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Aging, Gait Variability, and Adaptability

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AGING, GAIT VARIABILITY, AND ADAPTABILITY

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ABSTRACT

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The purpose of this work was to study the relationships between age, measures of gait variability, and locomotor adaptability. Measures of gait variability are used to identify maladapted locomotor behavior, motor disease, and risk of falls. The first aim was to determine the relationships between age and measures of gait variability. Thirty-four participants (23-71 years old) walked on a treadmill for 6 minutes at their preferred speed. Variability of stride times and lengths was computed via linear measures (standard deviation and coefficient of variation) and nonlinear measures (sample entropy and detrended fluctuation analysis). Movement trajectory variability of the dominant knee angle, and vertical and medial-lateral positions of the pelvis were quantified using nonlinear measures (correlation dimension and local dynamic stability). The results showed little association of age and variability measures. Additional analyses revealed that preferred gait speed was a better predictor of gait variability measures, suggesting that variations in gait variability are driven more by preferred gait speed than age. The second aim of this dissertation was to investigate the relationships between measures of gait variability. While the relationships between measures of gait variability have received little investigation, many have been suggested to quantify the same underlying component of locomotion, the ability of an individual to adapt. A principal component analysis was performed to examine if measures of variability were related to one or more underlying constructs of gait variability. Four independent constructs of gait variability were identified, indicating there is no single construct underlying gait variability and different variability measures can be associated with the same constructs. The final aim was to determine if measures of variability quantify the ability of an individual to adapt to a novel split-belt gait adaptation task, where two treadmill belts were set at different speeds. The findings showed no significant association between measures of gait variability from the preferred walking trial and adaptability performance. To conclude, gait variability is more speed-related than age-related, measures of gait variability quantify at least four separate components of gait, and gait variability measures are relatively unrelated to the adaptability performance of an individual.

This dissertation is dedicated to my friends and family who encouraged me to pursue higher education and provided me with love and encouragement throughout this endeavor. I also dedicated this work to Dr. Jessica McDonnell, my number one fan and supporter.

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CHAPTER I: INTRODUCTION

Measurements of gait variability are often used as an indicator of health, wellness, and performance of locomotion. By measuring gait variability researchers have noted differences between various populations and promoted the use of variability measures as a way to assess locomotor behavior and how gait behavior changes with age and disease (Hausdorff, 2007; Hausdorff, Rios, & Edelberg, 2001; Muñoz-Diosdado, Correa, Angulo-Brown, & Quevedo, 2005). There are numerous methods used to quantify the variability of gait. Historically, studies have quantified the magnitude of gait variability using linear measures such as standard deviation and coefficient of variation. Using these measures, studies have found older individuals to have increased standard deviation and coefficient of variation of gait measures such as step time and stance time during walking when compared to younger individuals (Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997). Further, when comparing older individuals who experience falls and those who do not experience falls, fallers have increased stride to stride gait variability magnitude (Hausdorff, Edelberg, et al., 1997). Therefore, by measuring the variability magnitude of individual's gait, researchers have attempted to quantify where an individual's gait is on the spectrum from young healthy gait to elderly falls risk gait (Callisaya et al., 2011; Hausdorff, Rios, et al., 2001; Paterson, Hill, & Lythgo, 2011). More recently, researchers have begun utilizing nonlinear measures of gait variability. Nonlinear measures do not quantify the magnitude of variability but instead quantify the sequential structure or patterns that occur during gait. Both linear and nonlinear measures of gait variability are used by researchers to understand what drives locomotor behavior and how locomotor behavior changes due to age and disease

(Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Callisaya, Blizzard, Schmidt, McGinley, & Srikanth, 2010; Karmakar, Khandoker, Begg, Palaniswami, & Taylor, 2007).

LINEAR MEASURES OF VARIABILITY

One of the earliest measures used to quantify variability was the standard deviation (s) shaped by Gauss in the early 1800s (David, 1998). This measure is used to quantify the magnitude of the spread of the data (x) by computing the average deviation of each value (x_i) from the mean ($\bar{x}$):

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}} \qquad \text{Equation 1.1}$$

where n refers to the number of data points. Each deviation from the mean is squared, to avoid the deviations above and below the mean canceling each other out when summed. The square root returns the units to the same as x. A similar measure known as the variance (s^2), does not take the square root and therefore results in squared units of the original data. Note that the sequence of values is irrelevant to the computation of either variance or standard deviation. If all the data points tend to be close to the mean, the standard deviation will be small and if the data points are relatively spread out away from the mean, the standard deviation will be larger. The coefficient of variation is sometimes referred to as the relative standard deviation and defined as the ratio of the standard deviation to the mean.

$$cv = \frac{s}{\bar{x}} \times 100 \qquad \text{Equation 1.2}$$

The coefficient of variation is expressed as a percentage and in this way allows for comparisons of variability between data with large relative differences in the mean. For example, if interested in comparing the differences in population height variability between a population of ants and a population of camels, the coefficient of variation may be a better measure for comparison. The standard deviation of height for the ants would be much smaller than the standard deviation of height for the camels regardless of the magnitude of variability in the populations.

Linear measures of variability began as a method used to quantify the dispersion of a measure in a population (e.g., height). In this example, a linear variability measure would be computed on data that is completely independent of one another. The height of one individual does not affect the height of another, baring all genetic components of things of this nature. The variability measure then quantifies how variable the population height is and can be used to compare populations and quantify how far away an individual is from the population mean. When modeling the data as a mean or a line in linear regression, standard deviation provides a measure of the error of the model of a population. Taking these concepts into the study of human movement has resulted in interpreting the mean of an individual’s movements as representing the signal of interest (e.g., stride times), and the standard deviation as quantifying the error or noise around that signal. This assumes that each step or movement for an individual is independent of every other movement (e.g., stride times are unrelated to one another), an assumption that can cause complications during the interpretation of an individual’s variability.

As mentioned, standard deviation and coefficient of variation are both used to investigate the variability of locomotor behavior between differing populations to understand how behavior changes over time or what changes can become detrimental to gait performance. Studies frequently have shown that elderly and fall risk populations have increased variability magnitude when using standard deviation and coefficient of variation. For example, increased stride time variability, stride width variability, step time variability, step length variability, double support time variability, and increased trunk, hip, and knee movement trajectory variability are associated with older age and increased falls risk (Beauchet et al., 2009; Callisaya et al., 2010; Kang & Dingwell, 2008; Kyvelidou, Kurz, Ehlers, & Stergiou, 2008; Montero-Odasso et al., 2011). Variability magnitude during gait has traditionally been considered unwanted noise or error within the system, i.e. the body. Thus, the finding that the old and falls risk populations have increased variability magnitude suggests that they are generating more movement noise during gait and this is viewed as a reason why falls are more common in the elderly.

What is ignored when using only these linear measures of variability is the sequential structure of the movement variability. An illustration of how this can affect data interpretation is seen in figure 1.1. The top image is a sine wave, the middle image is the same data points randomly shuffled and the bottom image is the same data points arranged in ascending order from 0 to 600. All three signals have the same mean which is zero and standard deviation which is one. By simply looking at the time series, the structure of the signals is very different. Standard deviation and coefficient of variation are unable to differentiate these signals as they ignore the sequence of the data points, although visual inspection can easily reveal the differences. Movement data between individuals can also be structurally different while still having the same mean and magnitude of variability. Human movement and behavior are complex, showing evidence of chaotic behavior containing nonlinear properties (Diedrich & Warren Jr, 1995; Kubo, Wagenaar, Saltzman, & Holt, 2004; Newell & Corcos, 1993). A chaotic system is one that has long term aperiodic deterministic behavior and is sensitive to initial conditions. Aperiodic means system does not settle around fixed points over time but moves about in a seemingly random fashion. However, this behavior is not random but is deterministic (defined by initial condition with a predictable outcome). Human behaviors are difficult to predict because of their sensitivity to

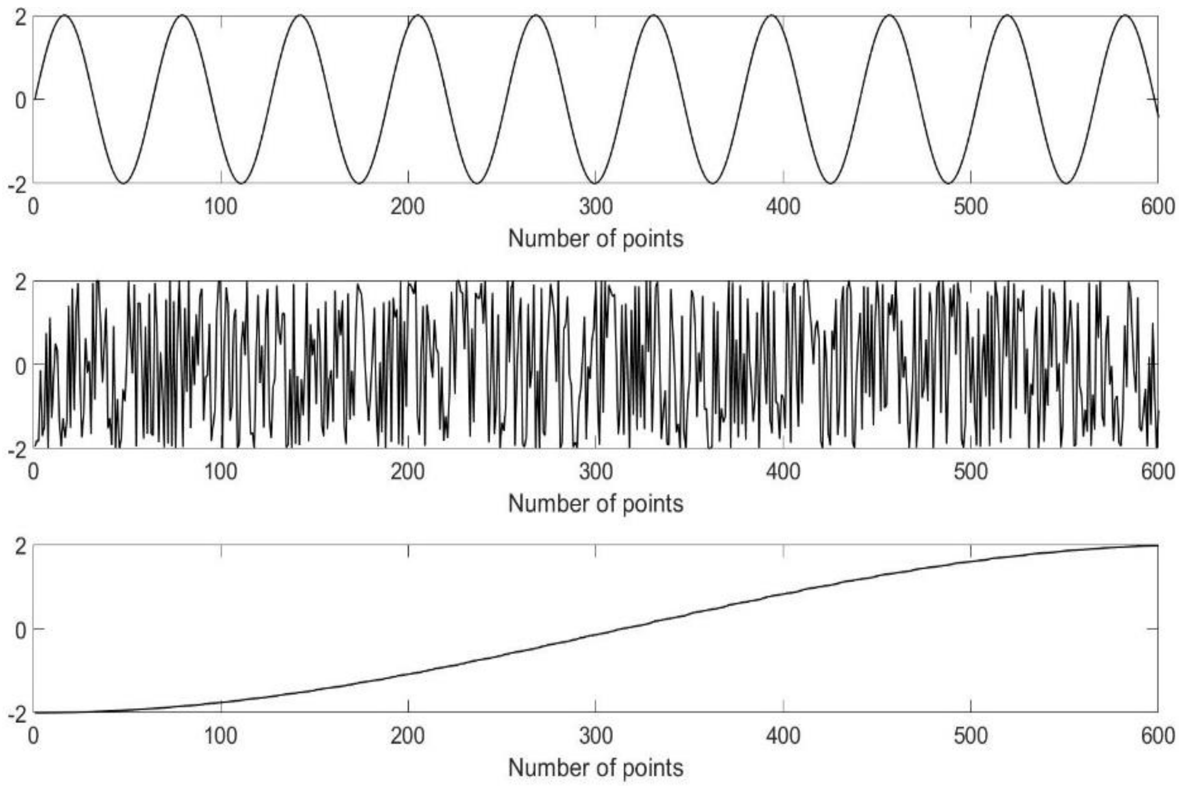

Figure 1.1: Example of different signals with the same mean and standard deviation. Top; sinewave. **Middle**; random shuffled sinewave, **Bottom**; sinewave data points in ascending order.

initial conditions. Therefore, nonlinear analysis techniques have been applied to quantify the underlying structure in data sequences in which standard linear techniques are unable to do so. These nonlinear techniques further our grasp of the complexity of human movement and are used to understand the properties of locomotion that drive movement (England & Granata, 2007; Lipsitz & Goldberger, 1992; Newell & Vaillancourt, 2001; Russell & Haworth, 2014).

NONLINEAR MEASURES OF VARIABILITY

Nonlinear analysis techniques are used to evaluate the structure, complexity, predictability, persistence, and stability of a time series. A time series which has structure refers to the presence of determinism, meaning the signal can be perfectly predicted if initial conditions and inputs are known. Data points in deterministic signals are related to and influenced by past data points. For example, a simple sine wave has a completely deterministic structure. It can be predicted with a very small amount of initial information, such as frequency and amplitude. A signal with two sine waves can also be predicted, but more initial information is needed to predict the signal (figure 1.2). This signal has therefore increased in complexity. Sine waves are examples of highly structured signals i.e. containing no noise or randomness, with little complexity. The stock market also has structure, although it is a much more complex system and difficult to predict over long periods. An infinite amount of infinitely precise information would be needed to predict what will happen over a long period of time, resulting in a system that can be considered chaotic. A chaotic system is deterministic, governed by laws that can be theoretically predicted but because of its sensitivity to initial condition, it is difficult to do so. Systems can still be chaotic while having relatively low complexity. For example, a Lorenz function illustrated at the bottom of figure 1.2 is defined by only three differential equations but

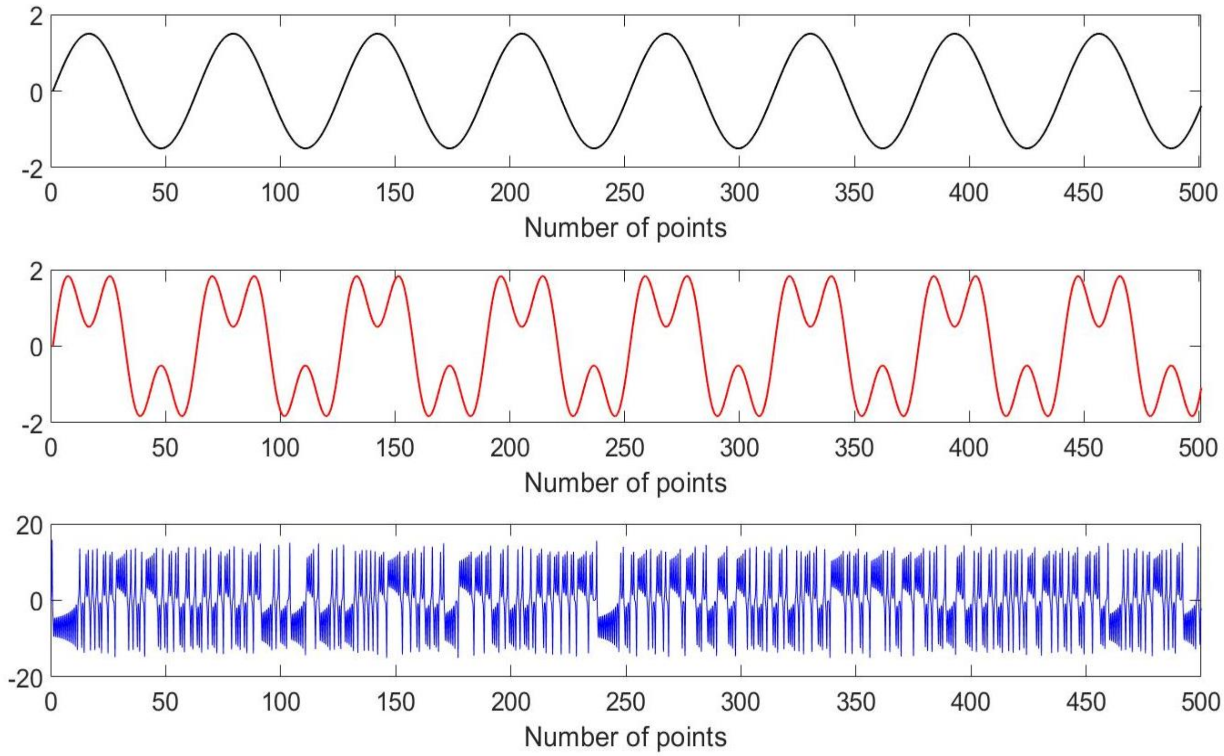

Figure 1.2. Examples of deterministic signals with varying degrees of complexity. Top sine wave, very little complexity. **Middle** the sum of 2 sine waves, low complexity. **Bottom** Lorenz system, high complexity.

behaves chaotically, meaning a small change in the initial conditions of these equations can result in wildly different patterns. These developments in chaos theory have demonstrated that rich complex patterns can arise from deterministic systems, and therefore variability should not be assumed to arise from noise or error in a system.

Differences between linear and nonlinear systems also exist in the way they can respond to signal noise. For a linear system, the magnitude of applied noise results in proportional response magnitude. In contrast, with a nonlinear system, small noise may be damped out or larger noise may result in exponential growth in the system response or transitions to different behavior. This can be quantified by the stability of a system. This refers to the system's resistance to change, investigating if a small external perturbation would knock the system out of its movement pattern, or the system moves back into its stable pattern quickly. Using nonlinear analysis techniques, signals can be quantified as being highly rigid, stable, or unstable. The persistence of a signal can also be quantified using nonlinear measures. The persistence of a signal refers to its trajectories over a period. The value of the variable at the current time point is closely related to previous values. Climate is often viewed as an example of persistent data and nonlinear measures can quantify the level or strength of persistence over time. A thousand years of an ice age is likely to be followed by another thousand years, and another thousand years. A desert is likely to remain a desert for a very long time. Human locomotion can also show persistence where future behavior is similar to previous behavior, though on a much shorter time scale. Depending upon the individual, the task, and the environment, human behavior has been described as deterministic and persistent with varying degrees of complexity and stability (Newell & Vaillancourt, 2001; Vaillancourt & Newell, 2002).

One of the first uses of nonlinear measures to quantify human biological signals began with heart rate variability. The mean and variance of heart rate over time between healthy individuals and individuals with heart disease were found to be similar, although the sequential structure of the heart rate was notably different. When visually inspecting the time series data, those with heart diseases had a heart rate that looked more similar to a sinewave, a more predictable pattern over time. Healthy controls had a more variable, less predictable heart rate. A nonlinear measure known as sample entropy was applied to these time series and it was able to differentiate between the two study populations(Goldberger et al., 2002). Those with heart disease had a decreased sample entropy value, interpreted as a more predictable, possibly less complex, time series. This has been interpreted as a loss of the ability for the cardiac system to adapt on a shorter time scale and change heart rate effectively (Lipsitz & Goldberger, 1992). This successful line of research in heart rate variability directed many to investigate the structure of gait variability and its importance in locomotor behavior instead of considering variability as simply unwanted noise. Some of the most common nonlinear measures used when studying human movement variability include entropy measures, local dynamic stability, correlation dimension, and detrended fluctuation analysis. We will consider each in turn.

Approximate Entropy and Sample Entropy

The measure approximate entropy was created by Pincus in the early 1990s based on Shannon's work in information theory (Shannon, 1948). It was created to quantify the predictability and possibly complexity of a time series revealing information about the structure of the signal, rather than the magnitude of the variability as given by linear measures such as standard deviation and coefficient of variation (Pincus & Huang, 1992). Approximate entropy can be interpreted as a measure of how repeatable or regular a time series is. To calculate approximate entropy, a time series of length N is broken up into many separate vectors of length m, a length that is chosen by the user (e.g., m=3 in Figure 1.3). A comparison is then made between vector *m(i)* and all other vectors including itself, *m(1), m(2), m(3), ...m(N-m+1).* The vectors are considered similar if the difference between each value in the vector pairs is less than *r* which is a buffer or filter chosen by the user, so the values of comparison do not have to be exactly the same to be considered similar (see Figure 1.3). Comparisons are then made between vector *m*(i+1) and all other *m* vectors. This process is repeated until all *m* vectors have been used for comparison. The ratio of like matches to possible matches for each *m* vector is then summed and divided by N-*m+1*, which we will call *C(1).* This entire process is then repeated to compute *C*(2) for a new set value for *m* which is *m*+1. Finally, the natural log of *C(1)* divided by *C(2)* is equal to the approximate entropy of the time series (Goldberger et al., 2000).

$$ApEn = \ln\left[\frac{c_m(r)}{c_{m+1}(r)}\right] \qquad \text{Equation 1.3}$$

Larger values of approximate entropy indicate that there is less repetition in a time series, rendering the signal less predictable/regular, while smaller approximate entropy values represent greater regularity, which is increased repetition or predictability within the signal. Often, approximate entropy measures are used as a surrogate measure of complexity in human movement. The interpretation in gait studies has been that healthy individuals typically have a healthy amount of gait complexity and fallers, the elderly, or individuals with disease have significantly different amounts of complexity, sometimes more and sometimes less, depending on the population or variable studied (stride time, width, length, body acceleration, etc.).

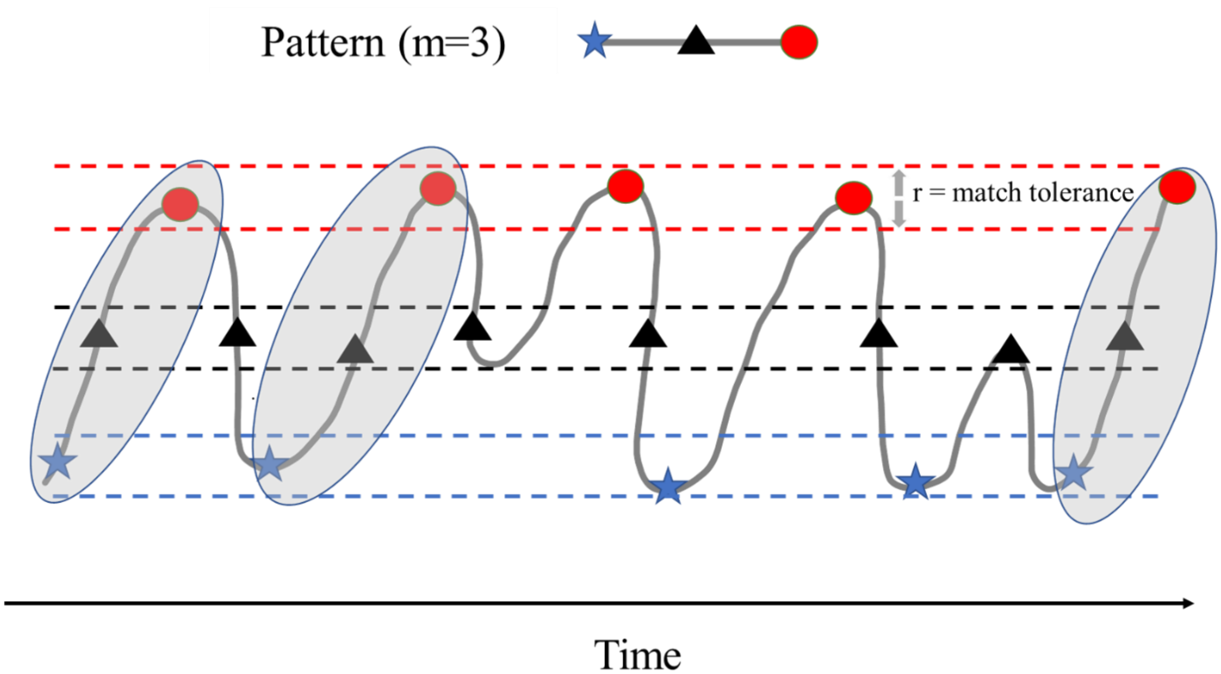

Figure 1.3: Depiction of sample entropy calculation for m=3. The sample entropy algorithm finds self-similar matches of a pattern of length *m* with a match tolerance of *r*. Redrawn and adapted from Kang, Dingwell, (2016).

A criticism of approximate entropy is that it includes self-matching because each m vector is compared to itself. This may suggest more similarity within a time series than is truly present. To address this issue, an alternate method for calculating approximate entropy was created by Richman and Moorman (2000), called sample entropy. This algorithm does not include self-matches and is less sensitive to a change in the length of the time-series data. Another critique of both approximate and sample entropy measures is their sensitivity to noise. If a time series has increased noise, repeatability of the signal is reduced and therefore the entropy value will increase. Hence, while some interpret larger approximate or sample entropy values as indicating increased complexity, the values could result from greater stochastic noise or more complex deterministic processes (e.g., more sinewave like oscillations at different frequencies).

Entropy measures have been used to reveal differences in movement patterns between populations based on age, activity, and fall risk. When comparing the regularity or predictability of movement trajectories of the joints of the lower extremity between younger and older adults, older adults have decreased regularity, which is represented by increased sample entropy value when compared to younger adults. This was suggested to lead to decreases in gait stability and thus increase the probability of experiencing a fall (Kurz & Stergiou, 2003). In a separate study measuring the variability of minimum foot clearance while walking, fallers were found to have increased approximate entropy value when compared to healthy adults. This was suggested to be a result of increased irregularities and randomness in the gait of those labeled as fallers which lead to the loss of gait control. However, these findings are not consistent across the literature. Sample entropy values have also been found to decrease with age as well as motor impairments (Acharya et al., 2013). A study using entropy measure calculated on body acceleration found older individuals to have decreased sample entropy, indicating increased regularity, when compared to younger adults. In this same population, older adults with impairments were found to have decreased sample entropy values compared to older adults with fewer motor impairments. Also, older adults who were highly physically active have been found to have increased sample entropy when compared to less active older adults (Cavanaugh, Kochi, & Stergiou, 2010). Here, the authors suggested that the increased entropy, decreased predictability, lead to a more complex gait pattern and an enhanced ability to adapt while the less active older adults who had increased predictability as measured by sample entropy had less complex gait patterns and a decreased ability to adapt one's gait. Examples of this bi-directional relationship between age or disease and regularity are common in the literature, showing that there is not a consistent finding (Arif, Ohtaki, Nagatomi, & Inooka, 2004; Bisi & Stagni, 2016; Ihlen, Weiss, Bourke, Helbostad, & Hausdorff, 2016; Leverick, Szturm, & Wu, 2014; Mills, Barrett, & Morrison, 2008; Tochigi, Segal, Vaseenon, & Brown, 2012)

These differences in gait regularity, as measured by sample and approximate entropy, between populations are often suggested to be associated with the ability to adapt gait to sudden changes in task demands or environmental conditions. When sample entropy is reduced in elderly and fall risk populations, it is interpreted as degeneration of some biological system resulting in more regular and predictable gait patterns and a reduced ability to adapt. In other studies, increases in entropy values indicating less regular and predictable gait patterns, the findings are interpreted as indicating a loss of gait control and stability, leading to unhealthy locomotor behavior. This has led to the claim that there is an optimal range for entropy values that is necessary for safe and healthy gait (Stergiou et al., 2016), but to date, there are no generally accepted healthy or unhealthy values of different entropy measures applied to particular aspects of gait. The interpretation of sample entropy seems to change with the finding of the study due to the lack of a pre-determined hypothesis set by authors and in the field itself. Without future work, these measures cannot be used to predict possible outcomes of gait, but instead are only used to separate populations post hoc, that are already known to be different i.e. young vs elderly.

Detrended Fluctuation Analysis

Detrended fluctuation analysis (DFA) is a nonlinear technique introduced by Peng et al. in 1994 that can be used to quantify persistence within a time series. This measure was developed by expanding on the Hurst exponent which was born out of the field of fractals. Fractals are a subset of geometry that studies systems that exhibit patterns of self-similarity on increasing small scales. Fractals are common in nature showing up in plants and leaves and even in our biological architecture such as the lungs. When observing an object with fractal-like properties, the smallest part of the object will be self-similar to the whole. For example, the branching of the bronchi of the lungs is similar to the branching of the bronchioles when considered at a smaller scale. The Hurst exponent is directly related to the properties of fractals, quantifying the amount of similarity between a small portion of the fractal and the fractal as a whole. Detrended fluctuation analysis expands on this technique and allows for non-stationary data to be used, hence the term detrended. Using detrended fluctuation analysis, time-series data can be defined as being persistent, where a large data value will likely be followed by a larger value, or similarly decreasing values are followed by further decreases. Alternatively, time series can be defined as anti-persistent, where an increase in value will likely be followed by a decrease, or vice versa, indicating constant change in the direction of the time series. An α-value computed from DFA above 0.5 is categorized as persistent and a value less than 0.5 is categorized as anti-persistent. In this way, it can always be used as a measure of smoothness within a time series. Additionally, α

= 0.5 can be interpreted as a white noise time series where each value is independent of the others (Arif, Ohtaki, Ishihara, & Inooka, 2002).

To apply a detrended fluctuation analysis, a large time-series is needed for accurate results. The mean of the time series is subtracted from each data point in the time series to center the signal around zero, resulting in X_t. X_t is then broken up into multiple segments of the same length *n* and the local trend of each segment is calculated by fitting a least-squares line to each segment separately resulting in a piecewise sequence of straight-line fits, Y_t (see Figure 1.4 middle panel) The root mean squared deviation of X_t from Y_t is them calculated. This process is repeated for many different segment lengths *n* and the logarithm of the root mean square values are plotted against the logarithm of the segment length (see Figure 1.4 bottom panel).

$$f(n) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - Y_t)^2} \qquad \text{Equation 1.4}$$

Finally, the linear slope of the log-log scale is calculated to determine the α-coefficient (Bryce & Sprague, 2012; Dingwell & Cusumano, 2010). Detrended fluctuation analysis results indicating persistence show that strides are influenced by preceding strides and will continue to influence strides in the future. Having a persistent gait suggests a smoother, more stable gait that oscillates slowly with longer-term drifts. An anti-persistent gait may suggest the occurrence of constant corrections and a lack of influence of one stride to strides in the future. Again, similar to other nonlinear measures, studies typically attempt to distinguish different populations or a change in external conditions such as a change in speed, cadence, or gait environment to see their impact on gait persistence.

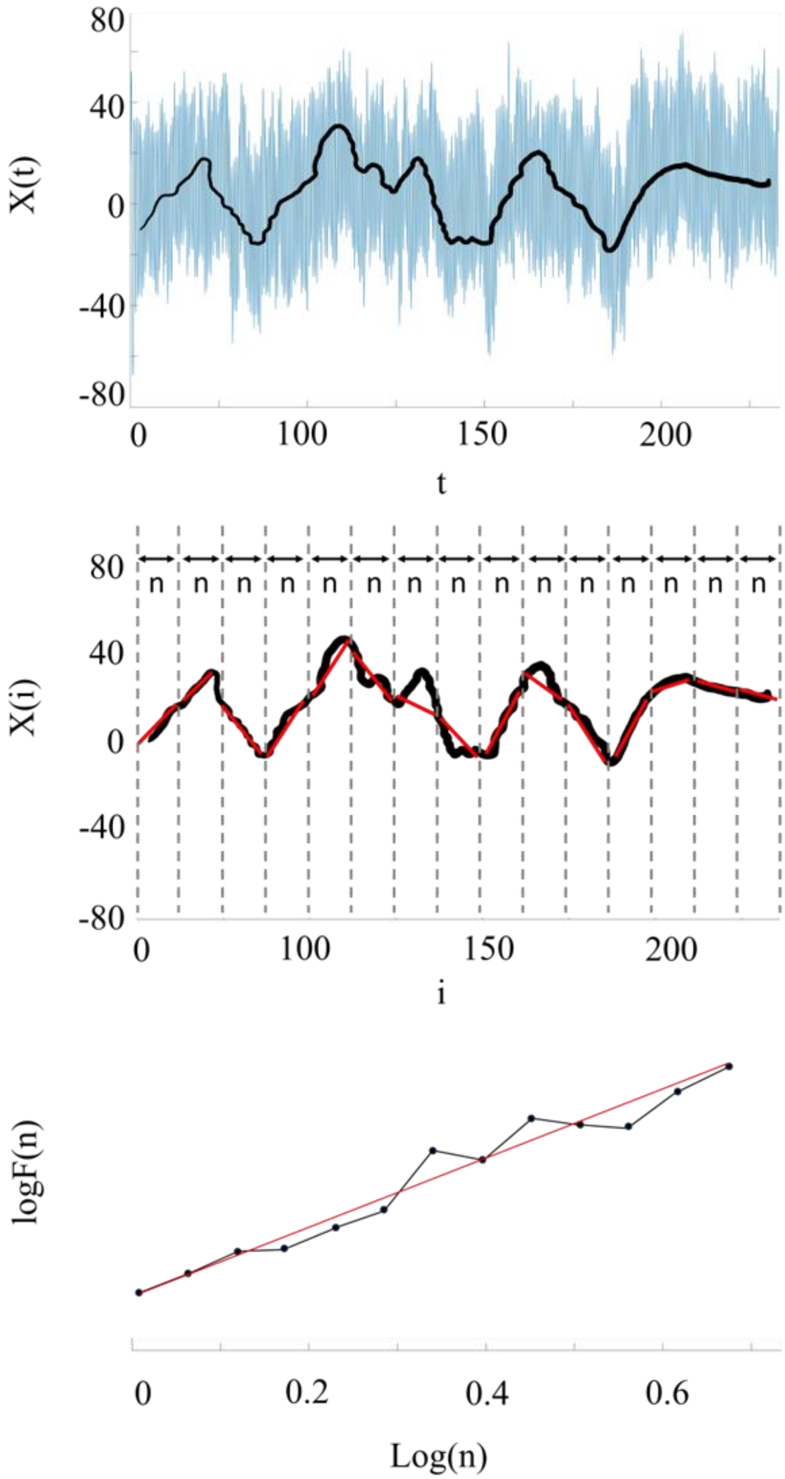

Figure 1.4. Depiction detrended fluctuation analysis calculation. The original time series **(top)** is demeaned and broken up into several segments of length n **(middle).** For each segment, the data is linearly detrended and the fluctuation around the linear trend is calculated. The mean fluctuation per window size is then plotted against the window size on a log scale **(bottom)**. The detrended fluctuation analysis exponent is then the slope of the best fit line of this plot. Redrawn and adapted from Decker, Cignetti, & Stergiou, (2010).

Using detrended fluctuation analysis, it has been shown that healthy adult gait has stride-to-stride correlations (i.e., $0.5 < \alpha < 1$) showing that current steps influence future steps, i.e. persistence (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Hausdorff et al., 1996). The data measures for these correlations are typically step/stride length and step/stride time. These stride to stride correlations are observed in both overground and treadmill walking (Dingwell & Cusumano, 2010). These findings indicate that fluctuations occurring during gait are not random white noise but contain deterministic structure and fractal-like properties indicating that each step influences steps that will occur in the future. However, with aging and disease, there is a breakdown in these strides to stride correlations resulting in less persistence and a more random gait behavior (i.e., $\alpha \approx 0.5$). This has been interpreted as a relationship between detrended fluctuation analysis, gait adaptability, and falls in the elderly (Arif et al., 2002; Hausdorff, 2007). For example, detrended fluctuation analysis was calculated between younger and older adults while walking at their preferred speed. The preferred walking speeds were not different between the groups, but the older adults had comparatively lower detrended fluctuation analysis values, closer to $\alpha = 0.5$, signifying a less persistent gait or more inherent noise within their walking pattern than the young adults. Similarly, when visually perturbed, older adults are affected more by this perturbation resulting in a less persistent walking pattern when compared to their unperturbed walking and visually perturbed younger adults (Franz, Francis, Allen, O'Connor, & Thelen, 2015). Detrended fluctuation analysis has also been found to be related to falls history in the elderly population (Norris, Marsh, Smith, Kohut, & Miller, 2005). Elderly individuals who are at a high risk of falling have decreased gait persistence, suggestive of gait instability. Taken together, detrended fluctuation analysis research shows a consistent pattern of results, implying the potential to use detrended fluctuation analysis to predict gait adaptability and individuals' risk of experiencing a fall.

Correlation Dimension

The correlation dimension is another nonlinear method that originates from the study of fractals. In normal geometrical figures, determining the dimensionality of an object is simple. Simple lines are one dimensional, planes are two dimensional, and solid objects are three dimensional. But then what is the dimension of a line winding through space and time with arcs and curves and angles? The von Koch curve seen in Figure 1.5 is an example of a fractal that shows how objects rendered one dimensional in normal geometry can look very different. The von Koch curve (Figure 1.5) at iteration stage 4 looks to be more than 1 dimensional but without an area it cannot be 2 dimensional. Fractal geometry is committed to quantifying this dimensionality which is somewhere between traditional integer geometrical dimensions. With the study of fractal properties, nonlinear analysis techniques can be used to quantify the successive iteration of the von Koch curve as having a higher level of dimensionality (Strogatz, 2018). While we are most used to the dimensionality of space, we can also consider the dimensionality of a time series. Correlation dimension is an approach to quantify the fractal dimension and has been used to investigate the dimensionality of human movement and behavior.

To quantify fractal dimensionality, one-dimensional data must be manipulated to reveal its nonlinear behavior over time. As seen in Figure 1.6 a one-dimensional time series produced by the Lorenz equations can be plotted against a time-lagged version of itself in two dimensions. This can be further plotted in three dimensions using another time-lagged version of the original time-series. This technique is known as reconstructing a state space, based on time-lagged versions of a one-dimensional time series, which can help to better understand how the time

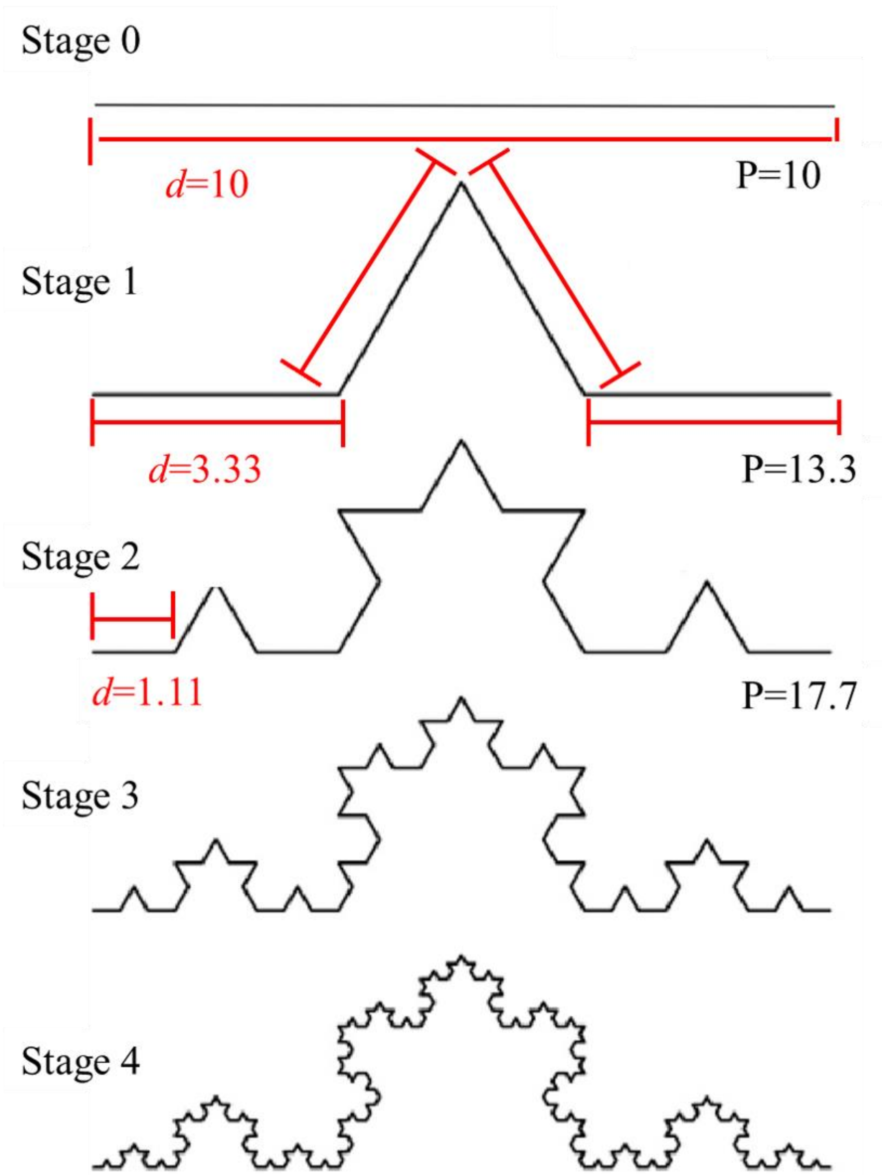

Figure 1.5. The von Koch curve. This two-dimensional shape is an example of an object with fractal properties. The von Koch curve has a finite area but infinite perimeter that increases with every iteration.

P= perimeter (sum of *d*); d= distance

series behaves over time and the dimensionality of the system. The Lorenz equations, when plotted in three dimensions (Figure 1.6 bottom panel), reveals that this signal is not noise, but rather displays a pattern within the state space revealing the richness of the system and further our understanding of its behavior through time and space.

The approach of phase space reconstruction can be used to study locomote behavior. While signals of dimensionality greater than three cannot be plotted, the dimensionality of a signal is can be computed as the correlation dimension using the Grassberger and Procaccia algorithm (1983). For example, the phase space of knee motion can be reconstructed from a time series of knee angle values recorded many times a second over many strides, using time-lagged versions of the original time series to create additional axis dimensions to identify the attractor with a higher dimensional state space to study its dynamics over time. Before the state space can be reconstructed and dimensionality computed using correlation dimension, the appropriate time lag and embedding dimension (number of dimensions in the reconstruction) are required, which are determined by the average mutual information (AMI) function (Fraser & Swinney, 1986) and false nearest neighbor (FNN) function (Kennel, Brown, & Abarbanel, 1992), respectively. The AMI function quantifies how much information is shared between two vectors of data over a set range of time delays. The first minimum of quantified information is chosen as the appropriate time delayed coordinates as this assures the time-delayed vector has minimum redundancy. A false neighbor occurs when data points are close together in lower dimensions but when embedded into a higher dimension, they are no longer close in distance. The FNN algorithm finds how many dimensions are necessary so that the number of false nearest neighbors approaches zero (Dingwell & Cusumano, 2000). To estimate the correlation dimension, the correlation sum C(r) is calculated, which quantifies the density of data points in a specified

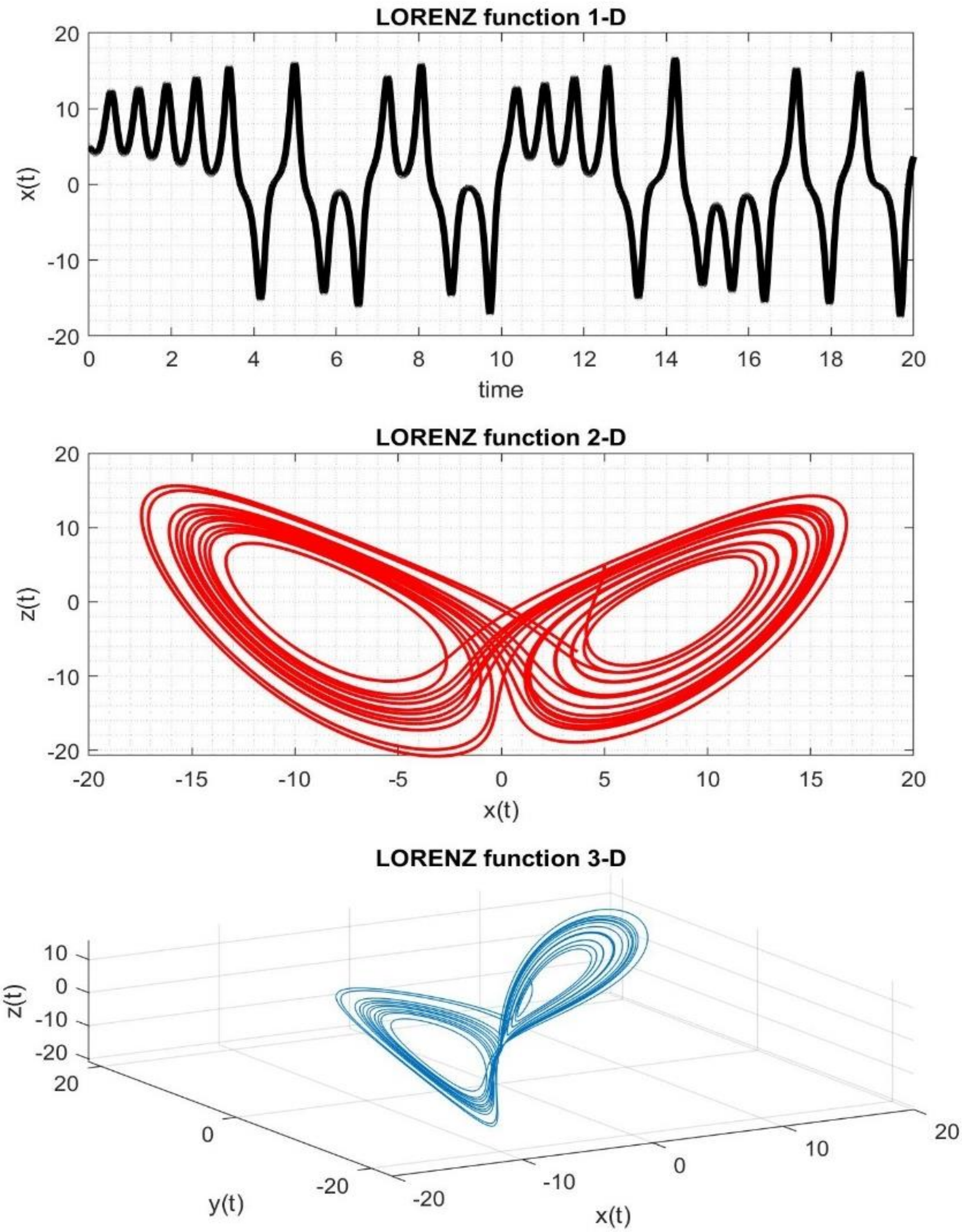

Figure 1.6. The Lorenz equations plotted in 1, 2 and 3 dimensions. One dimensional state space **(top)** time lagged 2-dimensional state space **(middle)** and time lagged 3-dimensional state space **(bottom)**.

radius *r* within the state-space. Many different radii are used to calculate the geometric structure of the time series embedded within the state space. A plot of logC(r), the probability value for that value of r, vs. log r is created. The linear slope of log[C(r,N)] and log(r), where N is the number of data points, is the estimated correlation dimension (CoD).

$$\mathrm{CoD} = \lim_{N \to \infty} \lim_{r \to 0} \frac{\log[C(r,N)]}{\log[r]} \qquad \text{Equation 1.5}$$

The correlation dimension is commonly used due to its ease of implementation. It is claimed that a low correlation dimension indicates a freezing of degrees of freedom (reduced number of components in a movement) and a higher correlation dimension indicates a releasing of the degrees of freedom (increased number of components in a movement, illustrating the stages of motor learning proposed by Bernstein (1967). The correlation dimension can be more directly used to measure the complexity of a deterministic system. The more embedding dimensions needed to fully describe the signal, the more complex the system is said to be. Compared to all the ways we could walk and the available degrees of freedom (possible joint motions), walking is a relatively simple process, typically found to occupy between 4 and 5-dimensional subspace when continuous knee angle is used

The effect of aging on walking complexity using correlation dimension has had mixed results. No differences in correlation dimensionality between young and old have been reported (Iqbal, Zang, Zhu, & Jie, 2015), while other studies have found an increase in correlation dimension in elderly individuals when compared to young One investigation, although using a slightly different technique to calculate correlation dimensionality, found young individuals, elderly individuals, and individuals with Parkinson’s to have increasingly complex gait patterns, respectively (Sekine et al., 2002). Further work is needed to understand the effect of aging and disease on gait dimensionality, but it does seem that an increase in age and task complexity/demand generally increases behavioral complexity as measured by correlation dimension measures. Thus, the correlation dimension is another method that can potentially reveal the health and proficiency of gait.

Local Dynamic Stability

Another nonlinear measure that can be computed based on the state space is known as local dynamic stability or the maximum Lyapunov exponent. Local dynamic stability quantifies the rate of divergence of nearby trajectories in state space over time (see Figure 1.7). It therefore directly attempts to quantify how stable the attractor is. Two of the most common methods for calculating local dynamic stability are the Wolf algorithm (Wolf, Swift, Swinney, & Vastano, 1985) and the Rosenstein algorithm (Rosenstein, Collins, & De Luca, 1993). Both are similar in procedure, but Rosenstein's method was designed especially for shorter data sets. This measure also uses the AMI and FNN functions to embed a time series into a reconstructed state space as previously discussed for the measure of correlation dimension. Briefly, local dynamic stability is the rate at which nearby trajectories in state space diverge.

$$d(t) = d_o e^{\lambda 1 t} \qquad \text{Equation 1.6}$$

Where d(t) is the mean divergence between trajectories in the state space at time *t*. d_0 is the initial separation between neighboring points and λ is the true Lyapunov exponent. The finite-time Lyapunov which is used to quantify local dynamic stability is defined as *t* approaches infinity and the initial separate approaches zero. The natural log of the average divergence distance is plotted against each time step and the slope of the linear portion of this line is taken to quantify the rate of divergence of trajectories of the system. In some instances, the slope of a second

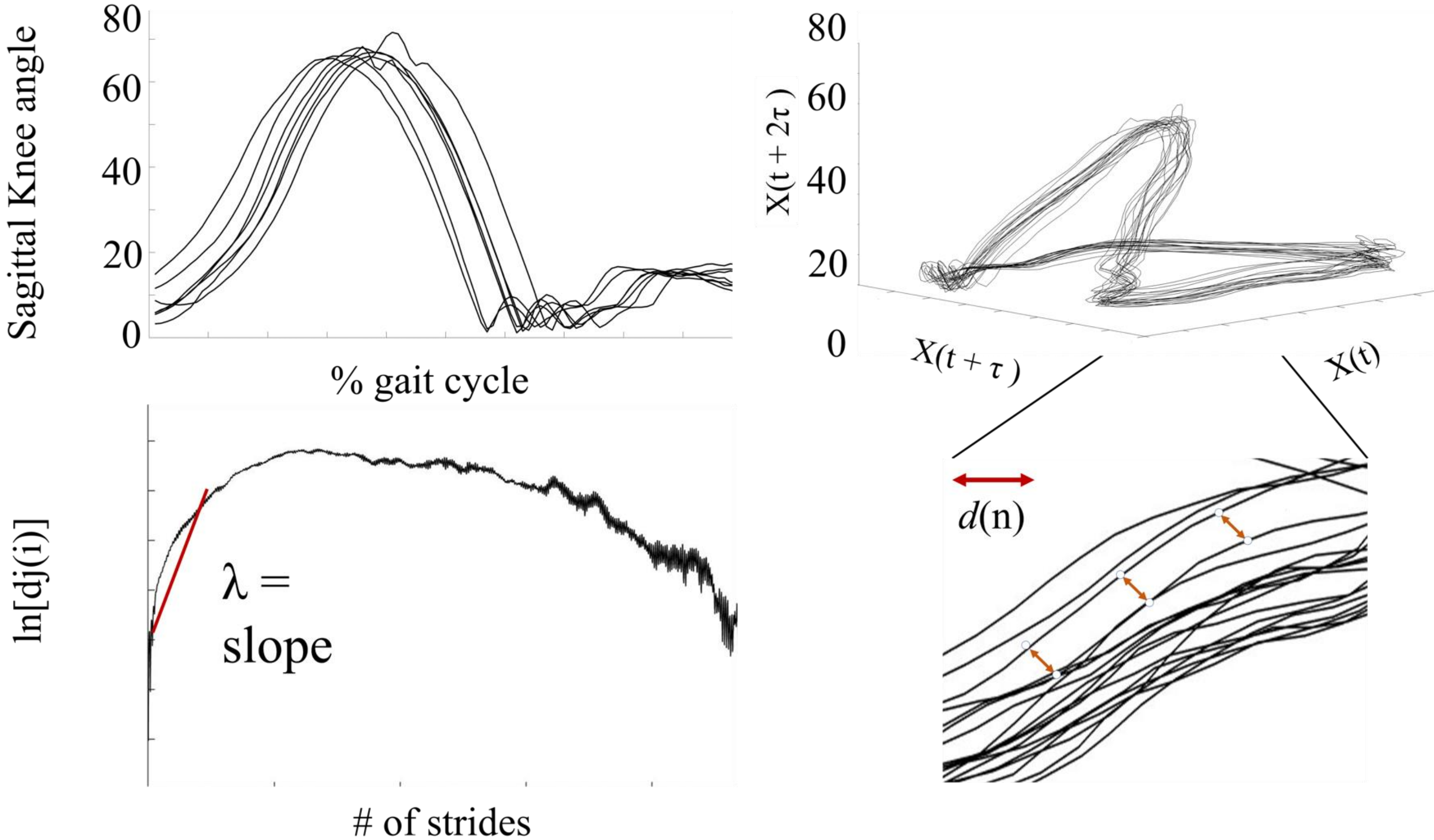

Figure 1.7. Depiction of local dynamic stability calculation. A time series **(top left)** is reconstructed using a time delayed embedding dimension **(top right)**. For each data point in turn, the nearest neighbor is found and the distance between them (*d*(n)) is computed for each time step **(bottom right)**. The natural log of the average divergence distance is plotted for each time step and the slope of the linear portion of this line for up to one stride is taken to quantify the exponential rate of divergence of the system **(bottom left).** Redrawn and adapted from Segal et al. (2008).

linear portion of the plot is taken and described as long-term divergence. These slopes are known as the largest or maximum Lyapunov exponent and provide a way to quantify local dynamic stability (Figure 1.7). Local dynamic stability is a tool that can be used to determine if a system has chaotic behaviors, defined as a system that has long term aperiodic deterministic behavior and is sensitive to initial conditions. Local dynamic stability can help categorize the structure of the system, whether it converges or divergences over time. If the trajectories that are near one another at time *t(i)* become separated in relatively few time steps, the system is considered unstable. If the distance between them in the state space stays consistent over time the system is said to be stable. This is quantified by the maximum Lyapunov exponent, the larger the exponent the faster the divergence, and therefore, the more locally unstable the system is said to be. Often local dynamic stability comparisons are made between young healthy adults and clinical, unhealthy, elderly, or rehabilitated populations. It can also be used to determine the change in stability of the system due to external conditions such as a change in speed, cadence, or gait environment. When comparing the young and the elderly, the elderly are typically less dynamically stable as measured by local dynamic stability (Mehdizadeh, 2018). For example, local dynamic stability was calculated on the hip, knee, and ankle coordinates as elderly and young females walked on a treadmill. It was found that the elderly had decreased local dynamic stability which is suggested to be a reason for the increased rate of falls in the elderly population (Buzzi et al., 2003). Similarly, local dynamic stability measures are used to differentiate healthy elderly individuals and the fall prone elderly individuals. It has been shown that the fall prone population and elderly individuals with a history of falls have decreased local dynamic stability, again suggesting that nonlinear measures of locomotor behavior can be used to quantify the strength of gait stability and assess gait performance or risk of falling (Granata & Lockhart, 2008; Terrier & Reynard, 2015; Toebes, Hoozemans, Furrer, Dekker, & van Dieën, 2012).

THEORIES OF AGE DEPENDENT CHANGES IN GAIT VARIABILITY

By studying the variability of locomotor behavior, researchers have found some age-dependent changes in linear and nonlinear measures of variability. Linear measures of variability have revealed older adults have increased stride to stride variability as measured by standard deviation and coefficient of variation, suggestive of increased noise or error within the older population (Hausdorff, Rios, et al., 2001). Measures of entropy have shown that the young healthy have significantly different amounts of stride to stride regularity and movement trajectory regularity compared to older adults. Interpretations of these results have been that young healthy individuals have an optimal amount of gait regularity and complexity and older adults fall out of the optimal range (Stergiou et al., 2016). Detrended fluctuation analysis has shown older adults to have decreased gait persistence which is suggestive to cause a loss of gait control. Correlation dimension has also been used to differentiate between young and old, finding differences in the dimensionality of their gait. Finally, local dynamic stability has shown that older adults have decreased stability in their movement trajectories when compared to younger adults, resulting in an unstable gait pattern. Therefore, it seems that the aging process has some ill effect on locomotor behavior, and this can be quantified using linear and nonlinear measures of gait variability. Two models have been developed to characterize what happens to gait patterns during the aging process which results in reduce locomotor health.

Loss of Complexity Hypothesis

It has been proposed that gait variability provides the necessary flexibility a person needs to manage a sudden change, such as a push or a change in the environment and these nonlinear measures discussed can quantify this ability (Decker, Cignetti, & Stergiou, 2010; Heiderscheit, 2000). One hypothesis suggests that there is a loss of complexity in biological systems as we age, which results in a reduced ability to adapt (Lipsitz & Goldberger, 1992). The core concepts of the loss of complexity hypothesis are that complexity is inherent and important to the biological system. As we age, there is a loss of this physiological complexity resulting from either structural changes within the system or a loss of communications between the structural elements within the system and this decrease is detrimental to the system. This loss can also be observed in individuals suffering from illness, injury, or disease (Lipsitz & Goldberger, 1992). Figure 1.8 illustrates the loss of complexity hypothesis. Figure 1.8A represents a healthy system where all structural elements are working and can communicate with one another through some communication channel. The ability for all elements within the system to communicate directly and indirectly represents the flexibility in the system that allows for adaptation to a changing environment. Figure 1.8B represent a system which has lost some of the communication channels, decreasing the systems complexity and flexibility. For example, neural connections in the human body that are not used or stimulated can begin to degrade possibly leading to decreased function. Loss of complexity can also occur due to the loss of an element in the system. In figure 1.8C, a structural element within the system has been lost leading to decreased flexibility and complexity. For example, post stroke individuals may have damaged tissue in certain areas of the brain, resulting in the loss of function associated with that brain area or structure such as speech or movement. The communication channels may still be functional, but no information or action is created from the damaged structural element. Together the loss of complexity model predicts that a loss of communicational (Figure 1.8b) or structural (Figure 1.8c) complexity in a system is associated with a decrease in function and general health that occurs with aging and illness. Loss of complexity through either means is expected to result in reduced adaptability by an individual to internal or external variation and changes in nonlinear measures of variability have then been interpreted as indicating reduced ability to adapt (Buzzi et al., 2003; Decker et al., 2010; Heiderscheit, 2000).

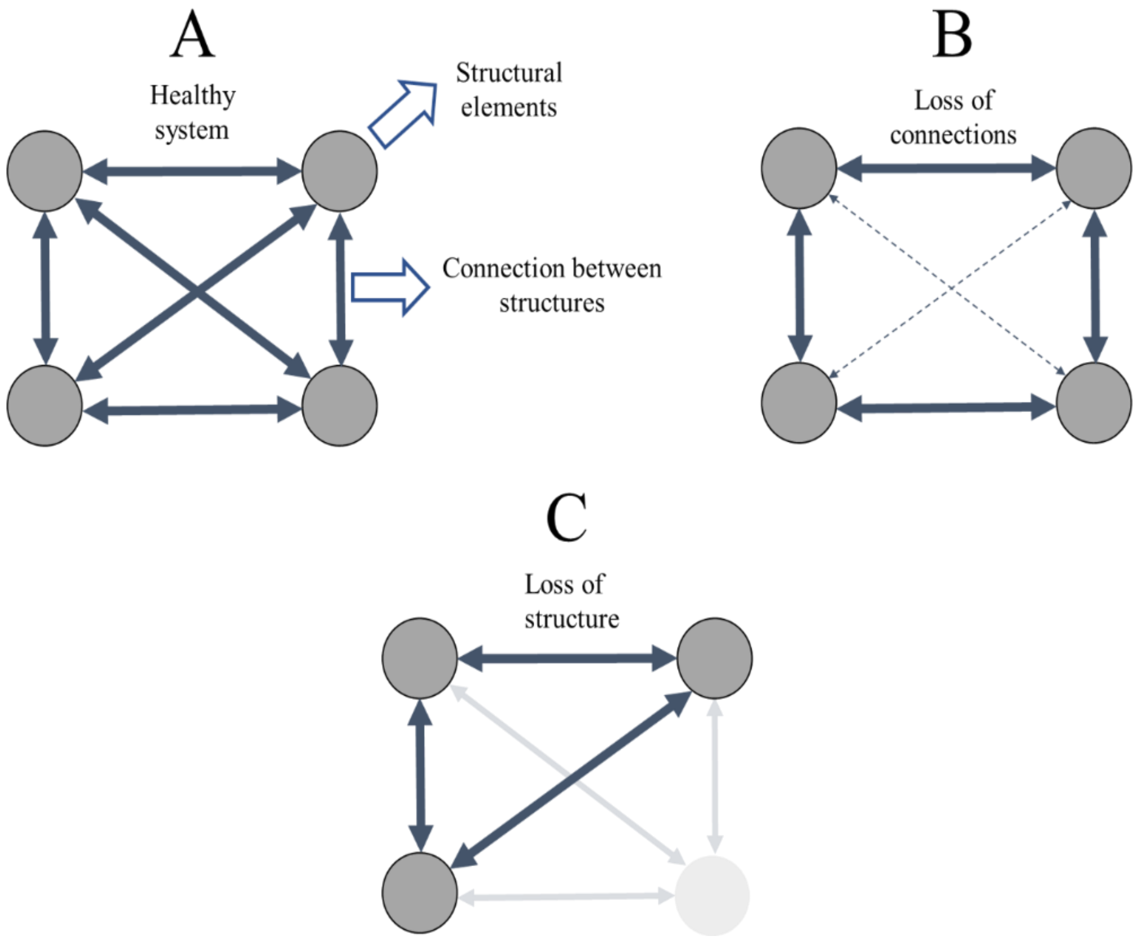

Figure 1.8: Loss of complexity model. Redrawn and adapted from Vaillancourt & Newell (2002).

Optimal Variability Hypothesis

Another hypothesis related to nonlinear measures of variability and adaptability suggests that there is an optimum level of variability that leads to a somewhat predictable, somewhat complex, and highly adaptable gait pattern which is depicted at the top of Figure 1.9. A system that produces random signals will have low complexity and low predictability, indicating a non-deterministic signal with little to no adaptability. A system can also produce highly predictable signals with limited complexity which also leads to reduced ability to adapt. A healthy system, at the top of Figure 1.9, produces relatively complex and relatively predictable signals which allows the system to be stable while also enhancing its ability to adapt. From the perspective of this hypothesis, young healthy individuals are expected to show optimal variability, with older adults and/or individuals with disease expected to show lower or higher levels of variability.

A concern with these models and the use of variability measures is that studies investigating the changes in locomotor behavior due to age and disease use inconsistent measurement techniques and inconsistent interpretations. Studies that used linear measures of variability to identify differences between populations have separately quantified variability using, stride length, stride time, trunk accelerations, etc., without understanding the relationship between these measures (Brach et al., 2010; Frenkel-Toledo et al., 2005; Toebes et al., 2012; Webster, Merory, & Wittwer, 2006), Studies also use nonlinear measures to differentiate between populations and again use different gait variables without understanding the relationship between the measures of data sources (Buzzi et al., 2003; Terada et al., 2015; Toebes et al., 2012). Little is known about the relationship between nonlinear and linear measures of different aspects of gait because only one or two measures of gait variability are used in each study investigating gait variability. Without understanding whether these measurement techniques and/or the type of data used are

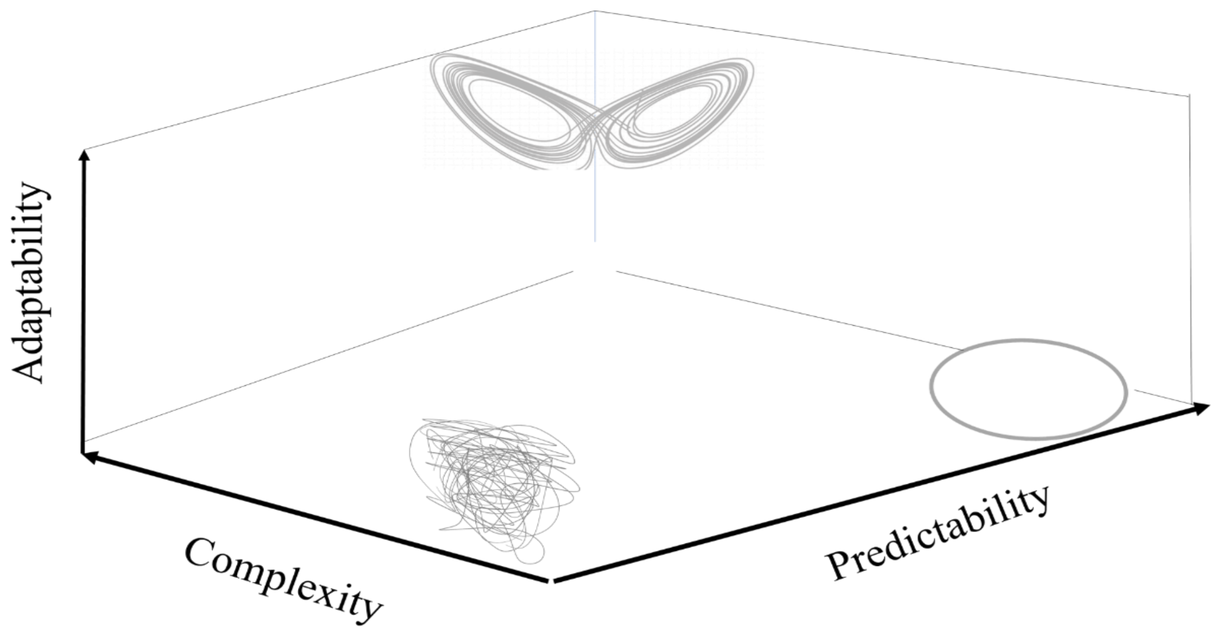

Figure 1.9. Optimal variability hypothesis. Redrawn and adapted from Stergiou, Kent, & McGrath (201)6.

correlated or independent of one another, it is difficult to conclude how variability, adaptability, and age are related. Very few studies have directly tested whether adaptability and gait variability are related, and no study has tested this claim using multiple measures of linear and nonlinear measures of variability in adults across the lifespan. There has been no consensus for which measures of variability on which type of data should be collected to accurately describe locomotor behavior and the change in this behavior due to age or disease (Hamacher, Singh, Van Dieen, Heller, & Taylor, 2011).

GAIT ADAPTABILITY

Gait adaptability can be defined as the ability of an individual to adjust to the task and environmental demands quickly and accurately. This ability seems to decrease with age as individuals become more hindered with neural, sensory, musculoskeletal, and cognitive declines (Maki & McIlroy, 2003; Maki, 1997) . The most popular method for investigating gait adaptability is the split-belt treadmill paradigm (Torres-Oviedo, Vasudevan, Malone, & Bastian, 2011). This paradigm uses a treadmill with two separate belts, each powered independently, allowing the belts to move at different speeds. By moving the belts at different speeds, participants are required to adapt their gait pattern. This paradigm has been used to test the ability of infants, children, adults, and clinical populations to adapt their gait (Reisman, Bastian, & Morton, 2010). The task creates a step length asymmetry which typically disappears over time as individuals adapt their kinetics and kinematic gait parameters to complete the split-belt walking task. Children, clinical populations, and the elderly have been shown to have a decreased ability to adapt to this task. These populations are unable to fully correct the step length asymmetry, have increased time to reach step length symmetry, and/or show smaller aftereffects in step length asymmetry which indicates that the new gait pattern was not "learned" (Bruijn, Van Impe, Duysens, & Swinnen, 2012; Musselman, Patrick, Vasudevan, Bastian, & Yang, 2011; Vasudevan, Torres-Oviedo, Morton, Yang, & Bastian, 2011). While studies have noted the differences in gait adaptability between old and young populations, no study has investigated how this ability changes over the aging process. Also, while the above mentioned nonlinear measures are suggestive to measure the adaptability of gait, only two studies have attempted to directly test if there is a relationship between gait variability and adaptability (Ducharme, Kent, & Van Emmerik, 2019; Ducharme & van Emmerik, 2018). In these works, only one measure of variability, detrended fluctuation analysis, was used which limited the scope of the research to investigate the relationship between adaptability performance and a single measure of variability. Using only one measure of variability, the authors found no relationship between variability and adaptability performance (Ducharme et al., 2019).

RELEVANCE OF GAIT MEASURES

The gait measures used to investigate locomotor variability included stride time, stride length, knee flexion angle, and pelvis motion in the medial-lateral and vertical directions. These gait measures were chosen from other numerous measures of gait for explicit reasons. First, this dissertation critically examines the literature on gait variability and therefore uses the same measures of gait that are commonly used in this research literature. Using the same gait measures allows the findings from these studies to be applied to previous studies. Additionally, because this study aims to find relationships between multiple measures of variability (chapter 3), comparisons between different measures of gait variability used in previous and future studies will be able to be made. For example, if there is a strong relationship between SD of stride time and LDS of pelvis vertical motion, previous or future studies using one or other of these measures can be related. The use of less common measures of gait would obviate these important contributions to the gait variability literature. These measures of gait were also chosen for their utility in the clinical setting. These measures can be quantified without highly specialized equipment and are functional and clinically important in gait as discussed below.

Walking strides and steps are fundamental to gait and movement. Manipulation of these spatiotemporal measures stride time and stride length (similarly step time and step length) are what allows for changes in gait speed (Lythgo, Wilson, & Galea, 2011) and are important for maintaining balance during gait (Schniepp et al., 2012). Clinically, the regulation of these measures is essential to gait health. Older individuals and individuals suffering from disease are less able to regulate these spatiotemporal aspects of gait leading to increased falls risk (Kobsar, Olson, Paranjape, Hadjistavropoulos, & Barden, 2014; Richardson, Thies, DeMott, & Ashton-Miller, 2005; Woo, Ho, Lau, Chan, & Yuen, 1995). For example, older individuals and individuals experiencing freezing of gait due to Parkinson's disease are less able to appropriately regulate their stride time when compared to younger individuals and individuals not experiencing freezing of gait, respectively (Hausdorff et al., 2003; Kobsar et al., 2014; Woo et al., 1995). Stride time and stride length variability have also been associated with cognition and executive function. Individuals with cognitive impairments have altered spatiotemporal patterns of gait demonstrating the significance and usefulness of these measures (Montero-Odasso, Verghese, Beauchet, & Hausdorff, 2012). Stride time and stride length have also been found to be a driving force for the locomotor system as individuals tend to walk at the speed which optimizes the stride time and stride length variability (Schniepp et al., 2012). These studies highlight the utility of using spatiotemporal measures of strides or steps in gait-related research.

The angular movement of the knee joint during walking is another fundamental aspect of gait and commonly used in gait research. While walking, the knee joint rotates about the medial-lateral axis in the sagittal plane. When the foot first leaves the ground, the knee begins to flex along with flexion of the hip and ankle allowing for proper foot clearance as the leg swings forward during each step. As the foot approaches the ground, the foot moves further away from the body by producing flexion of the knee joint. This allows for the absorption of the ground reaction force and adequate step length to safely progress the rest of the body forward. The inability to properly move the knee joint due to injury or deficits in neuromuscular control can result in problems concerning balance, shock absorption, and joint health. (Chaudhari, Briant, Bevill, Koo, & Andriacchi, 2008; Hart et al., 2016; Henriksen et al., 2006; Luc-Harkey et al., 2016). Compromised knee joints can also lead to decreased neuromuscular control resulting in more irregular movement patterns of the knee and possible gait imbalances (Moraiti et al., 2009; Rathleff et al., 2013; Yakhdani et al., 2010). This continued study of knee joint movement is important as it may also drive locomotor behavior. Similar to measures of stride time and stride length, individuals walk at a speed that optimized the stability of the knee joint motion illustrating its importance in the study of gait (Russell & Haworth, 2014).

Measuring the center of mass oscillations during walking can reveal a considerable amount of information about an individual’s gait balance and deficits(Tesio & Rota, 2019). However, directly measuring the center of mass of individuals as they walk can be impracticable as the center of mass is located inside the body, and the center of mass location changes between individuals because of differences in body type and shape. The motion of the pelvis is often used as an accurate surrogate measure for the center of mass of the body (Gard, Miff, & Kuo, 2004; Saini, Kerrigan, Thirunarayan, & Duff-Raffaele, 1998). The interaction of the center of mass and base of support (the area around the sections of the body which are in contact with the ground) is how balance is maintained during locomotion(Lugade, Lin, & Chou, 2011). During walking, the center of mass oscillates in the vertical direction from peak to valley as the body switches from single stance to double stance. The center of mass position in the medial-lateral direction oscillates from left to right with each step as the feet alternate from left foot ground contact and right foot ground contact (Tesio & Rota, 2019). If the center of mass moves outside the base of support, the individual will need to quickly increase the base of support or move their center of mass back into the base of support to avoid a fall. Maintaining the proper regulation of this movement is necessary to keep the body's center of mass stable and inside the base of support while moving in the forward direction. The indirect measure of the center of mass is a feasible measure to detect gait imbalances. Its use has shown elderly patients to be less able to properly control their center of mass (Chen & Chou, 2010; Lee & Chou, 2006; Lugade et al., 2011). This inability to properly regulate the center of mass results in decreased head stability and altered vestibular input which is associated with aging, and increased fall risk (Berthoz & Pozzo, 1994; Mazzà, Iosa, Pecoraro, & Cappozzo, 2008; Spoor, Wood, & Zonneveld, 1994). However, acutely increasing or decreasing the magnitude of the center of mass oscillation has been shown to increase the metabolic cost of walking (Gordon, Ferris, & Kuo, 2009; Ortega & Farley, 2005). This indicates that the movement of the center of mass is another driving factor of locomotion that must be properly regulated to maintain a safe and stable pattern of gait. Altogether, these gait measures are commonly used in research, in clinical practice, and are essential to gait performance. Altered spatiotemporal patterns or the movement patterns of the knee and center of mass have been associated with injury, disease, and gait imbalances supporting the notion that these parameters may be driving forces behind locomotion.

Statement of the Problem

Measures of gait variability are used to assess gait performance and assess fall risks for populations and specific individuals. There are numerous techniques used to measure gait variability including linear and nonlinear techniques. Further, these analysis techniques are applied to many different data sources of gait such as step length, step time, joint angles, and movement trajectories. Nonlinear measures are claimed to measure gait adaptability, which is often said to allow for safe and healthy ambulation that is necessary to adjust to changing external or internal environments and task demands. However, the research investigating gait variability has not come to a consensus on 1) how measures of gait variability change with age 2) the relationship between gait variability measures, and 3) the relationship between gait variability measures and adaptability performance. The purpose of this work was to investigate how measures of gait variability change with age. This work also investigated the relationship between measures of variability to determine which if any measures of gait variability are related. Finally, this work investigated if measures of variability were predictive of an individual's performance on a gait adaptability task.

AIMS

Aim 1

The loss of complexity hypothesis theorizes that the loss of communications between structures in the body due to age and the loss of structures themselves leads to a loss in the overall movement complexity of gait. This loss of complexity is proposed to occur even in healthy aging across the lifespan and to especially result in changes in the variability of movement. The purpose of this work was to investigate if measures of gait variability during steady-state walking are sensitive to age-related changes in gait across the lifespan in healthy individuals. Linear measures such as standard deviation (SD) and coefficient of variation (CV) are typically used to quantify the magnitude of stride to stride fluctuations in stride time or length. Recently, nonlinear measures have been used to quantify structure in gait variability and are suggested to be more sensitive than linear measures to age-related changes in gait. Sample entropy (SampEn) is a nonlinear measure that quantifies the regularity or predictability of fluctuations in stride lengths or time during gait. Correlation dimension (CoD) is a nonlinear measure that quantifies dimensionality of movement trajectories (e.g., knee angle or pelvis position) during gait. Local dynamic stability (LDS) is a nonlinear measure that quantifies the stability of movement trajectories (e.g., knee angle or pelvis position) during gait. Detrended fluctuation analysis (DFA) is a nonlinear measure that quantifies the persistence in a sequence of stride times or lengths. These measures were used to investigate the relationship between aging and gait variability and to test the loss of complexity hypothesis. From the loss of complexity hypothesis, SD and CV are expected to increase with age as older adults are suggested to be less able to control their gait leading to larger stride to stride variations. Loss of complexity with age is expected to be observed as an increase in stride to stride regularity or predictability (decrease in SampEn values) as loss of structures or communication leads to a less complex sequence of stride times or lengths. Also, aging is theorized to result in a decrease in stride to stride persistence (DFA) due to the diminishing neuronal structures and communication between neuronal and musculoskeletal structures in the body. This loss of complexity is also expected to reduce the dimensionality of movement trajectories (CoD) and decrease stability (increase LDS values). Therefore, it was hypothesized that SD and CV of stride times and length and LDS (an inverse measure of stability) of knee and pelvis motion would be positively related with age, while SampEn (inverse measure regularity) of stride time and length, CoD of knee angle and pelvis motions, and DFA of stride time and length would be negatively related to age. Stride time, stride length, knee angle, and pelvis motion in the vertical and medial-lateral dimension were calculated as adults across the lifespan walked on a treadmill at their preferred gait speed. The relationship between age and each measure of gait variability was determined using simple linear regression analyses.

Aim 2

Measures of variability including SD, SampEn, CoD, LDS, and DFA have all been suggested to quantify an underlying construct of gait that is related to an individual's ability to adapt. However, studies that evaluate movement variability typically compute only one or two measures of gait variability making it difficult to recognize the relationship between measures of variability and the constructs of gait they identify. The purpose of this work was to identify the relationships between measures of gait variability and the gait constructs they independently or dependently quantify. Identifying these relationships and constructs is important to understand if measures of variability are quantifying the same aspects of gait allowing researchers and clinicians to optimize data collection and more accurately compare results across studies. To determine the relationship between gait variability measures and identify underlying gait constructs a statistical procedure called principal component analysis (PCA) was applied to measures of gait variability. A principal component analysis (PCA) is a descriptive statistical technique that is used to reduce the dimensionality of a data set by revealing if and which measures are related to one another, and the strength of their relationship to the underlying component or construct they are measuring. In this study, the gait variability measures of interest included SD of stride length and stride time, SampEn of stride length and stride time, CoD of knee angle and pelvis motions, LDS of knee angle and pelvis motions, and DFA of stride length and stride time, which were calculated as adults walked on a treadmill at their preferred gait speed. Several hypotheses were tested in this study. In line with the literature, all measures of variability could load onto a single component possibly related to adaptability or, at the other extreme, all dependent variables could be unrelated and thereby quantifying different components of gait variability. Alternatively, the principal component analysis could reveal a smaller subset of constructs with variables grouping together. These groupings could be based on variability measure, i.e. SD of stride time is highly related to SD of stride length, or on some other underlying components of gait variability.

Aim 3

Measures of gait variability are suggested to reveal an individual's ability to adapt their pattern of gait when necessary. The types of adaptability tasks measures of variability are said to quantify is not defined in the literature, but instead refers to adaptability as a general construct. Very few studies have directly tested the claim that measures of variability are related to adaptability and no study has used multiple measures of gait variability to investigate the relationship between adaptability and measures of gait variability. The purpose of this study was to test the claim that measures of gait variability are related to an individual's ability to adapt. The split-belt treadmill paradigm is one of the most common adaptability tasks utilized to investigate an individual's capacity to adapt their gait pattern to a change in the walking environment. This study used the split-belt treadmill paradigm as the adaptability task. Measures of variability included SD of stride length and stride time, SampEn of stride length and stride time, CoD of knee angle and pelvis motions, LDS of knee angle, and pelvis motions, and DFA of stride length and stride time.

The relationship between constructs of variability discovered from the principal component analysis of study 2 and adaptability performance was also determined. Adaptability performance during the split-belt treadmill paradigm task was assessed using methodology from previous literature by calculating the step length asymmetry during the last 50 steps of the split-belt treadmill paradigm. Based on previous literature and the loss of complexity hypothesis, larger magnitude in stride to stride variability, quantified as SD of stride length and stride time, was hypothesized to be negatively related to adaptability performance. SampEn of stride length and stride time was predicted to be positively related to adaptability performance, as lower SampEn values indicate greater regularity and are assumed to mean the individual is less able to respond to a changing environment. CoD of knee angle and pelvis motion was hypothesized to be positively related to adaptability performance as greater dimensionality is assumed to provide a greater ability to adapt. LDS (an inverse measure of stability) of knee angle and pelvis motion was hypothesized to be negatively related to adaptability performance as individuals with a more stable gait are expected to better adapt to the environment. DFA of stride length and stride time was hypothesized to be positively related to adaptability performance as increased gait persistence is assumed to correspond with increased adaptability performance. Finally, age was hypothesized to be negatively related to adaptability performance due to age-related deleterious changes in gait behavior and outcomes. These relationships were determined using multiple simple linear regression analyses.

CHAPTER 2

GAIT SPEED IS A BETTER PREDICTOR OF GAIT VARIABILITY THAN AGE

INTRODUCTION

Identifying the changes in locomotor behavior that are associated with the aging process has long been of interest to researchers and clinicians as falls are a significant cause of morbidity and disability in the elderly (Al-Aama, 2011). One of the most noticeable and universal findings is the decline in walking speed (Alexander, 1996). As we age, walking speed is seen to decrease around 1 to 2% per decade until around the age of 60. After 60 years old, there is a rapid decrease in walking speed, estimated to be between 12 and 16% per decade (Himann, Cunningham, Rechnitzer, & Paterson, 1988) This decline in walking speed has been attributed to a decrease in step and stride length (Boyer, Andriacchi, & Beaupre, 2012; Elble, Thomas, Higgins, & Colliver, 1991; Himann et al., 1988). This decrease in gait length has been suggested to be an adaptation made by older individuals to increase gait stability (Finley, 1969; Maki, 1997; Winter, Patla, Frank, & Walt, 1990). Surprisingly, however, those who walk slower and with a step length fall more than those who walk faster and with a longer step length (Bergland, Jarnlo, & Laake, 2003; Gehlsen & Whaley, 1990; Guimaraes & Isaacs, 1980; Lipsitz, Jonsson, Kelley, & Koestner, 1991). This paradoxical finding leads to questions regarding what changes in gait behavior over the aging process can lead to gait instability and what analysis and techniques can be used to quantify gait performance and gait stability.

A common method used to analyze the performance of gait has been to use standard deviation and coefficient of variation of stride to stride gait dynamics. When doing so, it has been shown that older individuals have increased stride to stride variability of stride length, stride time, and stride width (Hausdorff, Rios, et al., 2001; Öberg, Karsznia, & Öberg, 1993; Owings & Grabiner, 2004) and this increase in variability is related to and predictive of falls (Bergland et al., 2003; Hausdorff, Rios, et al., 2001; Lord, Lloyd, & Keung Li, 1996). These works have led to the belief that increased gait variability, as measured by standard deviation and coefficient of variation, is detrimental to gait performance, possibly leading to an elevated fall risk (Hausdorff, Edelberg, et al., 1997). Historically, it has been believed that these measures were capturing error or noise within a signal, indicating that older adults produce more movement error leading them to be more susceptible to falls. However, standard deviation and coefficient of variation, characterized as linear measures, quantify the magnitude of variability but ignore the sequence in a time series. In contrast, nonlinear measures of variability quantify patterns and sequential structure in a time series and suggest that variability is not simply noise, but can be adaptive (Newell & Corcos, 1993). This has led researchers to use nonlinear measures of variability in an effort to further the understanding of how locomotor behavior changes with age.

Some of the most common nonlinear methods used to quantify gait are correlation dimension (CoD), local dynamic stability (LDS), sample entropy (SampEn), and detrended fluctuation analysis (DFA). These measures attempt to quantify different characteristics of variability, including, dimensionality, stability, regularity, and persistence. Considering the dimensionality of movement, sitting and swinging a leg forward and backward at the knee joint is a relatively low dimensional movement compared to movements of the knee during walking. This dimensionality can be computed via correlation dimension (CoD), a nonlinear technique created by Grassberger and Procaccia (1983) that originates from the study of fractals. While we are most used to the dimensionality of space, we can also consider the dimensionality of a time series. In standard geometrical figures, determining the dimensionality of an object is simple. Lines are one dimensional, planes are two dimensional, and solid objects are three dimensional. Using fractals, the dimensionality of a line winding through space and time can also be quantified. For example, a time series of knee angle recorded many times a second over multiple walking strides can be plotted against time-lagged versions of itself. Repeating the process with additional time-lagged dimensions creates a phase plot showing an attractor or consistent pattern. The number of dimensions needed to reveal this attractor approximates its dimensionality, however, only a limited region of state space is visited, hence dimensionality can be a non-integer value. CoD quantifies this non-integer dimensionality or complexity of the original knee angle (or other measures) time series. The direction of age-dependent changes in CoD has been mixed. No differences in CoD between young and old have been reported in some studies (Iqbal et al., 2015), while others have observed an increase in correlation dimension in elderly individuals when compared to the young (Buzzi et al., 2003). Results from another study, although using a slightly different technique to calculate correlation dimensionality, found young individuals, elderly individuals, and individuals with Parkinson's to have increasingly complex gait patterns, respectively (Sekine et al., 2002). Hence, while some previous research has identified differences between young, old and individuals with disease, change in dimensionality of gait across the lifespan has not been investigated.

Quantifying the dynamic stability of the movement during gait is another approach used to measure locomotor variability. Here, stability refers to the human movement system's resistance to change, the ability to move back into its stable pattern quickly after a perturbation, or how persistent a gait pattern is over time. Stability is typically measured as the maximum Lyapunov exponent and referred to as local dynamic stability (LDS) (Bizovska, Svoboda, Janura, Bisi, & Vuillerme, 2018; Dingwell & Cusumano, 2000). This measuring technique quantifies the stability of a gait pattern by measuring the divergence of movement trajectories over time. The larger the LDS value, the faster the rate of divergence, and therefore, the more locally unstable the system is said to be. Fall prone and elderly individuals with a history of falls have decreased local dynamic stability and therefore are less dynamically stable (Granata & Lockhart, 2008; Terrier & Reynard, 2015; Toebes et al., 2012). However, these studies do not typically investigate the age-dependent changes across the lifespan but instead compare separate groups of old and young adults.

Another approach to quantifying variability is to assess the regularity or predictability of time series such as stride length or stride time. Walking on a flat surface in a straight line would likely result in relatively predictable or repeatable stride lengths and times. Walking through the woods on a dirt trail would result in less predictable, more irregular stride lengths and times as gait will adjust to the changing environment. Sample entropy (SampEn) is a nonlinear measure adapted from approximate entropy that can be used to quantify this regularity or predictability of a time series by determining the probability of sequences of data points being repeated (Pincus & Huang, 1992; Richman & Moorman, 2000). A higher SampEn value indicates a low probability of repetition and therefore less regularity in the data, while smaller SampEn values represent increased regularity or predictability within the signal. However, research has found that aging can result in both increases or decreases in gait predictability when compared to younger counterparts (Arif et al., 2004; Karmakar et al., 2007; Leverick et al., 2014).

Finally, the persistence or smoothness of spatiotemporal gait parameters over time can be quantified. In a persistent gait pattern, a long stride length is likely to be followed by another long stride and a short stride is likely to be followed by a short stride. An anti-persistent gait would occur when a long stride is followed by a short stride which is then followed by another long stride. Detrended fluctuation analysis (DFA) is used to quantify persistence within a signal (Peng et al., 1994; Peng et al., 1995). A DFA value close to 1 suggests a more persistent, smoother, and slowly drifting gait pattern. A DFA value closer to 0.5, or less, suggests an anti-persistent gait. With aging and disease, there is a breakdown in gait persistence resulting in less persistence and a more random gait behavior (i.e., $\alpha \approx 0.5$), possibly indicating constant corrections and a lack of influence of one stride to strides in the future (Arif et al., 2002; Dingwell & Cusumano, 2010). In continuation of these findings, a cross-sectional study that used local dynamic stability to determine the effect of age on stability found that gait stability may begin to change between the ages of 40-50 (Terrier & Reynard, 2015). Further investigation of the age-dependent changes in LDS across the lifespan is necessary.

Utilizing these measures of variability, the movement of older individuals have often been found to become less dynamical stable (Buzzi et al., 2003; Mehdizadeh, 2018) less regular (Leverick et al., 2014) and less persistent (Arif et al., 2002; Hausdorff, 2007)when compared to young healthy controls. These findings support the loss of complexity hypothesis proposed by Lipsitz and Goldberger in 1992 (Lipsitz & Goldberger, 1992) which suggest that with age there is a decline in biological complexity, leading to a decline in the ability to adapt to new environments or tasks (Decker et al., 2010; Heiderscheit, 2000). A limitation of much of this prior research investigating changes in locomotor behavior with age using linear and nonlinear measures of variability is that they typically compare older adults to young adults, but do not consider the changes that occur across the lifespan. Also, these studies typically examine only one or two measures of variability making it difficult to understand the relationship between measures of variability, which has led to a lack of consensus on which techniques are appropriate to investigate and detect changes in locomotor behavior over the aging process.

The purpose of this work was to determine how aging affects individuals' gait variability Specifically, we will be testing whether age predicts linear measures (SD and CV) and nonlinear measures (LDS, CoD, SampEn, and DFA) of gait variability. It is hypothesized that our findings will support the loss of complexity hypothesis by showing a consistent unidirectional change in gait variability measures over the aging process. Specifically, SD and CV are predicted to be positively related to age, and CoD, LDS, DFA, and SampEn will be negatively related to age.

METHODS

This study was approved by the Old Dominion University Institutional Review Board (reference number 19-143). Participants included 34 volunteers (22 females, 12 males) ranging from 23 to 71 years old (see Table 2.1). Data collection took place between January and March 2020. Inclusion criteria included the ability to walk for at least 15 minutes at a time and the ability to walk for a total of 45 minutes with intermittent breaks. Exclusion criteria included any history of neuromuscular or neurological injury or disease or a current acute injury that affected gait. Following the participants' informed consent, demographic information including age, height, weight, daily physical activity participation, and sex were recorded. Participants were prepared for three-dimensional motion capture by attaching reflective sphere markers. The passive marker set was adapted from previous works (Bowersock, Willy, DeVita, & Willson, 2016; Petit, Willson, & Barrios, 2014): Four anatomical markers placed on the superior iliac crests to defined the pelvis, markers placed on the greater trochanters and femoral condyles defined the thighs, markers placed on the tibial plateaus and malleoli defined the shanks, a four-marker cluster placed on top of metatarsal head 1 to 5, and a marker on the heel cup of the shoe defined the feet. Tracking markers include the pelvis markers to track the pelvis. Clusters were used to decrease skin artifact movement and were placed on the lateral aspect of the thighs and posterior-lateral aspect of the shanks to track the lower limbs. The 5-foot markers remained to track the foot. All other markers were removed.

Table 2.1. Participant demographics	Mean	SD
Age (years)	41.8	14.5
Body weight (kg)	74.9	24.0
Body height (cm)	169	8.13
Preferred walking speed (m/s)	1.13	0.13

N=34 SD is the standard deviation

Kinematic data were collected using 10 cameras (Vicon) collecting at 100 Hz over a treadmill. A treadmill was chosen instead of assessing overground walking as continuous time-series data over many strides is necessary to calculate the nonlinear techniques used here. Before data collection began, participants preferred treadmill walking speed was determined by incrementally increasing the treadmill speed until the participant announced the current speed is their preferred walking speed. After one- and one-half minutes of walking at this speed, the treadmill slowed to a stop. The treadmill speed was then set to a speed that was approximately 15% higher than the participants stated the preferred speed. The treadmill then incrementally decreased until the participant announced the current speed is their preferred. The average of the two stated preferred speeds was taken as the preferred walking speed (Ducharme et al., 2019; Jordan, Challis, & Newell, 2007).

Participants first walked on the treadmill at their self-selected preferred speed for six-minutes to become acclimated to the treadmill. To capture gait variability, participants walked on the treadmill for six-minutes at their self-selected preferred speed. The variables of interest included stride length, stride time, knee joint sagittal plane angle for the dominant limbs (N=3 left foot dominant), and pelvis position in the medial-lateral and vertical axes. Stride length was defined as the anterior-posterior difference of the heel marker at the time of subsequent foot contacts of the ipsilateral limb (Reisman et al.). Foot contact was defined by the local minimum of the vertical position of the heel marker and foot off was defined as the peak vertical velocity of the heel marker (Pijnappels, Bobbert, & van Dieën, 2001; Roerdink, Lamoth, Kwakkel, Van Wieringen, & Beek, 2007). The flexion-extension knee angle was defined as the relative angle between the shank and the thigh segments. The pelvis position used to define pelvis position was defined as the center of the four anatomical markers placed on the back of the pelvis. Stride length, stride time, knee angle, and pelvis vertical and medial-lateral positions defined above were measured using the motion capture software (Vicon Nexus, Oxford, UK). These measures were chosen because of their consistent use in gait variability research, their functional importance in gait, and the feasibility of collection in a clinical and laboratory setting (Gordon et al., 2009; Kobsar et al., 2014; Lythgo et al., 2011; Moraiti, Stergiou, Ristanis, & Georgoulis, 2007; Russell & Haworth, 2014; Schniepp et al., 2012; Tesio & Rota, 2019). Gait variability analysis was completed using a custom MATLAB 2019b script. SD, SampEn, and DFA were implemented on stride measures, as is common. CoD and LDS were implemented on knee angle and pelvis motion.

The mean, SD, and CV were calculated on a stride to stride basis for stride length and stride time for each subject over the 6-minute trial (10 strides were trimmed from the beginning and end for all analysis). The SampEn value for stride time and stride length over the 6-minute trials was quantified using parameters m of 2 and r of .2 times the standard deviation of the time series (Pincus & Huang, 1992; Russell & Haworth, 2014; Yentes et al., 2013). DFA was calculated on the sequence of the last 250 stride times and stride lengths. Following recommendations in the literature, the window sizes used in the analysis ranged from six strides to the total number of strides divided by eight (Damouras, Chang, Sejdić, & Chau, 2010; Delignières, Almurad, Roume, & Marmelat, 2016; Weilert, 2017).

To begin calculating CoD and LYE, each movement trajectory time series was first normalized by extracting the last 100 strides from the 6-minute trial. These 100 strides were resampled so that on average 100 frames were equal to 1 stride. Therefore, each participant was analyzed using the same length and size of data, of 100 strides containing 100 frames each similar to previous works (Dingwell & Cusumano, 2000; Granata & Lockhart, 2008). The average mutual information (AMI) and false nearest neighbor (FNN) algorithms were used to determine the subject-specific time lag and number of dimensions to reconstruct the state space. The AMI function quantifies how much information is shared between two vectors of data and assures the time-delayed is appropriate and the vectors have minimum redundancy. The FNN algorithm finds how many dimensions are necessary so that the number of false nearest neighbors approaches zero. A false nearest neighbor occurs when data points are close together in lower dimensions but are no longer close when embedded into a higher dimension. Previous works have found a similar result between using subject-specific or the same values for all participants (Raffalt, Guul, Nielsen, Puthusserypady, & Alkjaer, 2017). The CoD of knee joint angle and pelvis medial-lateral and vertical positions were then quantified using the Grassberger and Procaccia algorithm (Dingwell & Cusumano, 2000; Grassberger & Procaccia, 1983; Raffalt et al., 2017). The short term local dynamic stability was quantified between 0 and 1 strides for knee joint angle and pelvis oscillation (Dingwell & Cusumano, 2000; Raffalt et al., 2017; Rosenstein et al., 1993).

Statistical analysis

Linear regression models were used to identify significant relationships between predictor variables (age, walking speed) and the outcome variables measured during gait. Model 1 used age as the predictor variable. Because age and preferred walking speed are known to be related, model 2 used speed as the predictor variable to determine if the outcome measures predicted by age could also be predicted using preferred walking speed. A third multiple linear regression model used a forced entry of both predictor variables which were age and speed to determine if the inclusion of both predictor variables improved the statistical model when compared to only one predictor variable. An alpha level of 0.05 was used to define a significant prediction. The predictor and outcome coefficients, 95% confidence intervals for the coefficients, standardized coefficients, and adjusted R^2 values are reported for model 1 (Table 2), and model 2 (Table 3). Additionally, the significant F change was reported for model 3 (Table 3) to test if age significantly improved prediction over speed alone. Effect sizes for regression analyses were interpreted as small ($0.01 \leq R^2 \leq 0.09$), medium ($0.09 \leq R^2 < 0.25$), and large ($R^2 \geq 0.25$) (Cohen, 2013). Separate independent t-tests were also implemented to compare differences in gait variability measures between the youngest and oldest participants. This analysis was conducted to compare this data with previous research which has investigated the mean variability differences between older and younger individuals, typically excluding middle-aged adults. Measures of gait variability of the youngest adults (n=12, age < 31 years old) were compared with measures of gait variability of the oldest adults (n=7, age > 59 years old) using independent t-tests with the level of significance set at $p \leq .05$ for all statistical tests. Effect sizes for the independent t-tests were computed using Hedge's g and interpreted as small ($0.3 \leq g < 0.5$), medium ($0.5 \leq g \leq 0.8$), and large ($g \geq 0.8$) (Cohen, 2013).

RESULTS

The results from model 1 are shown in table 2.2. The outcome measures mean gait speed and mean stride length were found to be predicted by age. Of all the linear measures outcome measures of gait variability, only CV of stride length was significantly predicted by age. Of the nonlinear measures, only SampEn of stride time was significantly predicted by age. Preferred gait speed and mean stride length decreased with age while stride length CV and SampEn of stride time were positively correlated with age. The largest effect of age was on preferred gait speed, accounting for 21% of the variance.

Model 2 shows that of the linear measures, mean stride time, mean stride length, and stride length CV were significantly predicted by the participant's preferred walking speed (Table 2.3). Of the nonlinear measures, SampEn of stride time, SampEn stride length, CoD of knee angle, and pelvis position in the vertical direction was significantly predicted by preferred walking speed. Outcome measures that were negatively related with preferred walking speed included mean stride time, CV of stride length, SampEn of stride time, and CoD of knee angle and vertical pelvis motion. Outcome measures that were positively related to preferred walking speed included mean stride length and SampEn of stride length. Comparing these results with model 1, all the outcome measures predicted by age were predicted using preferred walking speed. Also, more of the variance was explained by the preferred walking speed than age. Speed accounted for more than 50% of the variance in mean stride length and SampEn of the stride time between individuals. Large effects were also observed with speed accounting for approximately 30% of the variance in stride length CV, and knee angle CoD. The other significant linear relationships with speed were all moderately sized (11-24% of the variance).

Table 2.2. Results of simple linear regression analysis using age as the predictor variable

Variable Name	Constant Coefficient	95% CI		Outcome Coefficient	95% CI		Standardized Coefficient	*p* value	Adjusted R-Squared
Mean Gait Speed	1.30	1.18	1.43	0.00	-0.01	0.00	-0.48	**0.00***	0.21
Mean Stride Time	1.08	1.01	1.14	0.00	0.00	0.00	0.32	0.06	0.07
Mean Stride Length	985	901	1069	-2.40	-4.30	-0.50	-0.41	**0.01***	0.15
SD Stride Time	0.03	0.02	0.04	0.00	0.00	0.00	-0.04	0.84	-0.03
SD Stride Length	20.9	14.2	27.6	0.08	-0.07	0.23	0.18	0.30	0.00
CV Stride Time	0.03	0.02	0.03	0.00	0.00	0.00	-0.09	0.60	-0.02
CV Stride Length	0.02	0.01	0.03	0.00	0.00	0.00	0.35	**0.04***	0.09
SampEn Stride Time	1.44	1.16	1.73	0.01	0.00	0.01	0.38	**0.03***	0.12
SampEn Stride Length	2.15	2.09	2.21	0.00	0.00	0.00	-0.13	0.46	-0.01
DFA Stride Time	0.65	0.52	0.78	0.00	0.00	0.00	0.18	0.30	0.00
DFA Stride Length	0.64	0.53	0.75	0.00	0.00	0.00	0.00	1.00	-0.03
COD Knee Angle	3.19	2.90	3.48	0.00	0.00	0.01	0.19	0.28	0.01
COD Pelvis ML	3.66	3.52	3.79	0.00	-0.01	0.00	-0.23	0.19	0.02
COD Pelvis VT	3.62	3.54	3.71	0.00	0.00	0.00	0.04	0.84	-0.03
LDS Knee Angle	0.99	0.70	1.29	0.00	-0.01	0.01	0.02	0.91	-0.03
LDS Pelvis ML	0.09	0.00	0.18	0.00	0.00	0.00	0.25	0.16	0.03
LDS Pelvis VT	1.07	0.94	1.21	0.00	0.00	0.00	0.22	0.21	0.02

SD is standard deviation; CV is coefficient of variation; SampEn is sample entropy; DFA is detrended fluctuation analysis; CoD is correlation dimension; LDS is local dynamic stability; ML is medial-lateral direction; VT is vertical direction.

* indicates significance ($p < .05$)

Table 2.3. Results of simple linear regression analysis using gait speed as the predictor variable

Variable Name	Constant Coefficient	95% CI		Outcome Coefficient	95% CI		Standardized Coefficient	*p* value	Adjusted R-Squared
Mean Stride Time	1.36	1.18	1.54	-0.20	-0.36	-0.05	-0.42	**0.01***	0.15
Mean Stride Length	280	118	44.0	536	393	678	0.80	**0.00***	0.64
SD Stride Time	0.04	0.01	0.06	-0.01	-0.03	0.01	-0.14	0.41	-0.01
SD Stride Length	41.9	22.8	60.9	-15.7	-32.4	1.08	-0.32	0.07	0.07
CV Stride Time	0.03	0.01	0.05	0.00	-0.02	0.01	-0.07	0.69	-0.03
CV Stride Length	0.07	0.05	0.10	-0.04	-0.06	-0.02	-0.59	**0.00***	0.32
SampEn Stride Time	3.55	2.91	4.18	-1.59	-2.15	-1.03	-0.72	**0.00***	0.50
SampEn Stride Length	1.94	1.77	2.11	0.17	0.02	0.32	0.37	**0.03***	0.11
DFA Stride Time	0.80	0.41	1.18	-0.08	-0.41	0.26	-0.08	0.65	-0.02
DFA Stride Length	0.53	0.21	0.86	0.09	-0.19	0.38	0.12	0.50	-0.02
COD Knee Angle	4.72	4.02	5.43	-1.23	-1.85	-0.61	-0.58	**0.00***	0.32
COD Pelvis ML	3.52	3.12	3.93	0.04	-0.32	0.40	0.04	0.80	-0.03
COD Pelvis VT	3.99	3.77	4.20	-0.32	-0.51	-0.12	-0.51	**0.00***	0.24
LDS Knee Angle	0.45	-0.40	1.30	0.49	-0.26	1.24	0.23	0.19	0.02
LDS Pelvis ML	0.41	0.14	0.67	-0.23	-0.46	0.00	-0.33	0.05	0.08
LDS Pelvis VT	1.44	1.05	1.82	-0.25	-0.59	0.09	-0.26	0.14	0.04

SD is standard deviation; CV is coefficient of variation; SampEn is sample entropy; DFA is detrended fluctuation analysis; CoD is correlation dimension; LDS is local dynamic stability; ML is medial-lateral direction; VT is vertical direction.

* indicates significance ($p < .05$)

The purpose of model 3 was to determine if age predicts any variance in gait variables over and above the variance accounted for by speed. Therefore, a multiple linear regression was performed for each dependent outcome measure using both predictor variables, speed, and age. Age did not predict any variables over and above the variance accounted for by speed (Table 2.4).To relate these results with previous research which has focused on investigating differences in mean gait variability measures between the young and the old (Arif, Ohtaki, Nagatomi, & Inooka, 2004; Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Ducharme, Kent, & Van Emmerik, 2019; Hausdorff et al., 1997; Kang & Dingwell, 2008; Mehdizadeh, 2018) the oldest participants (n=7, age>59) and youngest participants (n=12 age<31) were placed into separate groups and compared. The oldest adults were found to have a significantly slower gait, decreased stride length, and an increased stride time SampEn value, all of which had large effect sizes (Table 2.5).

Table 2.4. Results of multivariate linear regression analysis using age and gait speed as predictor variables

Variable Name	Constant Coefficient	95% CI		Speed Coefficient	95% CI		Standardized Coefficient	*p* value	Age Coefficient	95% CI		Standardized Coefficient	*p* value	Model Significance	F	F-Significance	Adjusted R-Squared
Mean Stride Time	1.29	1.05	1.53	0.00	0.00	0.00	0.15	0.42	-0.17	-0.35	0.01	-0.35	0.03	0.03	0.67	0.52	0.15
Mean Stride Length	300	77.9	522	-0.19	-1.63	1.25	-0.03	0.79	525.33	360	690	0.79	0.00	0.00	0.07	0.93	0.63
SD Stride Time	0.04	0.01	0.08	0.00	0.00	0.00	-0.14	0.50	-0.01	-0.04	0.01	-0.21	0.57	0.57	0.47	0.63	-0.03
SD Stride Length	40.2	14.0	66.5	0.02	-0.15	0.19	0.04	0.85	-14.84	-34.3	4.66	-0.30	0.19	0.19	0.04	0.97	0.05
CV Stride Time	0.04	0.01	0.06	0.00	0.00	0.00	-0.17	0.42	-0.01	-0.03	0.01	-0.15	0.67	0.67	0.67	0.52	-0.04
CV Stride Length	0.07	0.04	0.10	0.00	0.00	0.00	0.08	0.62	-0.04	-0.06	-0.01	-0.55	0.00	0.00	0.25	0.78	0.31
SampEn Stride Time	3.45	2.58	4.32	0.00	0.00	0.01	0.05	0.74	-1.54	-2.19	-0.89	-0.69	0.00	0.00	0.11	0.90	0.48
SampEn Stride Length	1.92	1.68	2.15	0.00	0.00	0.00	0.06	0.75	0.18	0.01	0.35	0.40	0.10	0.10	0.11	0.90	0.08
DFA Stride Time	0.64	0.12	1.16	0.00	0.00	0.00	0.19	0.36	0.01	-0.38	0.40	0.01	0.59	0.59	0.86	0.43	-0.03
DFA Stride Length	0.48	0.03	0.93	0.00	0.00	0.00	0.07	0.72	0.12	-0.21	0.46	0.15	0.75	0.75	0.13	0.87	-0.05
CoD Knee Angle	4.95	3.99	5.91	0.00	-0.01	0.00	-0.12	0.48	-1.35	-2.07	-0.64	-0.64	0.00	0.00	0.51	0.61	0.31
CoD Pelvis ML	3.77	3.23	4.32	0.00	-0.01	0.00	-0.27	0.18	-0.09	-0.49	0.32	-0.09	0.39	0.39	1.88	0.17	0.00
CoD Pelvis VT	4.14	3.85	4.43	0.00	0.00	0.00	-0.27	0.12	-0.40	-0.61	-0.18	-0.64	0.00	0.00	2.60	0.09	0.27
LDS Knee Angle	0.12	-1.04	1.28	0.00	0.00	0.01	0.17	0.39	0.67	-0.19	1.53	0.31	0.30	0.30	0.74	0.48	0.02
LDS Pelvis ML	0.34	-0.02	0.70	0.00	0.00	0.00	0.11	0.56	-0.19	-0.46	0.08	-0.28	0.13	0.13	0.34	0.71	0.06
LDS Pelvis VT	1.32	0.79	1.85	0.00	0.00	0.00	0.13	0.53	-0.19	-0.59	0.20	-0.20	0.28	0.28	0.41	0.67	0.02

SD is standard deviation; CV is coefficient of variation; SampEn is sample entropy; DFA is detrended fluctuation analysis; CoD is correlation dimension; LDS is local dynamic stability; ML is medial-lateral direction; VT is vertical direction.

* indicates significance ($p < .05$)

Table 2.5. Independent t-test comparing outcome variables between the oldest (age > 59,) and youngest (age < 31) participants

	Old N=7		Young N=12			
Variable Name	Mean	SD	Mean	SD	Hedge's g	*p* value
Gait Speed (m/s)	0.99	0.17	1.16	0.07	1.37	**0.01***
Stride Time (s)	1.17	0.07	1.12	0.05	-0.71	0.14
Stride Length (cm)	801.07	118.49	906.46	60.97	1.17	**0.02***
SD Stride Time (s)	0.03	0.01	0.03	0.01	0.12	0.79
SD Stride Length (cm)	27.53	8.59	24.91	5.86	-0.36	0.44
CV Stride Time	0.02	0.00	0.03	0.01	0.22	0.63
CV Stride Length	0.04	0.01	0.03	0.01	-0.79	0.10
SampEn Stride Time	2.02	0.26	1.75	0.25	-1.03	**0.04***
SampEn Stride Length	2.11	0.08	2.12	0.04	0.22	0.63
DFA Stride Time	0.73	0.10	0.70	0.13	-0.20	0.67
DFA Stride Length	0.62	0.09	0.62	0.10	0.05	0.92
COD Knee Angle	3.53	0.23	3.41	0.26	-0.45	0.34
COD Pelvis ML	3.56	0.15	3.62	0.06	0.57	0.23
COD Pelvis VT	3.66	0.11	3.64	0.07	-0.20	0.66
LDS Knee Angle	1.00	0.38	0.95	0.25	-0.14	0.77
LDS Pelvis ML	0.18	0.09	0.12	0.07	-0.73	0.13
LDS Pelvis VT	1.23	0.16	1.16	0.13	-0.44	0.35

SD is standard deviation; CV is coefficient of variation; SampEn is sample entropy; DFA is detrended fluctuation analysis; CoD is correlation dimension; LDS is local dynamic stability; ML is medial-lateral direction; VT is vertical direction.

* indicates significance ($p < .05$)

DISCUSSION

The purpose of this study was to investigate the relationship between age and measures of gait variability. It was hypothesized that linear measures, standard deviation (SD) and coefficient of variation (CV), would be positively associated with age, and secondly, that nonlinear measures, correlation dimension (CoD), local dynamic stability (LDS), detrended fluctuation analysis (DFA), and sample entropy (SampEn) would be negatively associated with to age. In support of the first hypothesis, CV of stride length was positively related to age (r^2=.09), revealing stride length variability increased with age when normalized to the mean stride length, which decreases with age. However, age only accounted for 9% of the variance in CV stride length, and no other SD or CV measure was significantly related to age. SampEn of stride time increased significantly with age, as predicted by our second hypotheses, but only accounted for a moderate 12% of the variance. Contrary to our second hypothesis, age was not statistically significantly related to any of the other nonlinear measures: DFA, CoD, or LDS. Overall, these findings contradict some previous research which has found differences in nonlinear measures of gait variability between different the young and old populations (Buzzi et al., 2003; Hausdorff, Mitchell, et al., 1997; Kang & Dingwell, 2008; Mehdizadeh, 2018), although some studies have also failed to find significant effects (Bollens, Crevecoeur, Detrembleur, Guillery, & Lejeune, 2012; Iqbal et al., 2015). Differences between the current study and prior literature such as the sample population age range and walking environment could be partially responsible for the alternative findings.

Previous gait variability research has typically focused on identifying differences between young and old groups of participants and reported on age-related changes. In contrast, the present study used regression analyses to assess the relationship between age and measures of variability.

However, the inclusion of middle-aged individuals in this sample population may have obscured the effects of age that have previously been reported(Buzzi et al., 2003; Hausdorff, Mitchell, et al., 1997; Mehdizadeh, 2018). We, therefore, investigated differences in outcome measures between the oldest and youngest participants to compare with previous findings. The oldest individuals were found to walk significantly slower and with shorter strides than the youngest participants. These findings are in line with previous studies that have found a decline in walking speed around the age of 60 are attributed more to shorter stride lengths than shorter step times (Alexander, 1996; Himann et al., 1988). Of all measures of variability, only SampEn of stride time was found to be significantly different between the young and the old ($p=.037$, $g=1.03$). Older individuals produced strides that were less regular than younger individuals (Karmakar et al., 2007; Leverick et al., 2014). Given that the current study replicated the common finding of previous aging studies, that preferred walking speed and stride length decrease with age, the limited effects of aging on gait variability appears to be a robust finding. In fact, the regression analysis suggests that age explained significantly more variance in preferred walking speed (21%) than any other variable, and that gait speed was more predictive of measures of gait variability than age.

Considering the effect of gait speed on linear measures of variability, a decrease in gait speed, whether natural or experimentally, results in increased SD and CV of stride dynamics (Beauchet et al., 2009; Brach, Berthold, Craik, VanSwearingen, & Newman, 2001; Kang & Dingwell, 2008; Kang & Dingwell, 2008). Our finding of a negative relationship between stride length CV and gait speed supports these findings. However, this increase in gait variability magnitude is not found to be detrimental to the dynamic stability of gait. The slower gait speed used by older adults, accomplished by shortening stride lengths, is suggested to be a strategy used to increase dynamic gait stability, as measured by LDS. Studies that directly investigated the effect of gait speed on dynamic stability have found that experimentally slowing individuals' gait increases the dynamic stability of joints in the lower extremity (Dingwell & Marin, 2006; England & Granata, 2007). However, these studies only included young adults and did not consider the effect of age. A later study that included both young and older adults found older adults to also increase their dynamic stability when gait speed was slowed, even more than younger adults. (Kang & Dingwell, 2008). Our results are in support of this finding as a nearly significant finding ($p=0.05$) between self-selected preferred gait speed and LDS was found. Those who naturally walk slower had a nearly significant increase ($p>0.05$) in the dynamic stability of the pelvis movement in the medial-lateral direction and had decreased knee angle and vertical pelvis movement dimensionality as measured by CoD. No clear directional change was found between gait speed and measures and SampEn. Thus, a decrease in gait speed, whether naturally or experimentally, leads to increased variability magnitude but increased dynamic stability of gait decreased.

In conclusion, our results found age to be a poor predictor of gait variability measures. Instead, preferred walking speed, which was negatively associated with age, was predictive of more gait outcome measures and accounted for more of the variance. Numerous studies have found gait speed to decrease in age, especially in the elderly and frail who are at the highest risk of falls. The decrease in gait speed in the older populations may explain why previous findings often indicate a relationship between age and measures a gait variability. As age increases, speed typically decreases which was found to be a driving factor of gait variability measures. Further investigations on the effect of gait speed and measures of gait variability across the lifespan are needed to confidently quantify and interpret any possible relationship

CHAPTER 3

IDENTIFICATION OF FOUR INDEPENDENT COMPONENTS OF GAIT VARIABILITY

INTRODUCTION

Human movement is inherently variable. Although healthy adults have extensive experience walking, the motions of the body vary from stride to stride, even when walking over smooth, flat ground or on a treadmill. Each stride looks slightly different than the last. Traditionally, gait variability has been quantified by linear measures, such as the standard deviation, and was computed on spatiotemporal parameters such as stride time and stride length (Newell & Corcos, 1993). Increased linear variability measures quantify a larger magnitude of variability and have been interpreted as indicating more neuromuscular noise and a potential sign of underlying disease and increased risk of falling (Callisaya et al., 2011; Hausdorff, 2007; Paterson et al., 2011). Linear measures, however, ignore the temporal sequence in the movement trajectories or strides while nonlinear analysis techniques have been developed to quantify structure in a data sequence. These nonlinear measures appear to be more sensitive than linear measures and have been used to detect differences in gait variability between young and old, fallers and non-fallers, and individuals with and without different neurological diseases (Bizovska et al., 2018; Buzzi et al., 2003; Cavanaugh et al., 2010; Ducharme et al., 2019; Hausdorff, 2009; Hausdorff, Rios, et al., 2001; Weilert, 2017). The nonlinear measures of gait variability have been interpreted as quantifying neuromuscular health and the ability of an individual to adapt their gait to changes in the task (e.g., different speeds) and environment (e.g., obstacles) (Buzzi et al., 2003; Decker et al., 2010; Heiderscheit, 2000).

Nonlinear measures of gait variability are viewed as quantifying the same underlying construct of gait (i.e., locomotor healthy), but there are several different approaches for computing variability: regularity, persistence, dimensionality, and stability. Sample entropy (SampEn) can be used to quantify the regularity of a gait sequence by computing the probability of a sequence of values being repeated (Pincus & Huang, 1992; Richman & Moorman, 2000). If the sequence of stride times followed a sine wave pattern then the predictability or regularity would be high (SampEn would be closer to 0), but if it was a more complex combination of sine waves or random noise then the signal would be less regular (SampEn would be closer to 2). Previous works have found older adults and individuals who fall to have increased entropy, signifying decreased movement regularity (Karmakar et al., 2007; Kurz & Stergiou, 2003). Detrended fluctuation analysis (DFA) takes a different approach by quantifying persistence in the data time series (Hausdorff et al., 1995; Peng et al., 1994). Higher DFA values ($\alpha > 0.5$) indicate persistence, whereby longer stride times are typically followed by even longer ones, and shorter stride times subsequently get shorter. An $\alpha \leq 0.5$ indicates anti-persistence, where short stride times are typically followed by longer values and vice versa. Typically, young healthy adults have DFA values closer to $\alpha = 1$, indicating persistence in stride times or lengths, while older adults have values closer to $\alpha \approx 0.5$, indicating an anti-persistent gait pattern (Dingwell & Cusumano, 2010; Hausdorff, Ashkenazy, et al., 2001; Maraun, Rust, & Timmer, 2004).

Nonlinear measures of dimensionality and stability are typically applied to movement trajectories such as knee angle position or pelvis/trunk motion. To begin calculating the dimensionality and stability of movement during gait, a state-space of movement trajectories is reconstructed using time-lagged versions of itself, revealing a self-replicating pattern. Correlation dimension (CoD) is a technique that can then be used to estimating the number of dimensions of state space the movement trajectory exists in (Grassberger & Procaccia, 1983). The greater the dimensionality the more complex the movement trajectory. Studies show older individuals have increased CoD, signifying an increase in movement complexity (Buzzi et al., 2003). The local dynamic stability (LDS) of the trajectories in state space can also be quantified by the rate at which nearby trajectories diverge, computed as the maximum Lyapunov exponent (Rosenstein et al., 1993). Higher values indicate a greater rate of divergence and therefore reduced dynamic stability. When comparing young and older adults, the elderly have movement patterns that are typically less dynamically stable (Mehdizadeh, 2018).

While these nonlinear techniques take different approaches to quantify gait variability, it remains unknown whether they can be interpreted as measuring the same underlying construct of neuromuscular health. Unfortunately, studies typically compute only one or two of these measures at a time. Therefore, the current study applied multi measures of gait variability to investigate the relationships between measures. Specifically, regularity and persistence of stride times and stride lengths, and dimensionality and stability of knee angle, vertical pelvis motion, and medial-lateral pelvis motion, were quantified as adults across the lifespan walked using their preferred gait. To identify the number of underlying constructs a statistical procedure called principal component analysis (PCA) was applied to twelve linear and nonlinear measures of gait variability. There are several possible hypotheses that this approach will test. In line with the literature, all measures of variability could load onto a single construct or, at the other extreme, all dependent variables could be unrelated and thereby quantifying different independent characteristics. Alternatively, the PCA could reveal a smaller subset of constructs with variables grouping together. These groupings could be based on nonlinear techniques (e.g., all regularity measures load highly on the same construct) or on some other aspect of gait.

METHODS

Participants

This study was approved by the Old Dominion University Institutional Review Board (reference number 19-143). Thirty-four healthy adults (23-71 years of age) volunteered to participate in the study (Table 3.1). Inclusion criteria included the ability to walk for at least 15 minutes at a time and the ability to walk for a total of 45 minutes with intermittent breaks. Exclusion criteria included any history of neuromuscular or neurological injury or disease or a current acute injury that affects gait. Participants were prepared for the protocol by adhering reflective sphere markers used for three-dimensional motion capture to anatomical landmarks on the lower limbs and trunk (Bowersock et al., 2016; Petit et al., 2014). Ten motion capture cameras (Vicon) recorded motion of the markers. Participants walked on a treadmill as many continuous strides are necessary to calculate the nonlinear measures. Before data collection began, participants self-selected their preferred treadmill walking speed. The individuals then became acclimated to walking on the treadmill for at least 6 minutes. The experimental protocol included one six-minute walking trial in which participants walked at their self-selected speed on the treadmill.

Table 3.1. Participant demographics	Mean	SD
Age (years)	41.8	14.5
Body weight (kg)	74.9	24.0
Body height (cm)	169	8.13
Preferred walking speed (m/s)	1.13	0.13
Falls risk score (0-10)	9.99	0.04
Exercise (days per week)	3.7	2.0

N=34 SD is the standard deviation

Data Analysis

Based on the motion capture data stride length, stride time, knee joint angle for the dominant leg (N=3 left foot dominant), and pelvis position in the medial-lateral and vertical axes were computed. Stride length was defined as the anterior-posterior difference of the reflective heel marker at the time of subsequent foot contacts of the ipsilateral limb (Reisman et al.). Foot contact was defined by the local minimum of the vertical position of the reflective heel marker, and foot off was defined as the peak vertical velocity of the reflective heel marker (Roerdink et al., 2007). The flexion-extension knee angle was defined as the relative angle between the thigh and shank segments which were based on marker clusters placed upon the thigh and shank. The pelvis position used to define pelvis oscillation was defined as the center of four anatomically placed markers on the back of the pelvis. Stride times and lengths, knee sagittal angle, and pelvis motion were calculated using the motion capture software (Vicon Nexus, Oxford, UK).

Gait variability dependent variables were computed using a custom-written MATLAB 2019b script. SD, SampEn, and DFA were implemented on stride measures and CoD and LDS were implemented on knee angle and pelvis trajectories as is customary in the literature. For the stride-to-stride measures, all the strides for the 6-minute trial were used except for the first 10 and last 10 strides. Standard deviations of the stride lengths and stride times for each subject were calculated. SampEn was computed for stride times and stride lengths using the input parameters m = 2 and r = 0.2 times the standard deviation of the time series (Pincus & Huang, 1992; Russell & Haworth, 2014; Yentes et al., 2013). DFA was calculated on the sequence of the last 250 stride times and stride lengths. Following recommendations in the literature, the window sizes used in the analysis ranged from six strides to 250/8 (Damouras et al., 2010; Delignières et al., 2016; Weilert, 2017).

To begin calculating CoD and LDS, the movement trajectory time series for the knee and pelvis were normalized first by extracting the last 100 strides from the 6-minute trial. These 100 strides were resampled so that on average 100 frames were equal to 1 stride. Therefore, each participant was analyzed using the same length and size of data, of 100 strides containing 100 samples each, similar to previous works (Dingwell & Cusumano, 2000; Granata & Lockhart, 2008). The average mutual information (AMI) and false nearest neighbor (FNN) algorithms were used to determine the appropriate time lag and number of dimensions to reconstruct the state space. The AMI function quantifies how much information is shared between two vectors of data and assures the time-delayed is appropriate and the vectors have minimum redundancy. The FNN algorithm finds how many dimensions are necessary so that the number of false nearest neighbors approaches zero. A false nearest neighbor occurs when data points are close together in lower dimensions but are no longer close when embedded into a higher dimension. The CoD of knee joint angle, vertical pelvis, and medial-lateral pelvis motion was then quantified using the Grassberger and Procaccia algorithm (Dingwell & Cusumano, 2000; Grassberger & Procaccia, 1983; Raffalt et al., 2017). The LDS was quantified by the maximum Lyapunov exponent between 0 and 1 stride, for knee joint angle, and vertical and medial-lateral pelvis motion using the Rosenstein algorithm (Dingwell & Cusumano, 2000; Raffalt et al., 2017; Rosenstein et al., 1993).

Statistical Analysis

A principal component analysis (PCA) is a descriptive statistical technique that is used to reduce the dimensionality of a data set. Using a set of measured variables, a PCA will define several relatively uncorrelated components which are separately quantified by these variables, revealing previously unseen relationships between variables. For example, a PCA could be used to determine the relationship between the circumference of an individuals' waist, arms, neck, and the length of the legs, toes, hands, and arms. In this example, A PCA could reveal two separate components. Component one would show a relationship between the measures of waist, arms, and neck circumference, which could be interpreted as a component related to an individual's weight. Component two would show a relationship between leg, toe, arm, and leg length independent of component one. Component two could be interpreted as a component related to an individual's height. In this study, a PCA was used to determine how many components of gait these measures of gait variability identify and the relationship between the measures of variability. A PCA was performed on all twelve measures of gait variability using Varimax orthogonal rotation to investigate the interrelations between measures and the construct(s) of gait the measures quantify.

RESULTS

Four components were identified by PCA based on Kaiser's criterion of retaining components with eigenvalues > 1 (Kaiser, 1970). These four components explained 72% of the variance in the data. The Kaiser-Meyer-Olkin measure (KMO = .551) indicated that the sample size was adequate for this analysis, while Bartlett's test of sphericity, $\chi^2(66) = 173.08$, $p < .000$, showed that correlations between measures were sufficiently different from zero. The loadings for each dependent variable on the four identified components are displayed in Table 3.2. Four dependent variables load highly (absolute value > .6) onto component 1 (24.1% of variance), which included LDS of vertical pelvis oscillations, SampEn of stride time, SD of stride time, and SD of stride length. Four dependent variables loaded onto component 2 (21.7% of variance), including LDS on knee angle, CoD of vertical pelvis motion, CoD of knee angle, and SampEn of stride length. Only two dependent variables loaded onto component 3 (13.9% of the variance), including the CoD of medial-lateral pelvis motion and LDS of medial-lateral pelvis motion. The fourth component (12.7% of variance) also had only two dependent variables with high loadings, which included DFA of stride length and DFA of stride time. No measure of variability failed to display a large load on one component from the PCA.

Table 3.2. Loadings from principle component analysis based on twelve measures of gait variability

	Component			
	1	2	3	4
LDS Pelvis V	**.86***	-.26	-.11	.17
SampEn Stride Time	**.84***	.35	-.13	.00
SD Stride Length	**.76***	.07	.06	.09
SD Stride Time	**.68***	-.01	.33	.11
LDS Knee Angle	.25	**-.87***	.03	.06
CoD Pelvis V	.03	**.82***	-.08	.01
CoD Knee Angle	.51	**.71***	.08	.16
SampEn Stride Length	-.13	**-.63***	-.14	-.22
CoD Pelvis ML	.11	.14	**.88***	-.06
LDS Pelvis ML	.05	.09	**-.84***	-.13
DFA Stride Length	.02	-.02	-.02	**.90***
DFA Stride Time	.28	.24	.12	**.76***

CoD is correlation dimension; DFA is detrended fluctuation analysis; LDS is local dynamic stability; SampEn is sample entropy; SD is standard deviation; ML is medial-lateral dimension; V is vertical dimension.

* indicates large loading (> .6)

DISCUSSION

The purpose of this study was to investigate the relationship between measures of gait variability. Specifically, we implemented a PCA to investigate whether variability measures quantify a single characteristic of gait, whether each variability measure quantifies an independent characteristic of gait, or if measures of variability group together around independent components of gait. Gait variability measures of magnitude (SD), regularity (SampEn), persistence (DFA), dimensionality (CoD), and stability (LDS) were computed for 34 participants across the adult lifespan, walking on a treadmill at their preferred speed. Using a PCA analysis, we identified four independent components of gait variability from the twelve measures of gait variability. The four components were interpreted to be related to (1) vertical impulse attenuation, (2) knee stability, (3) medial-lateral stability, and (4) persistence based on the relationship between gait variability measures in each component.

The measures which loaded heavily onto component 1 show that the stability of the pelvis motion in the vertical direction (0.86), the regularity of stride time (0.84), and the magnitude of stride length (0.76) and time (0.68) variability all quantify the same underlying characteristic of gait variability. Larger component 1 scores are associated with decreased stability in the vertical direction, decreased stride length regularity, and increased magnitude of stride length and time variability. The dimensionality of the knee also loaded onto component 1 (0.51), but as it loads higher onto component 2 (0.71) it will be considered later. What relates these dependent variables together is the vertical impulse attenuation. As we walk, our center of mass oscillates in the vertical direction as we push off the ground to move our body in a forward and upward direction, and then as we fall back to the ground. Regulation of the vertical impulse is an important aspect of gait. Vertical impulse regulation is conserved across all walking speeds, not just preferred walking speed which indicates its importance in gait (Jordan et al., 2007). This is an essential ability as stabilizing vertical oscillations of the pelvis plays an important role in stabilizing the head, which in turn provides steady optic flow and enhances vestibular system processes (Berthoz & Pozzo, 1994; Spoor et al., 1994). Unfortunately, there is an age-related decline in the ability to walk with a stable upright posture, associated with increases in vertical body accelerations, and in an increase in stride time and length variability, all of which have been associated with falls (Decker et al., 2010; Iosa, Fusco, Morone, & Paolucci, 2014; Mazzà et al., 2008). Our results further show a relationship between a reduced ability to dynamically stabilize vertical body oscillations and reduced regulation of stride times and increases the magnitude of variability in stride times and lengths. This can be understood as related to a single component of gait variability, interpreted as vertical impulse regulation. This relationship points to the importance of vertical impulse regulation and its use as a possible marker of gait health.

The second strongest component of gait variability included the dependent variables: stability and dimensionality of knee angle motion (-0.87 and 0.71, respectively), the dimensionality of vertical pelvis motion (0.82), and regularity of stride length (-0.63). Greater component 2 scores were associated with increased knee stability (local dynamic stability measure is inversely related to stability), increased dimensionality of the knee and vertical pelvis motion, and more regular stride lengths (lower Sample Entropy). Walking at the preferred stride frequency optimizes local dynamic stability of knee motion, suggesting knee stability is a critical parameter in an individual’s freely chosen gait (Russell & Haworth, 2014). Along with increased knee stability, the sequence of stride lengths is more regular. Similarly, individuals with compromised knee joint motions due to injury have altered stride variability and decreased stability supporting our findings of the relation between knee stability and stride regularity. Our finding of greater dimensionality in both knee motion and vertical pelvis motion correlating with increased stability is also in line with previous research. Increased dimensionality has been found to stabilize coordination in the upper body and we see the same inclination in the lower body (Fink, Kelso, Jirsa, & De Guzman, 2000). Greater dimensionality has also been linked with an unlocking of degrees of freedom which allows for better movement proficiency and stability (Buzzi et al., 2003; Harbourne & Stergiou, 2003; Tuller & Turvey, 1982). Overall, component 2 can be interpreted as relating to dynamic stability and complexity of knee motion which is related to lower body movement regularity.

Both dimensionality and local stability of medial-lateral pelvis motion loaded highly onto component 3 (0.88 and -0.84, respectively). High component 3 scores correlate with greater medial-lateral dimensionality and stability of the pelvis. Our results again show an increase in dimensionality corresponds to greater movement stability which is in line with previous research on coordination (Fink et al., 2000). Medial-lateral measures of gait are used as a predictor of falls, just as vertical measures are associated with falls (Bizovska et al., 2018; Swanenburg, de Bruin, Uebelhart, & Mulder, 2010). Older adults typically walk with an increased step width possibly to improve balance (Aboutorabi, Arazpour, Bahramizadeh, Hutchins, & Fadayevatan, 2016). However, older adults have excessive medial-lateral movement of the body (Kaya, Krebs, & Riley, 1998) when compared to the younger population and older adults also have difficulty controlling this medial-lateral movement (Maki, 1997). This may lead to the age-related difficulty in controlling medial-lateral head oscillation (Mazzà et al., 2008) which again is important in stabilizing the head allowing for proper gait. Further, the exclusion of any vertical measurement in this construct (such as the measures from construct 1 or 2) suggests that while vertical and medial-lateral variability measures are important constructs of gait, medial-lateral stability is independently controlled. Therefore, individuals must appropriately regulate the local stability of body oscillation in both directions to retain a dynamically stable gait. A decrease in the stability in either direction could result in deleterious gait effects but may go unnoticed if the appropriate directional measure of variability is not considered. It is therefore important to capture both vertical and medial-lateral gait stability to quantify the dynamic stability of gait. Further, some older adults have been shown to have decreased anterior-posterior regularity movement while having no differences in vertical or medial-lateral movement regularity (Kobsar et al., 2014). This lends the question if vertical, medial-lateral, and anterior-posterior stability are all independently regulated. Because the participants in this study walked on a treadmill, anterior-posterior trajectories were unnaturally affected. Further works could investigate if gait variability measures in the anterior-posterior axis also quantify an independent component of gait variability. Overall, this component points to the importance of medial-lateral stability.

Component 4 can be interpreted as quantifying the persistence of the stride parameters. Both detrended fluctuation analysis measures loaded highly onto this component, while the other dependent variables had relatively low loadings (< .22). High detrended fluctuation analysis values ($\alpha > 0.5$) indicate persistence, whereby longer stride lengths or times are typically followed by longer lengths or times, and shorter stride lengths or times subsequently get shorter. While $\alpha \leq 0.5$ indicates anti-persistence, where short lengths or times are typically followed by longer values. Higher detrended fluctuation analysis values have been linked with young healthy adults and values closer to $\alpha \approx 0.5$ are observed with aging or disease. As neither detrended fluctuation analysis measures load highly onto the other three components it appears that these measures of persistence are quantifying an aspect of gait variability that is independent of the other variability measures.

In conclusion, measures of gait variability are not quantifying a single construct such as the locomotor health or adaptability of an individual. Gait variability also does not breakdown into two components described in the literature as linear measures of magnitude (e.g., SD) and nonlinear measures of structure (e.g., SampEn, DFA, CoD, and LDS). Based on the measures used here, we identified four independent components of gait variability, which appear to represent: (1) vertical impulse attenuation, (2) knee stability, (3) medial-lateral stability, and (4) persistence. Measures based on magnitude (SD), regularity (SampEn), dimensionality (CoD), and stability (LDS) are interrelated when quantifying the same component. Indeed, increased dimensionality occurs concurrently with greater stability in both knee motion and medial-lateral pelvis motion, which are important aspects of gait that decline with age and disease. Similarly, decreased stability coincides with decreased stride regularity and greater step magnitude of variability. In contrast, the persistence of stride-to-stride parameters during gait were found to be unrelated to the other measures of gait variability. Thus, multiple measures of variability are necessary to quantify an individual's pattern of gait

CHAPTER 4

MEASURES OF GAIT VARIABILITY DO NOT PREDICT THE ADAPTABILITY PERFORMANCE OF SPLIT-BELT TREADMILL WALKING

INTRODUCTION

Human locomotion is considered to provide a window into the health of an individual, just as heart rate and blood pressure are used by physicians to identify underlying health issues (Farrokhi, O'Connell, Gil, Sparto, & Fitzgerald, 2015; Hanakawa et al., 1999; Lewek, Poole, Johnson, Halawa, & Huang, 2010; Sosnoff, Broglio, Shin, & Ferrara, 2011). Those studying human locomotion have long been concerned with identifying individuals' risk of experiencing a fall. Measuring the variability of gait is one technique that has been used to identify the risk of falling. Traditionally, linear measures of dispersion such as standard deviation (SD) have been used to investigate the magnitude of gait variability. These analysis techniques have typically shown that older individuals and individuals at a higher fall risk have a larger magnitude of gait variability than their healthy counterparts (Callisaya et al., 2011; Hausdorff, Edelberg, et al., 1997; Hausdorff, Rios, et al., 2001). However, linear measures are limited in their interpretation as they can only quantify the magnitude of variability and therefore may not be sensitive to individual differences.

Over the last few decades, analysis techniques known as nonlinear measures have been created and implemented to not only discern old from young, or fallers from non-fallers, but to investigate what factors of gait lead to unhealthy patterns of locomotion (Buzzi et al., 2003;

Dingwell & Cusumano, 2000; Grassberger & Procaccia, 1983; Leverick et al., 2014). Linear measures of variability ignore the sequence of a time series while nonlinear techniques seek to quantify the sequential structure in a time series. In doing so, nonlinear measures are used to analyze how the sequential patterns of gait change with age and disease, and their relation to the risk of falls. Studies using nonlinear measures of variability have repeatedly found differences between healthy gait patterns and gait patterns associated with locomotor difficulty and falls (Buzzi et al., 2003; Cavanaugh et al., 2010; Decker et al., 2010; Dingwell & Cusumano, 2000). Therefore, they have been interpreted as quantifying an individual's ability to adapt to a change in the walking environment (Buzzi et al., 2003; Decker et al., 2010; Heiderscheit, 2000). However, the general claim that differences in nonlinear measures recorded from steady-state walking performance indicate better gait adaptability have not been adequately tested (Ducharme et al., 2018; Ducharme & van Emmerik, 2018).

While nonlinear measures of variability are considered to index adaptability, they have been developed from different approaches to quantify characteristics of gait stability, dimensionality, regularity, and persistence. Here, stability refers to the human movement system’s resistance to change, that is the ability to move back into a stable pattern quickly after a perturbation, Stability is typically measured as the maximum Lyapunov exponent and referred to as local dynamic stability (LDS) (Bizovska et al., 2018; Dingwell & Cusumano, 2000). This measurement technique quantifies the stability of a gait pattern by measuring the divergence of movement trajectories over time. The larger the LDS value, the faster the rate of divergence, and therefore the more locally unstable the system is said to be. Fall prone and elderly individuals with a history of falls have decreased local dynamic stability and therefore are less locally stable

(Granata & Lockhart, 2008; Terrier & Reynard, 2015; Toebes et al., 2012). Therefore, the increased LDS of the younger, healthy group has been interpreted as a greater ability to adapt.

Another approach to quantifying gait variability is its complexity or dimensionality. Vertically raising and lower of a foot on and off the ground is a low dimensional movement and is less complex than the combined vertical and anterior movement of the foot during walking. This dimensionality can be computed via correlation dimension (CoD), a nonlinear technique created by Grassberger and Procaccia (1983) that originates from the study of fractals. While we are most used to the dimensionality of space, we can also consider the dimensionality of a time series. In standard geometrical figures, determining the dimensionality of an object is simple. Lines are one dimensional, planes are two dimensional, and solid objects are three dimensional. Using fractals, the dimensionality of a line winding through space and time can also be quantified. For example, a time series of knee angle recorded many times a second over multiple walking strides can be plotted against time-lagged versions of itself. Repeating the process with additional time-lagged dimensions creates a phase plot showing an attractor or consistent pattern. The number of dimensions needed to reveal this attractor approximates its dimensionality, however, only a limited region of state space is visited, hence dimensionality can be a non-integer value. CoD quantifies this non-integer dimensionality or complexity of the original knee angle (or other measures) time series. A study has shown older individuals to have increased movement dimensionality which has been interpreted as gait instability and a reduced ability to adapt (Buzzi et al., 2003)

A third approach to quantify structure in variations is to compute the regularity or predictability of movement. Walking on a flat surface in a straight line would likely result in relatively predictable or repeatable stride lengths or times, but when walking through the woods on a dirt trail the stride lengths or times would be more irregular and more difficult to predict. Approximate entropy and sample entropy (SampEn) are nonlinear measures used to quantify this regularity or predictability in a time series by determining the probability of sequences of data points being repeated (Pincus & Huang, 1992; Richman & Moorman, 2000). A higher SampEn value indicates a low probability of repetition and therefore less regularity in the data, while smaller SampEn values represent increased regularity or predictability within the signal. Using this measure, research has found that disease and aging can result in both increased and decreased levels of gait predictability when compared to their younger counterparts (Arif et al., 2004; Karmakar et al., 2007; Leverick et al., 2014). Because of the noted difference in SampEn values between these populations and the association between aging, disease, and falls, it has been theorized than an optimal amount of entropy exists which allows for movement flexibility necessary for gait adaptability (Decker et al., 2010; Stergiou et al., 2016)

Finally, a fourth approach to assess the structure of variability is to quantify persistence or smoothness of spatiotemporal gait parameters. In a persistent gait pattern, a long stride length is likely to be followed by another long stride and a short stride is likely to be followed by a short stride. An anti-persistent gait would occur when a long stride is followed by a short stride which is then followed by another long stride. Detrended fluctuation analysis (DFA) is used to quantify persistence within a signal (Peng et al., 1994; Peng et al., 1995). A DFA value close to 1 suggests a more persistent, smoother, and slowly drifting gait pattern. A DFA value closer to 0.5 suggests an anti-persistent gait. With aging and disease, there is a breakdown in gait persistence resulting in less persistence and a more random gait behavior (i.e., $\alpha \approx 0.5$), possibly indicating constant corrections and a lack of influence of one stride to strides in the future (Dingwell & Cusumano, 2000; Dingwell & Cusumano, 2010). This in turn can be associated with and falls in the elderly due to an inability to appropriately regulate gait and adapt to pertinent changes in the environment (Arif et al., 2002; Hausdorff, 2007).

Altogether, measures of nonlinear variability are assumed to measure gait adaptability, which can be defined as the ability for an individual to quickly and accurately adjust to the task and environmental demands or constraints (Maki et al., 2008). To date, the most commonly used method to investigate gait adaptability is the split-belt treadmill paradigm (Bruijn et al., 2012; Ducharme et al., 2019; Ducharme et al., 2018; Musselman et al., 2011; Ogawa, Kawashima, Obata, Kanosue, & Nakazawa, 2015; Reisman et al., 2010; Vasudevan et al., 2011). This paradigm uses a treadmill with two separate belts, each powered independently, allowing the belts to move at different speeds. The task creates a step length asymmetry that typically reduces or disappears throughout a trial in healthy adults. This paradigm has been used to test the ability of infants, children, adults, and clinical populations to adapt their gait (Torres-Oviedo et al., 2011). The ability to adapt to this split-belt paradigm is decreased in children, clinical populations, and the elderly. These populations are unable to fully correct the step length asymmetry, have increased time to reach step length symmetry, and/or show smaller aftereffects in step length asymmetry which indicates that the new gait pattern was not “learned.” (Bruijn et al., 2012; Musselman et al., 2011; Vasudevan et al., 2011). This reduced adaptability that has been demonstrated in older adults and clinical populations is in line with research studies described earlier which have distinguished these populations using nonlinear measures of variability in steady-state walking. However, it is a logical fallacy to conclude from the findings of all these studies that nonlinear measures of variability therefore index adaptability of individuals.

To assess the validity of the claim that nonlinear measures of variability quantify adaptability, the current study aimed to test whether these measures of variability (SD, SampEn, DFA, CoD, LDS) could predict adaptability in the split-belt treadmill paradigm. Only two studies could be found that have directly assessed this question, at least in part. In a study of young healthy individuals, persistence, quantified via DFA, was not found to be related to gait adaptability (Ducharme & van Emmerik, 2018). Later work which included older adults also found there to be no overall correlation between DFA and adaptability performance across the lifespan (Ducharme et al., 2019). As only DFA was computed, it remains possible that other nonlinear measures of variability are correlated with adaptability. Hence, the purpose of the current study was to investigate if any variability measure of steady-state walking could predict the ability to adapt gait. If nonlinear measures of variability are to be useful indicators of adaptability and health, they should show a relationship across the lifespan, and not only distinguish populations that have already been distinguished through other measures. Therefore, age and measures of variability were used to predict adaptability performance in adults across the lifespan. Measures of gait variability from a steady-state walking trial at the individual's preferred speed included: standard deviation, SampEn, and DFA of stride times and stride lengths, and LDS and CoD of knee sagittal plane motion, and pelvis vertical and medial-lateral motion. Also, based on recent findings in chapter 3 of this dissertation, the components from the principal component analysis (PCA) were tested for predicting adaptability performance. The results from the PCA showed measures of gait variability to be interdependently related to four components of gait interpreted as vertical impulse regulation, knee stability, medial-lateral stability, and gait persistence. It was hypothesized that the four components from the PCA will be better predictors of gait adaptability than any single variability measure.

METHODS

This study was approved by the Old Dominion University Institutional Review Board (reference number 19-143). Participants included 34 volunteers (22 females, 12 males) ranging from 23 to 71 years old (see Table 4.1). Data collection took place between January and March 2020. Inclusion criteria included the ability to walk for at least 15 minutes at a time and the ability to walk for a total of 45 minutes with intermittent breaks. Exclusion criteria included any history of neuromuscular or neurological injury or disease or a current acute injury that affected gait. Following the participants' informed consent, demographic information including age, height, weight, daily physical activity participation, and sex was recorded.

Table 4.1. Participant demographics	Mean	SD
Age (years)	41.8	14.5
Body weight (kg)	74.9	24.0
Body height (cm)	169	8.13
Preferred walking speed (m/s)	1.13	0.13
Falls risk score (0-10)	9.99	0.04
Exercise (days per week)	3.7	2.0

N=34 SD is the standard deviation

Participants were prepared for three-dimensional motion capture by attaching reflective sphere markers. The passive marker set was adapted from previous works (Bowersock et al., 2016; Petit et al., 2014): Four anatomical markers placed on the superior iliac crests to defined the pelvis, markers placed on the greater trochanters and femoral condyles defined the thighs, markers placed on the tibial plateaus and malleoli defined the shanks, a four-marker cluster placed on top of metatarsal head 1 to 5, and a marker on the heel cup of the shoe defined the feet. Tracking markers include the pelvis markers to track the pelvis. Clusters were used to decrease skin artifact movement and were placed on the lateral aspect of the thighs and posterior-lateral aspect of the shanks to track the lower limbs. The 5-foot markers remained to track the foot. All other markers were removed.

Kinematic data were collected using 10 cameras (Vicon) collecting at 100 Hz over an instrumented split-belt treadmill with two embedded force plates collecting at 1000 Hz. An instrumented treadmill was chosen instead of assessing overground walking as continuous time-series data over many strides are necessary to calculate the nonlinear techniques used in this study. Before data collection began, participants preferred treadmill walking speed was determined by incrementally increasing the treadmill speed until the participant announced the current speed is their preferred walking speed. After one- and one-half minutes of walking at this speed, the treadmill slowed to a stop. The treadmill speed was then set to a speed that was approximately 15% higher than the participants stated the preferred speed. The treadmill then incrementally decreased until the participant announced the current speed is their preferred. The average of the two stated preferred speeds was taken as the preferred walking speed (Ducharme et al., 2019; Jordan et al., 2007).

To collect steady-state walking variability the protocol began with one six-minute walking trial at the participant's self-selected speed with the treadmill belts going the same speed. To test whether gait variability measures are related to gait adaptability performance, the split-belt treadmill paradigm was utilized. From the participant's self-selected walking speed, the treadmill belt corresponding to the participant's non-dominant limb was set to 50% of their preferred walking speed while the other belt was set at their preferred walking speed to create a 1 to 2 walking ratio. The trial lasted 10 minutes. After 10 minutes, the treadmill was stopped. During all trials, participants were asked to look forward as much as possible. At the beginning of each trial, participants were instructed to put their hands on the handrails until they felt comfortable walking without the assistance of the handrails. All subjects were able to complete all trials without the need for assistance. The variables of interest included stride length, stride time, knee joint sagittal plane angle for the dominant limbs (N=3 left foot dominate), and pelvis position in the medial-lateral and vertical axes. Stride length was defined as the anterior-posterior difference of the heel marker at the time of subsequent foot contacts of the ipsilateral limb (Reisman et al., 2010). Foot contact was defined by the local minimum of the vertical position of the heel marker and foot off was defined as the peak vertical velocity of the heel marker (Pijnappels et al., 2001; Roerdink et al., 2007). The flexion-extension knee angle was defined as the relative angle between the shank and the thigh segments. The pelvis position used to define pelvis position was defined as the center of the four anatomical markers placed on the back of the pelvis. Stride length, stride time, knee angle, and pelvis vertical and medial-lateral positions defined above were calculated using the motion capture software (Vicon Nexus, Oxford, UK). Gait variability analysis was completed using a custom MATLAB 2019b script. SD, SampEn, and DFA were implemented on stride measures, as is common. CoD and LDS were implemented on knee angle and pelvis motion. Adaptability performance was quantified as the mean step length symmetry over the last 50 strides of the trial (Ogawa et al., 2015). Gait length symmetry was calculated as (Bruijn et al., 2012):

$$ST_{Symmetry} = \frac{ST_{Fast} - ST_{slow}}{ST_{Fast} + ST_{slow}} \quad \text{Equation 4.1}$$

The mean, SD, and CV were calculated on a stride to stride basis for stride length and stride time for each subject over the 6-minute trial (10 strides were trimmed from the beginning and end for all analyses). The SampEn value for stride time and stride length over the 6-minute trials was quantified using parameters m of 2 and r of 0.2 times the standard deviation of the time series (Pincus & Huang, 1992; Russell & Haworth, 2014; Yentes et al., 2013). DFA was calculated on the sequence of the last 250 stride times and stride lengths. Following recommendations in the literature, the window sizes used in the analysis ranged from six strides to the total number of strides divided by eight (Damouras et al., 2010; Delignières et al., 2016; Weilert, 2017).

To begin calculating CoD and LYE, each movement trajectory time series was first normalized by extracting the last 100 strides from the 6-minute trial. These 100 strides were resampled so that on average 100 frames were equal to 1 stride. Therefore, each participant was analyzed using the same length and size of data, of 100 strides containing 100 frames each similar to previous works (Dingwell & Cusumano, 2000; Granata & Lockhart, 2008). The average mutual information (AMI) and false nearest neighbor (FNN) algorithms were used to determine the subject-specific time lag and number of dimensions to reconstruct the state space. The AMI function quantifies how much information is shared between two vectors of data and assures the time-delayed is appropriate and the vectors have minimum redundancy. The FNN algorithm finds how many dimensions are necessary so that the number of false nearest neighbors approaches zero. A false nearest neighbor occurs when data points are close together in lower dimensions but are no longer close when embedded into a higher dimension. Previous works have found a similar result between using subject-specific or the same values for all participants (Raffalt et al., 2017). The CoD of knee joint angle and pelvis medial-lateral and vertical positions were then quantified using the Grassberger and Procaccia algorithm (Dingwell & Cusumano, 2000; Grassberger & Procaccia, 1983; Raffalt et al., 2017). The short term local dynamic stability was quantified between 0 and 1 strides for knee joint angle and pelvis oscillation (Dingwell & Cusumano, 2000; Raffalt et al., 2017; Rosenstein et al., 1993).

Statistical Analysis

Linear regression analysis was used to assess whether age or measures of variability from steady-state walking predicted adaptability performance. Using simple linear regression, each predictor was tested individually for its relationship with the outcome measure, adaptability performance. Chapter 3 of this dissertation identified four components of gait variability using a PCA: vertical impulse attenuation, knee stability, medial-lateral stability, and persistence. Each of the four components was used for each participant. An alpha level of < 0.05 was used to define a significant relationship. Effect sizes were interpreted as small ($0.01 \leq R^2 < 0.09$), medium ($0.09 \leq R^2 < 0.25$), and large ($R^2 \geq 0.25$) (Cohen, 2013).

RESULTS

Figure 4.1 displays step length symmetry plotted throughout the split-belt protocol. The participants have been plotted in three separate age groups, young (less than 30 years old) middle age (30 to 59 years old) and old (over 59 years old) to improve the visual clarity of adaptability performance. The statistical analysis did not separate the population into age groups but used age as a continuous outcome variable. Participants began the split-belt treadmill trial with asymmetry between left and right step lengths, which decreased over the 10 minutes of walking. No age group differences could be discerned. This is supported by finding a small non-significant relationship between age and adaptability performance (see Figure 4.2 and Table 4.2). Figure 4.3 displays scatter plots between variability measures (SD, SampEn, and DFA) and stride measures (time and length). SD, SampEn, and DFA measures of stride length and stride time were not significantly predictive of adaptability performance (Table 4.2). Figure 4.4 displays scatter plots between measures of knee, vertical pelvis, and medial-lateral pelvis variability and step length symmetry. CoD and LDS of the knee and pelvis medial-lateral and vertical motion were not significantly (none to small effect sizes) related to adaptability performance (See Table 4.2). Adaptability performance was not significantly predicted by any of the component scores from the PCA and the effects were small (See Figure 4.5 and Table 4.2).

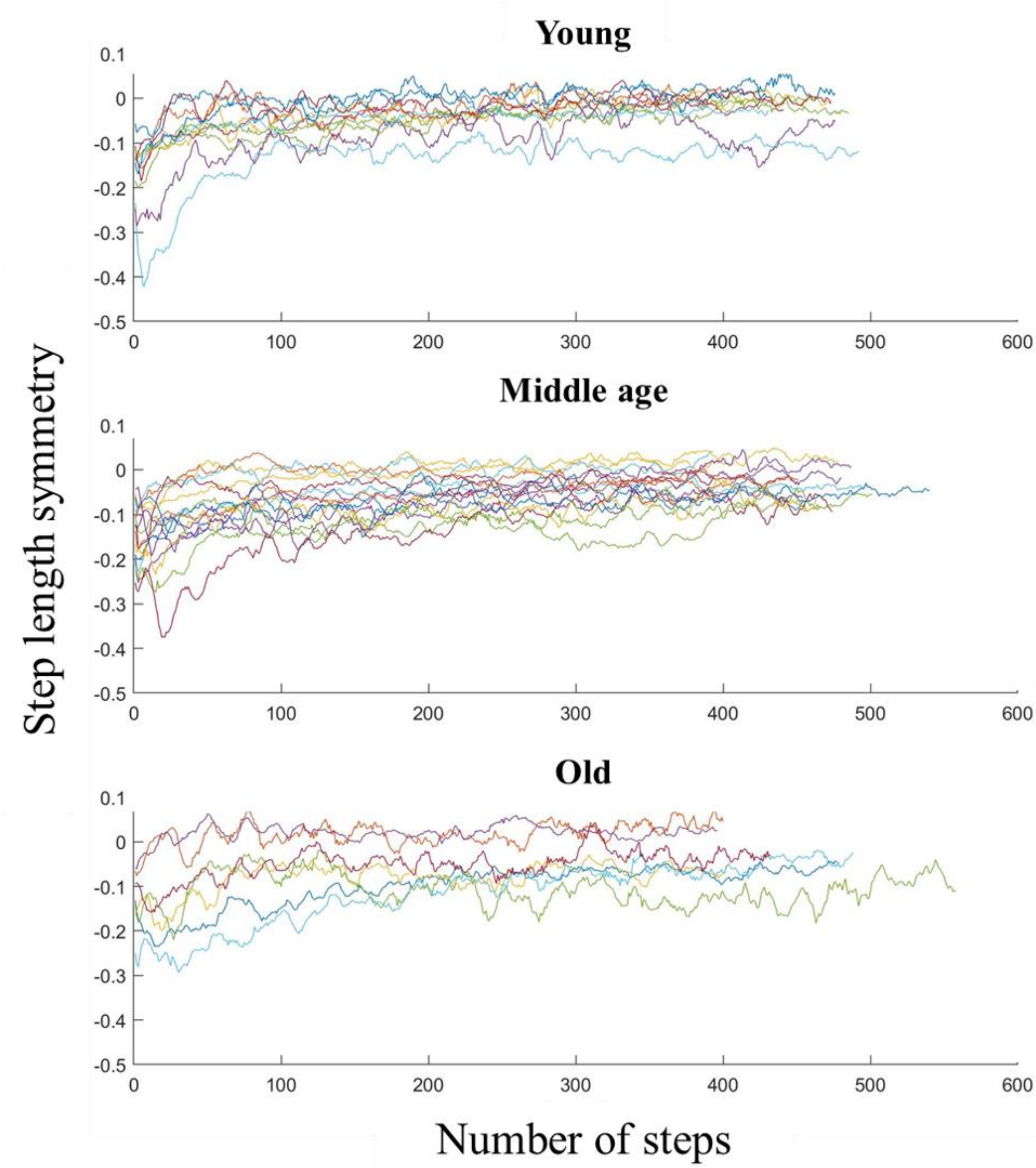

Figure 4.1. Step length symmetry (dimensionless) during the split-belt treadmill trial for an individual at each step during the 10-minute trial. Top panel: younger <30 years old; Middle panel: middle age 30 to 59 years old; Bottom panel: older >59 years old). Each colored line represents the step length symmetry values for an individual.

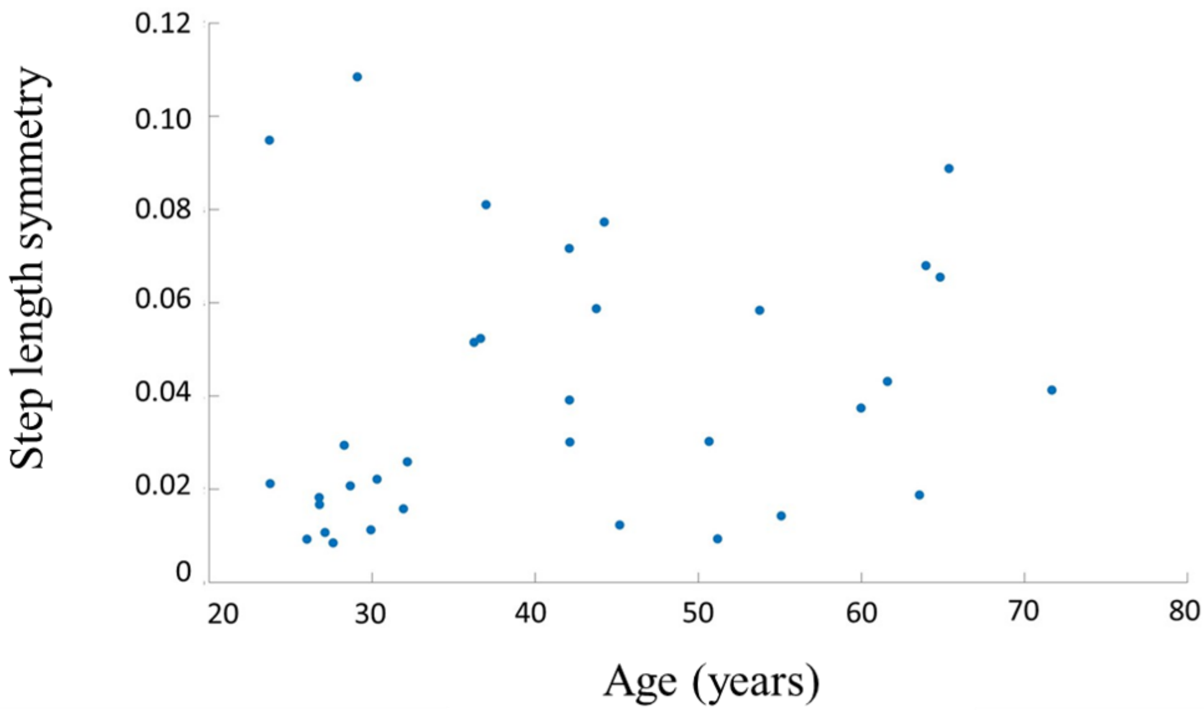

Figure 4.2. Scatter plot of age and average step length symmetry of last 50 steps from split-belt treadmill paradigm. Data points represent individual participants.

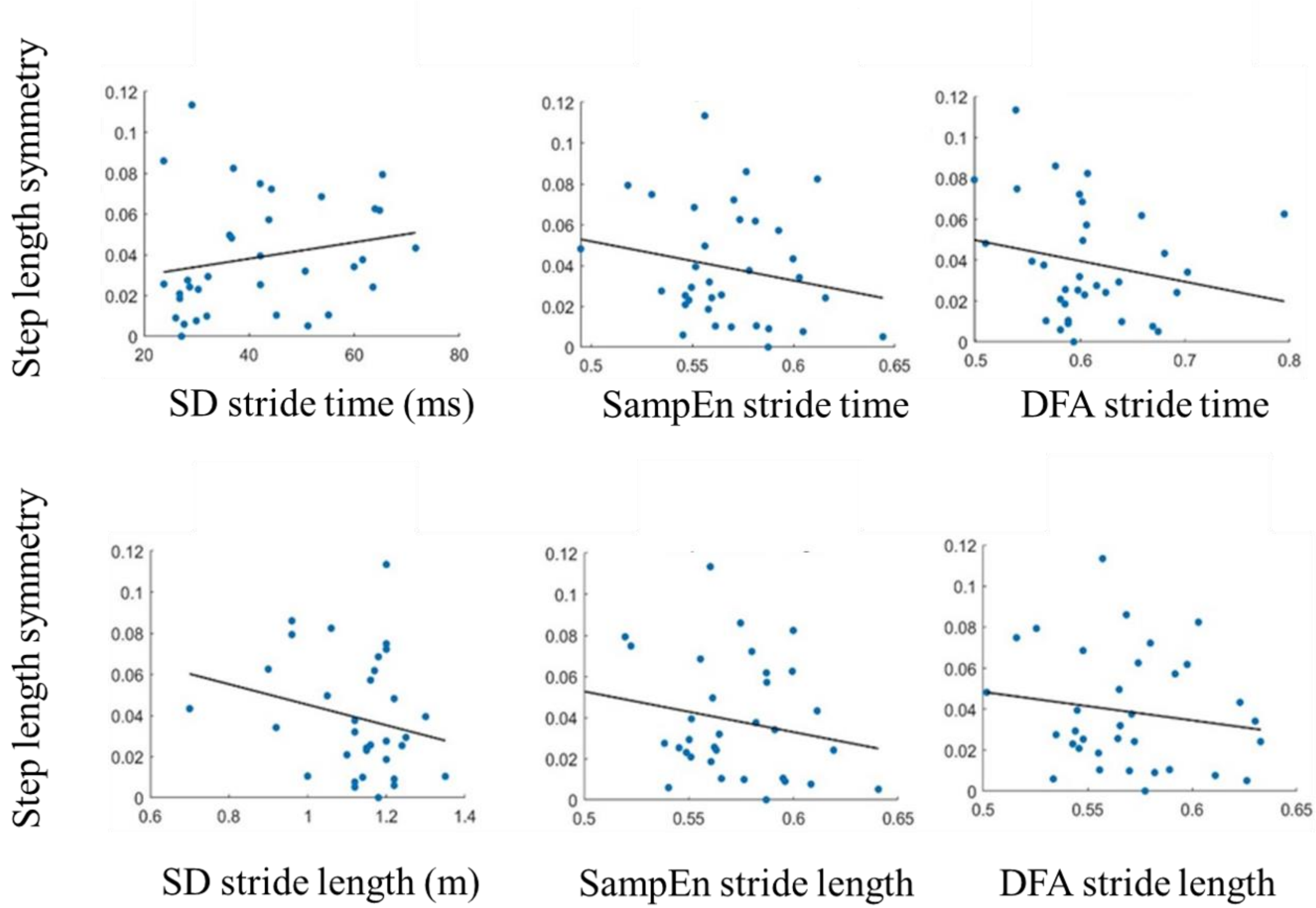

Figure 4.3. Scatter plot between step length symmetry and spatiotemporal measures of variability. Top: stride time variability. Bottom: stride length variability. SD is standard deviation, SampEn is sample entropy DFA is detrended fluctuation analysis. No statistically significant regressions were found.

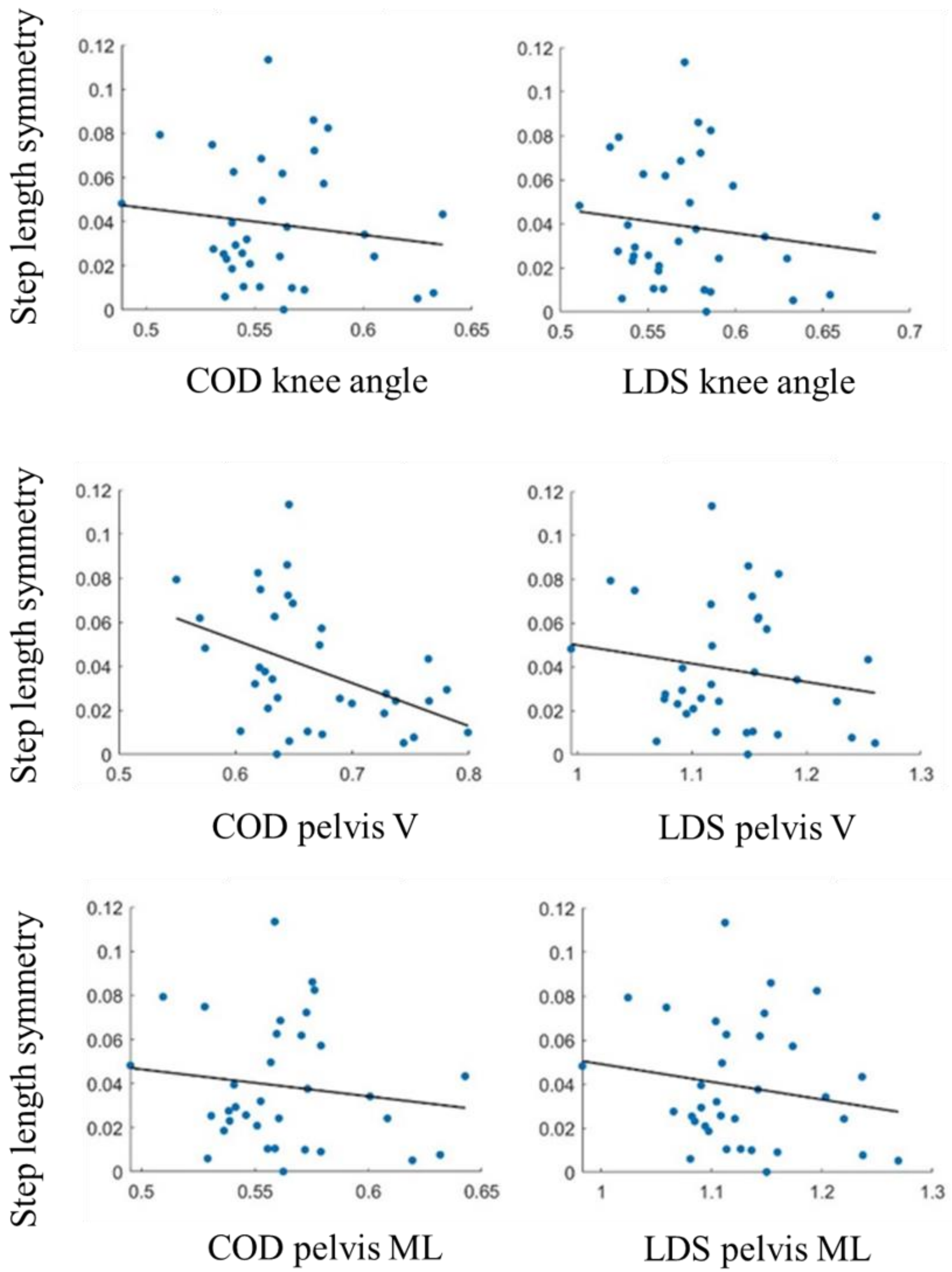

Figure 4.4. Scatter plot between step length symmetry and movement trajectory variability. Top: knee angle variability. Middle: vertical pelvis variability. Bottom: medial-lateral pelvis variability. CoD is correlation dimension; LDS is local dynamic stability. ML is medial-lateral direction, V is vertical direction. No statistically significant regressions were found.

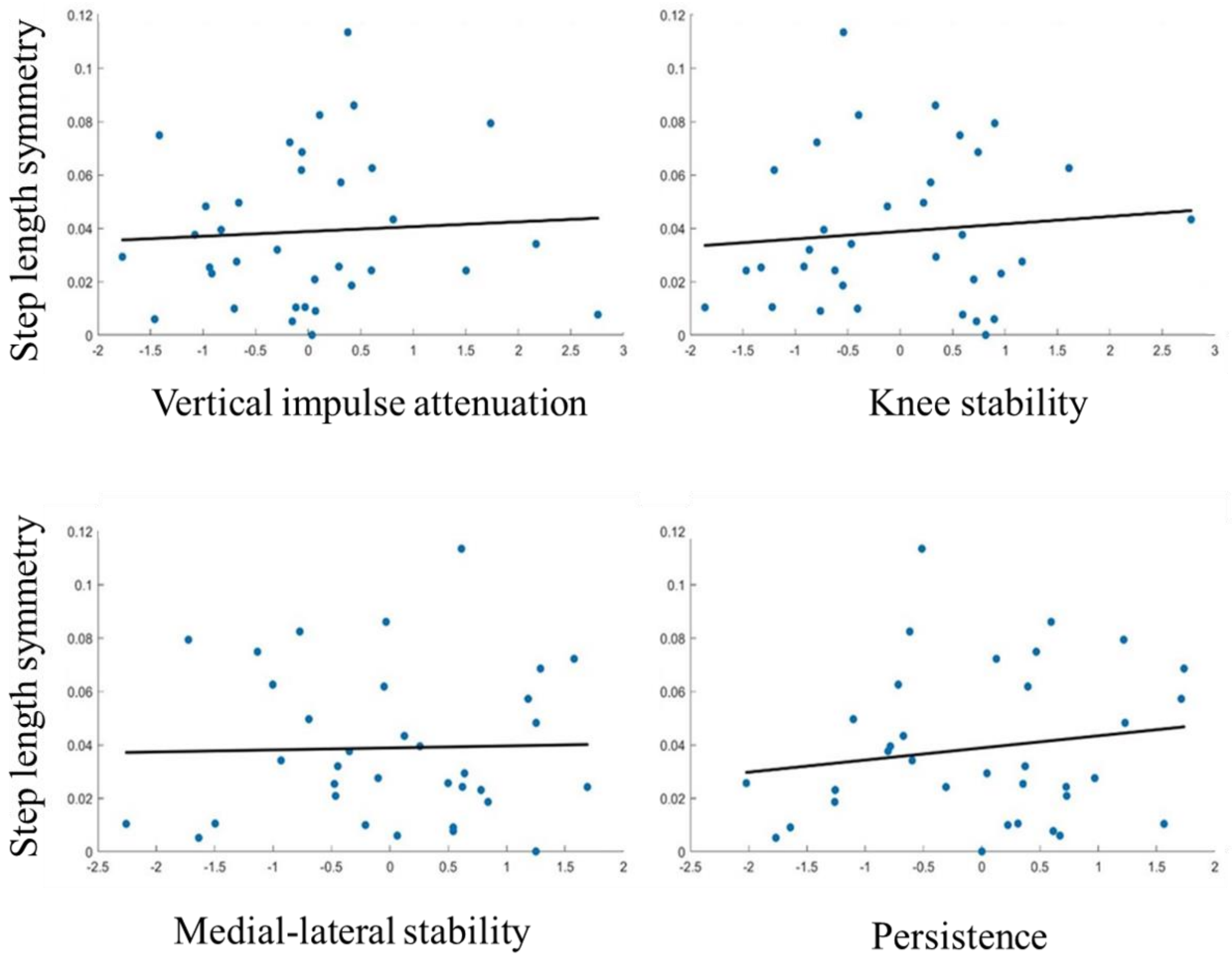

Figure 4.5. Scatter plot between the four gait variability components from principal component analysis and step length symmetry. Best fitting lines are provided for each plot. No significant regressions were found.

Table 4.2. Results of simple linear regression analyses for predicting adaptability performance.

Variable Name	Constant Coefficient	95% CI		Linear Coefficient	95% CI		Standardized Coefficient	p-value	Adjusted R-Squared
Age	0.02	-0.01	0.05	0.00	0.00	0.00	0.21	0.24	0.01
SD StrideTime	0.02	-0.02	0.06	0.7	-0.62	2.02	0.19	0.29	0.01
SD StrideLength	0.01	-0.03	0.05	0.00	0.00	000	0.28	0.1	0.05
SampEn StrideTime	0.03	-0.03	0.09	0.01	-0.03	0.04	0.05	0.76	-0.03
SampEn StrideLength	0.09	-0.29	0.47	-0.02	-0.2	0.16	-0.04	0.8	-0.03
DFA StrideTime	0.02	-0.04	0.08	0.03	-0.05	0.12	0.13	0.46	-0.01
DFA StrideLength	0.01	-0.06	0.07	0.05	-0.05	0.15	0.18	0.3	0.00
CoD KneeAngle	0.02	-0.1	0.15	0.01	-0.03	0.04	0.05	0.78	-0.03
CoD Pelvis ML	0.1	-0.19	0.38	-0.02	-0.1	0.06	-0.08	0.67	-0.03
CoD Pelvis VT	-0.17	-0.63	0.3	0.06	-0.07	0.18	0.16	0.37	-0.01
LDS Knee Angle	0.05	0.01	0.09	-0.01	-0.05	0.03	-0.08	0.64	-0.02
LDS Pelvis ML	0.04	0.02	0.06	-0.03	-0.15	0.09	-0.09	0.61	-0.02
LDS Pelvis VT	0.07	-0.03	0.16	-0.03	-0.11	0.06	-0.11	0.52	-0.02
VT Impulse Attenuation	0.04	0.03	0.05	0.00	-0.01	0.01	0.06	0.72	-0.03
Knee Stability	0.04	0.03	0.05	0.00	-0.01	0.01	0.10	0.58	-0.02
ML Stability	0.04	0.03	0.05	0.00	-0.01	0.01	0.03	0.88	-0.03
Persistence	0.04	0.03	0.05	0.00	-0.01	0.01	0.16	0.36	0.00

Linear regression analysis for predicting adaptability performance. No dependent variable significantly predicated adaptability performance. SD is standard deviation; SampEn is sample entropy; DFA is detrended fluctuation analysis; COD is correlation dimension; LDS is local dynamic stability; ML is medial-lateral; VT is vertical

DISCUSSION

The purpose of this work was to directly test the claim in the literature that measures of gait variability from steady-state walking are indicative of the ability to adapt. For steady-state walking, participants walked on a treadmill for 6 minutes at their preferred speed, after already acclimating to the treadmill. Multiple measures of gait variability were computed from this trial, which included SD, SampEn, DFA of stride length and stride time as well as CoD, LDS of knee angle, and pelvis position in the medial-lateral and vertical directions. Gait adaptability was assessed using the most commonly investigated task in the literature, the split-belt treadmill paradigm, where the same participants walked at a 2:1 speed ratio with the belt for dominant leg set at the preferred speed and the belt for the non-dominant leg set at half of the preferred speed. Gait adaptability performance was quantified as the mean step length symmetry over the last 50 strides of the trial. As older adults have been found to have reduced ability to adapt to the split-belt treadmill, adult participants across the lifespan were recruited to participate in the study. The relationship between age and gait adaptability performance was tested, as well as the relationships between measures of steady-state gait variability and adaptability performance. Contrary to our prediction, age was not significantly related to gait adaptability. Even more importantly, there was no significant relationship between any single or combined nonlinear measure of gait variability and gait adaptability, which contradicts the claim made in much of the literature.

Age and Adaptability

The results of this work indicated no relationship between age and adaptability performance during the split-belt paradigm. While older adults have been found to adapt their gait less and more slowly when assessed by step length symmetry (Bruijn et al., 2012), a more recent study also found no age-dependent difference in adaptability performance (Ducharme et al., 2019). The authors of this study pointed to the disregard of participants' physical activity in previous research. The convenience sample population of this work comprised of volunteers who concluded they would be able to complete the adaptability protocol may have resulted in older adults who were physically active. Ducharme and colleagues suggested that the activity level of the older negated the previously found age-related adaptability declines (Ducharme et al., 2019). Similarly, the older participants in the current study were active, exercising on average 4.4 days per week, and those with gait difficulties were excluded. The inclusion of healthy, active older adults is likely to have led to the absence of a statistically significant relationship between age and gait adaptability. The benefits of exercise on cardiovascular and musculoskeletal health in mitigating the effects of age are well documented (Faulkner, Larkin, Claflin, & Brooks, 2007; Lavie, Ozemek, Carbone, Katzmarzyk, & Blair, 2019; Pollock et al., 2018). The results in this work and from Ducharme et al (2019) indicate that gait adaptability can be retained through remaining physically active supporting the notion that exercise can reduce the age-related declines in neuromotor function (Ducharme et al., 2019).

Measures of Variability and Adaptability

The current research found no significant relationships between measures of variability and adaptability performance. This finding is in agreement with other research which has directly examined this relationship. Ducharme and colleagues computed DFA of stride time during symmetrical walking at the subject’s preferred walking speed and half the subject’s preferred walking speed. This study also used the split-belt treadmill paradigm at a 2:1 ratio and found no relationship between DFA results and adaptability performance or time of adaptability performance (Ducharme et al., 2019; Ducharme et al., 2018). The results of the current study extend these findings by also quantifying SD, SampEn, CoD, and LDS. Similar to the results for DFA, none of these measures of steady-state variability alone significantly predicted adaptability performance. While each variable was not significantly related to gait adaptability, it remained possible that a group of variables might be. The principal component analysis in chapter 3 found independent groups of variability measures to be correlated and able to quantify four separate components of gait variability. Based on this finding, the relationship between each component score and adaptability performance was assessed. Gait adaptability performance in the split-belt treadmill task was not significantly predicted by any of the component scores. In summary, these results again show that measures of gait variability from steady-state walking are not significantly related to the performance of on a gait adaptation task

A limitation of this work includes the possibility that the participants in this experiment produced a limited range of performance and gait variability values. However, the participants had ranges of adaptability performance comparable with other studies investigating the split-belt adaptation performance among health adults thus the range of performance can be considered acceptable for this adaptability task (Reisman, Block, & Bastian, 2005; Torres-Oviedo et al., 2011; Vervoort et al., 2019). Previous research has investigated differences in more extreme groups (i.e. Parkinson and stroke vs healthy) but the purpose of this work was to test if gait variability and adaptability performance were sensitive to changes in individuals that cannot easily be separated. In this study, adaptability performance was not especially sensitive to age-related changes but more likely related to participation in physical activity throughout the lifetime. Also, as no work to our knowledge has defined healthy ranges of measures of variability but many suggest their sensitivity to changes in gait stability and adaptability, we are confident in the merit of our findings and their meaningful addition to the literature.

Due to logistical constraints and appreciation for participants' time and safety, only one gait adaptability task was implemented. The split-belt paradigm task does not completely represent locomotor adaptation. Other tasks of gait arability may be more related to age and measures of gait variability. However, this task is one of the most common techniques used to investigate a system's ability to change kinetic and kinematic properties of gait to produce a novel gait pattern necessary to move in the new walking environment. Also, researchers do not specify what kind of adaptability tasks are related to measures of variability but refer to adaptability as a general ability. At the very least, this work has demonstrated the lack of relationship between adaptability performance during a split-belt treadmill paradigm and measures of variability. Therefore, this methodology was appropriate to test the claim that measures of variability reflect an individual ability to alter and adapt their pattern of gait.

In conclusion, this study does not support the claim that measures of gait variability are associated with an individual ability to adapt. Neither the employment of single measures nor multiple measures of gait variability accurately predict adaptability performance. While a moderate relationship between age and adaptability performance may exist, participation in daily physical activity may impact the ability to adapt.

CHAPTER 5

FINAL DISCUSSION

The purpose of this work was to study the relationship between age, measures of variability, and locomotor adaptability. In the past few decades, measures of variability, specifically nonlinear measures of variability, have been used to study patterns of gait to identify unhealthy locomote behavior, motor disease, and risk of falls (Bizovska et al., 2018; Hausdorff, 2009; Hausdorff, Edelberg, et al., 1997; Lipsitz et al., 1991; Mehdizadeh, 2018). Typically, studies have used one or possibly two variability measures and compared young and old populations considering any age-related differences to be unfavorable. The findings, however, have been mixed without a consistent directional change in measures of gait variability due to age. Therefore, the first aim of this work was to determine the relationship between aging and multiple measures of gait variability. Further, because only one or two measures of variability are used at a time, it is difficult to understand the relationship between variability measures. Therefore, the second aim of this work was to examine the relationship between measures of variability to determine if they measure a single or multiple constructs of locomotor behavior. These measures have been claimed to quantify some underlying characteristics of the locomotor system and assess the ability for an individual to adapt (Buzzi et al., 2003; Cavanaugh et al., 2010; Decker et al., 2010). The final aim of this work was to investigate these claims and determine if measures of variability quantify the ability of an individual to adapt to a novel gait adaptation task.

AGE-RELATED CHANGES IN MEASURES OF GAIT VARIABILITY

Human movement is inherently variable, and scientists have utilized numerous methods including linear and nonlinear analyses to quantify this variability. From these works, a relationship between measures of variability and age has been suggested by many researchers (Buzzi et al., 2003; Hausdorff, Rios, et al., 2001; Mehdizadeh, 2018; Newell & Corcos, 1993; Owings & Grabiner, 2004). However, these studies often use only one or two measures of variability and examine only young and old adults, without consideration of middle-aged adults. With multiple measures of variability used across different studies, it is difficult to identify a consistent change in these measures of variability and how changes occur over the lifetime. To investigate the age-dependent change in measures of gait variability, thirty-four volunteers from ages 23 to 72 years walked at their self-selected preferred speed for six minutes. During this time, stride length, stride time, knee angle, medial-lateral pelvis position, and vertical pelvis position were measured to capture locomotor variability. Linear variability measures, standard deviation (SD) and coefficient of variation (CV), and nonlinear measures, sample entropy (SampEn) and detrended fluctuation analysis (DFA), were applied to stride length and stride time. Nonlinear measures correlation dimension (CoD), and local dynamic stability (LDS) were applied to knee angle and pelvis motion in the medial-lateral and vertical dimensions. A simple linear regression model was used to investigate age-related changes in these measures.

In this work, age was not found to be a strong predictor for the measures of gait variability. The only variability measures predicted by age were CV of stride length and SampEn of stride time, revealing an increase in the magnitude of variability in stride lengths and a decrease in the regularity of stride time with age. The strongest relationship between age and the outcome variables was the negative relationship with the mean preferred walking speed (moderate effect size). The age-related decline in walking speed has been shown in previous research (Himann et al., 1988). We, therefore, investigated the relationship between gait speed and variability measures to investigate if gait speed was a better predictor of gait variability than age. Using a simple linear regression model, we found preferred gait speed to significantly predict more measures of gait variability and explain more of the variance than age. CV of stride length, SampEn of stride time and stride length, CoD of knee angle, and pelvis movement in the vertical direction was significantly predicted by preferred walking speed. Those who walked slower had decreased stride length variability magnitude (CV), increased stride time regularity (SampEn), decreased stride length regularity (SampEn), and decreased dimensionality of vertical pelvis movement and knee angle (CoD). A third linear multivariate model that used both age and gait speed as predictors found that age did not significantly explain any additional variance than speed alone. Because of the strong correlation between age and speed, it is not surprising that studies that compare only young and old populations have found significant age-related differences in measures of variability. The inclusion of middle-aged adults and physically active older adults may have nullified this finding as middle-age adults had a large variance in gait variability measures. Overall preferred gait speed has a bigger impact on these measures of gait variability than age. Older individuals who can maintain a higher gait speed are likely to preserve the same level of gait variability as younger individuals.

RELATIONSHIP BETWEEN MEASURES OF GAIT VARIABILITY

Measures of gait variability are used to assess the health and performance of individuals' gait patterns. There are numerous different methods used to quantify variability, including linear and nonlinear measures. Both types of variability measures have identified differences due to older age, disease, and risk of falls (Bizovska et al., 2018; Buzzi et al., 2003; Lipsitz et al., 1991; Lord et al., 1996; Owings & Grabiner, 2004). However, the direction of change in these measures is inconsistent, making interpretations and conclusions between studies difficult. Typically, studies utilize one or two measures of variability and compare these values between a population of young individuals and a population of old individuals. It is was therefore unknown if measures of variability are related and if they are all measuring the same construct if measures of variability are unrelated and each measure separate constructs of gait, or if groups of variability measures are addressing independent constructs of gait. In chapter 3, a principal component analysis (PCA) was implemented to investigate the relationship between variability measures. For this analysis, standard deviation (SD), sample entropy (SampEn), and detrended fluctuation analysis (DFA) of stride time and length were computed. SD quantifies the magnitude of stride variability, SampEn quantifies stride regularity, and DFA quantifies stride persistence. Correlation dimension (CoD) and local dynamic stability (LDS) of the knee angle and pelvis position in the vertical and medial-lateral dimensions were computed. CoD quantifies the dimensionality or complexity of movement and LDS quantifies the stability of movement.

The results of the PCA identified four separate components of gait. Component 1 showed the stability of the pelvis motion in the vertical direction, the regularity of stride time, and the magnitude of stride length and time variability to all quantify the same underlying characteristic of gait. These measures appear to be related to attenuation of the vertical impulse exhibited during walking. The regulation of vertical impulse is an important aspect of walking as it enables individuals to control the vertical oscillations of the head which is necessary for steady optic flow and vestibular system processes (Berthoz & Pozzo, 1994; Spoor et al., 1994). The literature has shown an age-related decline in this ability to walk with appropriate vertical posture and regulate body accelerations (Iosa et al., 2014; Mazzà et al., 2008). This may be the cause of the age-related differences found in these measures of variability (Acharya, Joseph, Kannathal, Lim, & Suri, 2006; Kurz & Stergiou, 2003; Mehdizadeh, 2018), which points to the importance of vertical impulse regulation.

Component 2 showed the stability and dimensionality of knee angle motion, the dimensionality of vertical pelvis motion, and regularity of stride length to quantify the same characteristic of gait. We proposed that these measures quantify the stability of the lower limb movement. The positive relationship between dimensionality and stability has previously been observed, with increased dimensionality being associated with releasing degrees of freedom, which allows for better movement proficiency and stability (Buzzi et al., 2003; Fink et al., 2000; Harbourne & Stergiou, 2003; Tuller & Turvey, 1982). Therefore, knee stability appears to be an important aspect of gait proficiency. Further, walking at the preferred stride frequency optimizes local dynamic stability of knee motion, alluding to the importance of knee stability in the gait parameters individuals freely adopt (Russell & Haworth, 2014). Knee stability is associated with increased stride length regularity and individuals with compromised knee joint motions due to injury have altered stride variability and decreased stability supporting our findings of the relation between knee stability, dimensionality and stride regularity (Moraiti et al., 2007; Yakhdani et al., 2010). Overall, component 2 reveals the importance of knee stability and its relation to lower body movement regularity. A decrease in either of these features of gait can be detrimental to gait.

Component 3 showed that dimensionality and local stability of medial-lateral pelvis motion quantify the same characteristic of gait. We proposed that these measures are quantifying the stability of medial-lateral movement during walking. Regulation of medial-lateral motion has previously been identified as an import aspect of gait that declines with age (Bizovska et al., 2018; Kaya et al., 1998; Maki, 1997; Swanenburg et al., 2010), and is independent of vertical movement regulation as seen in component 1. Therefore, individuals must appropriately regulate the local stability of body oscillation in both directions to retain an overall dynamically stable gait. A decrease in the stability in either direction could result in deleterious gait effects but may go unnoticed if the appropriate directional measure of variability is not considered. Further, some older adults have been shown to have decreased anterior-posterior regularity movement while having no differences in vertical or medial-lateral movement regularity (Kobsar, Olson, Paranjape, Hadjistavropoulos, & Barden, 2014). Regulation of vertical, medial-lateral, and anterior-posterior movements are necessary for proper gait and appear to be independently regulated by the locomotor system as shown by the results of the PCA.

Component 4 for the PCA showed that the persistence of the stride parameters is independent of the other gait variability measures. As with vertical and medial-lateral gait stability, there is also an age-related decline in gait persistence as measured by DFA (Hausdorff, Ashkenazy, et al., 2001). High detrended fluctuation analysis values ($\alpha > 0.5$) indicate persistence, whereby longer stride lengths or times are typically followed by longer lengths or times, and shorter stride lengths or times subsequently get shorter. An $\alpha \leq 0.5$ indicates anti-persistence, where short stride lengths or times would be followed by longer stride lengths or times and vice versa. The persistence of strides appears to be another important component of gait that is independent of the other variability measures and characteristics of gait variability. Therefore, multiple measures of variability are necessary to understand the specific declines in gait an individual or population may have.

Measures of gait variability are used to indirectly access an individual's ability to adapt. It has been suggested that gait variability measures indicate movement flexibility and adaptability (Buzzi et al., 2003; Cavanaugh et al., 2010; Decker et al., 2010) Only two studies have directly investigated this claim and the findings do not support this claim so far (Ducharme et al., 2019; Ducharme et al., 2018). However, these previous studies have only investigated the relationship between one measure of gait variability (DFA) and adaptability. Chapter 4 expanded on this work by investigating the relationship between several measures of gait variability and adaptability performance. The split-belt treadmill paradigm was adopted, because it is the most commonly used approach for assessing the ability for individuals to adapt to a novel gait task (Reisman et al., 2010). Specifically, participants walked at a 2:1 split-belt ratio where the treadmill belt associated with their dominant limb moved half the speed of the belt associated with their non-dominant limb. The belt speed of the non-dominant limb was set at the subject's self-selected preferred speed, determined during baseline walking trials. Performance was quantified using step length symmetry which has previously been used as a measure of adaptability performance in this protocol. Linear regression models were used the compute the relationship between measures of gait variability and adaptability performance. Further, the four components of gait found using the PCA in chapter 3 were used to determine if these components were independently or dependently more predictive of adaptability performance than any single measure of gait variability.

Results from this work found no relationship between measures of gait variability and adaptability performance. This is in further support of the two previous studies that found no relationship between the single measure of DFA and gait performance (Ducharme et al., 2019;

Ducharme et al., 2018). Therefore, no single measure of gait variability during steady-state walking predicts how well an individual will adapt to a change in the walking environment using the split-belt treadmill paradigm. Clearly, this task does not represent all possible forms of locomotor adaptation. To avoid a fall after suffering a trip, a different type of locomotor adaptation is needed than was studied here, and of course, there are others. However, the split-belt treadmill paradigm does represent a system's ability to change kinetic and kinematic properties of gait to produce a novel gait pattern necessary to move in a unique walking environment and has been the most extensively investigated adaptability paradigm. If measures of gait variability do not predict adaptability in the split-belt treadmill task, then the general claim of the relationship between variability and adaptability must be questioned.

CLINICAL RELEVANCE

The findings presented in this study not only add to the current scientific literature and further our knowledge of gait variability and adaptability, but this work is also applicable to clinicians and the work being done in clinical settings. The biggest impact was the finding of relationships between measures of gait variability. Using nonlinear measures of gait variability as a sort of vital sign of gait health has been promoted in the research field but because of the need for special algorithms, data collection tools, and knowledge of appropriate protocols, their use in the clinical settings has been stifled. However, the linear measure SD is often used clinically to quantify gait improvements, deficiency, or detect possible fall risks of individuals (Balasubramanian, Neptune, & Kautz, 2009; Brach et al., 2010; Brach et al., 2001). This work was able to further unlock the benefits of linear measures by showing associations between linear and nonlinear measures of variability. A relationship between the linear measure SD calculating on the simple spatiotemporal measures stride time and stride length, and the nonlinear measures SampEn and LDS was discovered. This allows clinicians to use the familiar measures of an individual's SD of stride time and stride length and extrapolate information about the individual's gait regularity (SampEn) and stability (LDS). Further, this information can be used together to uncover possible deficiency in vertical impulse attenuation, an important aspect of gait as discussed in chapter 4. This work's aim of relating measures of variability has increased the clinical utility of nonlinear measures, which have been previously shown to be useful tools in identifying risks, deficits, and changes in gait.

Other findings in this work showed gait speed and not age to be the driving factor behind the changes in gait variability measures seen between the young and old population. Previous studies have shown higher gait speeds achieved either naturally or through exercise training in older and frail adults to be beneficial and accompanied by a decrease in balance, fear of falling, mortality, and overall improvements in ambulation (Chou, Hwang, & Wu, 2012; Hardy, Perera, Roumani, Chandler, & Studenski, 2007). Training otherwise healthy older individuals to increase their preferred walking speed may help to also maintain gait variability values like those seen in younger adults, possibly improving the functionality and stability of their gait. Although no relationship between measures of gait variability and adaptability performance were found using the split-belt treadmill adaptability task, measures of variability are related to falls in older adults (Buzzi et al., 2003; Hausdorff, 2007; Norris et al., 2005). Therefore, achieving variability measures those seen in non-fallers or youths by increasing gait speed may be beneficial to decrease falls risk. Future work investigating the effect of training programs to increase preferred walking speed on measures of gait variability is needed to uncover further benefits of preserving gait speed.

SUMMARY

To conclude, this work intended to understand the relationships between age, measures of variability, and locomotor adaptability. Age was found to be a poor predictor of gait variability measures, while instead, preferred walking speed predicted more of the variance in these measures of variability. Measures of variability are not quantifying a single construct of locomotor health or adaptability. Instead, we identified four components of gait variability which are independently regulated by the motor system. However, neither these four components nor any single measure of variability is associated with an individual's ability to adapt their gait. This dissertation contributes to our understanding of the concepts of variability and adaptability. This work has shown that gait variability does not quantify a single component but at least four independent components for gait. Finally, adaptability cannot be inferred from linear or nonlinear measures of gait variability.

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Education

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M.S.	East Carolina University: Biomechanics and Motor Control	2014-2016
B.S.	Texas Tech University: Sport and Exercise Science	2011-2014
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Professional Development

Modeling and Simulation Certificate in Health Sciences. Old Dominion University	2019
Graduate Teaching Assistant Institute Certification	2018
Nonlinear Analysis Workshop. The University of Nebraska at Omaha	2017

Research Awards

Recipient of the Graduate Schools & Office of Research's Graduate Summer Award Program. Old Dominion University	2019
Best Presentation award in the General Sciences & Engineering Track at the 13th annual Modeling, Simulation and Visualization Student Capstone Conference. Old Dominion University-Virginia Modeling, Analysis & Simulation Center.	2019
Progress in Clinical Motor Control National Science Foundation Graduate Student Travel Grant. Penn State University	2018
Best Presentation award in the General Sciences & Engineering Track at the 12th annual Modeling, Simulation and Visualization Student Capstone Conference. Old Dominion University-Virginia Modeling, Analysis & Simulation Center.	2018

Research Positions

Graduate Research Assistant: Virginia Modeling, Analysis, and Simulation Center, Old Dominion University	2017-2020
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