymmetric walking; Adj = adjustment; Right and Left = Right and Left legs. Third row displays the results of paired t-tests between legs. Rows 4-5 are results of the randomly shuffled surrogate analysis, and rows 6-7 display results of paired t-tests between fractal scaling values of observed versus surrogate data. All data are reported as mean (standard deviation).

Condition	PWS	Half-PWS	Split 1	Split 2	Split 3	F (4,56)	P	Adj.
$\alpha$ -Right	0.69 (.09)	0.79 (.09)	0.94 (.13)	0.85 (.14)	0.83 (.13)	11.004	< .001	None
$\alpha$ -Left	0.72 (.08)	0.79 (.08)	0.86 (.18)	0.79 (.15)	0.76 (.14)	3.02	.043	Huynh-Feldt
$\alpha$ Left vs. $\alpha$ Right	$p = 0.229$ $t = -1.26$	$p = 0.214$ $t = -1.30$	$p < .001$ $t = 6.33$	$p < .001$ $t = 4.84$	$p < .001$ $t = 9.45$			
$\alpha$ -Right Surrogate	0.53 (.04)	0.51 (.03)	0.52 (.04)	0.53 (.04)	0.51 (.04)			
$\alpha$ -Left Surrogate	0.52 (.03)	0.52 (.07)	0.52 (.05)	0.50 (.05)	0.51 (.05)			
$\alpha$ -Right vs. $\alpha$ -Right Surrogate	$p < .001$ $t = 5.40$	$p < .001$ $t = 11.12$	$p < .001$ $t = 11.62$	$p < .001$ $t = 8.79$	$p < .001$ $t = 11.19$			
$\alpha$ -Left vs. $\alpha$ -Left Surrogate	$p < .001$ $t = 8.90$	$p < .001$ $t = 11.50$	$p < .001$ $t = 7.60$	$p < .001$ $t = 7.11$	$p < .001$ $t = 5.66$			

For fractal scaling exponents across conditions, there was an overall main effect of condition (Table 5.1, Figure 5.3) for the right leg ( $F_{4,56} = 11.004$ ,  $p < .001$ ) and left leg ( $F_{4,56} = 3.02$ ,  $p = .043$ ). The left leg fractal scaling data violated the assumption of sphericity (Mauchly's  $p = .039$ ), so a Huynh-Feldt adjustment was applied. For the right



**Figure 5.3: Fractal scaling exponents across conditions.** Scaling values (mean  $\pm$  SEM) reported for the left (blue circles) and right (red triangles) legs of the first 512 strides for each walking trial. Horizontal pink dotted line located at  $y = 1.0$  represents  $1/f$  pink noise (optimal fractality). \* = significantly greater than PWS for right leg. ^ = significantly greater than PWS for left leg. % = significantly greater than Half-PWS and Split-Belt 3 for right leg. # = significant difference between right and left leg scaling exponents.

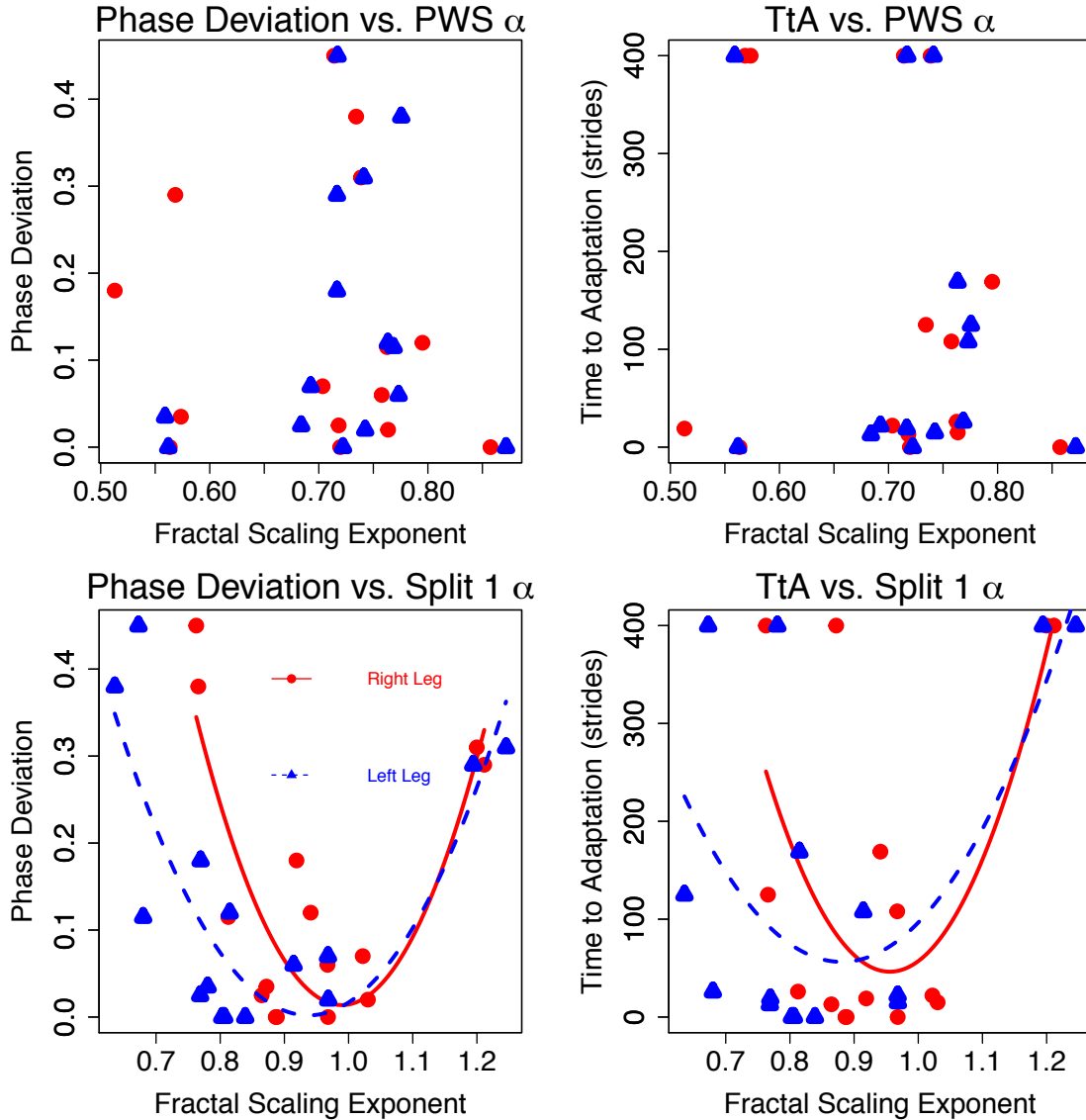
leg, paired samples t-tests revealed significant differences between PWS and all other conditions ( $p = .008, < .001, < .001,$  and  $.002$  for half-PWS, Split 1, Split 2, and Split 3, respectively). Half-PWS was significantly lower than Split 1 ( $p < .001$ ). Finally, Split 1 was greater than Split 3 ( $p = .030$ ). For the left leg, paired t-tests revealed significant differences between PWS and half-PWS and Split 1 ( $p = .005$  and  $.014$ , respectively).

Both slow walking (Half-PWS) and the first asymmetric trial (Split 1) yielded higher fractal scaling values compared to PWS. PWS across participants was  $1.21 \pm 0.12 \text{ m}\cdot\text{s}^{-1}$ .

Linear and quadratic regression equations revealed no significant relationships between fractal scaling during steady state unperturbed walking (PWS or half-PWS) and Phase<sub>DEV</sub> or TtA (Table 5.2, all  $p$ 's > 0.05,  $r^2$ 's < 0.13). However, there were significant

**Table 5.2: Comparison of gait adaptability performance during asymmetric walking to fractal scaling exponents.** Adaptive performance (PhaseDEV and TtA) compared separately for the right ( $\alpha_R$ ) and left ( $\alpha_L$ ) legs fractal scaling during steady state walking at preferred (PWS) and half-preferred (Half-PWS) speeds and asymmetric walking (Split 1). Linear models did not yield any significant effects, but a quadratic model fit resulted in significant associations between adaptability measures and both  $\alpha_R$  and  $\alpha_L$  during asymmetric walking.

Dependent Variable	Independent Variable	Model	$p$	$R^2$	Significant
Phase <sub>DEV</sub> at 1 <sup>st</sup> Split-Belt Condition	$\alpha_R$ at PWS	Linear	0.75	-0.07	
		Quadratic	0.64	-0.08	
	$\alpha_L$ at PWS	Linear	0.51	-0.04	
		Quadratic	0.29	0.05	
	$\alpha_R$ at Half-PWS	Linear	0.69	-0.06	
		Quadratic	0.40	-0.00	
	$\alpha_L$ at Half-PWS	Linear	0.55	-0.05	
		Quadratic	0.84	-0.13	
	$\alpha_R$ at Split 1	Linear	0.98	-0.08	
		Quadratic	< .001	0.70	*
	$\alpha_L$ at Split 1	Linear	0.87	-0.07	
		Quadratic	< .001	0.65	*
TtA at 1 <sup>st</sup> Split-Belt Condition	$\alpha_R$ at PWS	Linear	0.41	-0.02	
		Quadratic	0.51	-0.04	
		Linear	0.46	-0.03	
	$\alpha_L$ at PWS	Quadratic	0.71	-0.10	
		Linear	0.19	0.06	
	$\alpha_R$ at Half-PWS	Quadratic	0.30	0.04	
		Linear	0.22	0.04	
	$\alpha_L$ at Half-PWS	Quadratic	0.49	-0.03	
		Linear	0.29	0.01	
	$\alpha_R$ at Split 1	Quadratic	0.01	0.43	*
		Linear	0.18	0.06	
	$\alpha_L$ at Split 1	Quadratic	0.03	0.34	*



**Figure 5.4: Relationship between gait adaptability performance and fractal scaling exponent.** Gait adaptability performance (Phase Deviation and Time-to-Adaptation) and fractal scaling ( $\alpha$ ) shown during steady state (PWS, top row) and the 1<sup>st</sup> split-belt (Split 1, bottom row) conditions. Right leg = red circles and solid lines. Left leg = blue triangles and dotted lines. Right leg traveled at preferred speed, and left leg at half of preferred speed. Points display each participant, while lines are quadratic fits. There were no associations between PWS  $\alpha$  and Phase Deviation or TtA during asymmetric walking. However, there were significant relationships for phase deviation and the asymmetric walking scaling exponent of the right ( $p < .001$ ,  $r^2 = .70$ ) and left ( $p < .001$ ,  $r^2 = .65$ ) legs, and for time-to-adaptation and the asymmetric walking scaling exponent of the right ( $p = .01$ ,  $r^2 = .43$ ) and left ( $p = .034$ ,  $r^2 = .34$ ) legs.

quadratic relationships between both measures of adaptability performance (Phase<sub>DEV</sub> and TtA) and both legs' fractal scaling exponents during the first asymmetric (Split 1) walking trial (Phase<sub>DEV</sub> vs. right and left legs  $r^2 = .70$  and  $.65$ , respectively, and TtA vs. right and left legs  $r^2 = .43$  and  $.34$ , respectively). Specifically, the data displayed a U-shaped relationship, whereby compared to the group mean, lower or higher fractal scaling measures were associated with the poorest performance (Figure 5.4).

Finally, comparing the scaling exponents of the right versus left leg, paired samples t-tests revealed no differences during PWS or Half-PWS. However, the right leg  $\alpha$  was significantly higher than the left for all three asymmetric walking conditions (Table 5.1, Figure 5.3,  $p < .001$  for Split 1, Split 2, Split 3). The right leg's  $\alpha$  remained elevated for all asymmetric conditions, and did not return to that of PWS.

## 5.5 Discussion

The purpose of this experiment was to determine if unperturbed or asymmetric walking fractal dynamics were related to the adaptive capacity of the locomotor system. To test this, participants were exposed to task-level constraints in the form of asymmetric treadmill walking. No associations between fractality during preferred or half preferred speed walking and adaptability performance during asymmetric walking were evident. However, a relationship between asymmetrically constrained fractality and adaptability did emerge. As a group, stride interval fluctuations exhibited increased fractality closer to  $\alpha = 1.0$  in response to forced asymmetric walking. Those individuals whose stride time fluctuations manifested as  $\alpha \sim 1.0$  also displayed the best adaptive gait performance in response to the asymmetric walking task. Repeated exposure to asymmetric walking

yielded fractal scaling values that were statistically similar to those observed during unperturbed preferred speed walking in the non-dominant (but not the dominant) limb. Finally while both limbs'  $\alpha$  increased during asymmetric walking, it was the faster moving dominant leg that yielded higher scaling values compared to the slower moving non-dominant limb.

### **5.5.1 Fractal Structure During Steady State Walking is Not Associated with Gait Adaptation**

The main purpose of this study was to determine the potential relationship between steady state unperturbed stride time fractal dynamics and the capacity for individuals to adapt their locomotor patterns effectively. PWS and half-PWS fractal dynamics were not associated with adaptation performance during the asymmetric walking conditions (see Table 5.2, all  $p$ 's  $> .05$  and  $r^2$ 's  $< .13$ ). Thus, prediction of gait adaptability does not appear to be possible by simply analyzing unperturbed walking fractality.

These results speak to a broader discussion regarding research in gait adaptability and stability. Scientists continue to search for gait measures during steady state, unperturbed walking that may predict an individual's ability to successfully respond to a future perturbation or environmental stressor. While these attempts are clearly worthwhile, it is also apparent that unperturbed walking behavior is fundamentally different from the behavior that emerges when individuals are exposed to external perturbations or organismic, task, or environmental constraints. Indeed, in a study of 97 healthy older women who were assessed for gait parameters, and then prospectively monitored for falls over a period of 12 months, stride time fractality was not different

between those who eventually did experience a fall and those who did not (Paterson et al., 2011). The findings from this current study support this notion, as unperturbed walking fractal scaling could not predict adaptive gait performance.

### **5.5.2 Fractal Structure During Perturbed Walking Associates with Gait Adaptation**

While fractal dynamics during unperturbed walking were not correlated to adaptive gait behavior, the group as a whole displayed increased fractality in response to asymmetric walking constraints compared to steady state walking (see section 5.5.3 below, Figure 5.3 and Table 5.1). Moreover, this increase was not the same for everyone. In particular, some individuals displayed minor increases in fractality ( $\alpha \sim 0.7$ ), while others displayed large increases ( $\alpha \sim 1.2$ ). The lower scaling exponents indicate a more random, less organized behavior, while the higher scaling exponents indicate overly rigid and constrained behavior. These ‘extreme’ participants performed the poorest in adapting to anti-phase walking (Figure 5.4). That is, asymmetric walking fractal dynamics were quadratically related to gait adaptability performance.

These findings provide information regarding the purpose and utility of fractality in biological systems; these structured fluctuations may in fact benefit the locomotor system. Shifting fractality too high (i.e.,  $\alpha > 1.0$ , closer to the less flexible Brownian-type motion) may yield deviations that persist. Conversely, it appears that not shifting fractality closer to  $\alpha = 1.0$  (i.e.,  $\alpha \sim .7$ ) may yield patterns that are not persistent enough. The often observed fractality exhibited by healthy young adults is  $\alpha \sim 0.75$ . This value is directly between random ( $\alpha = 0.5$ ) and optimally fractal ( $\alpha = 1.0$ ). Rhea and Kiefer (2013) argue that this level of fractality allows for the locomotor system to behave in a



complex, flexible manner, while also preserving ‘adaptive variation’ in response to internal or external demands. While this may hold true during unperturbed walking, exposure to an individual, task, or environmental constraint appears to require that the system reorganize to increase interactions across the many subsystems at various spatiotemporal scales. This is precisely what occurred in this experiment, and those who reorganized in a manner that manifested as  $\alpha \sim 1.0$  exhibited the least deviation from intended phasing and fastest adaptation to the imposed walking constraints. Exhibiting fractal scaling  $\sim 0.75$  during unperturbed, symmetric walking may not be optimizing fractal dynamics because some other component of the system is instead being optimized, such as metabolic cost or dynamic stability. When exposed to challenging gait, the increase in fractal scaling may improve adaptability but also likely comes at a cost to a different system, such as metabolic or biomechanical work performed.

### **5.5.3 1/f Fractality Emerges in Response to Task-Level Constraints During Walking**

As mentioned in the previous section, fractality increased from unperturbed to asymmetric walking. This finding did not support the hypothesis that exposure to asymmetric walking would break down long-range correlations (i.e., fractal scaling closer to random or  $\alpha = 0.5$ ). This idea was based on the assumption that prolonged perturbed walking would introduce randomness to the patterns. Perturbations have been known to weaken long-range correlations within a behavior (Diniz et al., 2011). To the best of the authors’ knowledge, determining the effects of constraining the locomotor system’s symmetry on fractality has not yet been tested. Contrary to the hypothesis, stride time fractality increased closer to  $\alpha = 1.0$ .

The fact that fractality increased closer to  $1/f$  noise in response to a constraint is supported by research in alternative paradigms in motor behavior. Research in bimanual coordination has provided evidence that  $1/f$  fluctuations may emerge close to phase transitions (Torre, 2010). Dynamical systems display criticality when approaching a shift from one stable state to another (Kelso, 1995; Kelso & Ding, 1993; Van Emmerik, Miller, et al., 2013). Specifically, systems exhibit critical fluctuations, as shown by increased variability, as well as critical slowing down, characterized by increased time to return to a stable state following perturbations. Critical fluctuations allow systems to exit locally stable states to transition to a more stable state. These fluctuations near phase transitions have typically been considered to be equivalent to white noise (e.g., see the Haken-Kelso-Bunz model (Haken, Kelso, & Bunz, 1985; Kelso, 1995). However, physics-based numerical simulations provide evidence that self-organized criticality exhibits  $1/f$  fluctuations (Bak & Chen, 1991). Empirically, Torre and colleagues (2011) posited that  $1/f$  fluctuations would increase the likelihood of phase transitions due to the inherently ‘persistent’ nature of the behavior. The authors provided evidence in bimanual coordinative transitions from locally stable anti-phase to a more globally stable in-phase that these fluctuations do in fact become more fractal-like closer to the transition point. It should be noted, though, that fractal-like fluctuations that emerge from self-organized criticality are thought to arise from local interactions (i.e., interactions between processes at neighboring scales) that manifest as globally scale-invariant behavior (Kelty-Stephen et al., 2013). Alternative methods, such as a multifractal approach, may be needed to provide further evidence for interactivity across various spatiotemporal scales.

In the postural literature, the shift from quiet stance with eyes open to eyes closed, an organism-level constraint, results in fractal scaling shifting closer to  $1/f$  in young healthy adults (Caballero Sanchez, Barbado Murillo, Davids, & Moreno Hernandez, 2016; Tanaka, Uetake, Kuriki, & Ikeda, 2002). Moreover, inducing task-level constraints to posture, such as reducing the diameter of the standing surface, also results in fractality closer to  $1/f$  (Caballero Sanchez et al., 2016). Meanwhile, postural complexity (as measured by multiscale entropy) is reduced when eyes are closed (Busa, Jones, Hamill, & van Emmerik, 2016). This may indicate that the postural system reorganizes to strengthen the interactivity between temporal scales (i.e.,  $\alpha$  closer to 1.0) when confronted with reduced complexity at and across temporal scales (i.e., reduced entropy) (Busa, Ducharme, & van Emmerik, 2016).

Perhaps the only evidence of increased fractality caused by a constraint in human locomotion has been via manipulation of gait speed. When individuals walk faster or slower than their preferred walking speed, fractality may increase closer to  $1/f$  (Hausdorff et al., 1996; Jordan et al., 2007b). Our results agree with previous studies, as fractal scaling increased from  $\sim 0.70$  in PWS to  $\sim 0.79$  in half-PWS (Figure 5.3, Table 5.2). While preferred speed walking could be considered the most stable attractor state, slow or fast walking could reasonably be considered to be states that are approaching a transition to standing and running, respectively. Thus, the increase in fractality during fast, slow, or asymmetric walking may indicate that the system is preparing for a phase transition by increasing fractal-like critical fluctuations.

#### **5.5.4 Habituation to Repeated Exposure to Asymmetric Gait**

The hypothesis that repeated exposure to asymmetric constraints would yield more fractal-like structured variability was not confirmed, as the second and third split-belt trials yielded decreasing fractal scaling values (Figure 5.3, Table 5.1). However, this hypothesis was based on the earlier hypothesis that asymmetric gait would yield lower fractal scaling values, and thus greater exposure to asymmetric walking would increase fractality closer to that of symmetric walking. Considering the initial asymmetric condition (split 1) exhibited fractal scaling indices that deviated from those observed during unperturbed walking (PWS), the final asymmetric walking trials'  $\alpha$  (split 2 and split 3) returned to that of PWS for the non-dominant left leg, thus indicating a learning or habituation effect. During a novel gait task, the locomotor system reorganizes, manifesting as greater fractal scaling exponents. After several minutes of asymmetric walking, the task is no longer novel and the system returns to fractal scaling exponents similar to those observed during PWS. However, the dominant right leg  $\alpha$  did not return to that of steady state, indicating differential response by legs of either differing dominance, belt speed, or possibly task difficulty (see section 5.5.5 below).

#### **5.5.5 The Magnitude of Increased Fractality is Not Constant Across Limbs**

The general phenomenon in gait fractality research is that walking slower than preferred gait speeds yields higher scaling exponents, i.e., closer to  $\alpha = 1.0$  (Hausdorff et al., 1996; Jordan et al., 2007b). Again, the results from this study support this observation. Surprisingly, though, while the asymmetric walking increased fractal scaling in both legs, it was the right dominant leg that increased to a greater extent (Figure 5.3), and remained elevated compared the left leg for all asymmetric trials. These findings are

of interest because the right leg was traveling at PWS, while the left leg traveled at the slow walking speed. Thus the hypothesis that the slower moving leg would yield larger fractal scaling values during asymmetric walking is rejected. If gait speed generated a fixed effect on fractality, our hypothesis would have likely been confirmed. Given these findings, it appears that the relationship between gait speed and fractal dynamics is not absolute. Rather, this relationship emerges under imposed constraints as a functional coupling between limbs to achieve the task goal.

One possible explanation for these results is that task difficulty was not the same for both limbs. The sustained increase in the dominant leg's  $\alpha$  may be because the faster moving leg experienced a more difficult component of the walking task. While PWS is generally considered the most comfortable and stable speed, contrasting this speed with a slower moving belt causes a disharmony between legs. Anecdotally, the greatest challenge (and possibly least stable aspect) of the asymmetric walking task was controlling the faster moving limb. In general, walking constraints that increase task difficulty appear to manifest as increased fractal scaling ( $\alpha$  closer to 1.0) in order to best respond to the challenge. It stands to reason that the less challenged, slower moving leg habituated to the task (and whose  $\alpha$  returned to that of symmetric walking) more rapidly than the more challenged faster moving leg.

Alternatively, these limb-specific differences may be a result of their inherent relationship as coupled oscillators. There is a general lack of research regarding the role of limb dominance in split-belt walking adaptation. Moreover, the adaptive changes to symmetry in response to asymmetric walking do not appear to be consistently driven by either the faster or slower moving leg (Bruijn et al., 2012). Thus, the independent or

interactive effects of speed and limb dominance on outcome measures are difficult to ascertain. However, the interaction between lower limbs during locomotion could be considered a mutual coupling between nonlinear oscillators (Sternad, Turvey, & Saltzman, 1999). In the study herein, the limbs' resonant frequencies were not altered (e.g., via changing limb length or center of mass location), but rather the velocity of (at least) one component of each cycle. Even though one treadmill belt traveled at twice the speed of the other, the limbs were still in 1:1 relative anti-phasing. This indicates considerable co-dependence. That is, each stride time of the right leg was dependent upon the step and stride timing of the left leg, and vice versa. All of the participants were right-leg dominant. While the locomotor system was able to respond to the asymmetry by retaining 1:1 phasing, the dominant leg/oscillator may have hierarchically presumed control of the system's requirement for increased interactivity across temporal scales when exposed to perturbed gait. Indeed, it is plausible that limb dominance, stride speed, or task difficulty may affect the organization of fractal dynamics when gait is constrained.

### **5.5.6 Limitations**

Assessment of fractality was based on stride times, and therefore all reported findings in this study are based on a single gait measure, whereas a multitude of other parameters could have been evaluated. However, the choice to evaluate stride time was twofold: 1) stride time includes the entire gait cycle (e.g., dual support, single support, heel strike, push-off), and thus represents the 'final output' of the many processes occurring within the locomotor system (Hausdorff, 2007), and 2) stride time has by far

been the most analyzed gait parameter in the literature, and therefore analysis of stride time herein allows for comparisons with other studies.

Gait adaptability performance was defined based on the relative phasing between right and left legs. It can be argued that all participants displayed adaptive gait in that all participants were able to successfully continue walking on the treadmill (i.e., no participants fell or walked-off the treadmill). However, the phasing of the limbs during PWS and Half-PWS was anti-phase ( $180^\circ$ ). By the middle or end of the first asymmetric walking condition, nearly all participants returned to  $180^\circ$  phasing. Finally, when treating the legs as two coupled oscillators performing a rhythmic motion, it has been generally accepted to assess stable performance via the relative phasing between oscillators (Sternad et al., 1999).

Another potential limitation was that the same (left, non-dominant) leg was slowed down for each participant during the asymmetric trials. However, the main outcome in this study was that speed was the driving factor, and the faster moving leg/oscillator enslaved the slower moving one. Although leg dominance may affect oscillator dynamics, in this case it would be unlikely to modify the results.

## **5.6 Conclusion**

Stride time fractal dynamics during steady state, unperturbed walking did not predict the ability for participants to adapt their gait patterns in response to asymmetric walking constraints. However, during asymmetric split-belt walking, most participants' fractal dynamics increased closer to  $\alpha = 1.0$ . Individuals who displayed extreme fractal scaling during this condition (i.e.,  $\alpha < \sim 0.8$  or  $\alpha > \sim 1.1$ ) also exhibited the poorest

adaptive performance, as measured by lower limb relative phase. Based on this experiment, stride time fractality during unperturbed walking can vary considerably without apparent detriment to the locomotor system. However, stride time fractality closer to  $\alpha = 1.0$  while walking under more challenging conditions was associated with faster adaptations to asymmetric walking. The increase in fractality closer to  $\alpha = 1.0$  may be explained by notions such as self-organized criticality, representing the meta-stability of the locomotor system, which would allow different gait patterns to be quickly adopted. Finally, the relationship between gait speed and fractal dynamics is not maintained during asymmetric walking, and under these task constraints, limb dominance or task difficulty may be a more important factor.



## CHAPTER VI

# STRIDE TIME FRACTAL DYNAMICS AND GAIT ADAPTABILITY ARE SIMILAR IN ACTIVE YOUNG AND OLDER ADULTS UNDER NORMAL AND ASYMMETRIC WALKING

### 6.1 Abstract

The ability to adapt locomotor patterns to task or environmental demands is a key component of maintaining balance. Older adults may be less adaptable, and therefore more prone to falling. However, physical activity status may be a critical consideration when attempting to evaluate age-based changes to gait. Assessment of the correlation structure of gait parameters (i.e., fractal dynamics) may reveal the overall adaptive capacity of the system. Behaviors whose fluctuation magnitudes exhibit proportional scale-invariance (i.e., slope ( $\alpha$ )  $\sim 1.0$ , i.e.,  $1/f$ ) may be considered more adaptable. The purpose of this study was to investigate potential differences between physical activity-matched young and older adults' fractal dynamics and gait adaptability during asymmetric walking, and to determine if fractal dynamics predict adaptive capacity. Fifteen young and 15 older active adults walked at their preferred speed, at half of their preferred speed, and asymmetrically whereby their dominant leg moved at preferred speed, and non-dominant leg at half preferred speed. Relative phasing of the lower limbs was used to determine adaptation to asymmetric walking, and detrended fluctuation analysis was used to assess the fractal correlation structure of stride times. Results revealed that the young and older cohorts displayed similar unperturbed and asymmetric walking fractal dynamics and adaptive gait performance. Fractal dynamics during

preferred speed walking was moderately associated with gait adaptability performance in the young but not older cohort. Fractal dynamics during constrained asymmetric walking was moderately associated with gait adaptability performance in the older adult cohort, whereby larger  $\alpha$  values coincided with better adaptive performance. Fractal dynamics increased ( $\alpha$  closer to 1.0) from steady state unperturbed to asymmetrically constrained walking in both young and older adults in the faster moving dominant leg, but not in the slower moving, non-dominant leg. The observed increase in fractal dynamics during asymmetric walking may represent a reorganization of the locomotor system (i.e., enhanced cooperativity of processes across spatiotemporal scales) when constrained in some manner, and this modification may aid in successfully adapting gait patterns. Findings from this study indicate there are no age-based differences in fractal dynamics or gait adaptability when active participants are assessed, and that fractal dynamics moderately associate with gait adaptability performance.

## 6.2 Introduction

Aging is associated with naturally occurring reductions in muscle mass and impairments to visual, somatosensory, and vestibular information. Perhaps expectedly, fall incidents are problematic in adults aged 65 years and older. Falls are the main cause of injury-based deaths and hospitalization in older adults (CDC, 2011, 2012). For this reason, an abundance of studies have attempted to better understand why falls occur, and how to reduce the likelihood of future falls. Although the issue of falls is likely multifaceted, one potential reason for the prevalence of falls in older adults is that their gait may become generally less adaptable (Bierbaum, Peper, Karamanidis, & Arampatzis, 2010; Bruijn et al., 2012). Gait adaptability can be defined as the locomotor system's ability to respond to changing demands (Balasubramanian et al., 2014). Specifically, adaptive gait is capable of changing locomotor patterns based on imposed constraints. These constraints may be at the individual, task, or environmental level (Newell, 1986). Indeed, successful navigation through any environment or under imposed constraints requires continual adjustments to otherwise steady state rhythmic patterns. However, describing and quantifying adaptability in locomotion has proven to be challenging. Generally, gait adaptability paradigms involve walking tasks that directly require locomotor patterns to change in response to imposed constraints. In recent decades, however, an alternative approach involves algorithms derived from statistical physics and applied to steady state gait dynamics that may inform about the overall adaptive capacity of the locomotor system.

Chaos theory has provided valuable insights regarding the empirical investigation of biological signals. By abandoning the notion that a given behavior or structure only

exists on a single temporal or spatial scale, scientists have gained access to entirely new information about the organization of the system of interest. Benoit Mandelbrot developed the concept of a 'fractal', which reflects a structure or behavior that is self-similar across temporal or spatial scales (Mandelbrot, 1977). That is, small behaviors across short temporal or small spatial scales are statistically similar to the behavior at longer temporal or larger spatial scales; the small behaviors are smaller 'copies' of larger behaviors (Liebovitch, 1998). These behaviors appear to be exponentially related. That is, log-transforming these behaviors or structures across various scales reveals a linear relationship, indicating power law scale-invariance. The behavior's description (mean, variance) is not universal but rather a function of the scale size that is being examined (Schroeder, 1991). This phenomenon can also be evaluated by examining a structure's autocorrelation properties. A random process will approach a value of 0 at lag-1, indicating each data point lacks dependence upon any other. In contrast, a fractal-like process will remain correlated at lag-1, and this correlation decays in a power law fashion. This characteristic indicates the signal at any given point exhibits dependence upon previous and future states. For this reason, fractal-like processes are also known as long-range correlated because they depend not only upon nearby previous and future states, but also across several dozen observations.

In human physiology, statistical analyses have provided evidence for the existence of fractal behavior in various temporal and spatial structures. For example, analysis of the time interval between heart beats has shown that heart rate variability in young, healthy adults displays scale invariance in which the magnitude of fluctuations is directly proportional to the scale (i.e., number of inter beat intervals) analyzed (Peng et

al., 1995). This relationship represents  $1/f$  scaling, whereby the power of the signal is inversely proportional to the frequency (Diniz et al., 2011; Keshner, 1982; West & Shlesinger, 1990). Exhibiting  $1/f$  organization signifies a behaviorally complex system that is considered adaptable (Lipsitz, 2002; Lipsitz & Goldberger, 1992).

Fractal analyses in human locomotion have shed light into the possible organization of the locomotor system that yields adaptive capabilities. The variability of timing from heel strike to subsequent heel strike of the same foot (i.e., stride time) has been a gait parameter of interest in terms of its relation to fall risk (Hausdorff, 2007; Maki, 1997). However, whereas numerous studies have evaluated the *magnitude* of stride time variability as a measure of systemic control, fractal analyses evaluate the *structure* of this variability. Fluctuations from stride to stride have traditionally been considered random noise that is not only unbeneficial but unwanted. Deeper investigation into these biophysical signals has provided evidence that this variance is actually structured in a complex manner. Fluctuations at short temporal scales are statistically correlated to larger fluctuations at longer scales (Hausdorff, 2007; Hausdorff et al., 1995; Hausdorff et al., 1996). That is, the magnitude of fluctuations increases at longer time scales, yet this increase is not random but rather systematic. These long-range correlations have been observed across hundreds of strides. Fractal or long-range correlated organization may represent an adaptive locomotor system because these correlations across scales may characterize interactions within physiological processes across various temporal scales that ultimately help attenuate internal or external perturbations (Delignieres & Marmelat, 2012; Delignieres et al., 2006; Rhea & Kiefer, 2013; Stergiou & Decker, 2011). For example, cross bridge cycling at a single sarcomere occurs at very small spatiotemporal

scales, yet must cooperate with other sarcomeres throughout a motor unit, which must combine with other motor units within a muscle, which must interact with other muscles to generate coordinated motion of the limbs. In this example, limb dynamics would represent processes occurring at large spatiotemporal scales.

While evidence of fractal organization in gait parameter variability exists in young adults, fractal dynamics may change across the lifespan (Hausdorff et al., 1997). That is, the organization of variability at different temporal scales may be inherently different in young and older adults. Older adults have been shown to exhibit less structured, more random stride interval fluctuations (Hausdorff et al., 1997). This may indicate a reduction in the interactions across spatiotemporal scales, and a corresponding reduction in gait adaptability. Alternatively, these fluctuations may simply represent higher stride-to-stride variability (that is, variance at short temporal scales) that may represent an overall reduction in systemic control. A separate study, though, reported no age differences in fluctuation structure (Bollens, Crevecoeur, Detrembleur, Guillery, & Lejeune, 2012). However, the study that did not observe age-related differences used a modified analysis to detect long-range correlations. In addition to healthy older adults, those with neurological disorders such as Huntington's (Hausdorff et al., 1997) and Parkinson's (Hausdorff, 2009) disease also display reduced fractality. Altered fractality in those with neurological disorders have led some researchers to conclude that higher order brain centers are the origin of locomotor fractal behavior. However, this brain-emphasized concept contradicts the notion that fractal behavior emerges as a result of interactivity across spatiotemporal scales that involve all systems involved in the control of locomotion. Given that the gait parameters analyzed are typically global

representations of the locomotor system, explaining fractal behavior via one or a few physiological systems would require rejection of process interactivity. Finally, older adults who report a history of previous falls demonstrate reduced fractality beyond that of healthy older adults (Herman et al., 2005). However, these findings are not ubiquitous, as another study did not find differences between fallers and non-fallers (Paterson et al., 2011). Clearly, more research is warranted to understand the relationship between gait fractality and healthy and diseased aging.

The concept of ‘gait adaptability’ has been scrutinized theoretically and mathematically, yet it is difficult to assess experimentally. For example, common experimental designs used to evaluate adaptability entails walking over obstacles (Heijnen et al., 2012), stepping onto specified locations on the floor (J. T. Choi et al., 2016), or exposure to repeated slip perturbations (Pai & Bhatt, 2007). Generally, these paradigms consist of various discrete perturbations that require adaptive changes to locomotor patterns (e.g., greater toe clearance to step over an obstacle) over the course of several trials.

In addition to the abovementioned paradigms, advances in equipment have allowed for an entirely new line of experimental design for the study of adaptive gait. Specifically, the advent of the split-belt treadmill paradigm affords new experiments that evoke discrete or prolonged walking constraints (Bruijn et al., 2012; J. T. Choi & Bastian, 2007; J. T. Choi et al., 2009; Dietz et al., 1994). A split-belt treadmill has two adjacent belts with separate motors that are independently controlled, thereby allowing researchers to change one belt’s velocity, acceleration, and even direction of travel from the other. In essence, researchers can elicit prolonged asymmetric walking constraints in

order to quantify how and how well participants adapt. The general response to eliciting asymmetric belt speeds is that participants attempt to maintain or regain symmetry between legs, such as leg relative phasing (anti-phase) or step length symmetry, possibly in order to become more stable (Bruijn et al., 2012; J. T. Choi & Bastian, 2007; Dietz et al., 1994; Mawase et al., 2016). Older adults have been shown to modify their gait patterns at a slower rate and show fewer aftereffects (i.e., evidence of adaptation) compared to young adults (Bruijn et al., 2012), suggesting a lower capacity to adapt.

One important note is that the study by Bruijn and colleagues (Bruijn et al., 2012) did not take into account participants' daily physical activity habits. Considering that ~60% of older adults report participating in little or no moderate or vigorous physical activity regularly (Brach, Simonsick, Kritchevsky, Yaffe, & Newman, 2004; Crespo, Keteyian, Heath, & Sempos, 1996), their older adults may have been more sedentary than their young adults, which could be a confounding factor. Accounting for physical activity has been shown to eliminate previously-observed differences between age groups in other areas of physiology, such as muscular oxidative capacity (Larsen, Callahan, Foulis, & Kent-Braun, 2012).

Fractal analyses are thought to quantify the adaptive capacity of the locomotor system (Delignieres & Marmelat, 2012; Delignieres et al., 2006; Rhea & Kiefer, 2013). However, most of the studies assessing fractality have not incorporated paradigms that probe the system's adaptability by evoking a task constraint. Without this probing, it is difficult to determine if these measures actually describe gait adaptability. Preliminary research has provided empirical support that stride time fractality during constrained (asymmetric) walking, but not during unperturbed steady state walking, is associated with



participants' abilities to adapt their locomotor patterns effectively and expeditiously (Ducharme, Liddy, Haddad, Claxton, & Van Emmerik, 2017). When exposed to asymmetric walking, young adults' fractality increased to more 1/f-like organization. Those individuals who exhibited fractal dynamics that deviated from 1/f-like organization (more random or overly structured/constrained) were less able to adapt to the constraint.

However, while constrained-walking fractality may be associated with gait adaptability in healthy young adults, this has not been tested in older adults. Older adults are a more vulnerable cohort in terms of experiencing falls and sustaining more severe injuries as a result. Moreover, while Bruijn et al. (2012) observed reductions in gait adaptability in older compared to young adults on a split-belt treadmill, physical activity level was not taken into account. Thus, the purpose of this study was to investigate the relationship between stride time fractal dynamics and gait adaptability in young and older adults. To control for the potential effects of physical activity, this study recruited individuals who self-reported being highly physically active. It was hypothesized that: 1) older adults would exhibit reduced fractality compared to young adults during unconstrained walking, and in line with the previous study (Ducharme et al., 2017), 2) unperturbed walking would not be associated with gait adaptability, while irrespective of hypothesis 1, 3) young and older adults' asymmetric walking stride time fractality would be associated with gait adaptability performance. In addition, while young adults' fractal behavior increases when exposed to challenging gait (Ducharme et al., 2017), there is still evidence that perturbations weaken long-range correlated behavior (Diniz et al., 2011). Thus, it was hypothesized that 4) older adults fractality would decrease (i.e., become more random) from unconstrained to constrained walking. Next, and based on prior

research (Bruijn et al., 2012), it was hypothesized that 5) older adults would exhibit reduced gait adaptability compared to young adults. Finally, the previous split-belt experiment (Ducharme et al., 2017) observed a learning effect from the first to third asymmetric walking condition, whereby fractal dynamics returned to values observed during unperturbed walking. Thus, it was hypothesized that: 6) repeated exposure to asymmetric walking will yield a learning effect, characterized by decreased fractal scaling values across asymmetric walking conditions.

## **6.3 Methods**

### **6.3.1 Participants**

Fifteen young (9 female, mean  $\pm$  SD age 28.9 $\pm$ 5.6 years, height 169.9 $\pm$ 10.3 cm, mass 74.3 $\pm$ 10.3 kg) and 15 older (9 female, mean  $\pm$  SD age 64.7 $\pm$ 2.7 years, height 168.7 $\pm$ 9.1 cm, mass 74.98 $\pm$ 9.4 kg) adults volunteered for this study. Participants' limb dominance was determined by asking which leg they would likely use to kick a ball. As part of the inclusion criteria, all participants self-reported partaking in at least 150 minutes per week of moderate intensity physical activity, based on a Godin Leisure-Time Exercise questionnaire (Godin & Shephard, 1997). All participants were free from neurological, visual, or vestibular disease or impairments, or any orthopedic issues that may affect walking. In addition, participants declared that they were familiar walking on a treadmill, but had not experienced asymmetric walking on a split-belt treadmill. Finally, all participants completed a Physical Activity Readiness Questionnaire (PAR-Q) and informed consent document. The local Institutional Review Board approved this study.

### **6.3.2 Experimental Apparatus**

Participants stood and walked on a split-belt treadmill (Bertec Corporation, Columbus, OH, USA). This treadmill has two parallel belts whose speed, acceleration, and direction of motion could be independently controlled. Participants wore a shoulder-strapped harness at all times to prevent contact with the ground in the event of a fall. The treadmill was surrounded by 4 high speed cameras (Oqus, Qualisys, Gothenburg, Sweden) that collected kinematics at 120 Hz. Eight markers were placed bilaterally on each participant in the following locations: toe (5<sup>th</sup> metatarsal), heel (3cm inferior to the lateral malleolus), knee (femoral lateral epicondyle), and hip (greater trochanter). One additional marker was placed near each participant's 1<sup>st</sup> sacral vertebrae.

### **6.3.3 Experimental Protocol**

This study took place over the course of two sessions, one week apart. Session 1 first entailed determination of preferred walking speed (PWS) using a modified protocol to that of Jordan and colleagues (2007b). Participants were informed that the speed of the treadmill would continuously increase, and to verbally declare when they were walking at their 'preferred' or 'comfortable' speed. That is, the speed he or she would choose to walk as if walking through town, neither in a rush nor a leisurely stroll. The treadmill belts (tied) began at  $0.5 \text{ m}\cdot\text{s}^{-1}$  and increased by  $0.1 \text{ m}\cdot\text{s}^{-1}$  every 7-10 seconds until participants declared the speed to be their preferred speed. The treadmill was then increased to a speed  $0.3 \text{ m}\cdot\text{s}^{-1}$  greater than their preferred speed and subsequently reduced in speed  $0.1 \text{ m}\cdot\text{s}^{-1}$  every 7-10 seconds until participants again declared the speed to be their preferred. If the increasing and decreasing values were the same, it was considered

their PWS. If they differed, the process was repeated until a stable preferred speed was attained.

Following a standing calibration, participants then performed two walking bouts, each followed by a 5-minute seated rest. Participants first walked for 15 minutes at PWS, and then for 20 minutes at half-PWS. A final trial consisted of habituation to asymmetric, split-belt walking, whereby the non-dominant leg traveled at PWS and the dominant leg shifted between PWS and 75% of PWS five times over the course of six minutes. During all walking trials, participants were instructed to walk normally, generally near the center of the treadmill, and to avoid touching the handrails as much as possible. After all of the walking trials, participants were provided a hip worn accelerometer (ActiGraph GT3X, ActiGraph, Pensacola, FL, USA) and a physical activity log. They were instructed to wear the activity monitor for all waking hours, except for events involving water such as swimming or bathing.

Session 2 occurred one week later, and consisted of several walking bouts. After a standing calibration and 10-minute warm-up at PWS, participants performed three asymmetric walking trials, each 12 minutes long. During these trials, the treadmill belt under the dominant leg traveled at PWS, while the belt under the non-dominant leg traveled at half-PWS. Participants were encouraged to only touch the handrails initially while the treadmill speed ramped up if needed, and to try to not touch them otherwise. After the third asymmetric trial, participants walked again at PWS for 10 minutes with the belts tied. Following each trial, participants were provided a 5-minute, seated rest on a chair placed upon the treadmill.

### **6.3.4 Data Analysis**

All kinematic data were collected using Qualisys Track Manager (Qualisys, Gothenburg, Sweden). Once kinematic trajectories were labeled, they were exported to MATLAB (The MathWorks, Natick, MA, USA) for all analyses. Kinematic data were low pass filtered at 7 Hz using a 4<sup>th</sup> order Butterworth filter. Heel strikes were obtained using kinematics of the maximum peaks in the anterior-posterior (AP) direction of the heel marker. Stride time was defined as the timing from heel strike to subsequent heel strike of the same foot. Of the 180 total trials, most (n=165) were at least 512 strides in length, and thus truncated to the first 512 stride times. Some of the trials (n=15) contained less than 512 strides, and thus entire data sets were used, ranging from 468-506 strides. Minutes per day of moderate-to-vigorous physical activity (MVPA) were ascertained within the ActiLife software (version 6.13.3, ActiGraph, Pensacola, FL, USA) using the Freedson cutpoints of the vertical axis (Freedson, Melanson, & Sirard, 1998). The accepted wear time criterion was at least 3 days of 10 or more hours per day of wear time.

#### **6.3.4.1 Determination of Correlation Structure**

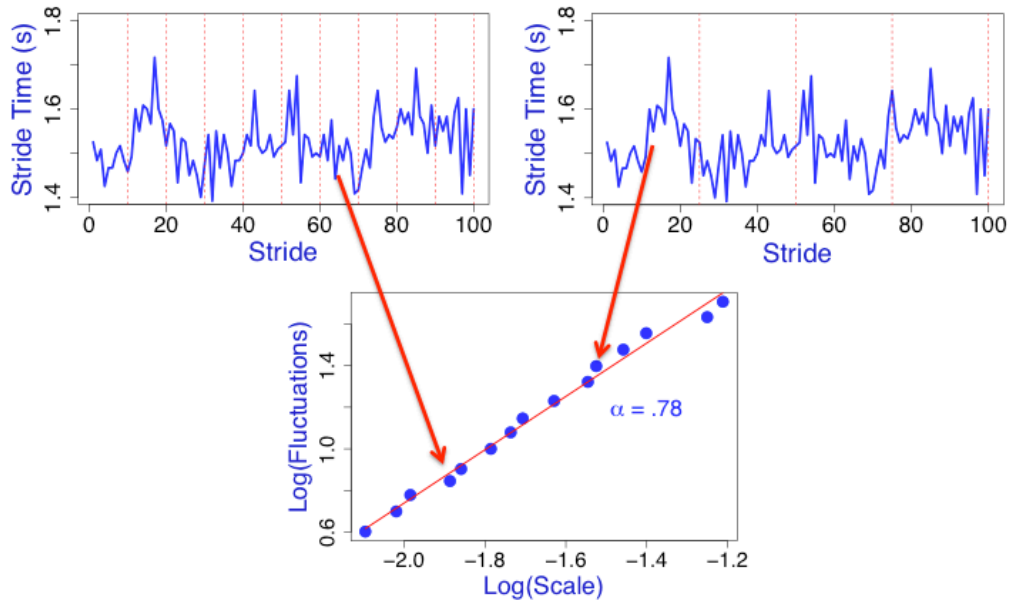
Stride time fractal dynamics were evaluated using detrended fluctuation analysis (DFA) (Hausdorff et al., 1995; Hausdorff et al., 1996; Peng et al., 1995). DFA assesses the potential presence of statistical long-range correlations by evaluating the correlation structure of the time series. This is achieved by quantifying the magnitude of localized fluctuations across various temporal scales. The DFA algorithm is a modified random walk analysis that uses signal integration to determine the degree of self-similarity (i.e., statistical resemblance across various scales) within a signal that exhibits long-range

correlations (Hausdorff et al., 2000). After integration, the signal is sectioned into non-overlapping windows of length  $n$ . Within each window, a least-squares linear trend line is fit to the signal. To calculate the magnitude of local fluctuations, a root-mean-square analysis is applied to each data point of the signal within the window, relative to the local trend line by subtracting the trend line's y-coordinate from the corresponding signal. This process is performed across all windows of size  $n$ , and finally averaged to yield a fluctuation magnitude at scale size  $n$ , or  $F(n)$ :

$$F(n) = \sqrt{\frac{1}{\lfloor N/n \rfloor} \sum_{j=1}^{\lfloor N/n \rfloor} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_i)^2} \quad \text{Equation 6.1}$$

where  $F(n)$  is the fluctuation magnitude at window  $n$ ,  $N$  is the total number of strides,  $X_i$  is the integrated signal at stride interval  $i$ , and  $\bar{X}_i$  is the y-coordinate location of the local trend within window  $n$ .  $F(n)$  is obtained for all non-overlapping windows ( $j$ ) of size  $n$  (total number of windows =  $N/n$ , Figure 6.1), and then averaged so that a single fluctuation magnitude represents each scale size. This procedure was performed for all window sizes ranging from the minimum and maximum windows of 4 and  $N/10$ , respectively. The selection of  $N/10$  for a maximal window size is based on the potential under sampling of the more traditional  $N/4$  value (Hu et al., 2001; Paterson et al., 2011). When  $F(n)$  is plotted against  $n$  on a double logarithmic plot, a linear relationship signifies power law scale invariance (Figure 6.1). The slope of the line of best fit on this graph represents the scaling exponent, or  $\alpha$ , based on the following relationship:

$$F(n) \approx n^\alpha$$



**Figure 6.1: Evaluation of fluctuation magnitude across a range of non-overlapping windows.** The top left and right graphs display the same time series sectioned into windows (red vertical dotted lines) of 10 and 25 strides, respectively. The fluctuation magnitudes are averaged across a window size, and double logarithmically plotted (bottom graph). A linear relationship (red line) on this double-log plot indicates power law scale invariance. The slope of the line of best fit represents the scaling exponent, or  $\alpha$ . Adapted from Rhea et al. (2014).

When  $0.5 > \alpha \geq 1.0$ , the signal exhibits fractal-like persistent structure. A persistent structure is one in which a large stride time is likely to be followed by another large stride time, and vice versa (i.e., long-range correlated).  $\alpha = 1.0$  is the special case in which the power of the signal is inversely proportional to the oscillation period, that is, the so-called  $1/f$  phenomenon (Bak, Tang, & Wiesenfeld, 1987; Diniz et al., 2011; Farrell, Wagenmakers, & Ratcliffe, 2006; Keshner, 1982). When  $\alpha \sim 0.5$ , the signal lacks long-range correlations, equivalent to white noise. Finally, when  $\alpha$  exceeds 1.0 the signal approaches fractional Brownian motion ( $\alpha \sim 1.5$ ), or the integration of white noise. In this event, the signal is characterized by highly correlated structure that is heavily

dependent upon previous and future trends. This characteristic represents an overly structured and constrained signal or behavior, and therefore less complex and adaptive.

#### **6.3.4.2 Surrogate Data Analysis**

In order to distinguish between time series data with long-range scaling characteristics and that of random or uncorrelated processes, surrogate data sets were created. The surrogate data sets were randomly shuffled empirical time series for each participant and condition. If the empirical time series exhibits true long-range correlations (i.e., dependence upon previous and future states), the surrogate data sets should eliminate these correlations, and manifest as lower scaling exponents.

#### **6.3.4.3 Analysis of Gait Adaptability Performance**

To quantify the adaptive capacity of the locomotor system, relative phasing between the legs was assessed. Each 'leg' was constructed as a segment from the greater trochanter to the ipsilateral heel. The sagittal plane angle was calibrated to the leg angle during upright quiet standing. Each stride (i.e., from heel strike to subsequent heel strike) was normalized to 100 data points, and a cross correlation function was applied to each stride for the right and left legs. The cross correlation function determines correlative properties bi-directionally between two signals across various temporal or spatial offsets by systematically shifting one signal (leg angle) by one data frame. The function yields a series of correlation values across the entire range of possible lags/offsets (Figure 6.2). By normalizing these data to a range  $[-1, 1]$  of stride lags, maximal negative correlation for signals that are moving in opposite directions occurs around when the lag = 0. Given that unperturbed, steady state walking entails perfect anti-phasing, gait performance was



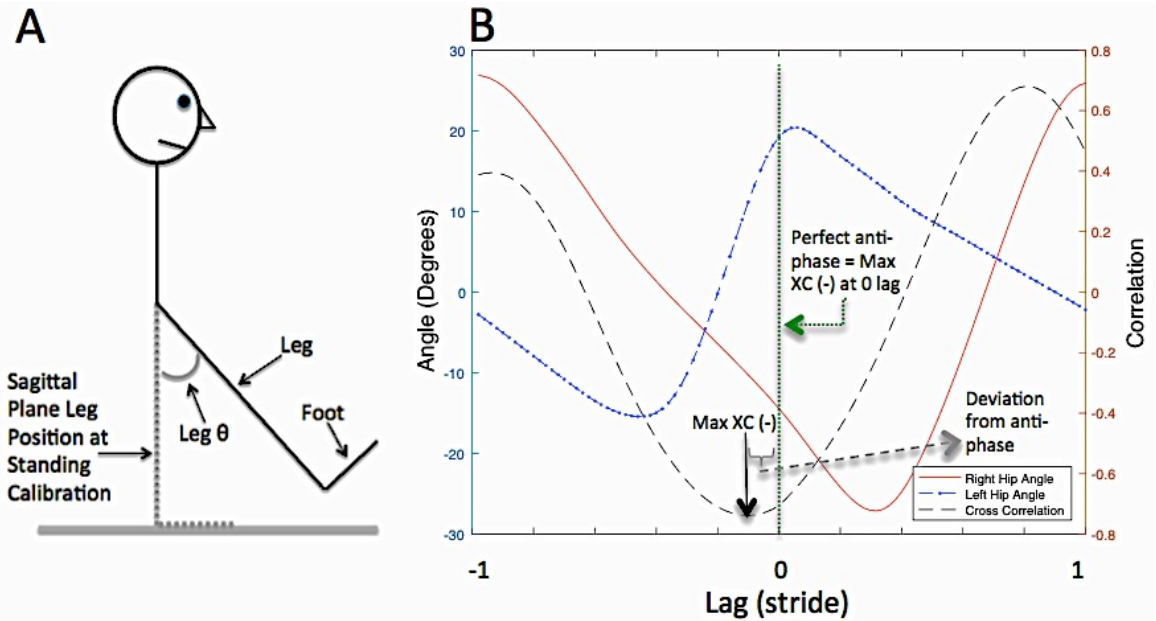
calculated as the deviation from intended phasing (anti-phase, i.e., maximal negative correlation at zero lag) for each stride (J. T. Choi & Bastian, 2007). From these data, two variables were calculated. First, absolute magnitude of deviation from intended phasing ( $\text{Phase}_{\text{DEV}}$ ) across the first 50 strides. This variable represents the magnitude of initial error. Second, in order to evaluate the temporal ‘error’ component, a time-to-adaptation (TtA) variable was ascertained (Figure 6.3). This variable represents the time required to ‘settle’ or ‘stabilize’. TtA was quantified by fitting an exponential decay model to the first 400 strides of the phase data using the equation:

$$Y(x) = \exp(a - b * x) \quad \text{Equation 6.2}$$

where  $Y(x)$  is the model fit at stride ( $x$ ),  $a$  is the initial value, and  $b$  is the rate of decay. TtA was determined using the principles employed by Rabuffetti et al. (2011) to calculate ‘time to stabilize’ in postural center of pressure data:

$$TtA = \frac{1}{b*3} \quad \text{Equation 6.3}$$

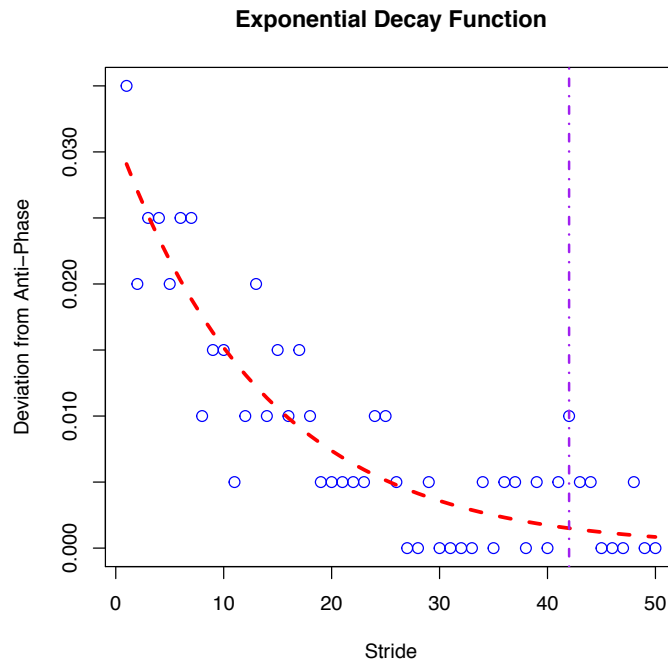
This analysis is generally considered a practical approximation of the time taken for the model to shift from its initial value ( $a$ ) to infinity, i.e., the time required to dissipate 95% of the instability that is first observed (Rabuffetti et al., 2011).



**Figure 6.2: Determination of leg relative phasing.** A) Construction of the ‘leg’ angle ( $\theta$ ) using ipsilateral markers of the greater trochanter and heel. The sagittal plane leg angle is standardized to the upright quiet standing position during the calibration trial. B) Deviation from anti-phase determined based on the cross correlation (grey dashed line) maximal negative correlation (Max XC (-)) for the left (blue dash-dotted line) and right (red line) limb angles.

### 6.3.5 Statistical Analyses

Demographic data between cohorts were evaluated using independent samples t-tests. To confirm the presence of long-range correlations, paired-samples t-tests were performed between the empirically derived time series fractal scaling exponents and that of the surrogate data sets. If the empirical data’s fractal scaling was statistically greater than the surrogate data, the original time series was considered a signal that exhibits long-range correlated behavior. Fractal scaling exponents across cohorts and targeted conditions were assessed by submitting the data to a within-subject, repeated measures analysis of variance (ANOVA), with conditions as the within-subject factor, and age cohort as the between-subject factor. The targeted condition comparisons included: 1)



**Figure 6.3: Exponential decay function.** Example of an exponential decay model fit (red dashed line) for phase deviation across the first 50 strides of asymmetric walking. Each blue circle represents a deviation value (y-axis) at a given stride (x-axis). Time-to-adaptation is the point at which 95% of the initial disturbance is dissipated (shown here at stride 42, purple dash-dotted vertical line).

PWS vs. half-PWS, 2) PWS vs. split-belt 1, and 3) split-belt 1 vs. split-belt 2 vs. split-belt 3. These targeted comparisons were assessed separately for each leg. The relationship between gait adaptability performance ( $\text{Phase}_{\text{DEV}}$  and  $\text{TtA}$ ) and fractal scaling at PWS, Half-PWS, and during asymmetric split-belt trials was determined by fitting linear and quadratic regression equations to the data. All statistics were conducted using R-Studio (Version 1.0.136, R Foundation for Statistical Computing, Vienna, Austria).

## 6.4 Results

### 6.4.1 Subject Demographics

All demographic data are reported in Table 6.1. Cohorts were not different in terms of height, mass, PWS, self-reported physical activity and objectively monitored physical activity.

**Table 6.1: Subject Demographics.** Data reported as (mean  $\pm$  SD). Significance based on independent samples t-tests. MVPA = moderate-to-vigorous physical activity; TM = treadmill. Age was the only significantly different variable.

	Young (n = 15)	Older (n = 15)	Significance (p-value)
Sex	9 F, 6 M	9 F, 6 M	-----
Age	28.9 $\pm$ 5.64	64.7 $\pm$ 2.7	-----
Height (cm)	169.9 $\pm$ 10.3	168.7 $\pm$ 9.1	0.73
Mass (kg)	74.3 $\pm$ 10.3	74.9 $\pm$ 9.4	0.85
TM Preferred walk Speed (m*s <sup>-1</sup> )	1.17 $\pm$ 0.16	1.08 $\pm$ 0.16	0.13
Self-report MVPA*day <sup>-1</sup>	43.3 $\pm$ 17.6	48.9 $\pm$ 26.9	0.50
Objective MVPA*day <sup>-1</sup>	53.7 $\pm$ 17.8	42.8 $\pm$ 26.3	0.20

**Table 6.2: Comparison of fractal scaling exponent between surrogate and empirical data.**  $\alpha_D$  and  $\alpha_N$  = dominant and non-dominant leg stride time fractal scaling exponents, respectively. Empirical = original time series data. Surrogate = randomly shuffled time series data.

	PWS	Half-PWS	Split 1	Split 2	Split 3	Readapt
$\alpha_D$ -Empirical vs. $\alpha_D$ -Surrogate	p < 0.001 t = 13.61	p < 0.001 t = 13.81	p < 0.001 t = 15.71	p < 0.001 t = 20.11	p < 0.001 t = 19.25	p < 0.001 t = 13.74
$\alpha_N$ -Empirical vs. $\alpha_N$ -Surrogate	p < 0.001 t = 14.55	p < 0.001 t = 14.68	p < 0.001 t = 10.11	p < 0.001 t = 8.33	p < 0.001 t = 14.15	p < 0.001 t = 14.71

### 6.4.2 Surrogate Analysis

Table 6.2 demonstrates that for both the dominant and non-dominant leg's fractal scaling across all conditions and age groups, the empirically derived data were statistically different from the surrogate data sets (all p's < 0.001). Specifically, all

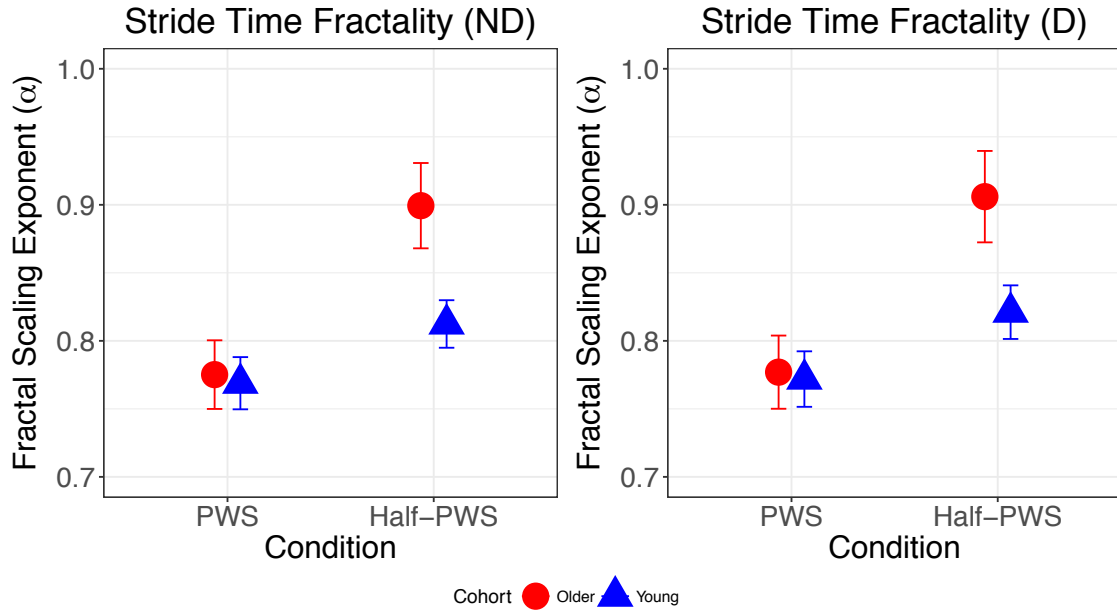
surrogate tests exhibited lower scaling exponents (closer to  $\alpha \sim 0.5$ ) compared to the corresponding original time series data.

### 6.4.3 Fractal Scaling During Steady State Unperturbed Walking

Table 6.3 displays the results of stride time fractal scaling indices for all conditions. For unperturbed walking (PWS and half-PWS, Figure 6.4), there was a main effect of condition ( $F_{1,28} = 20.98$ ,  $p < .001$  and  $F_{1,28} = 21.35$ ,  $p < .001$ ) and an age by condition interaction effect ( $F_{1,28} = 4.85$ ,  $p = .036$  and  $F_{1,28} = 4.28$ ,  $p = .047$ ) for both the non-dominant and dominant legs, respectively. Young and older adults exhibited similar scaling exponents during PWS. Walking slower yielded larger  $\alpha$  values, and the older group's scaling increased more so than that of the young group.

**Table 6.3: Gait parameter fractal scaling exponents.** Data reported as mean (95% CI). Y = young adults, O = older adults. N = non-dominant leg. D = dominant leg.

	PWS	Half PWS	Split 1	Split 2	Split 3	Re-Adapt
<b>Stride</b>	Y .77 (.04)	Y .81 (.04)	Y .74 (.03)	Y .74 (.05)	Y .72 (.04)	Y .78 (.04)
<b>Time-N</b>	O .78 (.05)	O .90 (.07)	O .78 (.05)	O .71 (.05)	O .72 (.04)	O .84 (.05)
<b>Stride</b>	Y .77 (.04)	Y .82 (.04)	Y .85 (.06)	Y .84 (.04)	Y .83 (.04)	Y .75 (.04)
<b>Time-D</b>	O .78 (.06)	O .91 (.07)	O .89 (.06)	O .83 (.05)	O .82 (.04)	O .80 (.04)



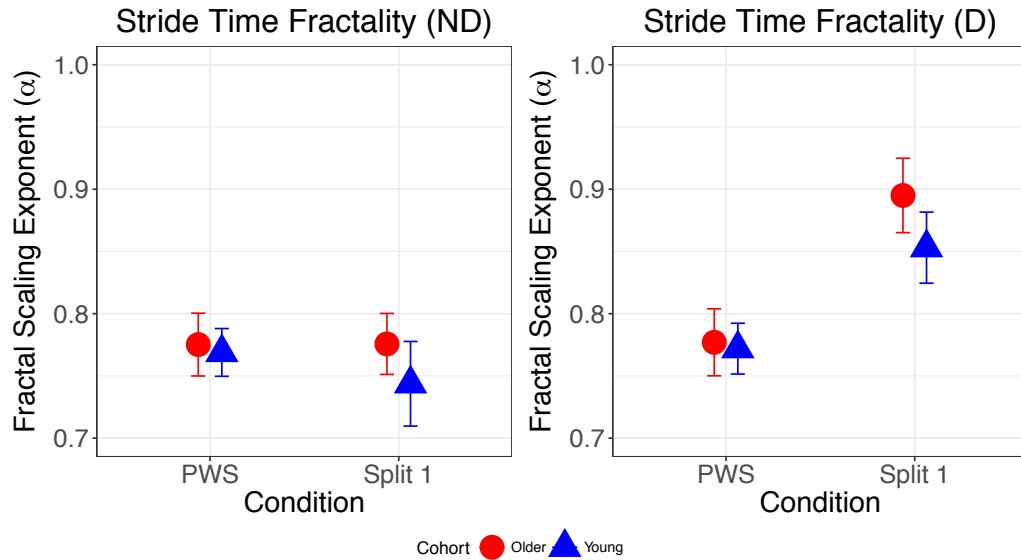
**Figure 6.4: Steady state walking fractality in young and older adults.** Unperturbed walking fractality (PWS and half-PWS) shown for the non-dominant (ND) and dominant (D) limbs in young (blue triangles) and older (red circles) adults. Data reported as mean  $\pm$  SEM.

#### 6.4.4 Fractal Scaling During Asymmetric Walking

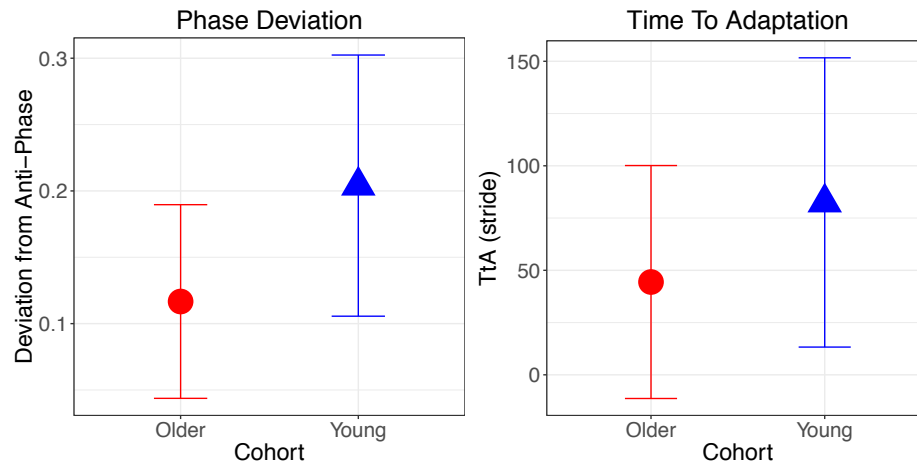
Stride time fractality in the dominant leg increased in the first split-belt condition compared to PWS for both groups ( $F_{1,28} = 12.30$ ,  $p = 0.002$ , Figure 6.5), but not for the non-dominant leg ( $F_{1,28} = 0.19$ ,  $p = .66$ ). There was no effect of age for either leg ( $p$ 's  $> 0.35$ ).

#### 6.4.5 Age Effects of Gait Adaptability

There was no main effect of age for phase deviation ( $F_{5,140} = 2.34$ ,  $p = 0.14$ ) or time-to-adaptation ( $F_{5,140} = 0.84$ ,  $p = 0.37$ , Figure 6.6).



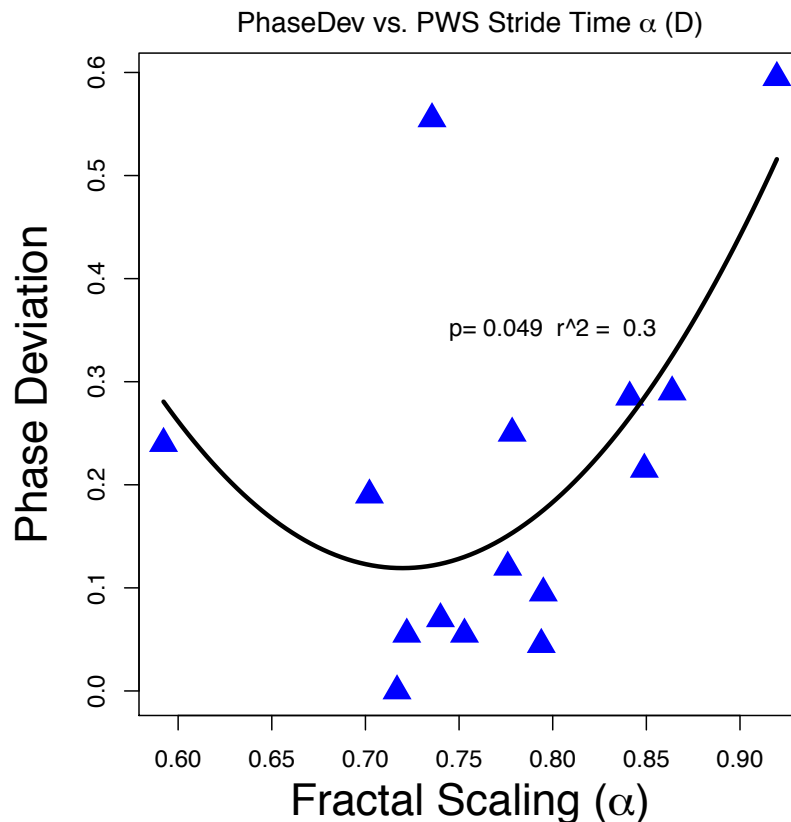
**Figure 6.5: Unperturbed versus asymmetric walking fractal dynamics.** Stride time fractal scaling exponents (mean  $\pm$  SEM) for the non-dominant (ND, left) and dominant (D, right) legs in young (blue triangles) and older (red circles) adults. PWS = Preferred walking speed; Split 1 = Asymmetric split-belt conditions.



**Figure 6.6: Gait adaptability in young and older adults.** Quantification of gait adaptability performance (mean  $\pm$  95% CI) during the first asymmetric walking trial (Split 1) based on deviation from intended leg phasing (anti-phase, left plot), and time-to-adaptation (right plot).

#### 6.4.6 Prediction of Gait Adaptability from Steady State Walking Fractality

Regression analyses of young adults' stride time fractal dynamics during steady state preferred speed walking and gait adaptability ( $\text{Phase}_{\text{DEV}}$ ) revealed a single quadratic association between the dominant leg's PWS  $\alpha$  and phase deviation (Table 6.4, Figure 6.7,  $p = 0.049$ ,  $r^2 = 0.30$ ). All other  $r^2$  values were  $\leq 0.20$  and  $p$ 's  $> 0.05$  for PWS and half-PWS associations with  $\text{Phase}_{\text{DEV}}$  and TtA. Older adults' scaling exponents during PWS and half-PWS were all uncorrelated to adaptability performance (Table 6.5, all  $p$ 's  $> 0.05$ ,  $r^2$ 's  $\leq 0.15$ ).

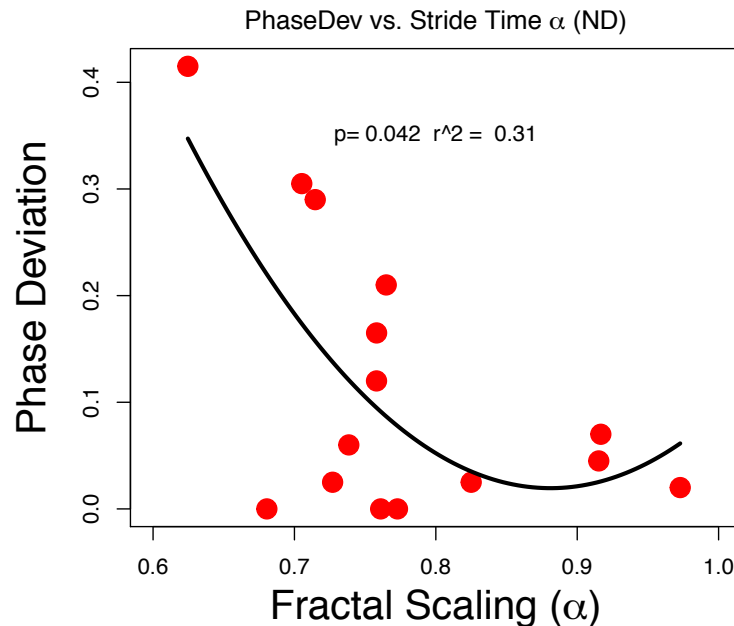


**Figure 6.7: Relationship between phase deviation and preferred walk speed stride time fractal dynamics** for the dominant limb in the young adult group. Line of best fit (black solid line) indicates a moderate quadratic association ( $r^2 = 0.30$ ) between the dominant limb  $\alpha$  and phase deviation.



### 6.4.7 Prediction of Gait Adaptability from Asymmetric Walking Fractality

Young adults' stride time fractal dynamics during the first split-belt condition were not associated with gait performance (Table 6.4). However, older adults' stride time fractal dynamics were associated with both Phase<sub>DEV</sub> and TtA (Table 6.5). For Phase<sub>DEV</sub>,



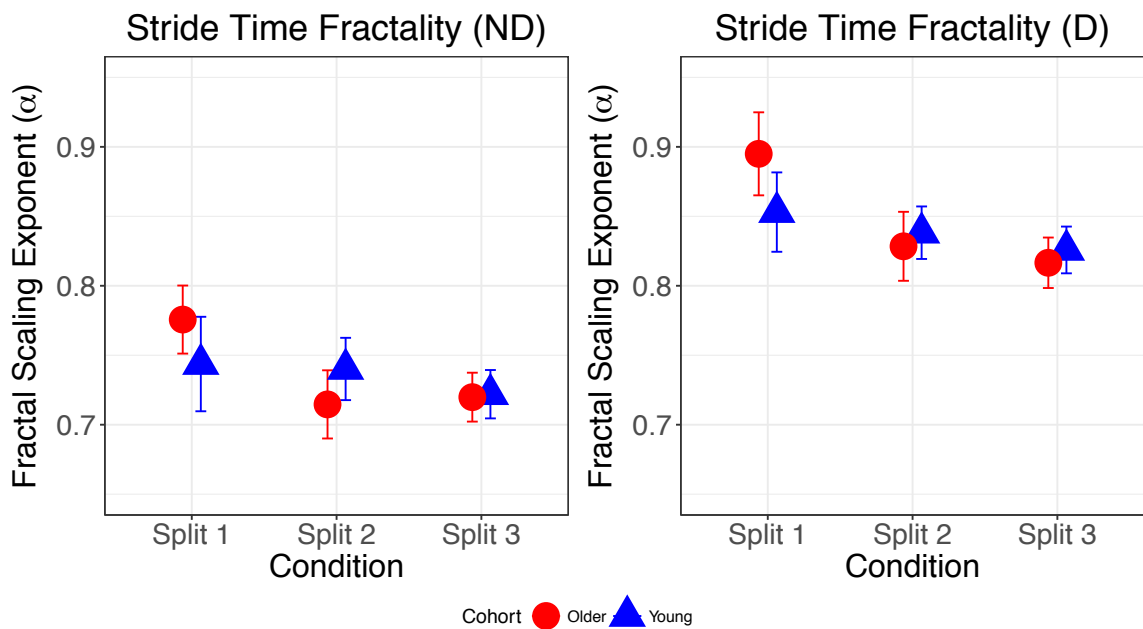
**Figure 6.8: Comparison of Gait Adaptability performance and non-dominant limb fractal scaling during asymmetric walking in older adults.** Line of best fit (black line) indicates a moderate curvilinear association ( $r^2 = 0.31$ ) between the non-dominant (ND) limb  $\alpha$  and phase deviation.

non-dominant leg scaling exponents approaching  $\alpha = 1.0$  were associated with better gait adaptability performance (Figure 6.8) for the older adults. TtA (not shown) was poorest for those older individuals with dominant leg  $\alpha$  values greater than 1.0. However, these TtA relationships appear to have been influenced by a major outlier (TtA = 400, i.e., he/she did not adapt). Removing this individual erased the association for TtA in the dominant leg ( $p = 0.25$ ). For the young cohort, removing two clear outliers (TtA = 400)

from the regression equation did not change the results (i.e., there were still no associations).

#### 6.4.8 Effects of Repeated Exposure to Asymmetric Walking on Stride Time Fractality

To examine the effects of repeated exposure to asymmetric walking, a repeated-measures ANOVA was conducted for stride time fractality across the three split-belt



**Figure 6.9: Stride time fractal dynamics as a function of asymmetric walking trial.** Data reported as mean  $\pm$  SEM. Non-dominant (ND, left plot) and dominant (D, right plot) legs shown for the young (blue triangles) and older (red circles) adults. Split = Asymmetric split-belt conditions.

conditions. There was an overall main effect of condition for the dominant leg ( $F_{2,56} = 3.354, p = .042$ ) but not for the non-dominant leg ( $F_{2,56} = 1.71, p = 0.19$ ). Dominant leg stride time fractality decreased closer to scaling exponents observed during the initial PWS condition. Neither leg exhibited an age effect ( $F_{1,28} = 0.13, p = 0.72$ , and  $F_{1,28} < 0.01, p = 0.95$  for the dominant and non-dominant legs, respectively) nor an age by

condition interaction ( $F_{2,56} = 0.92, p = 0.40$  and  $F_{2,56} = 0.84, p = 0.44$  for the dominant and non-dominant legs, respectively, Figure 6.9).

**Table 6.4: Association between young adults' gait adaptability performance and fractal scaling exponents.**  $\alpha_D$  and  $\alpha_N$  = dominant and non-dominant leg scaling exponents, respectively.

Dependent Variable	Independent Variable	Model	$p$	$R^2$	Significant
Phase <sub>DEV</sub> at 1 <sup>st</sup> Split-Belt Condition – Young Adults	$\alpha_D$ at PWS	Linear	0.17	0.07	*
		Quadratic	0.049	0.30	
	$\alpha_N$ at PWS	Linear	0.24	0.03	
		Quadratic	0.10	0.20	
	$\alpha_D$ at Half-PWS	Linear	0.77	-0.07	
		Quadratic	0.91	-0.15	
	$\alpha_N$ at Half-PWS	Linear	0.85	-0.07	
		Quadratic	0.75	-0.11	
	$\alpha_D$ at Split 1	Linear	0.17	0.08	
		Quadratic	0.22	0.09	
	$\alpha_N$ at Split 1	Linear	0.20	0.06	
		Quadratic	0.28	0.06	
TtA at 1 <sup>st</sup> Split-Belt Condition – Young Adults	$\alpha_D$ at PWS	Linear	0.15	0.09	
		Quadratic	0.11	0.20	
	$\alpha_N$ at PWS	Linear	0.19	0.06	
		Quadratic	0.22	0.10	
	$\alpha_D$ at Half-PWS	Linear	0.99	-0.08	
		Quadratic	0.99	-0.16	
	$\alpha_N$ at Half-PWS	Linear	0.92	-0.08	
		Quadratic	0.59	-0.07	
	$\alpha_D$ at Split 1	Linear	0.19	0.06	
		Quadratic	0.16	0.14	
	$\alpha_N$ at Split 1	Linear	0.19	0.06	
		Quadratic	0.15	0.15	

**Table 6.5: Association between older adults' gait adaptability performance and fractal scaling exponents.**  $\alpha_D$  and  $\alpha_N$  = dominant and non-dominant leg scaling exponents, respectively.

Dependent Variable	Independent Variable	Model	$p$	$R^2$	Significant
Phase <sub>DEV</sub> at 1 <sup>st</sup> Split-Belt Condition – Older Adults	$\alpha_D$ at PWS	Linear	0.53	-0.04	
		Quadratic	0.80	-0.12	
	$\alpha_N$ at PWS	Linear	0.76	-0.07	
		Quadratic	0.94	-0.15	
	$\alpha_D$ at Half-PWS	Linear	0.89	-0.08	
		Quadratic	0.37	0.01	
	$\alpha_N$ at Half-PWS	Linear	0.83	-0.07	
		Quadratic	0.60	-0.06	
	$\alpha_D$ at Split 1	Linear	0.12	0.11	
		Quadratic	0.26	0.07	
	$\alpha_N$ at Split 1	Linear	0.046	0.22	*
		Quadratic	0.04	0.31	*
TtA at 1 <sup>st</sup> Split-Belt Condition – Older Adults	$\alpha_D$ at PWS	Linear	0.99	-0.08	
		Quadratic	0.91	-0.15	
	$\alpha_N$ at PWS	Linear	0.80	-0.07	
		Quadratic	0.94	-0.15	
	$\alpha_D$ at Half-PWS	Linear	0.23	0.04	
		Quadratic	0.29	0.05	
	$\alpha_N$ at Half-PWS	Linear	0.22	0.04	
		Quadratic	0.31	0.04	
	$\alpha_D$ at Split 1	Linear	0.06	0.19	
		Quadratic	0.04	0.33	*
	$\alpha_N$ at Split 1	Linear	0.10	0.14	
		Quadratic	0.19	0.11	

## 6.5 Discussion

The purpose of this study was to examine differences in stride time fractal dynamics in young and older adults during steady state and asymmetric walking, and to ascertain if gait parameter fractality is associated with the adaptive capacity of the locomotor system. The first hypothesis that older adults would exhibit reduced fractality compared to young adults during unperturbed walking was not supported. The young and older groups exhibited fractal dynamics of  $\sim \alpha = .78$  (both legs) during unperturbed

preferred speed walking. In contrast to hypothesis 1, half-PWS revealed age-based changes in that the older cohort's fractality increased more so than that of the young cohort. The second hypothesis that unperturbed walking  $\alpha$  would not associate with gait adaptability performance was confirmed for the older cohort, but not for the young cohort. There was a moderate quadratic relationship between young adults dominant leg PWS  $\alpha$  and gait adaptability performance, whereby  $\alpha$  values less than or greater than the mean were associated with poorer performance. The third hypothesis that asymmetric stride time fractality would be related to gait adaptability performance was supported in the older cohort by a moderate quadratic relationship; those older adults whose stride time fractality approached  $\alpha = 1.0$  exhibited the greatest adaptive gait performance in Phase<sub>DEV</sub>. The fourth hypothesis that stride time fractality would decrease in older adults when exposed to asymmetric walking was not supported. Rather, older adults' dominant leg stride time fractality during asymmetric walking increased closer to  $\alpha = 1.0$  ( $\alpha \sim .87$ ), similar to the increase observed in young adults. Also similar to young adults, older adults' non-dominant limb's  $\alpha$  was unchanged from PWS to asymmetric walking. The fifth hypothesis that older adults would exhibit reduced gait adaptability compared to young adults was not supported, as both cohorts exhibited similar adaptive gait performance. Finally, the hypothesis that repeated exposure to asymmetric walking would yield a learning effect was supported, as the fractal scaling decreased from the first to last asymmetric walking condition, but this effect was only observed for the dominant leg's scaling characteristics.

### **6.5.1 Preferred Speed Walking Fractality was not Different between Young and Older Adults**

Stride time fractal dynamics were first reported to decrease in older versus young adults (Hausdorff et al., 1997). These findings were interpreted as the manifestation of impaired neurological functionality. In a more recent experiment, age did not impact stride time fractality (Bollens et al., 2012). This current study provides evidence that accounting for physical activity negates previously observed age-related differences in stride time fractal dynamics (Figure 6.4). That is, while healthy yet otherwise sedentary older adults may potentially exhibit reductions in stride time fractality, participating in regular physical activity appears to attenuate or eliminate these reductions. However, in order to provide further evidence to support the role of PA in stride time fractality, a study would need to assess both physically active and sedentary older adults.

### **6.5.2 Slow Walking Fractality was Greater in Older Adults**

Slow walking has been shown to yield higher fractal scaling values compared to preferred speed walking (Hausdorff et al., 1996; Jordan et al., 2007b), and the results from this study further support this notion (Figure 6.4). Interestingly, though, the older adults fractal scaling increased more so than that of the young adults. Considering fractal scaling closer to  $\alpha = 1.0$  (i.e.,  $1/f$ ) represents greater adaptive capacity, these findings could suggest that the older adults displayed more adaptive gait than the young adults during slow walking. This finding again may highlight the fact that highly active individuals participated in this study. While there were no differences in PA levels (Table 6.1), type of activities performed may have differed between groups that might yield these results. Alternatively, constraints and difficulty appear to impact fractal scaling (see

section 6.5.4 below). Thus, the higher fractal scaling in older adults during the slow walking condition may indicate that slow walking is more challenging for this group. Slow walking does not allow for the same extent of passive limb dynamics (e.g., inverted pendulum) observed in preferred speed walking. For this reason, slow walking requires greater relative muscle force and balance compared to preferred speed walking. Older adults may have simply required greater physical or attentional effort to perform this task. One final explanation may be that older adults' preferred walk speeds were slower (though not significantly) than the young adults, and therefore the half-PWS speeds were also slower. Thus, while all participants walked at the same relative speeds (half of preferred speed), the older adults absolute speeds were slightly slower ( $0.54 \text{ m}\cdot\text{s}^{-1}$  vs.  $0.58 \text{ m}\cdot\text{s}^{-1}$  for young adults) during half-PWS walking. However, this minor discrepancy in speed likely would not result in such a large difference in fractal scaling.

### **6.5.3 Relationship Between Fractality and Gait Adaptability**

Recent work (Ducharme et al., 2017) has provided evidence that steady state fractality does not predict adaptive gait performance. This current study surprisingly displayed a quadratic relationship between young adults' PWS  $\alpha$  and constrained walking gait performance (Figure 6.7). Those individuals whose  $\alpha$  during symmetric PWS walking were larger or smaller than the average eventually performed poorer on during the challenging walking task. These findings are promising in that a major goal of fall prevention research involves predicting gait adaptability via unperturbed gait analysis. However, the observed relationship between preferred speed fractal scaling and gait performance (Phase<sub>DEV</sub>) was relatively weak ( $r^2 = 0.30$ ) and possibly influenced by a few outliers. In addition, these findings were not observed in the non-dominant limb, nor in

either limb for the older adults, nor in either limb in the previous study (Ducharme et al., 2017). Clearly, in order to establish that a relationship exists between unperturbed walking  $\alpha$  and adaptive gait, more research is warranted.

In the previous study (Ducharme et al., 2017), fractality during asymmetric walking was strongly associated with gait adaptability performance in young adults. The participants whose stride time fractality increased close to  $\alpha = 0.9-1.0$  exhibited the best adaptive performance, while those participants whose fractality did not increase (i.e.,  $\alpha \sim 0.7$ ) or increased excessively (i.e.,  $\alpha \sim 1.2$ ) displayed the poorest performance. In this study, these results were not repeated with our young cohort. However, the older adults stride time fractality displayed a similar relationship previously observed, and expected to see with this young adult cohort. The older adults whose non-dominant leg's stride time fractal dynamics increased close to  $\sim \alpha = 0.9-1.0$  exhibited the lowest deviation from intended phasing (Figure 6.8). These findings are further evidence for the potential functional advantages of stride time fractal dynamic ranges in responding to task or environmental stressors. The reduction in fractal dynamics in some individuals may be a result of more large-scale error correcting behavior at short temporal scales that the DFA algorithm would translate into a decrease in the scaling exponent. The requirement for large error correcting may be due to reduced systemic stability, similar to the interpretation that greater gait parameter variance represents reduced control of the locomotor system. However, this statement requires empirical investigation.

The fact that no association emerged between constrained walking fractality and adaptability in young adults was in contrast to earlier findings (Ducharme et al., 2017). Young adults' dominant leg fractality increased closer to  $\alpha = 1.0$  during the asymmetric



condition, and was not statistically different from the older cohort. However, the non-dominant leg's  $\alpha$  did not increase in response to asymmetric walking. The differential responses of the limbs may have affected the overall relationship with adaptive performance. Moreover, the lack of association may be because highly active participants were recruited. Finally, the absence of associations could have been a result of the inherent variance of biological systems, or a result of other unknown factors. Even the older adults' fractal dynamics explained only a portion of the observed variance, indicating other factors must be responsible for the emergent behavior.

#### **6.5.4 Fractality Increased When Exposed to Task-Level Constraint Comparably in Both Cohorts**

Similar to previous observations in young adults (Ducharme et al., 2017), both groups' dominant leg stride time fractal dynamics increased when exposed to asymmetric gait. Earlier research in gait fractal dynamics provides evidence for increased fractality when participants walk faster or slower than their self-selected preferred walking speed (Hausdorff et al., 1996; Jordan et al., 2007b). It appears that constraining the locomotor system into tasks other than steady state preferred speed walking yields fractal dynamics that increase closer to  $\alpha = 1.0$ . Beyond gait, task-level constraints have been shown to shift fractality closer to  $1/f$  ( $\alpha = 1.0$ ) in postural studies. For example, fractality migrates towards  $1/f$  when participants transition from eyes open to eyes closed during quiet standing (Caballero Sanchez et al., 2016; Tanaka et al., 2002), or when the size of the support surface is reduced (Caballero Sanchez et al., 2016). This shifting of fractal scaling may be the manifestation of modified interactivity of processes across the various temporal scales being investigated. Earlier research has provided evidence that dynamical

systems exhibit critical fluctuations (i.e., increased variability) when approaching transitions to a different state (Kelso, 1995; Kelso & Ding, 1993; Van Emmerik, Miller, et al., 2013). These fluctuations are a key characteristic of phase shifts because this increased variability is required to change from locally stable to potentially more globally stable states. While traditionally believed to be random in nature, critical fluctuations may actually exhibit fractal-like characteristics (Bak & Chen, 1991). If the fluctuations are persistent, the likelihood of a phase transition will increase, compared to that of random fluctuations (Torre, 2010). If persistent fluctuations are functionally beneficial, evidence of altered fractality represents an emergent reorganization of the locomotor system that provides a better ability to respond to task stressors and shift to more stable states. This idea has been tested empirically in a bimanual coordination task, and findings indeed suggest that fractality shifts closer to  $1/f$  when approaching a potential phase shift (Torre, 2010). Regarding locomotion, walking slower or faster than preferred speed may be perceived as approaching a transition to standing or running, respectively.

The increase in  $\alpha$  during split-belt walking was not observed in the non-dominant limb. This is in contrast to the earlier study's (Ducharme et al., 2017) observance of increased fractality of the non-dominant leg during constrained walking. The main difference between this and the previous study's protocol was that, in this study, participants wore a body-supporting harness. This may have been perceived as an additional constraint because the harness partially limited total body displacement in the anterior-posterior directions. This additional constraint, while allowing the locomotor system to maintain persistence of the dominant, preferred speed leg, may have restricted the variance in stride times (e.g., reduced range) in the non-dominant leg.

The lack of differences in fractal dynamics during asymmetric walking between the young and older groups was unexpected but promising. That is, one potential explanation for these findings is that the participant pool consisted of active young and older adults. The previously observed reductions in fractal scaling in older adults were considered a result of age-related neurological decrements. This loss in neurological function may in fact be a consequence of disuse or underuse that often accompanies physical activity behavior of older adults (Brach et al., 2004; Crespo et al., 1996). Recruiting healthy and highly active adults aged 60-70 years may have diluted potential age-related differences in performance or fractality. If sedentary adults or much older adults (e.g., aged > 75 years) were recruited, age effects may have emerged. However, this statement is speculative and necessitates empirical investigation.

#### **6.5.5 Young and Older Adults Exhibited Similar Adaptive Performance**

Older adults were hypothesized to display poorer adaptive performance in the form of greater deviation from intended phasing, and greater time-to-adaptation in response to the asymmetric walking constraints compared to young adults. Instead, older adults exhibited similar values to that of the young group. Phase<sub>DEV</sub> values were  $0.204 \pm 0.18$  and  $0.117 \pm 0.13$  for the young and older groups, respectively. TtA values were  $82.47 \pm 124.95$  and  $44.4 \pm 100.6$  strides for the young and older groups, respectively. These values were highly variable, and were largely impacted by a few large outliers (TtA > 300). When these three participants (2 young, 1 older adult) are removed, TtA for the young and older adults were  $36.69 \pm 33.51$  and  $19 \pm 21.95$ , respectively. However, omitting outliers still does not reveal group differences (independent samples t-test  $p =$

0.12). One plausible explanation for the lack of differences between cohorts is again that everyone recruited was physically active. Thus, perhaps previously observed discrepancies between young and older adults (Bruijn et al., 2012) may have been based on the possibility that the older adults recruited were also more sedentary, and/or had been sedentary for a longer time (e.g., the past 30 vs. 5 years). In addition, the older cohort was relatively young (60-70 years) considering studies of older adults often span 60-85 years of age.

### **6.5.6 Repeated Exposure to Asymmetric Walking**

Stride time fractal dynamics of the dominant limb in both cohorts systematically decreased from the first to third asymmetric walking conditions (Figure 6.9). This phenomenon was not observed for the non-dominant limb, however. These findings of the dominant limb  $\alpha$  coincide with the previous study in which three asymmetric trials were also performed, and fractal scaling eventually returned to values similar to observed PWS  $\alpha$ 's (Ducharme et al., 2017). Each participant had no prior experience walking asymmetrically before the first asymmetric trial, and therefore were naïve to this type of walking. By the third trial, this gait had now been performed for 24+ minutes, and thus was no longer a novel experience. Fractal scaling increases when participants are experiencing a challenging gait task, and once the task is no longer challenging (or at least less challenging), fractal scaling returns to that of unperturbed symmetric walking. These findings further strengthen the argument that, when exposed to a challenging, perhaps less stable, walking task, the system reorganizes to better respond to exposure to perturbations. This reorganization manifests as higher fractal scaling (i.e., closer to  $\alpha = 1.0$ ).

### 6.5.7 Limitations

All participants self-reported being physically active. This was confirmed with objective monitoring using accelerometry (Table 6.1). This study did not recruit sedentary young or older adults, and therefore can suggest but not determine conclusively the effects of physical activity on gait fractality or adaptive performance.

In addition, the non-dominant leg speed was always reduced during the asymmetric walking trials. It is currently unknown how leg dominance affects responses to asymmetric split-belt walking in terms of both adaptive performance and fractality. One challenge with this paradigm, and similar to other perturbation studies, is that individuals rapidly adapt to these constraints. Thus, evaluating the differences between reducing the speed of the dominant versus non-dominant leg would likely yield an order effect. In order to truly establish effects of leg dominance, researchers would need to develop a paradigm that does not exhibit such a rapid rate of learning or recruit a large sample size for a between-subject study design.

Moreover, fractal dynamics were assessed using stride time dynamics. Thus, while a plethora of gait parameters could have been analyzed, the results presented in this study are based on a single measure. The selection of stride time was based on the general acceptance that it is the best overall representation of the locomotor system because it includes all of the phases of a gait cycle (e.g., double support, stance, swing) for both legs, and could therefore be considered the ‘final output’ of the many processes of the system (Hausdorff, 2007).

Finally, assessing fractal dynamics using the DFA algorithm assumes monofractality, that is, a constant fractal scaling exponent across the time series. In order to

truly evaluate the potential presence of fractality within a signal, a multifractal analysis would need to be employed. This multifractal analysis would confirm or reject the potential presence of interactivity of processes across various temporal scales.

## **6.6 Conclusion**

Stride time fractal dynamics were not different between young and older adults during normal unperturbed walking, and older adults even exhibited higher fractal scaling during slow walking. Young adults fractal scaling during unperturbed, preferred speed walking associated moderately with adaptive gait performance. Fractality during constrained walking was moderately associated with gait adaptability performance in older, physically active adults. While both cohorts displayed increased fractality (i.e.,  $\alpha$  closer to 1.0) in the dominant (but not the non-dominant) limb when required to walk asymmetrically, those older adults whose fractality was closer to  $\alpha = 1.0$  exhibited the best adaptive gait performance. These findings are in agreement with an earlier study that observed similar changes to gait fractality in response to constrained walking in young adults (Ducharme et al., 2017). In this current study, though, young adults asymmetric walking fractal dynamics did not associate with adaptive performance. The observed increase in fractal dynamics during asymmetric walking may be a manifestation of altered self-organization of the locomotor system when phase transitions are perceived to be imminent. The emergent relationship between stride time fractal dynamics and adaptive gait capacity indicates this modified self-organization may allow for improved adaptability during challenging gait tasks.

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**CHAPTER VII**  
**MULTIFRACTALITY OF UNPERTURBED AND ASYMMETRIC**  
**LOCOMOTION**

**7.1 Abstract**

Steady state walking in humans has been previously described as monofractal or slightly multifractal in nature. The degree of multifractality in perturbed locomotion is unknown. The purpose of this study was to explore the potential extent of multifractality in steady state unperturbed and constrained human locomotion, and to determine if multifractality predicts gait adaptability performance. To achieve this, young, healthy participants ( $n=15$ ) experienced unperturbed preferred and slow walking, as well as asymmetric walking, whereby their legs traveled at different speeds on a split-belt treadmill. Participants' dominant and non-dominant legs traveled at preferred and half preferred speed, respectively. Multifractality of stride time variance was assessed via a local detrended fluctuation analysis, which evaluates fluctuations both spatially and temporally. Preferred speed walking and slow walking both exhibited monofractal behavior. Asymmetric walking displayed an increase in multifractal spectrum width (overall range and interquartile range) in the faster moving limb, indicating greater intermittent periods of extreme high or low variance. In all, these findings provide further evidence that unperturbed human locomotion is essentially monofractal, and establish that perturbed walking yields multifractal behavior.



## 7.2 Introduction

Upright, bipedal locomotion provides numerous benefits to humans, such as improved vantage and unrestricted upper limbs. However, these advantages come at the cost of reduced systemic stability. Thus, the locomotor system utilizes many degrees of freedom to generate stable cyclic patterns to maintain a sufficient level of stability. Here ‘degrees of freedom’ refers to the various independent components of the locomotor system. Although these components are autonomous by definition, by interacting with other components, they can generate the same task goal in an infinite number of ways.

While the system benefits from its ability to generate rhythmic patterns, true human locomotion must take into account emergence of various environmental, task, or individual factors. Indeed, locomotion might best be described as intermittently cyclic, or more precisely, cyclic with intermittent periods of corrective control. In other words, the locomotor system may allow various gait parameters to persist until an adjustment is necessitated. For example, stride time variance may increase steadily and indefinitely until it interferes with the task goal (in gait, the task goal would be continued upright, relatively stable locomotion). The concept of intermittent control may be likened to that of the uncontrolled manifold (Scholz & Schoner, 1999) or goal equivalent manifold (Cusumano & Dingwell, 2013) analyses, or the theoretical concept of the minimum intervention principle (Todorov, 2004). While different algorithms, these analyses generally adhere to the concept that some or many of the system’s degrees of freedom do not need to be tightly controlled, or at least not at all times, as they do not affect the task goal. The ‘task goal’ may consist of maintaining upright overground walking (i.e., not falling), or staying on the treadmill while treadmill walking (i.e., not walking off the front

or back of the machine). If any parameter does threaten the task goal, it is regulated so that the goal can be attained. Variance is a common parameter of interest in assessing intermittency. In response to the many internal and external stressors placed upon a biological system, an expected and necessary output is gait parameter variance. The essence of intermittency is that, instead of attempting to minimize variance, the system may regulate this variance in a beneficial way (Cusumano & Dingwell, 2013). Here sensory feedback can be utilized intermittently to parameterize control variables (Loram, Van de Kamp, Gollee, & Gawthrop, 2014). For example, in human upright standing, instead of continuously modulating center of mass motion, ballistic muscular bursts are used to regulate center of mass motion to maintain upright homeostasis (Loram, Maganaris, & Lakie, 2005). This is similar to the ‘serial ballistic control’ method of balancing an inverted pendulum (Loram, Gollee, Lakie, & Gawthrop, 2011). Intermittency may be preferred over continuous control because active, continuous adjustments might arguably entail greater cognitive and metabolic load.

Regarding gait variability, any variance has historically been considered a consequence of imprecise control (i.e., indicative of error in the locomotor system). However, the emergence of chaos theory and fractal physiology has further challenged the previously established notion that variability is a negative effect. Utilizing an alternative measurement approach and theoretical underpinning (Mandelbrot, 1977), structures or behaviors were no longer observed from a single temporal or spatial scale. The magnitude of gait parameter variability is not universal across a time series, but rather dependent upon the temporal scale observed. For example, the magnitude of stride time variability across 10 consecutive strides is dissimilar from that of 100 consecutive

strides. What is of particular interest, however, is the relationship between the magnitude of variability and the size of the observed scale across various scales (Liebovitch, 1998). A behavior is considered ‘self-similar’ when it exhibits statistical similarities at various temporal or spatial scales. Self-similar behaviors are also referred to as ‘fractal’ in nature, characterized by a lack of a single representative ‘scale’ and infinitely-repeating patterns across a multitude of temporal or spatial scales.

While several methods have been developed to evaluate the self-similarity of a biological signal (e.g., power spectral analysis or examination of the signal’s autocorrelation properties), perhaps the most commonly used measure is Detrended Fluctuation Analysis (DFA). DFA benefits from locally detrending of the data, and thus is often the most appropriate measure when dealing with inherently nonstationary biological signals. DFA quantifies the magnitude of variance about a local trend across various temporal scales. When logarithmically transformed, a self-similar structure or behavior exhibits a linear, power-law relationship between fluctuation magnitude and scale size. The slope of the relationship between fluctuation size and scale size indicates the correlation structure, or fractal-like organization of the system, also known as the scaling exponent or  $\alpha$  (Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996; Peng et al., 1995). An example of a gait parameter that exhibits scale invariance is the temporal evolution of stride time variability.

The principle shortcoming of fractal analyses is that the fluctuation magnitude at a given scale is averaged across many windows of the same scale size. This inherently assumes the fluctuation magnitude is constant through the time series across windows of a particular window size, and thus a single global scaling exponent can accurately

describe the fractal nature of the system. In other words, this method assumes monofractality and thus is considered a ‘monofractal approach’. As mentioned earlier, locomotion is likely not perfectly cyclic as it requires constant adaptations to imposed constraints. Thus, fractal analyses of behaviors that are not precisely cyclic require a multifractal approach. Multifractality indicates the behavior of interest is not constant throughout a time series, but rather changes based on demands (West & Scafetta, 2005). If the behavior is not monofractal, the temporal evolution of fractal scaling exponents across a time series will yield a spectrum of scaling exponents (Scafetta, Griffin, & West, 2003; Struzik, 1999, 2000). There may be intermittent periods of high or low variance that would manifest as varying fractal characteristics (Ihlen & Vereijken, 2013b).

In assessment of the spectrum of exponents that results from the temporal evolution of physiological signals, the width of this spectrum indicates the degree of multifractality. That is, a monofractal signal would have a narrow spectrum width, as the fractal characteristics would not change throughout the temporal evolution of the signal. In fact, the spectrum width approaches zero as the data length approaches infinity for a monofractal signal. A multifractal signal, on the other hand, would have intermittent periods of high and low variance, manifesting as low and high scaling indices, respectively, and thus a greater spectrum width across the time series (Ihlen & Vereijken, 2013b). Researchers generally define a wider multifractal spectrum width as a more complex and adaptable system (Ivanov et al., 1999; Munoz-Diosdado et al., 2003).

Multifractal analysis of human locomotion has indicated that steady state walking appears monofractal or slightly multifractal in nature (Dutta, Ghosh, & Chatterjee, 2013; Ihlen & Vereijken, 2014; Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003; Scafetta

et al., 2003; Scafetta, Marchi, & West, 2009; West & Scafetta, 2005). Further, age and disease may alter multifractal behavior. Muñoz-Diosdado and colleagues reported that, compared to healthy controls, the multifractal spectrum width was wider in both children (aged 3-10 years) and healthy older adults, and is even wider in individuals with Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis (Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003). In contrast, Dutta and colleagues (2013) observed a reduction in multifractal spectrum width in those with Parkinson's and Huntington's disease compared to healthy controls. Moreover, Ihlen and Vereijken (2014) reported decreased multifractality in older adults compared to young, which was interpreted as reduced active regulation of the system.

Given the aforementioned studies, it is difficult to assess the functional meaning of the multifractal spectrum for the locomotor system. On one hand, more stable rhythmic patterns would be expected to yield nearly monofractal-like behavior, absent of the need for intermittent corrections and thus extreme fractal scaling values. On the other hand, this monofractal-like behavior may indicate a constrained locomotor system, incapable of producing rapid corrections when needed. It could be predicted that persistent fluctuations in gait dynamics will yield little or no intervention, while stressors, such as task constraints or organism-level errors (e.g., missteps) may require rapid, discrete periods of intermittent anti-persistence. In the event of intermittent periods of anti-persistence, variance at short scales would increase, thereby decreasing the fractal scaling exponent, and thus the range of observed fractal scaling exponents would be expected to widen.

One paradigm that may elucidate the potential multifractality of locomotion is asymmetric walking using a split-belt treadmill. This experimental design allows one leg to move at a different speed than the other, thus inciting asymmetries. The split-belt paradigm has been used to measure the adaptability of locomotor patterns, such as leg relative phasing (J. T. Choi & Bastian, 2007; J. T. Choi et al., 2009) or leg symmetry adaptation (Bruijn et al., 2012). In general, individuals are able to adapt to asymmetric belt speeds by adopting a more symmetrical pattern of walking. This adaptation paradigm provides valuable information in terms of how the locomotor system organizes or reorganizes in response to constrained walking. That is, does constrained walking yield greater or lesser multifractal behavior, and does the multifractal behavior correlate to enhanced adaptive gait performance? The only other study to evaluate multifractality in response to imposed constraints entailed walking with or without an auditory metronome at various speeds (Ihlen & Vereijken, 2014). In this study, participants walked with and without a metronome at slow, preferred, and fast walking speeds. Multifractality increased during metronome-constrained walking compared to walking without a metronome at various speeds, likely a result of more anti-persistence in response to temporal regulations, which the authors' suggested was indicative of 'healthy' adjustments being made.

While a multifractal analysis has been conducted on steady state and metronome-entrained walking, what has not been evaluated is how forced asymmetric walking alters multifractality. When individuals are exposed to a novel gait pattern (i.e., forced asymmetry), how does the locomotor system's organization respond? Moreover, while monofractality is thought to represent the adaptive capacity of the locomotor system

(Delignieres & Marmelat, 2012; Delignieres et al., 2006; Rhea & Kiefer, 2013), the extent to which multifractality describes the adaptive organization has not been tested. Thus, the purpose of this study was to determine: 1) if steady state, unperturbed locomotion exhibits multifractal characteristics, 2) how forced asymmetries affect the multifractality of human locomotion, and 3) if steady state, unperturbed multifractality describes systemic control and predicts adaptive gait capacity. It was hypothesized that: 1) unperturbed preferred speed locomotion would exhibit monofractal behavior, 2) exposure to asymmetries would yield greater multifractal behavior as a result of increased intermittent corrections applied, and 3) greater multifractality in steady state walking may represent more complex and adaptive gait, and thus associate with better adaptive gait capacity.

## **7.3 Methods**

### **7.3.1 Participants**

Fifteen young, healthy adults (8 male, mean  $\pm$  SD age  $28.5 \pm 4.7$  years, height  $169.4 \pm 8.2$  centimeters, mass  $75.7 \pm 15.8$  kilograms) participated in this study. All participants were free from neurological, visual, or vestibular impairments that might affect walking. Every participant described themselves as right-leg dominant, based on the question of which leg he or she would likely use to kick a ball. Each participant completed a PAR-Q document and provided written informed consent. The local Institutional Review Board approved this study.

### 7.3.2 Experimental Setup

All data were collected on a split-belt treadmill (Bertec Corporation, Columbus, OH, USA). This treadmill has two belts side-by-side, and each belt can be independently controlled in terms of displacement, speed, acceleration, and direction of travel. Six markers were placed bilaterally on each participant's heel (lateral malleolus), toe (5<sup>th</sup> metatarsal), and hip (greater trochanter). A 7<sup>th</sup> marker was placed near the 1<sup>st</sup> sacral vertebrae. Kinematics were collected at a sample rate of 120 Hz using high-speed cameras (Oqus, Qualisys, Gothenburg, Sweden) and recorded by Qualisys Track Manager. Once trajectories were identified, data were exported to MATLAB (The MathWorks, Natick, MA, USA) for further analysis. Kinematic trajectories were filtered at 8 Hz using a 4<sup>th</sup> order, low pass Butterworth filter.

### 7.3.3 Experimental Protocol

Participants were first instructed to stand still for 10 seconds in order to obtain a standing calibration. Next, preferred walking speed (PWS) was acquired by progressively increasing and decreasing the treadmill belt speeds in a manner similar to Jordan et al. (2007b). Specifically, the belt speed began at 0.5 m\*s<sup>-1</sup> and increased 0.1 m\*s<sup>-1</sup> every 5-10 seconds until participants verbally declared they were walking at their 'preferred' or 'comfortable' speed, that is, the speed at which they choose to travel if walking through town while neither in a rush nor on a leisurely stroll. Once PWS at increasing speeds was reported, the treadmill increased 0.3 m\*s<sup>-1</sup> faster than declared PWS, and decreased in speed by 0.1 m\*s<sup>-1</sup> until participants again declared their PWS. This process was repeated another time if the increasing and decreasing speeds differed, in this case increasing or decreasing by .05 m\*s<sup>-1</sup> when participants were unable to assert a specified speed.



Following determination of PWS, participants performed three 15-minute walking bouts, each followed by a 5-minute seated rest on the treadmill (a chair was placed upon the treadmill). For each trial, participants were instructed to walk as normal as possible, to remain in the general center of the treadmill, and to avoid touching handrails as much as possible. The first trial consisted of walking at the participant's PWS. In the second trial, participants walked at half of their preferred walking speed (half-PWS). This was performed so that a baseline level of fractal dynamics at slow walking could be ascertained. The last trial consisted of participants walking asymmetrically, whereby the right (dominant) leg travelled at PWS and the left (non-dominant) leg at half-PWS. This asymmetric condition was also called the 'split-belt' condition.

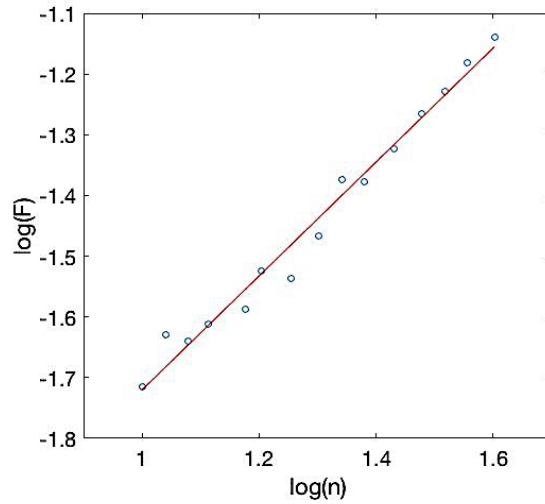
#### **7.3.4 Evaluation of Multifractality**

The timing from heel strike to subsequent heel strike of the ipsilateral heel (i.e., stride time) was used for analysis. The temporal evolution of the local fractal scaling exponent was determined to assess the extent of multifractality, as described by Ihlen (Ihlen, 2012; Ihlen & Vereijken, 2013a, 2014). While the q-order statistics method (e.g., see Ivanov et al. (1999)) is more commonly used to assess multifractality, evaluating the local fractal scaling is more appropriate for shorter data sets (e.g., < 5000 data points)(Ihlen, 2012), and importantly provides the spatiotemporal evolution of the localized fractal behavior (Ihlen, 2012). First, the standard DFA algorithm is performed on the time series signal. DFA assesses the potential presence of statistical persistence of a behavior, whereby a persistent signal is characterized by interval trends that are likely to be followed by intervals of similar sizes. For example, large stride times tend to be followed by additional large stride times. This algorithm is a modified random walk

analysis, whereby DFA first integrates the signal, and then sections it into windows of various sizes from the smallest to largest parameterized. Here the smallest and largest window sizes were 10 and 50 strides, respectively. Within each window, a local trend line is fit to the data, and a root-mean-square analysis determines the magnitude of fluctuation:

$$F(n) = \sqrt{\frac{1}{\lfloor N/n \rfloor} \sum_{j=1}^{\lfloor N/n \rfloor} \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_i)^2} \quad \text{Equation 7.1}$$

where  $F(n)$  is the fluctuation magnitude at window  $n$ ,  $N$  is the total number of strides,  $X_i$  is the integrated signal at stride interval  $i$ , and  $\bar{X}_i$  is the y-coordinate position of the local trend in window  $n$ .  $F(n)$  is obtained for all non-overlapping windows ( $j$ ) of size  $n$  (total number of windows =  $N/n$ , Figure 7.1), and then averaged so that a single fluctuation magnitude represents each scale size. This process is performed for all window sizes, and the fluctuation magnitudes and scale sizes are then logarithmically transformed. A linear relationship in this double-log plot indicates power law scale-invariance. The slope of this linear fit (Figure 7.1, red line) represents the fractal scaling exponent. The local DFA (DFA<sub>LOC</sub>) method (Ihlen, 2012; Ihlen & Vereijken, 2013a, 2014) is a continuation of earlier work by Struzik (Struzik, 1999, 2000) and later West and colleagues (Scafetta et al., 2003; Scafetta et al., 2009; West & Scafetta, 2005) who used wavelet transform to determine local singularity strengths or Hölder exponents. DFA<sub>LOC</sub> computes a ‘local scaling’ value by evaluating the fluctuation magnitude at a given temporal location.



**Figure 7.1: Dispersion plot of fluctuation magnitudes across temporal scales.** Red line represents line of best fit between the logarithmically transformed scale size ( $n$ ) and fluctuation magnitude ( $F$ ). The slope of this fit line represents the fractal scaling exponent.

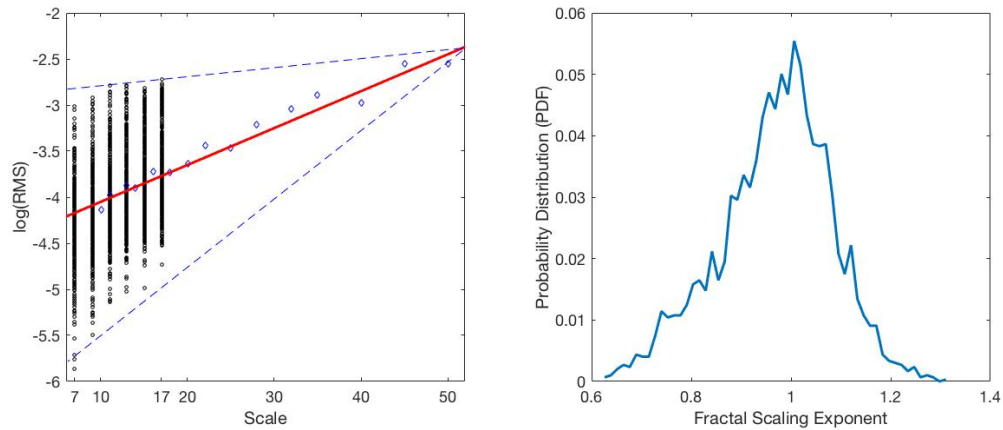
The local scaling exponent is defined as the slope of the fit line from the fluctuation magnitude at scale  $x$  (here determined from scale 7-17) to the position of the original DFA's regression line fit at the largest scale (i.e., 50, Figure 7.2 left):

$$\alpha(t, n) = \frac{\log(F(t, n)) - (\alpha(\log(n) + C))}{\log(n) - \log(n_N)} + \alpha \quad \text{Equation 7.2}$$

where  $\log(F(t, n))$  is the local fluctuation at scale  $n$  and time  $t$ ,  $\alpha(\log(n) + C)$  represents the regression line at scale  $n$  of the original DFA. The DFA's regression line fit at the largest scale is represented by  $\log(n_N)$ . In this equation (7.2), the scaling exponent  $\alpha$  is a function of both window size  $n$  and local time  $t$  (Ihlen & Vereijken, 2014). The result is a series of fractal scaling exponents within the probability distribution function (PDF, Figure 7.2 right)  $p(h)$  that represent the multifractal spectrum  $D(h)$ :

$$D(h) = \frac{\log(p(h)/p_{\max}(h))}{-\log(e)} + 1 \quad \text{Equation 7.3}$$

where  $p_{\max}(h)$  is the maximal probability of the PDF  $p(h)$ . Here the multifractal spectrum  $D(h)$  is directly proportional to the distribution of local scaling exponents  $p(h)$ .



**Figure 7.2: Quantification of multifractality based on local fluctuations.** Left) Fluctuation magnitudes (black dots) at various time scales (7-17 strides) across the time series. Local scaling is based on the slope of linear fit from magnitude of fluctuation to the location of the original DFA regression line (red line) at the largest scale (50). Blue diamonds represent the original DFA dispersion plot values. The largest and smallest fluctuation magnitudes coincide with the smallest and largest slopes, respectively, of the dotted blue lines. Right) All local scaling exponents are entered into a probability distribution function in order to obtain the multifractal spectrum width (max – min) and interquartile range.

The spectrum width was defined based on the overall range (minimum and maximum) of scaling exponents within the PDF. Because this method is sensitive to outliers within the PDF, the interquartile range (IQR) width (25<sup>th</sup> to 75<sup>th</sup> percentile) was also evaluated (Ihlen & Vereijken, 2014). A monofractal time series spectrum width will converge to zero as the series length approaches infinity. However, because the data herein involves discrete time series, the monofractal spectrum width is expected to be greater than zero.

Thus, to provide evidence for the presence or absence of multifractality, as opposed to a monofractal signal with inherent noise characteristics, we assessed the data based on the conventions suggested by Scafetta and colleagues (2003). First, several ( $n=15$ ) time series signals were generated that exhibited fractal-like power spectral characteristics and the same mean preferred walking speed monofractal scaling exponent ( $\alpha = 0.71$  [0.69-0.73]). Second, DFA<sub>LOC</sub> was performed to determine the multifractal spectrum width for each generated signal. Finally, if the spectrum width of the generated time series signals were statistically less than the empirically derived data, the original data were accepted as more heterogeneous and thus more likely to be multifractal (Kelty-Stephen et al., 2013; Scafetta et al., 2003).

### **7.3.5 Assessment of Gait Adaptability Performance**

Gait adaptability was measured by determining the phasing between left and right legs. Sagittal plane leg segments were constructed as a rigid segment from the greater trochanter to the ipsilateral heel for each leg. The leg angle was defined based on the angle of the leg segment at the hip (greater trochanter) relative to its standing calibration position. These angles were normalized to 100 data points for each stride. Cross correlation analysis was used to calculate the bi-directional correlations across a range of positive and negative lag values. The cross correlation data were normalized to a range [-1, 1] stride cycles such that maximal negative correlations observed at 0-lag represented perfect anti-phase (i.e., legs moving in opposite direction). Because steady state walking entails nearly perfect anti-phasing, gait adaptability performance was assessed as deviation (in lags) from this intended anti-phasing, i.e., deviation of the maximal negative correlation from 0-lag (J. T. Choi & Bastian, 2007; J. T. Choi et al., 2009). From the

phase deviation data, gait adaptability was quantified as the summed absolute magnitude of deviation from perfect anti-phase across the first 50 strides.

### **7.3.6 Statistical Analysis**

Evidence of multifractality was assessed via paired-samples t-tests between the artificially generated monofractal signals and the corresponding multifractal spectrum widths of the empirical data. The choice to use paired samples was founded on the rationale by Scafetta et al. (2003), whereby the spectrum widths are based on the length of the time series and the monofractal scaling exponent. Because these parameters are the same for both empirical and artificial data, the variance is assumed to be a result of identical point-to-point fluctuations or effects. Multifractal ranges ( $MF_{\text{RANGE}}$ ) and interquartile widths ( $MF_{\text{IQR}}$ ) were assessed across conditions by submitting the data to a one-way, repeated measures analysis of variance (ANOVA) with participant as the within-subject factor and walking condition (PWS, half-PWS, asymmetric) as the between-subject factor. Separate ANOVAs were performed for the right and left legs. Cohen's D effect sizes (ES) were performed for comparisons between conditions, with 0.2, 0.5, and 0.8 indicating small, moderate, and large effects, respectively (Vincent & Weir, 2012). By convention, negative ES values indicate an increase in multifractality from 1) PWS to half-PWS, 2) PWS to asymmetric walking, or 3) half-PWS to asymmetric walking. Linear and quadratic regression analyses were used to determine associations between gait adaptability (Phase Deviation) and  $MF_{\text{RANGE}}$  and  $MF_{\text{IQR}}$  across all three walking conditions. In addition, the IQR may be categorized as too conservative, as it only considers the spread of half the data. Thus, to evaluate the overall range by maintaining the majority of its width characteristics while not being influenced by a few

outliers within a given participant's PDF, the 95% percentile range ( $MF_{95}$ , 2.5% to 97.5%) was also assessed for correlations. In the event of significant findings, a simple leave-one-out validity analysis was performed to ensure that no single inter-participant observation influenced the relationship between variables. All statistics were performed using R-studio (Version 1.0.136, R Foundation for Statistical Computing, Vienna, Austria).

## 7.4 Results

The empirical time series data during PWS and half-PWS were monofractal in nature, as no differences between empirical and simulated time series were observed for both dominant and non-dominant limbs (Table 7.1). For asymmetric split-belt walking the dominant leg's asymmetric walking spectrum width ( $MF_{RANGE}$ ) was statistically larger than the expected monofractal signal ( $p = .02$ ), and close to significant for the  $MF_{IQR}$  ( $p = .06$ ), while no differences were found for the non-dominant limb (Table 7.1).

**Table 7.1: Multifractal evaluation of empirical versus generated signal.**

Generated Signal	Condition	p-value	Effect Size
<b><math>MF_{RANGE}</math> - Dominant</b>	PWS	.98	-0.01
	Half-PWS	.22	-0.47
	Split-Belt	.02	-1.04
<b><math>MF_{RANGE}</math> - Non-Dominant</b>	PWS	.82	-0.09
	Half-PWS	.12	-0.63
	Split-Belt	.32	-0.39
<b><math>MF_{IQR}</math> - Dominant</b>	PWS	.19	0.48
	Half-PWS	.49	-0.26
	Split-Belt	.06	-0.75
<b><math>MF_{IQR}</math> - Non-Dominant</b>	PWS	.35	0.38
	Half-PWS	.24	-0.47
	Split-Belt	.58	0.21

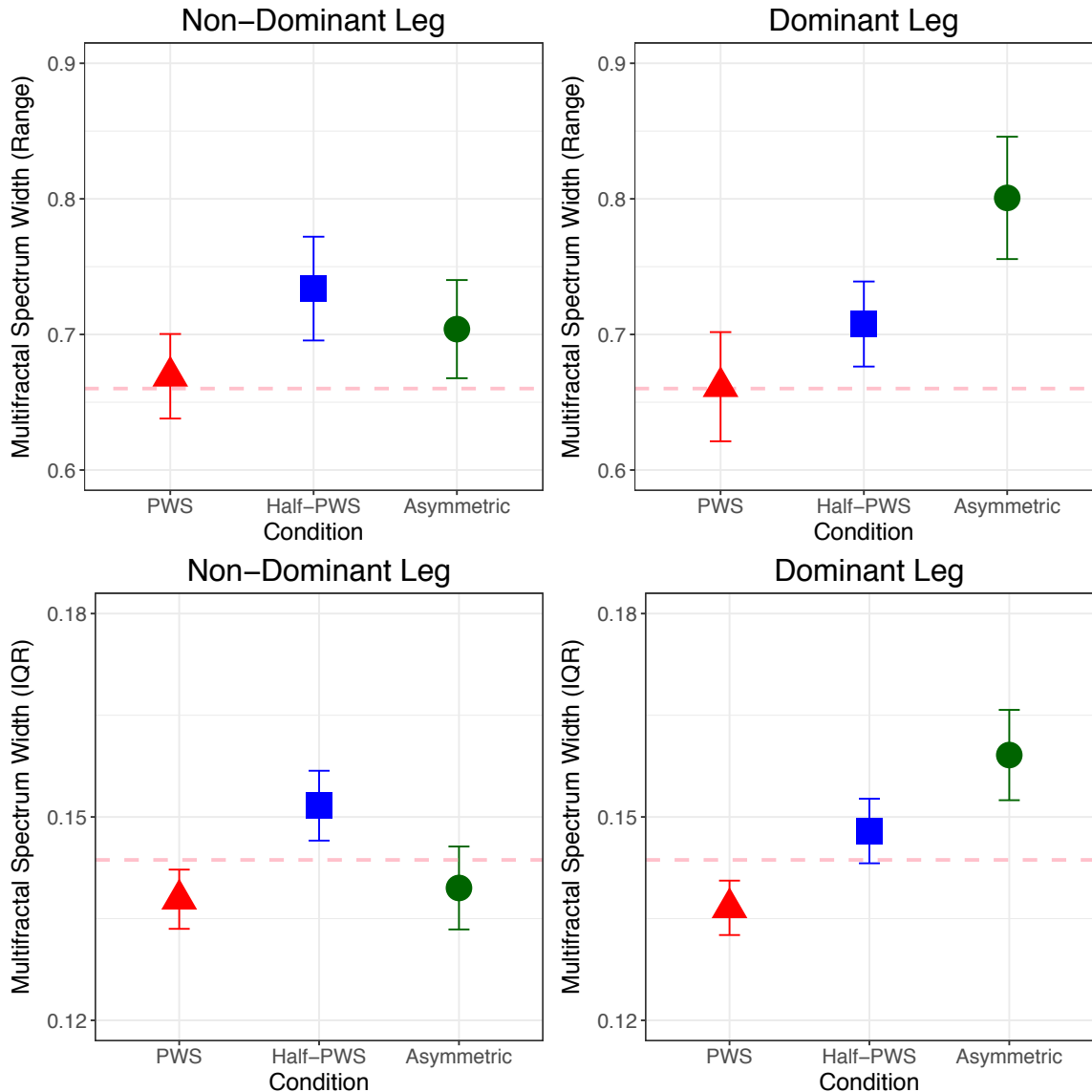
**Table 7.2: Multifractal ranges across conditions.** Total Range and interquartile range (IQR) displayed for the dominant (right) and non-dominant (left) legs. Data reported as mean (SD). Main effects based on one-way, repeated measures ANOVA. Targeted comparisons based on Cohen’s D effect sizes.

	Descriptive Statistics			
	MF <sub>RANGE</sub>		MF <sub>IQR</sub>	
	Non-dominant	Dominant	Non-dominant	Dominant
<b>PWS</b>	0.669 (0.12)	0.661 (0.16)	0.138 (0.02)	0.137 (0.02)
<b>Half-PWS</b>	0.734 (0.15)	0.708 (0.12)	0.152 (0.02)	0.148 (0.02)
<b>Asymmetric</b>	0.704 (0.14)	0.801 (0.17)	0.139 (0.02)	0.159 (0.03)
	Gait Condition Main Effect			
	F <sub>2,28</sub> = 1.66, p = 0.209	F <sub>2,28</sub> = 3.15, p = 0.058	F <sub>2,28</sub> = 2.07, p = 0.145	F <sub>2,28</sub> = 4.20, p = 0.025
	Targeted Comparisons (Effect Size)			
<b>PWS vs. Half PWS</b>	-0.48	-0.33	-0.75	-0.067
<b>PWS vs. Asymmetric</b>	-0.27	-0.84	-0.08	-1.06
<b>Half PWS vs. Asymmetric</b>	0.21	-0.62	0.55	-0.50

Multifractal spectrum widths (MF<sub>RANGE</sub> and MF<sub>IQR</sub>) are reported in Table 7.2. For the dominant, faster moving right leg, there was a main effect of condition for the dominant right leg MF<sub>IQR</sub> (F<sub>2,28</sub> = 4.202, p = .025), and nearly significant effect for the dominant leg MF<sub>RANGE</sub> (F<sub>2,28</sub> = 3.149, p = .058). The multifractal spectrum width (range and IQR) increased from preferred speed walking to half-speed walking, and further increased in response to the asymmetric walking condition. For the non-dominant, slower moving left leg, there was no main effect of condition. The dominant and non-dominant legs exhibited large and small effects (ES = -0.841 and -0.266, respectively) as MF<sub>RANGE</sub> increased from PWS to asymmetric walking. The dominant leg MF<sub>IQR</sub> increased from PWS to asymmetric walking (ES = -1.058). The large effect sizes observed in dominant leg MF<sub>RANGE</sub> and MF<sub>IQR</sub> between PWS and Asymmetric were further confirmed via two-tailed, paired samples t-tests (p < .05). Both legs showed small effects from PWS to half-



PWS in  $MF_{RANGE}$ , and moderate effects in  $MF_{IQR}$  for the non-dominant leg ( $ES = -0.746$ ). From half-PWS to Asymmetric, the dominant leg  $MF_{RANGE}$  and both legs  $MF_{IQR}$  exhibited moderate effects, whereby asymmetric walking increased and decreased multifractality for the dominant and non-dominant legs, respectively.



**Figure 7.3: Multifractal spectrum widths across all three conditions.** Plots (mean  $\pm$  SEM) illustrate the overall range (top row,  $MF_{RANGE}$ ) and interquartile range (bottom row,  $MF_{IQR}$ ) for the left (left column) and right (right column) legs. Dashed pink horizontal line represents the monofractal signal's mean spectrum width. All participants were right leg dominant. Asymmetric = split-belt walking condition.

**Table 7.3: Regression equations for gait adaptability and multifractal widths.** Linear and quadratic regression equations for steady state symmetric (PWS and half-PWS) and asymmetric walking conditions in relation to the gait adaptability measure, phase deviation. D = dominant leg; N = non-dominant leg.

Dependent Variable	Condition	Independent Variable	Model Type	<i>p</i> -value	Adj. R <sup>2</sup>
<b>Phase Deviation</b>	Preferred Speed	N-MF <sub>RANGE</sub>	Linear	0.63	-0.06
			Quadratic	0.37	0.01
		D-MF <sub>RANGE</sub>	Linear	0.93	-0.08
			Quadratic	0.60	-0.07
		N-MF <sub>IQR</sub>	Linear	0.26	0.03
			Quadratic	0.38	0.01
		D-MF <sub>IQR</sub>	Linear	0.49	-0.04
			Quadratic	0.12	0.18
		N-MF <sub>95</sub>	Linear	0.48	-0.03
			Quadratic	0.59	-0.07
		D-MF <sub>95</sub>	Linear	0.99	-0.08
			Quadratic	0.87	-0.14
	Half-Preferred Speed	N-MF <sub>RANGE</sub>	Linear	0.04	0.22
			Quadratic	0.10	0.21
		D-MF <sub>RANGE</sub>	Linear	0.03	0.26
			Quadratic	0.03	0.36
		N-MF <sub>IQR</sub>	Linear	0.80	-0.07
			Quadratic	0.26	0.07
		D-MF <sub>IQR</sub>	Linear	0.89	-0.08
			Quadratic	0.49	-0.03
		N-MF <sub>95</sub>	Linear	0.56	-0.05
			Quadratic	0.37	0.01
		D-MF <sub>95</sub>	Linear	0.42	-0.02
			Quadratic	0.71	-0.10
Split-Belt Asymmetric	N-MF <sub>RANGE</sub>	Linear	0.19	0.06	
		Quadratic	0.30	0.05	
	D-MF <sub>RANGE</sub>	Linear	0.11	0.12	
		Quadratic	0.29	0.05	
	N-MF <sub>IQR</sub>	Linear	0.28	0.02	
		Quadratic	0.39	0.00	
	D-MF <sub>IQR</sub>	Linear	0.19	0.06	
		Quadratic	0.26	0.07	
	N-MF <sub>95</sub>	Linear	0.34	0.00	
		Quadratic	0.23	0.09	
	D-MF <sub>95</sub>	Linear	0.19	0.06	
		Quadratic	0.41	0.00	

Preferred walking speed multifractal spectrum widths (MF<sub>RANGE</sub>, MF<sub>IQR</sub>, MF<sub>95</sub>) were not associated with adaptive gait performance (Table 7.3, all *p*'s > 0.05; r-squared < 0.18). Half-PWS speed walking MF<sub>RANGE</sub> exhibited a positive linear relationship with

gait adaptability. However, these results may have been heavily influenced by a single observation, and removing this observation yielded  $p = .23$ ,  $r^2 = .05$  and  $p = .29$ ,  $r^2 = .06$  for non-dominant and dominant legs, respectively. Finally, there was no relationship between asymmetric walking spectrum widths and phase deviation (all  $p$ 's  $> 0.05$ ,  $r$ -squared  $\leq 0.12$ ).

## **7.5 Discussion**

The purpose of this study was to investigate the potential extent of multifractality in steady state unperturbed and constrained human locomotion, and to determine if multifractality associates with gait adaptability performance. Young, healthy participants experienced unperturbed normal and slow walking, as well as asymmetric walking, whereby their legs traveled at different speeds on a split-belt treadmill. Based on the data presented herein, steady state stride time variance in humans appears to be monofractal. Moreover, exposure to asymmetric walking manifests as increased multifractal characteristics for the faster moving leg, but not the slower moving leg. Finally, neither unperturbed nor asymmetric walking multifractal spectrum widths were associated with adaptive gait performance.

### **7.5.1 Monofractal Nature of Human Locomotion**

Prior studies have indicated that unperturbed walking is monofractal, or that there is a slight presence of multifractality in young, healthy adults (Ihlen & Vereijken, 2014; Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003; Scafetta et al., 2003; Scafetta et al., 2009). Indeed, data from these earlier studies suggest that healthy gait may even qualify as purely monofractal in nature. Thus, it was hypothesized that steady state

preferred speed walking in the present study would be monofractal. However, one challenge with comparing the findings herein to those of other studies is that many of the earlier studies did not explicitly define multifractality, nor distinguish what constitutes mono versus multifractality. Rather, these studies assess comparative changes in spectrum widths across conditions, such as gait speed manipulations. Scafetta and colleagues (2003) addressed this issue by recommending that the observed multifractal spectrum widths be statistically compared to (presumably) monofractal signals that exhibit a similar Hölder exponent (i.e., similar to that of the scaling exponent). Adhering to these guidelines, the results from this study support the hypothesis that PWS would yield monofractal behavior, as the multifractal spectrum widths were statistically similar to the generated monofractal noise signals (Figure 7.3, Table 7.1). These findings are in agreement with the previously observed notion that steady state, unperturbed walking in healthy, young adults is monofractal. This is in contrast to the findings of Scafetta and colleagues (Scafetta et al., 2003; Scafetta et al., 2009) who observed slight multifractality in walking at various gait speeds.

Disparities between these findings of PWS monofractality compared to observed multifractality in PWS may be due to several differences between studies. In the current study, participants walked for 15 minutes at preferred speed, and the first 512 strides were analyzed. In the study by Scafetta and colleagues (2003), time series data used were from one hour of unconstrained walking and over 2,500 strides. Longer time series from human walking may produce more stable statistical output, but also may result in fatigue or boredom. In addition, while the wavelet transform methods used by Scafetta et al. (2003) and the  $DFA_{LOC}$  scaling methods used herein (Ihlen, 2012) are similar

theoretically and should be comparable, differences in the algorithms may have contributed to contrasting interpretations of the results. The use of wavelet analysis requires q-order statistics. Moreover, the studies by Muñoz-Diosdado et al. (Muñoz-Diosdado, 2005; Munoz-Diosdado et al., 2003) and Dutta and colleagues (2013) also entailed multifractal analysis using q-order statistics. The choice to use  $DFA_{LOC}$  instead of the q-order method was because q-order analysis requires several thousand data points for accurate assessment. In addition, while some authors refer to q-order statistics as a ‘direct’ estimation of multifractality (Keltz-Stephen et al., 2013), other authors argue that this method is an ‘indirect’ examination of time series data (Ihlen, 2012). This method artificially expands and shrinks different fluctuation magnitudes by raising the signal to positive or negative exponents. Weak exponents are amplified and large exponents suppressed with large negative q values, and vice versa for large positive q values (Struzik, 2000). Thus, the q-order method assesses the time series signals differently than the algorithm used herein and as such may not be comparable to the temporally localized scaling method.

Regarding slow walking, previous research (Scafetta et al., 2003; Scafetta et al., 2009) indicated that slow walking increased multifractality compared to preferred speed walking. While slow walking multifractal spectrum widths were statistically not different from the generated monofractal spectrum width, we observed moderate effects between the generated monofractal signal and slow walking spectrum widths (Table 7.1), as well as from PWS to half-PWS (Table 7.2, small and moderate effects for  $MF_{RANGE}$  and  $MF_{IQR}$ , respectively, for both legs). Given that previous studies describe multifractality as more complex (Ivanov et al., 1999; Munoz-Diosdado et al., 2003), these findings suggest

that slow walking is either similar to or slightly more biologically complex than walking at preferred speed. The forced speed constraint likely yielded suboptimal locomotor patterns that the system would have (perhaps intermittently) attempted to adjust. In general, slower walking is more variable, and thus would be expected to generate more fractal variability. While multifractality is generally considered to be the manifestation of more complex gait, the task of walking unperturbed at preferred speed on a treadmill may have not demanded that more complex gait emerge in this group. Assuming this young, healthy cohort was absent of balance or stability decrements, there may have not been a need for intermittent periods of high or low variability. Indeed, biological complexity may emerge only when the system is constrained in some manner that necessitates frequent corrections or adjustments. In order to verify this empirically, participants would need to be exposed to a more challenging locomotor task.

### **7.5.2 Forced Walking Asymmetry Begets Multifractality**

When exposed to asymmetric belt speeds on the split-belt treadmill, participants' multifractal spectrum widths (both  $MF_{\text{RANGE}}$  and  $MF_{\text{IQR}}$ ) expanded compared to that of steady state preferred or half-preferred speed in the dominant leg (Table 7.2, Figure 7.3), and was greater than the generated monofractal signals (Table 7.1). These findings are in agreement with the second hypothesis that a more challenging task would require greater intermittent corrections. From a constraints-based approach, these results also agree with the findings of Ihlen and Vereijken (2014) who observed increased multifractality when participants were required to match their foot strike timing to an auditory metronome. Scafetta et al. (2003) observed greater multifractality at slower and faster walking speeds

compared to preferred speeds. Albeit different constraints, in all instances constrained gait elicited greater multifractality.

While the faster moving dominant leg exhibited multifractality during asymmetric walking, the slower moving non-dominant leg did not. The faster moving leg could reasonably be considered to be performing the more challenging task compared to the slower moving leg. If this were true, it would support the idea that more challenging walking conditions trigger multifractality.

Walking in an asymmetric, potentially less stable manner may afford periods of strong persistence, but also will likely demand intermittent corrections that manifest as discrete moments of randomness or anti-persistence. In addition to the asymmetric constraints, participants walked on a finite sized treadmill. This spatial constraint may have also required anti-persistence to avoid walking off the treadmill. For example, Terrier and colleagues (2012) noted that, while stride time, stride length, and stride speed (stride length / stride time) exhibit monofractal persistence during overground walking, stride speed exhibits anti-persistence while walking on a treadmill in order to maintain the treadmill speed. It is likely that the attempt to maintain two independent treadmill belt speeds was more challenging, leading to greater errors from the task goal and therefore greater anti-persistent corrections, especially for the faster moving leg. Ultimately, greater errors in maintaining a neutral position on the treadmill, and thus more frequent intermittent corrections, are observed as greater multifractal spectrum widths.

### **7.5.3 Steady State Multifractal Spectrum Does Not Predict Gait Adaptability**

Multifractality is thought to represent complex gait behavior (Ivanov et al., 1999; Munoz-Diosdado et al., 2003). It was therefore hypothesized that greater multifractality

during steady state unperturbed walking would associate with greater adaptive gait performance. In contrast to our hypothesis, there was no relationship with unperturbed (PWS or half-PWS) or asymmetric multifractal spectrum widths and gait performance.

One possible reason why the multifractal analysis did not predict gait performance is that the paradigm involved a task that may not have been difficult enough to reveal multifractal behavior changes. The PWS and half-PWS conditions resulted in monofractal characteristics. A more challenging locomotor task may have more clearly revealed differences in adaptive gait performance and the multifractal nature of stride intervals across participants. As mentioned earlier regarding slow walking, young, ostensibly healthy adults were likely able to produce stable repeating locomotor patterns during unperturbed walking. A more challenging locomotor task, such as walking with varying terrains, might demand greater multifractal behavior, similar to that observed during asymmetric walking.

Alternatively, unperturbed walking multifractality may simply not be a critical parameter for adaptive gait in young healthy adults. Monofractal analyses consistently provide evidence that the locomotor system does not optimize the structure of stride interval variance during unperturbed walking, otherwise the observed fractal scaling exponent would be  $\alpha \sim 1.0$  (i.e.,  $1/f$ ). Instead, unperturbed walking monofractal scaling is often observed at  $\alpha \sim 0.75$  (Jordan et al., 2007b; Rhea & Kiefer, 2013; Rhea, Kiefer, D'Andrea, et al., 2014; Terrier, 2012), which represents the midline between highly correlated  $1/f$  pink noise and uncorrelated white noise. The system is likely attempting to regulate numerous components, such as minimizing metabolic cost or maintaining some threshold of dynamic stability. In this current study, the young, healthy group may have



been too homogenous to reveal any relationships between multifractal characteristics and gait adaptability. Multifractal analysis, though, may still be able to distinguish between cohorts, such as old versus young, or those with and without neurological disease.

#### **7.5.4 Limitations**

Given the relatively small sample in this study size ( $n=15$ ), the associations reported from regression analyses were likely affected by biological variability. A greater sample size would be needed to more accurately understand the potential relationship between stride time multifractality and adaptive gait performance. In addition, the 2:1 ratio asymmetric walking condition may not have been difficult enough to bring about changes in multifractal behavior for young, healthy adults. To confirm this notion, a study would require either 1) a more challenging experimental paradigm, or 2) less capable participants, such as older adults, or those with neurological impairments.

Also, the  $DFA_{LOC}$  method to assess multifractality is a less common technique compared to the more classic  $q$ -order statistical method. The rationale for using  $DFA_{LOC}$  is that it may be more appropriate for short data sets. To further confirm the findings reported herein, the  $q$ -order method may be used if very large data sets are collected. However, having participants walk for extended periods of time (i.e., over 1 hour) may result in fatigue or boredom, and therefore this experimental design might be limited in participant pool (i.e., highly fit individuals may need to be recruited).

#### **7.6 Conclusion**

Steady state locomotion in healthy, young adults appears to be monofractal in nature, characterized by stable, repeated gait patterns over the course of several hundred

strides. Exposure to asymmetric walking yielded multifractal stride time characteristics in the faster (but not slower) moving leg, likely a result of more intermittent corrections. Unperturbed and asymmetric walking multifractality was not associated with adaptive gait performance. In all, these findings provide further evidence that unperturbed human locomotion is essentially monofractal, and establish that perturbed walking yields multifractal behavior.

## CHAPTER VIII

### GENERAL DISCUSSION

#### **8.1 Introduction**

The purpose of this dissertation was to investigate the potential relationship between stride time fractality and gait adaptability. The structure of stride-to-stride fluctuations (i.e., fractal dynamics) is a conceptual representation of the overall adaptive abilities of the system. This series of studies provided an empirical attempt to connect the concept of fractal dynamics with a gait adaptability paradigm in order to validate the use of fractality as a measure of adaptive capacity. While the structure of variability is often cited as a theoretical measure of how well the system can adapt, this dissertation delivered the needed empirical investigation to support or refute such claims. By demonstrating the existence or absence of a relationship between fractal dynamics and gait adaptability, researchers may be able to better develop study questions and paradigms to reveal more information about the locomotor system, and ultimately quantify gait adaptability. If, for example, fractal dynamics are in fact associated with adaptive capacity, researchers might be able to use this fractal measure to assess interventions designed to enhance adaptability, or to quantify adaptability in order to potentially predict fall risk.

Chapters 4, 5, and 6 of this document are reported here as studies 1, 2 and 3, respectively. The purpose of the first study was to investigate if steady state, unperturbed walking fractal dynamics could predict an individual's ability to adapt locomotor patterns effectively when exposed to asymmetric walking constraints. The task to assess adaptive capacity consisted of walking on a split-belt treadmill in which each belt traveled at

different speeds. This was presumably the first study to extend beyond the standard analysis of steady state, unperturbed walking fractal characteristics by incorporating a constrained walking task requiring adaptation. The results revealed no associations between unperturbed walking fractal dynamics and adaptive gait capacity in young, healthy adults. However, this first study provided preliminary evidence for the emergent relationship between asymmetrically constrained fractal dynamics and gait adaptability. Individuals whose fractal scaling during asymmetric walking was higher or lower than the average (mean = 0.94 and 0.86 for right and left legs, respectively;  $\alpha$  close to  $1/f$ ) performed the poorest in the gait adaptability. In addition, fractal scaling increased (i.e.,  $\alpha$  closer to 1.0) compared to unperturbed walking when participants experienced asymmetric walking, possibly indicating enhanced adaptive capacity in response to a challenging task.

The aim of the second study was to determine the relationship between fractal dynamics and gait adaptability in older adults. Ultimately, the goal of quantifying gait adaptability is to improve the ability to predict and reduce the odds of a future fall. Young adults are at low risk of a fall, or at the least, a fall that is detrimental to one's physical, psychological, or emotional wellbeing. Thus, the second study evaluated if fractal dynamics during unperturbed or asymmetrically constrained walking could predict adaptive gait performance in healthy older adults. To avoid habitual physical activity level as a potential confounder, healthy, active young and older adults were recruited. Interestingly, young and older adults exhibited no differences in unperturbed (PWS and Half-PWS) or asymmetric walking fractal dynamics, as well as adaptive gait performance. Similar to the findings from study 1, unperturbed walking fractal dynamics

were not related to gait adaptability for either cohort, except for a modest association in the young adults' dominant leg ( $r^2 = 0.30$ ). Asymmetric walking fractal dynamics were moderately associated with gait adaptability in the older cohort in a similar fashion to that observed in study 1 with young adults. Those with fractal scaling values closer to 1.0 displayed the most adaptive gait. These results further strengthen the idea that changes to the organization and structure of stride time variance may enhance adaptive gait capacity.

Finally, while the first two studies investigated the relationship between stride time monofractal scaling and adaptive gait performance, study 3 evaluated the potential multifractality of unperturbed and asymmetric walking in young individuals. A monofractal analysis assumes that the relationship between fluctuations at various temporal scales remains constant across a time series. A multifractal behavior, on the other hand, exhibits brief intermittent bursts of extremely high or extremely low variance. These intermittent bursts manifest as a wider range of observed fractal scaling values across the temporal evolution of a time series. A greater range is thought to represent a more complex behavior. This experiment aimed to understand if multifractal characteristics could predict gait adaptability. These analyses were conducted using data acquired during study 1, and therefore the participant pool consisted of young, healthy adults whose physical activity status was unknown. Findings from study 3 suggest unperturbed walking exhibits monofractal behavior, while challenging asymmetric walking yields multifractality in young, healthy adults. These results suggest that challenging gait is more complex than unperturbed gait. In addition, the extent of mono or multifractality was not associated with gait adaptability.

## **8.2 No Relationship Between Unperturbed Walking Fractal Dynamics and Gait Adaptability**

In the first study, unperturbed preferred speed and slow speed walking fractal dynamics were not associated with gait adaptability. These results were repeated in the second study's older cohort (both dominant and non-dominant legs), and in the young cohort's non-dominant leg. The only association observed between unperturbed fractal dynamics and adaptive gait capacity was in the young adults' dominant limb in the second study. This relationship was quadratic, whereby those individuals whose unperturbed walking fractal dynamics were at the frontier between random and structured (i.e.  $\alpha \sim 0.75$ ) exhibited the most adaptive gait performance. These findings may be of interest, because if the manner in which individuals self-organize during unperturbed walking ultimately affects gait adaptability, the significance of fractal analyses is heightened. However, it should be reiterated that this relationship between unperturbed walking fractality and adaptive gait was not observed in the first study, or in the second study's older cohort, or in the second study's young cohort's non-dominant leg, and was not strong in the young adults' dominant leg ( $r^2 = 0.30$ ). The conflicting reports may be due to biological variability that presents difficulties when performing regression equations on small sample sizes ( $n = 15$  per cohort). Alternatively, the observed relationship between young adults' unperturbed walking fractal dynamics and gait adaptability may be a false positive. Finally, stride time variability is one of many gait variables to assess, and other parameters or combinations of parameters may potentially elucidate associations with adaptive gait performance. In all, results from the two studies indicate there is an overall lack of potential predictive power of unperturbed walking

fractal dynamics. Therefore, more research is warranted to elucidate potential associations.

### **8.3 Constrained Walking Fractal Dynamics Associate with Gait Adaptability**

In the first study, unperturbed preferred speed and slow speed walking fractal dynamics did not predict gait adaptability. However, fractal dynamics during the asymmetric walking task were quadratically associated with gait adaptability performance. Individuals whose fractal scaling was too high or low were also the poorest at adapting their gait patterns. These results provide the first indication that the correlation structure of gait variance during challenging gait associates with actual adaptive performance. While from a theoretical perspective it has been suggested that fluctuations exhibiting  $1/f$  characteristics represent the most adaptive, complex behavior (Lipsitz, 2002), this was not confirmed for unperturbed, steady state walking. However, this study provides preliminary empirical support that  $1/f$  fluctuations during a challenging gait task are indeed associated with enhanced gait adaptability. For this reason, the observed changes to fractality from unperturbed to perturbed walking suggest a systemic behavioral reorganization in order to better respond to stressors.

Findings from the second study further support the notion that asymmetrically constrained fractal dynamics are associated with adaptive gait performance. The older cohort exhibited a curvilinear relationship between asymmetric walking fractal dynamics and gait adaptability, whereby those individuals whose fractality approached  $1/f$  characteristics also displayed the best gait adaptation performance. Interestingly, these findings only existed in the slower moving, non-dominant leg. Although the dominant

limb's fractal scaling somewhat associated with gait adaptability performance ( $r^2 = 0.11$ ), these results were not statistically significant.

Unexpectedly, constrained walking fractal dynamics and gait adaptability did not associate in the young cohort. This lack of association is in contrast to the previous study's reports, and the reasons are unclear. The second study's young cohort consisted of healthy and highly active adults. The group as a whole exhibited an increase in fractal scaling from unperturbed to asymmetric walking. The group may have simply been too homogenous for minor differences among fractal scaling exponents to show a correlation with gait adaptability. In other words, if the homogenous group exhibited similar adaptive gait performance or fractal scaling values, potential associations may not have surfaced. The fact that these participants were all highly active may explain why these results differed from those in study 1. The first study's participant pool consisted of young healthy adults, but physical activity levels were not reported. Therefore the relationship observed in study 1 may have been a result of recruiting a mix of active and potentially inactive adults. However, it should be noted that the second study's young cohort could reasonably be defined as heterogeneous based on physical activity (range [28.5, 86.9] minutes per day moderate-to-vigorous physical activity).

#### **8.4 1/f Fluctuations Emerge During Constrained Asymmetric Walking**

Previous research has indicated that constraining individuals to walk slower or faster than preferred speed actually increases fractal scaling exponents closer to  $\alpha = 1.0$  (Hausdorff et al., 1996). Other work suggested that any constraint applied to the individual, task, or environment will break down long-range correlated behavior (Diniz et



al., 2011). In the current series of studies, it was predicted that the challenging, likely destabilizing, task of asymmetric walking would result in a breakdown of correlated structures. On the contrary, stride time fractal dynamics increased closer to  $\alpha = 1.0$  when participants were exposed to asymmetries. This occurred in both the faster and slower moving legs in study 1, and in the faster moving leg in study 2 for both cohorts. The essence of this finding is that enhanced fractality is a response to challenges to the locomotor system. This shift in fractality closer to  $1/f$  has been observed in various other paradigms in motor behavior, and may represent a system close to a phase transition and more poised to contest perturbations at various scales (Torre, 2010). The change in fractal scaling may reflect systemic reorganization to increase interactivity. It may be posited that the purpose of this reorganization is functionally relevant because, as discussed in section 8.3, the individuals whose fractality remained less structured or transitioned to an overly structured state were less adaptable. Therefore, the increased fractal scaling may in fact be indicative of the capacity to adapt locomotor patterns.

### **8.5 Fractal Dynamics are Similar in Active Young and Older Adults**

There is limited research investigating age-based differences in fractal dynamics between health young and older adults. It is generally expected that fractal scaling exponents decrease to more random fluctuations with aging (Hausdorff et al., 1997). Study 2 provides evidence that when recruiting healthy, active adults, there are no age-related differences in fractality across a range of walking conditions, including preferred speed, slow, and asymmetric walking. Fractal scaling is, in fact, higher in older adults during slower walking in both legs. This finding is of importance because often various

gait parameters are reported to diminish with age, yet physical activity status is rarely accounted for. By not accounting for physical activity, it is not possible to conclude that any differences between young and older groups are a result of age, physical activity, or an interaction between the two. While previous studies have stated that older adults stride time fluctuations are less structured than that of their younger counterparts, this study indicates physically active adults fractal scaling exponents are similar across a wide age range.

### **8.6 Unperturbed Walking Stride Intervals are Monofractal; Perturbed Walking Stride Intervals are Multifractal**

The findings from study 3 suggest that unperturbed walking is monofractal in nature, while more challenging asymmetric walking exhibits multifractality. Fractal qualities in general are posited to signify complex, adaptive behavior (Delignieres & Marmelat, 2012), and greater multifractal characteristics may represent further complexity (Ivanov et al., 1999). Multifractal behaviors exhibit intermittent bursts of very high or low variance that are absent in a monofractal behavior (Ihlen & Vereijken, 2014). The results herein suggest that challenging gait tasks necessitate more complex gait behavior. Interestingly, multifractality only emerged in the faster moving leg. This may be because the faster moving leg was qualitatively reported to be the more challenging portion of the task, compared to the slower moving leg. These differential effects support the idea that multifractality emerges based on task difficulty, even within a single locomotor system.

This third study indicated no relationship between multifractal characteristics and gait adaptability. Interestingly, monofractality during asymmetric walking associated

with gait adaptability, as fractal dynamics closer to  $1/f$  associated with better adaptive performance. While multifractal analysis indicated greater intermittency during asymmetric walking, this intermittency did not appear to assist gait adaptation. These lack of associations between multifractality and adaptive gait suggest that, while multifractality is an emergent behavior in response to challenging gait tasks, this modified behavior may not help to enhance adaptive gait. Alternatively, the modified behavior may afford to take on a large range of characteristics in young, healthy adults without consequence in the form of reduced gait adaptability. That is, there may have been a ceiling effect, whereby all participants were relatively successfully at performing the task, and thus minor differences in multifractality would not distinguish gait performance.

Finally, participants in study 3 consisted of healthy adults whose physical activity status was unknown. Thus, the observed monofractality in unperturbed walking, multifractality in asymmetric walking, and lack of associations between multifractality and gait adaptability may have been influenced by physical activity levels. At the least, these findings can be generalized to young adults who may or may not be physically active, while the findings may not describe highly active or highly sedentary individuals.

## **8.7 Future Directions**

Based on the findings in study 1, it is difficult to ascertain whether changes in fractal dynamics closer to  $1/f$  during asymmetric walking were caused by, an effect of, or simply associated with changes in gait adaptability. The findings herein alone do not provide sufficient evidence for clinical applications or recommendations. However, it is

of importance to note that earlier studies have provided evidence that fractal dynamics can be modified when entraining foot strike timing to a visual or auditory metronome that exhibits fractal-like inter-beat intervals (Hove et al., 2012; Marmelat et al., 2014; Rhea, Kiefer, D'Andrea, et al., 2014; Rhea, Kiefer, Wittstein, et al., 2014; Roerdink, Daffertshofer, Marmelat, & Beek, 2015; Terrier, 2016; Terrier & Deriaz, 2012). Future studies might determine if modifying fractal scaling via metronome entrainment can improve adaptive gait capacity when exposed to asymmetric or other constraints. By systematically changing fractal scaling characteristics and subsequently examining gait adaptability, causative effects may be discovered. If fractal entrainment improves adaptive gait capacity, it may behoove clinicians, fitness specialists, or community programs to include this type of training in a fall prevention intervention.

Study 2 recruited highly active young and older adults, and did not observe differences between cohorts. To strengthen the argument that physical activity mediates previously reported age-related decrements in fractal scaling and gait adaptability, either sedentary groups would need to be included, or a physical activity intervention would need to be employed. In addition, the 'older' age group might be classified as 'young-old' because the age range was 60-70 years (Forman, Berman, McCabe, Baim, & Wei, 1992), and therefore may not best represent the older population. One study found that fall occurrences increased from 21% in those aged 46-65 years to 35% in those aged 65 years and older (Talbot, Musiol, Witham, & Metter, 2005). Future studies may benefit from either an older group (i.e. ~ 75-80) or a larger sample size that incorporates a large range of ages (e.g., 60-85). In addition to older adults, determining the utility of the potential relationship between fractal dynamics and gait adaptability in other cohorts at high risk

and consequence of falls, such as those with neurological disease, would provide more relevant information from a clinical or applied perspective, especially if direct correlations can be made between quantified gait adaptability and fall risk.

Study 3 evaluated the potential existence of multifractality in the stride time variance of unperturbed and asymmetrically constrained walking. Long data sets are recommended in order to accurately capture the potential intermittency of stride time fluctuations (Ihlen, 2012). Gait paradigms, however, are confronted with the dilemma of dealing with either short datasets or extended trials that may result in participant fatigue or boredom. Researchers must determine a sufficient data length size in order to accept or reject their study hypotheses. In this third study, multifractality was evaluated across 512 strides, which is considered sufficient for monofractal analyses, and given the algorithm used, for multifractal analysis as well. Another issue aside from data length is that this study recruited young, healthy adults. The lack of associations between multifractality and gait adaptability may have been a consequence of having a healthy, homogenous group of participants. Recruiting sedentary and active groups, or special populations such as older adults or those with neurological disorders, may elucidate if multifractal characteristics are in fact describing the locomotor system in a meaningful way.

A remaining challenge in fractal gait analysis involves establishing a physiological explanation for fractal phenomena. That is, what are the different neurophysiological processes operating at different temporal or spatial scales? If specific processes can be identified, researchers may be better able to quantify the interactivity across spatiotemporal scales that are thought to produce this fractal behavior. However, this precision may be difficult in locomotion, as the gait parameters evaluated (e.g., stride

intervals) are discrete in nature. In contrast, fractal analyses of other tasks, such as standing posture, involve continuous signals (e.g., center of pressure or center of mass). In this case, researchers may be able to determine which process or temporal scales (i.e., frequency ranges) are being modified for different postural tasks. Although challenging, future research should continue to develop paradigms that aim to reveal more about the precise neurophysiological aspects of the emergent fractal behavior of walking.

As a general suggestion for all three studies, there are an infinite number of experimental designs that can be crafted to test gait adaptability by evoking constraints at the individual, task, or environmental level. This dissertation consisted of asymmetric walking on a split-belt treadmill, in which one belt traveled at twice the rate as the other, in order to assess how people adapt their gait to forced leg speed asymmetries. In order to confirm the findings reported herein, more paradigms involving various constraints should be developed to determine the robustness of these results. Even within the split-belt treadmill paradigm, various tasks can be employed, such as differing speed ratios, belt directions, or trial lengths. Importantly, adaptive gait must not only be able to alter behavior patterns and sustain this alteration for numerous strides, but also make various changes to gait behavior (e.g., step length, step width, stance time) on a step-to-step basis. The challenge of developing more ecologically valid gait adaptability paradigms is that the fractal analyses used herein require steady state walking. Future studies may benefit from the development of a paradigm that incorporates numerous required adaptations to locomotor patterns with steady state walking behavior.

## 8.8 Conclusion

This dissertation has aided in the advancement of gait adaptability studies through the examination of fractal dynamics as a measure of locomotor adaptive capacity. This series of studies may be the first to investigate fractal dynamics while concurrently testing gait adaptability via a challenging gait task. The studies herein provide evidence that stride time fractal dynamics during unperturbed walking do not associate with the adaptive abilities of the locomotor system. In contrast, asymmetric walking fractal dynamics are associated with adaptive gait capacity, and may help explain why certain participants perform better than others during a gait adaptability task. The observed increase in fractal scaling in response to asymmetric walking constraints may be functionally relevant by helping to attenuate perturbations at various scales. In addition, recruiting physically active young and older adults negates age-related differences in fractal scaling during unperturbed and asymmetric walking, as well as gait adaptability performance. Finally, while unperturbed walking in young healthy adults exhibits monofractal behavior, asymmetric walking appears to reveal multifractality, as more intermittent corrections may have been required. However, this multifractal feature does not associate with gait adaptability performance in young healthy participants during, suggesting multifractality may not be a critical control parameter in this split-belt adaptation paradigm.

## **APPENDICES**



**APPENDIX A**

**INFORMED CONSENT DOCUMENT FOR STUDY 1 AND STUDY 3**

Participant ID \_\_\_\_\_

Consent Form for Participation in a Research Study  
University of Massachusetts Amherst

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**Researcher(s):** Michael Busa PhD, Scott Ducharme MS, and Richard van Emmerik PhD  
**Study Title:** **Gait Adaptations During Split-Belt Walking in Young Healthy Individuals**

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**1. WHAT IS THIS FORM?**

This form is called a Consent Form. It will give you information about the study so you can make an informed decision about participation in this research. This consent form will give you the information you will need to understand why this study is being done and why you are being invited to participate. It will also describe what you will need to do to participate and any known risks, inconveniences or discomforts that you may have while participating. We encourage you to take some time to think this over and ask questions now and at any other time. If you decide to participate, you will be asked to sign this form and you will be given a copy for your records.

**2. WHO IS ELIGIBLE TO PARTICIPATE?**

You are being asked to participate in this study because you are a healthy adult with some experience walking on a treadmill. Persons between the ages of 18 and 45 years with no current lower extremity injuries will be eligible for participation. Your eligibility was assessed by the inclusion criteria on the flyer and completion of the PAR-Q questionnaire.

You will be excluded from participation if you currently: have a lower extremity injury in the past year that affects walking gait, have a neurological or visual impairment, vestibular dysfunction, cardiovascular or pulmonary disease, are pregnant, have no experience walking on a treadmill, or answered 'yes' to any of the modified PAR-Q questions and have not been cleared by your doctor.

### **3. WHAT IS THE PURPOSE OF THIS STUDY?**

The purpose of this study is to investigate how humans regulate changes in the time taken to complete each stride while walking, and if these changes are altered by walking speed or gait symmetry.

### **4. WHERE WILL THE STUDY TAKE PLACE AND HOW LONG WILL IT LAST?**

This study will take place in the Locomotion Neuromechanics Laboratory (room 28 Totman building) at the UMass Amherst campus. You will be asked to come to the lab for 1 visit lasting approximately 2.25 hours.

### **5. WHAT WILL I BE ASKED TO DO?**

If you agree to take part in this study:

1. You will be asked to participate in one testing session, lasting approximately 2.25 hours.
2. The testing session will begin with measurements of body mass and height, using a standard physician's scale. (5 min)
3. To be prepared for data collection, you will be asked to change into form fitting clothing and running shoes provided by the laboratory. (5 min)
4. Next, reflective markers will be placed on your on your body in order to record 3-D gait kinematics. The position of the reflective markers will be recorded by high-speed infrared cameras circling the data collection space containing the treadmill. (10 min)
5. After the placement of reflective markers, 1 non-invasive accelerometer will be placed on your torso for the determination of trunk fluctuations. (3 min)
6. Once markers have been placed, you will be asked to stand in the data collection space to record a standing calibration trial of the markers. The standing calibration trial will be used to create a computer model of you on which data analysis will be performed. (1 min)
7. You will then be asked to perform several short bouts of walking on a treadmill in order to determine your preferred speed. The treadmill speed will be based on determining your preferred walking speed. The treadmill will be either increased or decreased until you identify the same speed in successive attempts, as your preferred pace of walking. During this walking task researchers will note which

leg you take your first step, from a standing position, and this leg will be identified as your dominant leg. (8 mins)

8. Once this preferred speed has been determined you will be given a short period of rest, and the experiment will not continue until you have indicated you feel no residual fatigue from the protocol thus far.
9. After you indicate you are prepared to continue you will be asked to under go 5 15-minute bouts of walking: (total walking time: 75 minutes)
  - a) 1-bout at your preferred walking speed.
  - b) 1-bout at half your preferred walking speed.
  - c) 3-bouts where you walk with your dominant leg (identified previously) on the treadmill belt moving at your preferred walking speed and the other (non-dominant) leg walking on the treadmill belt going at your preferred walking speed.

Between each of these bouts you will be given 5 minutes of rest to recover from the effort (total rest time: 25 minutes)

10. After you complete all 5 bouts, all of the equipment will be removed. (3 min)

Total Estimated time: 135 min

## **6. WHAT ARE MY BENEFITS OF BEING IN THIS STUDY?**

You may not directly benefit from this research; however, we anticipate that your participation in this study will directly contribute to the understanding of how individuals regulate their stride fluctuations during walking and if these can provide information regarding the adaptability of gait. A better understanding of the extent humans can adapt to a novel walking task may provide information to assist in fall prevention programs and fall risk analysis.

## **7. WHAT ARE MY RISKS OF BEING IN THIS STUDY?**

During any type of exercise there are slight health risks. These include the possibility of fatigue and muscle soreness. However, any health risks are small in subjects who have no prior history of cardiovascular, respiratory or musculoskeletal disease or injury. Any ordinary fatigue or muscle soreness is temporary. In the unlikely event of balance loss, the treadmill has handrails on both sides that extend the entire length of the treadmill's walkable surface. You will be advised that you may hold onto the handrails at any time if you feel unstable.

## **8. HOW WILL MY PERSONAL INFORMATION BE PROTECTED?**

The following procedures will be used to protect the confidentiality of your study records. The data and records collected in this study are for research purposes only. Confidentiality will be maintained throughout the study.

All data will carry an identifying code, not the actual participant's name to ensure confidentiality. A master key that links names and codes and any identifiable health information will be maintained in a separate and secure location. All electronic data will be stored on secure and encrypted computer hard drives. The master key will be destroyed 6 years after the close of the study. Only investigators of this project will have access to this data. At the conclusion of this study, the researchers will publish their findings. Information will be presented in summary format and you will not be identified in any publications or presentations.

#### **9. WILL I RECEIVE ANY PAYMENT FOR TAKING PART IN THE STUDY?**

There is no payment for participating in this study.

#### **10. WHAT IF I HAVE QUESTIONS?**

Take as long as you like before you make a decision. We will be happy to answer any question you have about this study. If you have further questions about this project or if you have a research-related problem, you may contact the researchers, Scott Ducharme at (413) 545-6075 or Dr. Richard van Emmerik at (413) 545-0325. If you have any questions concerning your rights as a research subject, you may contact the University of Massachusetts Amherst Human Research Protection Office (HRPO) at (413) 545-3428 or [humansubjects@ora.umass.edu](mailto:humansubjects@ora.umass.edu).

#### **11. CAN I STOP BEING IN THE STUDY?**

You do not have to be in this study if you do not want to. If you agree to be in the study, but later change your mind, you may drop out at any time. There are no penalties or consequences of any kind if you decide that you do not want to participate.

#### **12. WHAT IF I AM INJURED?**

The University of Massachusetts does not have a program for compensating subjects for injury or complications related to human subject research, but the study personnel will assist you in getting treatment.

#### **13. SUBJECT STATEMENT OF VOLUNTARY CONSENT**

When signing this form I am agreeing to voluntarily enter this study. I have had a chance to read this consent form, and it was explained to me in a language which I use and understand. I have had the opportunity to ask questions and have received satisfactory answers. I understand that I can withdraw at any time. A copy of this signed Informed Consent Form has been given to me.

Participant Signature: \_\_\_\_\_ Date: \_\_\_\_\_

Print Name: \_\_\_\_\_

By signing below I indicate that the participant has read and, to the best of my knowledge, understands the details contained in this document and has been given a copy.

Signature of Person: \_\_\_\_\_ Date: \_\_\_\_\_  
Obtaining Consent

Print Name: \_\_\_\_\_

## APPENDIX B

### INFORMED CONSENT DOCUMENT FOR STUDY 2

Participant ID \_\_\_\_\_

Consent Form for Participation in a Research Study  
University of Massachusetts Amherst

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**Researcher(s):** Scott Ducharme MS, and Richard van Emmerik PhD  
**Study Title:** **Gait Adaptation and Re-Adaptation in Young and Older Adults**

---

#### 1. WHAT IS THIS FORM?

This form is called a Consent Form. It will give you information about the study so you can make an informed decision about participation in this research. This consent form will give you the information you will need to understand why this study is being done and why you are being invited to participate. It will also describe what you will need to do to participate and any known risks, inconveniences or discomforts that you may have while participating. We encourage you to take some time to think this over and ask questions now and at any other time. If you decide to participate, you will be asked to sign this form and you will be given a copy for your records.

#### 2. WHO IS ELIGIBLE TO PARTICIPATE?

You are being asked to participate in this study because you are a healthy active adult with some experience walking on a treadmill. Adults between the ages of 21-40 years and 60-70 years with no current lower extremity injuries will be eligible for participation. Your eligibility was assessed by the inclusion criteria on the flyer and phone screen, including verbal and written completion of the PAR-Q questionnaire.

You will be excluded from participation if you currently: do not self-report participation of at least 150 minutes per week of moderate intensity physical activity, have a lower extremity injury in the past year that affects walking gait, have a neurological or visual impairment, vestibular dysfunction (e.g., vertigo or vestibular neuritis) or any conditions causing dizziness or balance impairments, cardiovascular or pulmonary disease, are pregnant, have no experience walking on a treadmill, or answered 'yes' to any of the modified PAR-Q questions and have not been cleared by your doctor.

### **3. WHAT IS THE PURPOSE OF THIS STUDY?**

The purpose of this study is to investigate how humans regulate changes in the time taken to complete each stride while walking, and if these changes are affected by gait symmetry or age.

### **4. WHERE WILL THE STUDY TAKE PLACE AND HOW LONG WILL IT LAST?**

This study will take place in the Locomotion Neuromechanics Laboratory (room 28 Totman building) at the UMass Amherst campus. You will be asked to come to the lab for two (2) visits, each lasting approximately 1.5 hours. In addition, you will be asked to wear an activity monitor each day between laboratory visits (7 days), and provide notes regarding exercise or physical activities during this time.

### **5. WHAT WILL I BE ASKED TO DO?**

If you agree to take part in this study:

1. You will be asked to participate in two testing sessions, each lasting approximately 1.5 hours. In addition, you will be asked to wear an accelerometer on your hip for 7 days between these sessions, and complete a notebook of physical activities performed during these 7 days. The accelerometer will be worn for most of your waking hours, and will be used to measure your minutes per day of moderate or vigorous physical activity.
2. Session 1 will begin with reading and signing this informed consent document. (5 min)
3. The next step will be measurement of body mass and height, using a standard physician's scale. You will be asked to change into form fitting clothing and running shoes provided by the laboratory. (8 min)
4. Next, reflective markers will be placed on your body in order to record 3-D gait kinematics. The position of the reflective markers will be recorded by high-speed infrared cameras circling the data collection space containing the treadmill. In addition to reflective markers, 1 non-invasive accelerometer will be placed on your torso for the determination of trunk fluctuations. (10 min)
5. Once markers have been placed, you will be asked to stand in the data collection space to record the first postural condition in which you will be asked to stand quietly and minimize movement for 30 seconds. This trial will also serve as the standing calibration, which will be used to create a computer model of you on

which data analysis will be performed. There will be a brief rest (30 sec) following this trial. (1 min)

6. The second postural condition will again be standing quietly, but with eyes closed. This will again be for 30 seconds, followed by a 30 second rest. (1 min)
7. You will then be asked to perform several short bouts of walking on a treadmill in order to determine your preferred speed. The treadmill speed will incrementally change to determine your preferred walking speed. The treadmill will be increased and decreased until you identify the same speed in successive attempts, as your preferred pace of walking. During this walking task researchers will note which leg you take your first step, from a standing position, and this leg will be identified as your dominant leg. (10 min)
8. Once this preferred speed has been determined you will be given a short period of rest, and the experiment will not continue until you have indicated you feel no residual fatigue from the protocol thus far. (5 min)
9. After you indicate you are prepared to continue you will be asked to undergo two bouts of walking: (total walking time: 35 minutes)
  - a) 1 bout at your preferred walking speed. (15 min)
  - b) 1 bout at half of your preferred walking speed. (20 min)

Between these bouts you will be given 5 minutes of rest to recover from the effort. (5 min)

10. After you complete both bouts, all of the equipment will be removed, and you will be provided with a hip-worn accelerometer. The accelerometer data will be used to determine your actual level of physical activity. (10 min)

Session 1 Total Estimated Time: 90 min

11. During the intercession between lab visits, you will be asked to wear the accelerometer device for as many waking hours as possible (not including swimming or shower) for the next 7 days. You will also be provided with a notebook to keep track of activities performed over the next week. (7 days)
12. Session 2 take place 7 days following session 1. Session 2 will begin with collection of the accelerometer and notebook. (1 min)
13. Next you will again be asked to change into appropriate attire, and the same setup of markers and accelerometer will be placed on your body. (8 min)



14. You will again be asked to stand quietly on the treadmill for 30 seconds, followed by a 30-second rest. (1 min)
15. You will also be asked to stand quietly with eyes closed for 30 seconds, followed by 30-seconds of rest. (1 min)
16. You will then be asked to undergo four bouts of walking: (total walking time: 56 minutes)
  - a) 1 bout at your preferred walking speed. (10 min)
  - b) 3 bouts where you walk with your dominant leg (identified previously) on the treadmill belt moving at your preferred walking speed and the other (non-dominant) leg walking on the treadmill belt moving at half of your preferred walking speed. (12 min per bout, 36 min total)
  - c) 1 bout where the treadmill belts are again traveling at the same speed. (10 min)

Each walking trial will be followed by 5 minutes of rest sitting on a chair. (total rest time (20 min)
17. Following treadmill walking, markers and accelerometer will be removed. (3 min)

Session 2 Total Estimated Time: 90 minutes

**Total Laboratory Time: 3 hours**

**Time wearing accelerometer and filling out notebook: 7 days**

## **6. WHAT ARE MY BENEFITS OF BEING IN THIS STUDY?**

You may not directly benefit from this research; however, we anticipate that your participation in this study will directly contribute to the understanding of how individuals regulate their stride fluctuations during walking and if these can provide information regarding the adaptability of gait. A better understanding of the extent humans can adapt to a novel walking task, and if this ability to adapt is affected by age, may provide information to assist in fall prevention programs and fall risk analysis.

## **7. WHAT ARE MY RISKS OF BEING IN THIS STUDY?**

During any type of exercise there are slight health risks. These include the possibility of fatigue and muscle soreness. However, any health risks are small in subjects who have no prior history of cardiovascular, respiratory or musculoskeletal disease or injury. Any ordinary fatigue or muscle soreness is temporary. In the unlikely event of balance loss, participants will be placed into a total body harness prior to data collection. This will

eliminate the possibility for unwanted contact with the support surface. In addition, the treadmill has handrails on both sides that extend the entire length of the treadmill's walkable surface. You will be advised that you may hold onto the handrails at any time if you feel unstable.

## **8. HOW WILL MY PERSONAL INFORMATION BE PROTECTED?**

The following procedures will be used to protect the confidentiality of your study records. The data and records collected in this study are for research purposes only. Confidentiality will be maintained throughout the study.

All data will carry an identifying code, not the actual participant's name to ensure confidentiality. A master key that links names and codes and any identifiable health information will be maintained in a separate and secure location. All electronic data will be stored on secure and encrypted computer hard drives. The master key will be destroyed 6 years after the close of the study. Only investigators of this project will have access to this data. At the conclusion of this study, the researchers will publish their findings. Information will be presented in summary format and you will not be identified in any publications or presentations.

## **9. WILL I RECEIVE ANY PAYMENT FOR TAKING PART IN THE STUDY?**

After completion of both sessions, you will receive a \$15 Dunkin Donuts Gift Card.

## **10. WHAT IF I HAVE QUESTIONS?**

Take as long as you like before you make a decision. We will be happy to answer any question you have about this study. If you have further questions about this project or if you have a research-related problem, you may contact the researchers, Scott Ducharme at (413) 545-6075 or Dr. Richard van Emmerik at (413) 545-0325. If you have any questions concerning your rights as a research subject, you may contact the University of Massachusetts Amherst Human Research Protection Office (HRPO) at (413) 545-3428 or [humansubjects@ora.umass.edu](mailto:humansubjects@ora.umass.edu).

## **11. CAN I STOP BEING IN THE STUDY?**

You do not have to be in this study if you do not want to. If you agree to be in the study, but later change your mind, you may drop out at any time. There are no penalties or consequences of any kind if you decide that you do not want to participate.

**12. WHAT IF I AM INJURED?**

The University of Massachusetts does not have a program for compensating subjects for injury or complications related to human subject research, but the study personnel will assist you in getting treatment.

**13. SUBJECT STATEMENT OF VOLUNTARY CONSENT**

When signing this form I am agreeing to voluntarily enter this study. I have had a chance to read this consent form, and it was explained to me in a language which I use and understand. I have had the opportunity to ask questions and have received satisfactory answers. I understand that I can withdraw at any time. A copy of this signed Informed Consent Form has been given to me.

Participant Signature: \_\_\_\_\_ Date: \_\_\_\_\_

Print Name: \_\_\_\_\_

By signing below I indicate that the participant has read and, to the best of my knowledge, understands the details contained in this document and has been given a copy.

Signature of Person: \_\_\_\_\_ Date: \_\_\_\_\_  
Obtaining Consent

Print Name: \_\_\_\_\_

## **APPENDIX C**

### **SCRIPT TO READ BEFORE ISSUING THE PAR-Q**

Thank you for coming in today. Before you officially enroll in this research study, I will be asking you to complete a Physical Activity Readiness Questionnaire (PAR-Q). It should take you no more than 5 minutes to complete. This questionnaire is a screening tool that will ask you questions about your health history to determine your eligibility for participation in the study which involves physical activity.

If you are determined ineligible to participate, your completed questionnaire will be destroyed. If you are determined eligible to participate, your completed questionnaire will be retained until the study is complete. We will protect your information contained in the PAR-Q as confidential information safeguarding it from unauthorized disclosure. Only research personnel will have access to the information contained in your PAR-Q.

If the PAR-Q indicates that you are eligible to participate, we will proceed directly to obtaining your written informed consent for participation in the study. Do you have any questions?

**APPENDIX D**

**STUDY 2 PHONE SCREEN**

*Physical Activity Questions (modified Godin Leisure-Time Exercise Questionnaire)*

1. During a typical **7-day period** (a week), how many times on the average do you do the following kinds of exercise for **more than 15 minutes** during your free time (write on each line the appropriate number)

	<b>Times Per Week</b>	<b>Minutes Per Time/Bout</b>
<b>a) STRENUOUS EXERCISE (HEART BEATS RAPIDLY)</b> (e.g., running, jogging, hockey, football, soccer, squash, basketball, cross country skiing, judo, roller skating, vigorous swimming, vigorous long distance bicycling)	_____	_____
<b>b) MODERATE EXERCISE (NOT EXHAUSTING)</b> (e.g., fast walking, baseball, tennis, easy bicycling, volleyball, badminton, easy swimming, alpine skiing, popular and folk dancing)	_____	_____

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Strenuous Minutes x Times x 2 = \_\_\_\_\_

Moderate Minutes x Times = \_\_\_\_\_

**TOTAL MVPA** = \_\_\_\_\_ (if less than 150, individual is excluded)

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**Additional Exclusion Criteria:**

1. Are you unfamiliar with walking on a treadmill? \_\_\_\_\_
2. Have you ever experienced asymmetric walking on a split-belt treadmill? \_\_\_\_\_
3. Do you have a lower extremity injury that affects walking? \_\_\_\_\_

- 4. Do you have a neurological or non-corrected visual impairment? \_\_\_\_\_
- 5. Do you have vestibular dysfunction? \_\_\_\_\_
- 6. Do you have cardiovascular or pulmonary disease? \_\_\_\_\_
- 7. Are you pregnant? \_\_\_\_\_

if yes to any of these questions, individual is excluded

**APPENDIX E**

**PHYSICAL ACTIVITY MONITOR LOG**



**UNIVERSITY OF MASSACHUSETTS**  
School of Public Health & Health Sciences  
Department of Kinesiology



**ACTIVITY MONITOR LOG**

Participant ID#: \_\_\_\_\_

Monitor ID # \_\_\_\_\_

Start Date: \_\_\_\_\_

## INFORMATION ABOUT THE ACTIVITY MONITOR

The Activity Monitor is a small, plastic box containing electronic circuitry. When you wear the Activity Monitor, it measures how much you are moving.

Please remember a few important things about the monitor:

- Snap the belt around your waist.
- The monitor should be worn around your waist and positioned at the top of the right hipbone.
- **DO NOT GET THE MONITOR WET** (Sweat is okay).
- You should **wear** the monitor **while you are awake** for 7 days, removing the device only for sleep and water-based activities.
- Please return the monitor and this log to the UMass Muscle Physiology Laboratory, Totman Bldg., Room 22.

## INSTRUCTIONS FOR COMPLETING THIS ACTIVITY LOG

We want to know:

- When you woke up and when you went to bed
- When the monitor was put on and taken off
- Any activities you completed that day (e.g., long walks, yard work, etc.).
- If there was anything out of the ordinary about your activity pattern

If you went on a long walk from 11:00 am to 11:30 am, write walking in the activity column, 11:00 am to 11:30 am in the time column, and 30 minutes in the duration column.

If you have any questions please contact:

Scott Ducharme

UMass Motor Control Lab

Phone: (860) 573 - 7954

Email: [sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)



# Day 1

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 2

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 3

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 4

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 5

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:

Time:

Duration

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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 6

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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## Day 7

Date: \_\_\_\_\_ Day of the week \_\_\_\_\_

Wake up Time: \_\_\_\_\_

Bed Time: \_\_\_\_\_

Monitor on Time: \_\_\_\_\_

Monitor off Time: \_\_\_\_\_

1) Please list any physical activities (such as long walks, yard work, fitness club, etc), as well as any naps during the day:

Activity:	Time:	Duration
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Did you wear the monitor during all waking hours (except for showering)?

Yes

No, Times not worn: \_\_\_\_\_

Was there anything out of the ordinary about your activity pattern this day?

Yes, Explain Below

No

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APPENDIX F

STUDY 1 FLYER

# Motor Control Walking Study



## Research Volunteers Needed

### Are you:

- A healthy male or female?
- Between the ages of 18-45?
- Free of lower extremity injury?

### Excluded if:

- Lower extremity injury in past year
- Neurological/visual/vestibular impairments
- Cardiopulmonary disease
- No experience walking on a treadmill

### If so, you may be eligible!

#### Contact us:

(413) 545-6075

[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)

*\*\*requires approximately 2.25 hours*

Department of Kinesiology, University of Massachusetts

**Walking Study**

Scott

[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)  
(413) 545-6075

**Walking Study**

Scott

[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)  
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**Walking Study**

Scott

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(413) 545-6075



APPENDIX G

STUDY 2 FLYER

# Motor Control Walking Study



## Research Volunteers Needed

### Are you:

- An active, healthy male or female?
- Between the ages of 21-40 or 60-70?
- Free of lower extremity injury?

### If so, you may be eligible!

#### Contact us:

(860) 573-7954

[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)

### Excluded if:

- Lower extremity injury in past year
- Neurological/visual/vestibular impairments
- Cardiopulmonary disease
- No experience walking on a treadmill
- Participate in less than 150 minutes per week of moderate intensity activity

*\*\* requires two 1.5-hour sessions and 1 week of wearing a physical activity monitor and documenting physical activity*

Department of Kinesiology, University of Massachusetts

**Compensation: \$15 Dunkin Donuts Gift Card**

Walking Study

Scott

[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)  
(860) 573-7954

Walking Study

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[sducharm@kin.umass.edu](mailto:sducharm@kin.umass.edu)  
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