Fractal Dynamics, Variability, and Coordination in Human Locomotion

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In human locomotion, the magnitude of gait variability is a strong predictor of fall risk and frailty due to aging and disease. Beyond variability magnitude, the past two decades have provided emerging alternative methodologies for studying biological variability. Specifically, coordination variability has been found to be critically important within a healthy, adaptive system. While many activities aim to minimize end-point variability, greater coordination variability indicates a more flexible system, and is greater in experts compared to novices, or healthy compared to diseased individuals. Finally, variability structure (i.e., fractal dynamics) may describe the overall adaptive capacity of the locomotor system. We provide empirical support that fractal dynamics are associated with step length symmetry during challenging split-belt treadmill walking. Individuals whose fractal scaling approached 1/f fractal scaling during constrained walking also exhibited the best gait adaptability performance. Importantly, this relation between fractality and gait adaptability was not observed in unperturbed preferred speed walking.

Keywords: detrended fluctuation analysis, locomotor adaptability, self-similarity, split-belt treadmill, 1/f scaling

Biological systems are inherently variable, and this variability has been the focus of much research in the movement sciences. In human locomotion research, a commonly accepted convention has been that variability is a one-size-fits-all parameter; more is bad. This "negative" perspective towards variability has been strengthened by findings in the aging and clinical gait literature indicating links between increased gait parameter variability and falls (Maki, 1997; Verghese, Holtzer, Lipton, & Wang, 2009). The many aspects of variability and the identification of variance as an important area of study within human movement research was recognized over two decades ago (Newell & Corcos, 1993). In recent years, numerous studies have expanded upon the work of Nicolai Bernstein (1967) and provided compelling evidence that limb trajectories and coordinative relationships at the joint or segmental level display degrees of functional variability that benefit task performance (Lipsitz & Goldberger, 1992; Newell & Vaillancourt, 2001; Van Emmerik, Ducharme, Amado, & Hamill, 2016). Furthermore, although most previous work on variability has focused on the magnitude or scalar properties of fluctuations, the past two decades have provided evidence that the *structure* of variability may provide alternative and highly valuable information about the overall organization and adaptability of the locomotor system.

The purpose of this review is to present contemporary perspectives regarding the role of variability in the control of human movement, in particular human locomotion, and how fluctuations in gait patterns impact gait stability and adaptability. In the first section, we review how variability at the level of the gait parameters (e.g., stride length, timing, etc.) has been linked to gait changes related to aging and disease. In the second section, we provide an overview of past and current research on coordination dynamics that demonstrates the functional role of variability in human locomotion. Next, the major section of this paper addresses the concept of fractals that has provided new insights into the nature and structure of fluctuations. Following a general background discussion, this section reviews the current literature on fractals as they relate to human locomotion, aging, and disease. We then review how fractals are predicted to relate to adaptive behaviors. The final section offers results from a first empirical study that directly investigates this proposed link between fractal dynamics and adaptation during human locomotion.

Variability Magnitude

Variance refers to the overall dispersion of data. Variability is often quantified by the standard deviation (i.e., square root of the variance) about the mean. To avoid misinterpretations due to differences in relative magnitude of signals, researchers often determine the coefficient of variation, that is, the standard deviation divided by its mean. Variability has been predominately assessed based on its magnitude. Historically, gait parameter variance has been regarded as the manifestation of imprecise control of the locomotor system. In the clinical gait literature, the inability to generate rhythmic, repeatable patterns is thought to indicate a less stable system. This is shown in schematic form in Figure 1, where variability increases from left to right panels; the corresponding stability of the system associated with these variability patterns would also be decreasing from left to right. Variability magnitude has provided critical information regarding its association with fall risk. For example, stride time variability is associated with fall risk, whereby greater variability is correlated to a greater risk of falling (Hausdorff, 2007). In addition, greater step width variability (Maki, 1997; Owings & Grabiner, 2004a), stride length variability (Maki, 1997; Verghese et al., 2009), and swing time variability (Verghese et al., 2009) are also associated with greater fall risk.

Variability magnitude has been shown to increase with advanced aging. For example, Kang and Dingwell (2008) compared the gait kinematics of healthy young and older adults and reported that older adults exhibited greater variability in stride time, step length, trunk pitch, and trunk roll. Owings and Grabiner

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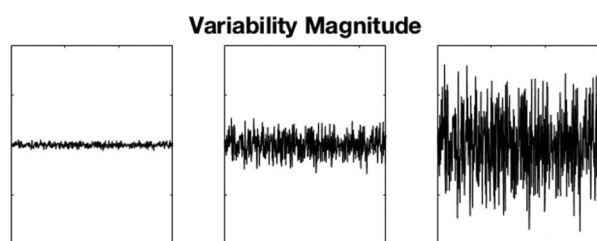
Variability Magnitude

Figure 1 — Magnitudes of variance for an arbitrary biological signal. All three signals exhibit the same mean value. The variability increases from left to right and this increase in variability has typically been associated with a less controlled and unstable locomotor system.

(2004a, 2004b) provided evidence that step width variability discriminates young versus older adults in that older adults are more variable. Moreover, compared to age-matched nonfallers, older adults who prospectively experienced a fall exhibited greater variability in stride length, stride velocity, and double support time (Maki, 1997).

Overall, it appears that a greater magnitude of variability in stride parameters appears to be related to gait changes due to aging and disease, and may be good predictors of falls. However, it is important to note that not all research on gait parameter changes has shown that increased variability is systematically linked to instability and falls. Brach and colleagues (Brach, Berlin, VanSwearingen, Newman, & Studenski, 2005) provided evidence that, in addition to a large magnitude of step width variability, exhibiting very little step width variability was also associated with greater fall risk. Findings such as those from Brach et al. (2005) suggests that some variability may be functional, and this has been recognized several decades ago in the context of clinical aspects related to human locomotion (Hamill, Van Emmerik, Heiderscheit, & Li, 1999; Wagenaar & Van Emmerik, 1994). Much of this research emerged from a dynamical systems perspective on human movement with a special emphasis on coordination and coordination variability. Next, we will briefly review what clinical gait and sports biomechanics literatures have contributed to our understanding of the functional role of variability in human movement.

Coordination Variability

While many researchers have studied variance from the perspective that the goal is minimization, others have focused on how variability at different 'levels' of the system (i.e., output vs. limb trajectories vs. joint/segmental) relate and are organized to create optimal and functional movements (Latash, Sholz, & Schöner, 2002; Scholz & Schöner, 1999; Van Emmerik et al., 2016). The multiple degrees of freedom involved in the coordination and control of human movement, as very early recognized by Bernstein (1967), are a potential source of variability. Again, variability is traditionally equated with noise in human movement, considered detrimental to system performance and typically eliminated from data as a source of error. However, the type of variability at the level of limb or segment coordination is very different from the gait 'output' variability described earlier (e.g., stride time variability). Although variability in gait parameters can be important indicators of age- and disease-related changes and predictors of falls (Verghese et al., 2009), this does not suggest that all variability present in human movement is inherently detrimental. There is a growing body of

literature in the biological and physical sciences that stresses the beneficial and adaptive aspects of variability for system functionality, and in this perspective the path to frailty is marked by a loss of variability in fundamental variables reflecting biological function (Lipsitz, 2002). This path is identified as a 'loss of complexity' and is characterized by reductions in effective degrees of freedom (i.e., interacting components and synergies involved in the control of the biological system) that become associated with a loss of variability. When these reductions in degrees of freedom and variability reach a critical threshold, injury or disease may emerge. Therefore, from this perspective, variability is not inherently good or bad, but rather indicates the range of coordination patterns used to complete the motor task. This updated consideration offers a different view in comparison to the more traditional "variability is bad" perspective. In contrast to the historical viewpoint, there is a functional role for variability that expresses the range of possible patterns and transitions between patterns that a movement system can accomplish. Both abnormally low and high levels of variability may be detrimental to the functioning of the system.

There is growing evidence in both sports performance and injury/disease literatures that coordinative variability is functional and important for the development of adaptive movement behaviors. Recent reviews on variability in sports biomechanics have provided clear evidence for the role of variability in optimizing performance (Bartlett, Wheat, & Robins, 2007; Davids, Glazier, Araujo, & Bartlett, 2003; Preotoni et al., 2013). These reviews emphasize the importance of movement variations from trial to trial within individuals, and these variations function to exploit the many potential solutions offered by the abundant degrees of freedom of the human body. These reviews have highlighted new concepts and tools from dynamical systems theory applied to movement systems that have been instrumental in demonstrating the functional role of coordinative variability. In this framework, the functional role of variability is considered in the context of the multitude of degrees of freedom that provide numerous solutions to a task (Bernstein, 1967; Latash, 2012), and the different and varying constraints present at the level of the organism, environment, and task (Newell, 1986).

Research on orthopedic injuries in runners has demonstrated that some degree of variability appears to be a signature of healthy, pain-free movement (Hamill et al., 1999; Heiderscheit, Hamill, & Van Emmerik, 2002; Miller, Meardon, Derrick, & Gillette, 2008; Seay, Van Emmerik, & Hamill, 2011; Wagenaar & Van Emmerik, 1994). Hamill et al. (1999) and Heiderscheit et al. (2002) found that runners with unilateral patellofemoral pain were less variable in segment couplings involving the knee joint than healthy runners. Seay and colleagues (2011) observed systematic decreases in coordination variability in runners with low back pain. Coordination variability between the pelvis and trunk was lower in runners with current low back pain compared to controls. Interestingly, those runners with previous low back pain but who were currently asymptomatic showed variability values between the controls and current low back pain runners (see Figure 2). These results can be interpreted in the context of the distinction between absolute and relative coordination as formulated by Von Holst (1939/1973). Two oscillators are in absolute coordination when they are phase and frequency locked. In contrast, oscillators in relative coordination maintain tendencies to particular phase couplings but exhibit a much wider array of observed frequency and phase relationships. The dynamics of relative coordination are thought to represent more adaptable coordination dynamics. The results from the Seay et al. study (Figure 2) nicely show this shift from more absolute
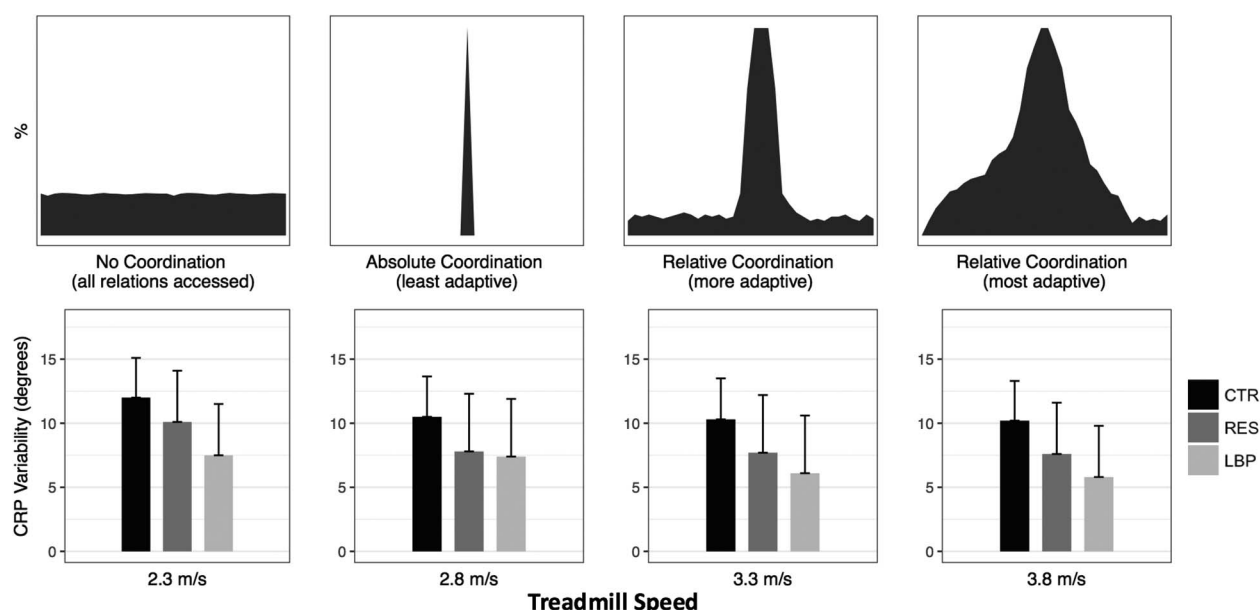
Figure 2 — Exemplar graph from Seay et al. (2011) study displaying the changes in coordination variability (continuous relative phase; CRP) during running at different speeds (bottom panels). CRP variability systematically decreases from healthy controls (CTR) to runners with resolved low back pain (RES) to runners who experienced low back pain during the testing (LBP). These variability patterns reflect the dynamics of absolute (low variability) and relative (higher variability) coordination as formulated by Von Holst (1939/1973) (upper panels). Adapted from Seay et al. (2011) and Palmer et al. (2012).

coordination in the low back pain runners to relative coordination in the healthy controls. Overall, these findings are indicative of a narrow range of coordination patterns in those with orthopedic injuries. In domains such as (running) footwear, designers should seek to optimize the variation in segmental relationships while maintaining the overall locomotion pattern, enabling an adaptable system that is also stable to unanticipated perturbations (Palmer, Van Emmerik, & Hamill, 2012).

Finally, research on coordinative movement variability in neurological disorders and rehabilitation has indicated clear and consistent links between reduced variability and pathology (Stergiou, Harbourne, & Cavanaugh, 2006; Van Emmerik, Wagenaar, Winogrodzka, & Wolters, 1999). In an early paper, Van Emmerik et al. (1999) showed reductions in coordinative variability between trunk and pelvis in patients recently diagnosed with Parkinson's disease (PD). This reduction in variability was posited to be the result of axial rigidity and associated with difficulty transitioning between different movement speeds. This reduction in coordinative variability was in contrast to the variability findings at the level of the gait parameters, whereby the PD patients did not differ from healthy controls. These results indicate that it is important to assess variability changes in neurological populations at different levels of the system. Rehabilitation protocols for neurological patients should therefore be aimed at promoting optimal levels of movement variability that allow different patterns to develop and be used flexibly, thereby promoting adaptability.

Variability Structure: Fractal Organization

While variability magnitude at various levels clearly describes key components of locomotor behavior, the past two decades have provided the motor behavior literature with a wealth of empirical research examining the *structure* of variability. Assessment of variability structure generally involves: (1) identifying a signal's correlation structure, (2) determining signal characteristics in the frequency domain, or (3) estimating the correlation structure by quantifying the power law statistical correlations of fluctuations across various temporal scales.

Statistical correlations of variance across temporal scales indicate self-similarity. Self-similarity is a key feature of a fractal structure or behavior. Mathematician Benoit Mandelbrot first coined the term fractal, which was based on the Latin word *fractus*, meaning fractured (Mandelbrot, 1977). A fractal is essentially an infinitely repeating pattern that is self-similar across multiple scales. A fractal may possess geometric self-similarity, as is the case in, for example, the Koch snowflake (Figure 3) or the Sierpinski triangle (Liebovitch & Shehadeh, 2005).

Alternative to geometric self-similarity, a fractal may possess statistical self-similarity. A statistically self-similar object or signal is one whereby smaller pieces (or time scales) resemble the entire piece (or time series) (Liebovitch & Shehadeh, 2005). Figure 4 shows an example of statistically similar stride time fluctuations at different time scales during human walking.
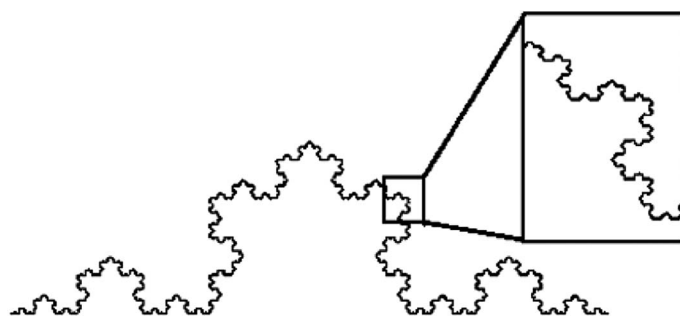

Figure 3 — Koch snowflake as an example of a geometric fractal object. The object is self-similar in that smaller pieces are copies of the entire piece. Here the small box is enlarged to reveal more details about its structure (large box). Adapted from Liebovitch (1998).
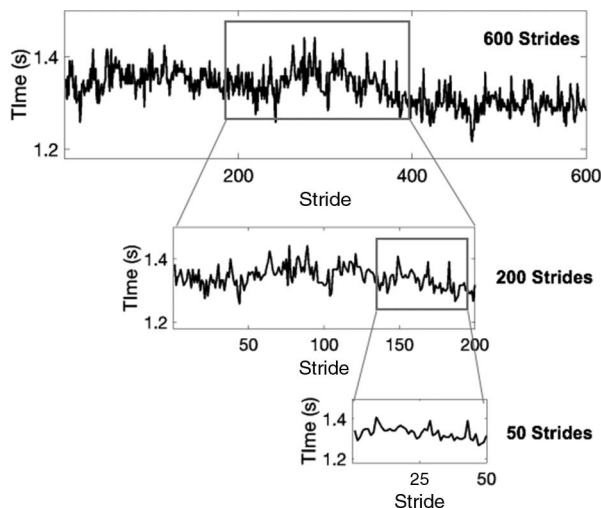
Figure 4 — Statistical self-similarity of locomotor stride times. As the time series is magnified to reveal less strides (i.e., smaller scale), the overall shape of the signal resembles the larger time series datasets.

Mathematically, this relationship is expressed as a power-law distribution. That is, when plotted on a double logarithmic graph, the probability density function (PDF) and scale size are linearly related (see Figure 5). The behavior's description (mean, variance) is not universal but rather a function of the scale size that is being examined (Schroeder, 1991). In other words, the behavior lacks a characteristic scale, and the traditional linear statistical components of overall mean and variance are not defined and therefore lack meaning or importance. This phenomenon is also represented

in the behavior's autocorrelation properties (i.e., its correlation structure). A random process will rapidly approach a value of 0 at lag-1, indicating each data point is independent from any other. In contrast, a fractal-like process will remain correlated at lag-1, and this correlation decays in a power law fashion. This characteristic indicates the signal at any given point exhibits dependence upon previous and future states.

Fractality appears to be ubiquitous, as several structures in natural phenomena (trees, lightning) and human physiology (nerves, blood vessels) exhibit a fractal nature. For this reason, various other components of biological systems have been evaluated. However, one challenge with assessing biological behavior is that these signals often exhibit nonstationarity. For this reason, Peng and colleagues (Peng et al., 1994; Peng, Havlin, Stanley, & Goldberger, 1995) developed a modified root-mean-square analysis of a random walk, termed detrended fluctuation analysis ([DFA] Equation 1). DFA benefits from the fact that the extent of self-similarity within a system that exhibits long-range correlations can be quantified via simple integration (Hausdorff, Peng, Wei, & Goldberger, 2000). DFA evaluates the magnitude of variability in a signal at different temporal scales, or window sizes. To accomplish this, the biophysical signal is first integrated, then sectioned into nonoverlapping windows (n, Figure 5). In each window, a least-squares linear fit line is applied to the signal. A root-mean-square analysis is then conducted by subtracting the local trend line's y-coordinate from the integrated signal's fluctuations. This process is performed and averaged across all windows of a given window size (n), as shown in Equation 1:

$$F(n) = \sqrt{\frac{1}{\lfloor N/n \rfloor} \sum_{j=1}^{\lfloor N/n \rfloor} \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X}_i)^2} \tag{1}$$
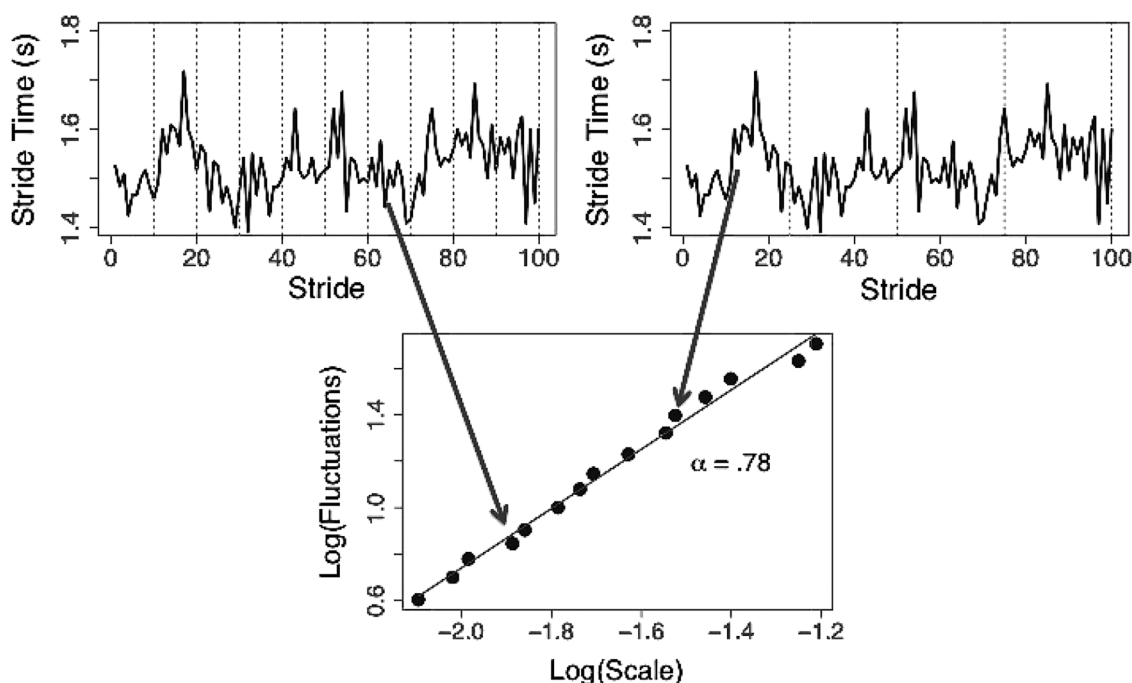
Figure 5 — Illustration of detrended fluctuation analysis (DFA) method on a biophysical signal (here, stride interval). The signal is sectioned into nonoverlapping windows of varying sizes; here illustrated as 10 (top left) and 25 (top right) strides. A local trend line is fit within each window. The average of the fluctuation magnitudes across varying scales are plotted on a double log diffusion plot (bottom). Adapted from Rhea and Kiefer (2014).

where $F(n)$ is the fluctuation magnitude at window n, N is the total number of strides in the time series, X_i is the integrated signal at stride interval i, and $\bar{X}_i$ is the y-coordinate location of the local trend within window n. This process is averaged across all non-overlapping windows (j) of size n (total number of windows $= N/n$). The average fluctuation (F) at a given window size (n) is then plotted in a log-log graph against the window size (n) (Figure 5). A linear relationship on this double-log graph indicates the existence of power law scaling (Peng et al., 1995).

The slope of the linear fit on the log-log graph is called the scaling exponent, singularity exponent, or α (Figure 5). A scaling exponent of α = 1.0 indicates 1/f phenomena, whereby the power of the signal is inversely related to the frequency (West & Shlesinger, 1990). This slope of α = 1.0 is also called "pink noise" and identifies strong long-term correlations between the different time scales (Figure 6; middle column). A scaling exponent of α = .5 represents an uncorrelated signal, equivalent to white noise (Figure 6; left column). A scaling exponent of .5 < α ≤ 1.0 indicates long-range persistence, whereby small or large fluctuations are likely to be followed by small or large fluctuations, respectively. In contrast, a scaling exponent of 0 < α < .5 indicates antipersistence, whereby small fluctuations are likely to be followed by large fluctuations, and vice versa. A scaling exponent > 1.0 no longer

signifies a power-law relationship, and a scaling exponent of 1.5 indicates Brown noise (i.e., the integration of white noise; Figure 6, right column) (Peng et al., 1995). Brown noise is characterized by nonstationary random drifts, whereby it is highly dependent upon its previous conditions, and at the same time exhibits randomness from point to point. That is, it exhibits random steps at short time scales, yet the overall distance traveled is dependent upon the number of iterations. This is in contrast to white noise (α = .5), which is absent of dependence upon previous or future states. Brown noise is thought to reflect an overly constrained system that is not very adaptable. Because both white and brown noises are considered extremes, 1/f or pink noise is a special class of signal organization that rests at the border between random stationarity and constrained nonstationarity. That is, pink noise exhibits both structure and stochasticity, and therefore reflects a complex system that is organized to optimize adaptive and flexible behavior.

The DFA algorithm is highly advantageous in biological signals because the local detrending avoids the aforementioned issues related to signal nonstationarity that might otherwise require some type of data reduction or manipulation. Peng et al. (1995) applied the DFA algorithm to the heart-beat interval timing of healthy adults with no history of heart disease, and compared it to heartbeat intervals of individuals with severe heart failure. The
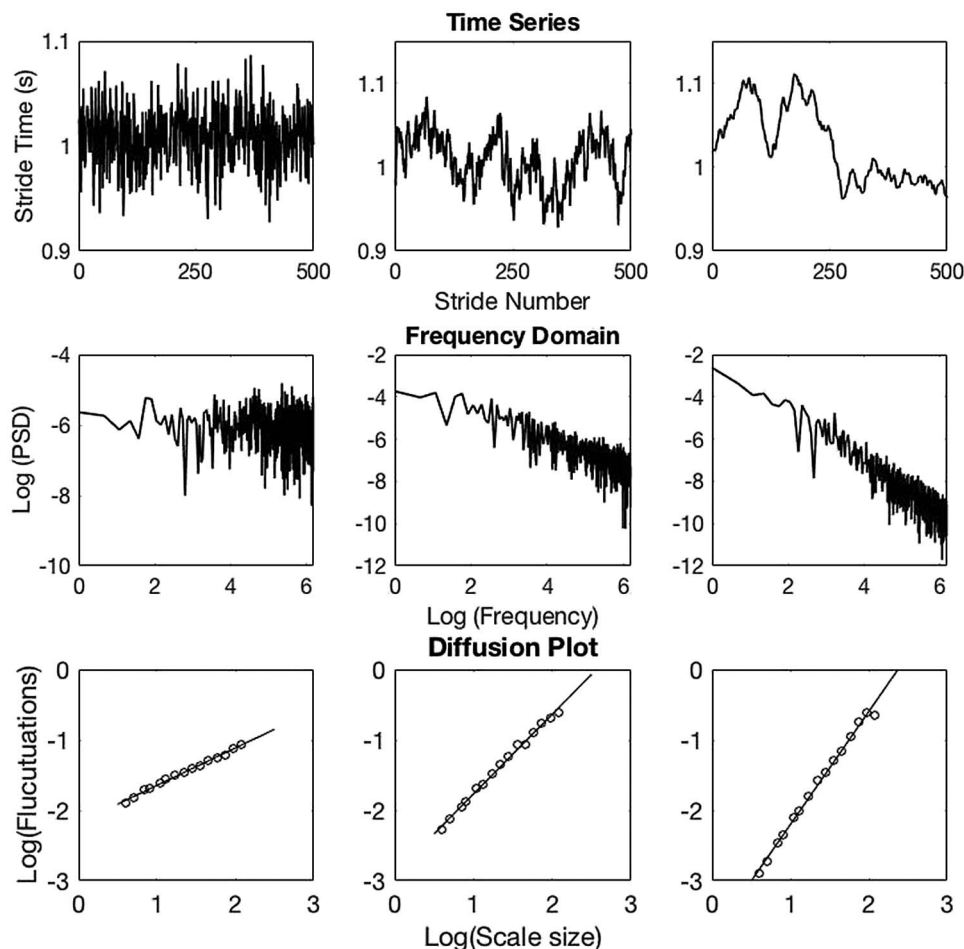
Figure 6 — White, pink, and brown noise signal characteristics (left, middle, and right columns, respectively) within a time series (top row), log transformed frequency domain (middle row), and log transformed fluctuation magnitude diffusion plot (bottom row). Note that the fractal scaling exponent is estimated by the slope of the line of best fit for the diffusion plots, here shown as 0.5, 1.0, and 1.5 for the white, pink, and brown noise signals, respectively.

healthy individuals exhibited a scaling exponent of 1.00 ± 0.11, suggesting long-range correlations and, more specifically, 1/f behavior. The individuals with severe heart disease, on the other hand, exhibited scaling exponents of 1.24 ± 0.22, a behavior that approached brown noise ($\alpha = 1.5$). This indicates these heartbeat intervals may be considered overly structured and constrained, characteristics often attributed to a diseased state.

Fractal Dynamics in Human Locomotion

In a series of follow-up experiments, and the first of their kind to evaluate the potential fractal-like nature of human locomotion, Hausdorff and colleagues (Hausdorff et al., 1996, 1997; Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995) employed the DFA algorithm on a time series of stride intervals. A stride time or stride interval is the time component from heel strike of one foot to the subsequent heel strike of the same foot. Although appearing relatively random (see Figure 6), deeper inspection of stride times over a multitude of strides provides evidence of underlying patterns. These studies provided the first indication that stride times of young, healthy adults exhibit persistent long-range correlations, that is, scaling exponents of $.5 < \alpha \leq 1.0$. Long-range correlated behavior is characterized by stride times that are statistically dependent upon previous and future iterations. The observed statistical dependence of stride times on preceding and forthcoming stride times has been described and modeled as a system exhibiting locomotor 'memory' (Hausdorff et al., 1995).

The precise scaling exponent of stride intervals varies by study. For example, young healthy adults walking at their preferred speed have reported scaling exponents of $\alpha = .76 \pm .11$ (Hausdorff et al., 1995) and .84 (Hausdorff et al., 1996). The discrepancies in scaling exponent values can likely be explained by differences in experimental design or parameterization. For example, greater trial lengths create a larger number of stride times, which may impact the stability and sensitivity of the DFA algorithm. That is, greater data lengths are generally less susceptible to influence from outliers. Additionally, determination of minimum and maximum window sizes have been a topic of debate, and while specific guidelines have been suggested (Damouras, Chang, Sejdic, & Chau, 2010), a clear consensus has not been agreed upon. Finally, treadmill versus overground walking may produce differences in scaling exponents, as treadmill walking generally reduces the scaling exponent (Terrier & Deriaz, 2011).

In addition to preferred speed walking conditions, long-range correlations in young adults have been observed at faster or slower walking speeds. In fact, walking slower or faster than preferred speed resulted in *greater* scaling exponents of $\alpha = .9$ and 1.0, respectively (Hausdorff et al., 1996). This phenomenon has been repeated in subsequent studies during both walking (Jordan, Challis, & Newell, 2007b) and running (Jordan, Challis, & Newell, 2007a).

One note of consideration is that young healthy adults do not exhibit "optimal" fractal scaling or pink noise with the strongest long-range correlations (i.e., $\alpha = 1.0$) while walking at preferred speed. Instead, scaling exponents are commonly observed to be almost exactly between 1/f ($\alpha = 1.0$) and random ($\alpha = .5$). Some have reasoned that scaling characteristics ~.75 represent a healthy system, optimally positioned between overly random and overly structured (Hausdorff, 2007; Rhea & Kiefer, 2014). We propose an alternative explanation, namely that at preferred gait speed the system is potentially minimally constrained and not sufficiently challenged to demonstrate pure 1/f fluctuations of $\alpha = 1.0$. Fractal

scaling near 1/f may not be optimal in terms of metabolic cost, which has consistently been demonstrated to be minimized at preferred gait speed. In addition, and as mentioned above, walking faster or slower than preferred speed yields greater scaling exponents. These findings have been argued to be a manifestation of increased constraint on the locomotor system at fast or slow speeds, thereby reducing the available degrees of freedom (Jordan et al., 2007b). Here we again offer an alternative hypothesis, namely that at gait speeds other than preferred, the greater demands and challenges elicit fluctuations in gait patterns that shift the locomotor system towards more optimal fractality ($\alpha = 1.0$) to increase long-range correlations and adaptive performance at these speeds, possibly at the expense of metabolic efficiency.

Changes in Fractal Dynamics With Aging and Disease

In contrast to young, healthy adults, older adults and individuals with Huntington's disease display a breakdown of long-range correlations, that is, scaling exponents closer to uncorrelated random fluctuations (Hausdorff et al., 1997). Older adults' average scaling values were $\alpha \sim .68$, while those with Huntington's disease displayed scaling exponents of $\alpha \sim .6$. Additionally, the scaling exponent of Huntington's disease participants was linearly associated with the disease severity ($r = .78$), whereby greater disease severity correlated to lower scaling exponents (i.e., closer to $\alpha = .5$) (Hausdorff et al., 1997). Considering this breakdown of long-range correlations with aging and Huntington's disease, the authors speculated that supraspinal processes may be responsible for the fractal behavior in gait. However, although neurological disorders such as Huntington's and Parkinson's disease can be attributed to degeneration in the basal ganglia area of the brain, this likely affects the entire movement system and variability relations between all the components and degrees of freedom involved.

Adaptability: A Key Characteristic of Fractal Organization

Fractal-like behavior is thought to represent a complex, adaptive system (Delignieres & Marmelat, 2012; Lipsitz & Goldberger, 1992). A system is complex when it has numerous components operating and interacting at various spatiotemporal scales, giving rise to overall functionality (Lipsitz, 2002). A more complex organization is indicative of a system that can utilize a greater number of functional solutions to respond to perturbations (Lipsitz, 2002). A fractal signal exhibits power at a wide range of frequencies, and the power is distributed such that it is proportional to the period of oscillation. When the signal's power is dispersed in this manner, perturbations at any given scale can be attenuated, and thus the system overall is more adaptable (Delignieres et al., 2006). In other words, this systemic organization allows perturbations at any given scale to be attenuated; thus, local destabilization does not propagate to global instability. For example, Sapoval and colleagues provided empirical support that a drum whose borders are organized in a fractal manner provide optimal sound wave dissipation characteristics (Sapoval, Gobron, & Margolina, 1991). Similar to the fractal drum, fractal-like coastlines are able to dissipate wave energies because the large surface area maximizes viscous damping (Sapoval et al., 1991). In human physiology, the fractal arrangement of the circulatory system provides requisite

dissipation of heart beat blood flow (Bassingthwaighte & van Beek, 1988). Thus, the fractal nature of these systems may be considered an emergent property and key characteristic of a complex dissipative and adaptive system (Seely & Macklem, 2012).

Does Fractal Behavior Represent Adaptability in Human Locomotion?

Fractal-like organization in natural and physiological structures is thought to represent complex, dissipative systems that are optimally organized to attenuate disturbances from stressors (Lipsitz, 2002; Seely & Macklem, 2012). Correspondingly, in the human locomotor system, the fractal properties observed in walking have been theorized to represent gait adaptability, defined as the capacity to alter locomotor patterns in response to imposed constraints (Balasubramanian, Clark, & Fox, 2014). Essentially, the long-range correlated behavior exhibited by fractal-like biological signals may indicate interactivity among biological processes (Van Orden, Holden, & Turvey, 2003) that ultimately serve to attenuate perturbations at various spatiotemporal scales (Delignieres & Marmelat, 2012; Delignieres et al., 2006; Rhea & Kiefer, 2014; Stergiou & Decker, 2011).

Another way to consider the advantage of fractal behavior is that an adaptive locomotor system needs to engage with the unexpected, dynamic environment in which it exists. If the system is highly variable from stride to stride, it may in fact be indicative of an unstable system unable to produce consistent patterns. However, if the system attempts to minimize stride-to-stride variance, the negative outcome is an overly rigid system, incapable of transitioning to more stable states depending on the imposed constraints (Van Emmerik et al., 1999). Thus, an adaptive system exhibits both structure and functional variance (Rhea & Kiefer, 2014).

Empirical Support for Fractality as Adaptive Locomotor System

Surprisingly, there is a general lack of empirical investigation into the potential relationship between adaptability and fractal behavior. Although various researchers subscribe to the framework that fractal-like fluctuations in gait variance indicate gait adaptability, most gait studies entail fractal analysis of steady state, unperturbed walking. In unperturbed conditions, individuals are not exposed to organism, task, or environment level constraints that demand changes to locomotor patterns (Newell, 1986). Importantly, the connection between gait variance fractality and adaptive capacity has been consistently inferred and presumed to exist in the locomotion literature, but not been systematically tested.

Our research group has recently begun to investigate empirically the link between fractal scaling and adaptive gait performance (Ducharme, 2017). Fifteen young, healthy adults walked on a split-belt treadmill that elicited gait asymmetries by moving treadmill belts at different speeds, thereby forcing participants to modify locomotor patterns. This treadmill has two adjacent but separate belts that can be programmed to travel at different speeds. Participants walked with the belts tied at their preferred walking speed, at half of their preferred speed, and asymmetrically. During the asymmetric walking condition, the treadmill belt under the dominant leg traveled at preferred walking speed, and the belt under the nondominant leg traveled at half of the preferred speed (i.e., 2:1 ratio asymmetry). This asymmetric condition initially causes
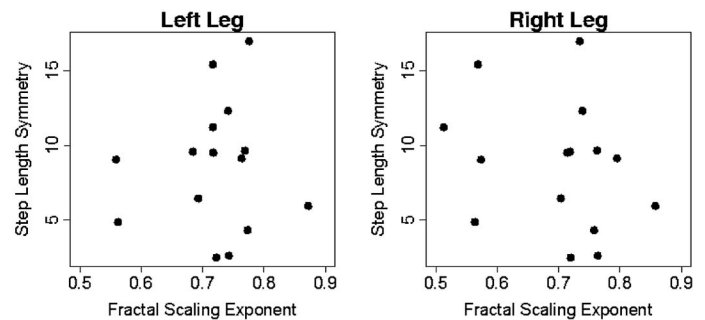

Figure 7 — Relationship between unperturbed walking fractal dynamics and step length symmetry during asymmetric walking. Symmetry measures are summed values over the first 100 strides, whereby smaller values represent greater symmetry. There was no association between variables for the left ($R^2 = -.11$, $p = .74$) or right ($R^2 = -.09$, $p = .65$) legs.

asymmetry of various gait parameters, including step length and limb angle relative phasing. Prior research has shown that both young and older adults eventually regain step length symmetry, but that older adults adapt slower and to a lesser extent (Bruijn, Van Impe, Duysens, & Swinnen, 2012).

In the Ducharme (2017) study, adaptability was quantified as the summed absolute magnitude of deviation from perfect step length symmetry across the first 100 strides of asymmetric walking. Detrended fluctuation analysis was used to quantify stride time fractal scaling. Findings suggest there is no relationship between unperturbed, preferred speed walking fractal scaling and gait adaptability performance (Figure 7). However, during the novel, perturbed walking task (i.e., asymmetric walking), fractal scaling increased, from $\alpha \sim .7$ during unperturbed walking to $\alpha \sim .9$ during asymmetric walking. Furthermore, a quadratic relationship emerged between fractal dynamics and step length symmetry. Specifically, those individuals whose fractal scaling approached $\alpha \sim 1.0$ (i.e., 1/f scaling) exhibited the most symmetric step length performance. Alternatively, individuals whose fractal scaling was less than ($\alpha < .9$) or greater than ($\alpha > 1.0$) 1/f scaling exhibited poorer, less symmetric performance (Figure 8).
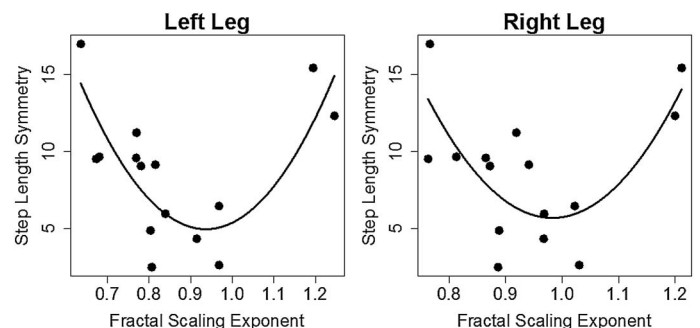

Figure 8 — Relationship between perturbed, asymmetric walking stride time fractal scaling and step length symmetry during asymmetric walking. Symmetry measures are summed values over the first 100 strides, whereby smaller values represent greater symmetry. There was a quadratic relationship between variables for both the left ($R^2 = .59$, $p = .002$) and right ($R^2 = 0.49$, $p = .007$) legs. Optimal performance corresponded with fractal scaling exponents $\sim \alpha = 1.0$.

To the best of the authors' knowledge, these findings represent the first empirical evidence that fractal scaling may be directly associated with adaptive gait performance. The original hypothesis that steady-state, unperturbed walking fractality would predict gait adaptability was rejected. It was not until participants were exposed to task-level constraints that greater stride time statistical persistence emerged. These changes in fractal scaling in response to challenging, asymmetric walking may represent a functional reorganization of the locomotor system to be better suited to attenuate perturbations. Individuals who did not shift fractal scaling from unperturbed to perturbed walking exhibited greater step length asymmetry. These scaling exponents are characterized by less correlated and complex structure. Likewise, those individuals whose fractal scaling increased above 1.0 towards more Brownian, overly structured, fluctuations (i.e., ~1.2) also displayed greater step length asymmetry. Similar to the higher scaling exponents observed in the heart beat dynamics of diseased versus healthy adults (Peng et al., 1995), this extreme fractal scaling is indicative of an overly constrained system. Certainly, more research is warranted to refute or further support the findings presented here. Nonetheless, these results are promising in that fractal analyses may provide a unique perspective and description of locomotor health. Further, there is evidence that fractal scaling is not unchangeable, but rather can be modified by adhering foot strikes to a visual or auditory metronome that has fractal-like intervals (Marmelat, Torre, Beek, & Daffertshofer, 2014; Rhea, Kiefer, D'Andrea, Warren, & Aaron, 2014).

Conclusion

Variability has deservedly received critical acclaim in human movement research. However, persistent interpretation of variability as being detrimental and associated with poor performance or disability has limited its potential as a descriptor or possible predictor of locomotor systemic health and capacity. The magnitude of variability appears to describe systemic stability and fall risk. Examining coordination variability has brought to light the implication that the level at which variability is assessed severely impacts its interpretation. Studies of coordination variability have provided empirically-supported evidence of the functionality of variability. This has been shown in research on sports performance as well as clinical gait, where both literatures consistently have reported the functional role of variability at the level of coordinative dynamics. In addition, the structure of variability (i.e., fractal dynamics) may be a key measure of locomotor adaptability. Herein we provide the first indication that stride time fractal dynamics may in fact be correlated to gait adaptability performance during exposure to novel gait tasks. Those individuals whose stride time fractality increased closer to $\alpha = 1.0$ when exposed to asymmetric walking also exhibited the most symmetric step length performance. Importantly, this relation between fractality and gait adaptability performance did not emerge under less constrained preferred walking conditions. Future research should continue to explore this potential relationship using various organismic- or task-level constraints.

Acknowledgments

References

Balasubramanian, C.K., Clark, D.J., & Fox, E.J. (2014). Walking adaptability after a stroke and its assessment in clinical settings. *Stroke Research and Treatment, 2014*, 1–21. doi:10.1155/2014/591013

Bartlett, R., Wheat, J., & Robins, M. (2007). Is movement variability important for sports biomechanists? *Sports Biomechanics, 6*, 224–243. doi:10.1080/14763140701322994

Bassingthwaighte, J.B., & van Beek, J.H.G.M. (1988). Lightning and the heart: Fractal behavior in cardiac function. *Proceedings of the IEEE, 76*, 693–699. doi:10.1109/5.4458

Bernstein, N.A. (1967). *The co-ordination and regulation of movements*. Oxford, UK: Pergamon Press, Ltd.

Brach, J.S., Berlin, J.E., VanSwearingen, J.M., Newman, A.B., & Studenski, S.A. (2005). Too much or too little step width variability is associated with a fall history in older persons who walk at or near normal gait speed. *Journal of Neuroengineering and Rehabilitation, 2*, 21–28. doi:10.1186/1743-0003-2-21

Bruijn, S.M., Van Impe, A., Duysens, J., & Swinnen, S.P. (2012). Split-belt walking: Adaptation differences between young and older adults. *Journal of Neurophysiology, 108*, 1149–1157. doi:10.1152/jn.00018.2012

Damouras, S., Chang, M.D., Sejdic, E., & Chau, T. (2010). An empirical examination of detrended fluctuation analysis for gait data. *Gait & Posture, 31*, 336–340. PubMed doi:10.1016/j.gaitpost.2009.12.002

Davids, K., Glazier, P.S., Araujo, D., & Bartlett, R.M. (2003). Movement systems as dynamical systems: The role of functional variability and its implications for sports medicine. *Sports Medicine, 33*, 245–260. PubMed doi:10.2165/00007256-200333040-00001

Delignieres, D., & Marmelat, V. (2012). Fractal fluctuations and complexity: Current debates and future challenges. *Critical Reviews in Biomedical Engineering, 40*, 485–500. doi:10.1615/CritRevBiomedEng.2013006727

Delignieres, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., & Ninot, G. (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *Journal of Mathematical Psychology, 50*, 525–544. doi:10.1016/j.jmp.2006.07.004

Ducharme, S.W. (2017). *Quantifying gait adaptability: Fractality, complexity, and stability during asymmetric walking* (Doctoral dissertation). University of Massachusetts, Amherst.

Hamill, J., Van Emmerik, R.E.A., Heiderscheit, B.C., & Li, L. (1999). A dynamical systems approach to lower extremity running injury. *Clinical Biomechanics, 14*, 297–308. PubMed doi:10.1016/S0268-0033(98)90092-4

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

Hausdorff, J.M., Mitchell, S.L., Firtion, R., Peng, C.K., Cudkowicz, M.E., Wei, J.Y., & Goldberger, A.L. (1997). Altered fractal dynamics of gait: Reduced stride-interval correlations with aging and Huntington's disease. *Journal of Applied Physiology, 82*, 262–269. PubMed doi:10.1152/jappl.1997.82.1.262

Hausdorff, J.M., Peng, C.K., Ladin, Z., Wei, J.Y., & Goldberger, A.L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of Applied Physiology, 78*, 349–358. PubMed doi:10.1152/jappl.1995.78.1.349

Hausdorff, J.M., Peng, C.K., Wei, J.Y., & Goldberger, A.L. (2000). Fractal analysis of human walking rhythm. In J.M. Winters, & P.E. Crago (Eds.), *Biomechanics and neural control of posture and movement* (1st ed., pp. 253–264). New York, NY: Springer.

Hausdorff, J.M., Purdon, P.L., Peng, C.K., Ladin, Z., Wei, J.Y., & Goldberger, A.L. (1996). Fractal dynamics of human gait: Stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology, 80*, 1448–1457. doi:10.1152/jappl.1996.80.5.1448

Heiderscheit, B.C., Hamill, J., & Van Emmerik, R.E.A. (2002). Variability of stride characteristics and joint coordination among individuals with unilateral patellofemoral pain. *Journal of Applied Biomechanics, 18*, 110–121. doi:10.1123/jab.18.2.110

Jordan, K., Challis, J.H., & Newell, K.M. (2007a). Speed influences on the scaling behavior of gait cycle fluctuations during treadmill running. *Human Movement Science, 26*, 87–102. doi:10.1016/j.humov.2006.10.001

Jordan, K., Challis, J.H., & Newell, K.M. (2007b). Walking speed influences on gait cycle variability. *Gait & Posture, 26*, 128–134. doi:10.1016/j.gaitpost.2006.08.010

Kang, H.G., & Dingwell, J.B. (2008). Separating the effects of age and walking speed on gait variability. *Gait & Posture, 27*, 572–577. PubMed doi:10.1016/j.gaitpost.2007.07.009

Latash, M.L. (2012). The bliss (not the problem) of motor abundance (not redundancy). *Experimental Brain Research, 217*, 1–5. PubMed doi:10.1007/s00221-012-3000-4

Latash, M.L., Sholz, J.P., & Schöner, G. (2002). Motor control strategies revealed in the structure of motor variability. *Exercise and Sport Sciences Reviews, 30*, 26–31. PubMed doi:10.1097/00003677-200201000-00006

Liebovitch, L.S. (1998). *Fractals and chaos simplified for the life sciences.* Oxford, UK: Oxford University Press.

Liebovitch, L.S., & Shehadeh, L.A. (2005). Introduction to fractals. In M.A. Riley, & G. Van Orden(Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences Web book.* Fairfax, VA: National Science Foundation.

Lipsitz, L.A. (2002). Dynamics of stability: The physiologic basis of functional health and frailty. *Journals of Gerontology Series A-Biological Sciences and Medical Sciences, 57*, B115–B125. PubMed doi:10.1093/gerona/57.3.B115

Lipsitz, L.A., & Goldberger, A.L. (1992). Loss of 'complexity' and aging. *Journal of the American Medical Association, 267*, 1806–1809. PubMed doi:10.1001/jama.1992.03480130122036

Maki, B.E. (1997). Gait changes in older adults: Predictors of falls or indicators of fear. *Journal of the American Geriatrics Society, 45*, 313–320. PubMed doi:10.1111/j.1532-5415.1997.tb00946.x

Mandelbrot, B.B. (1977). *The fractal geometry of nature.* New York, NY: W. H. Freeman and Company.

Marmelat, V., Torre, K., Beek, P.J., & Daffertshofer, A. (2014). Persistent fluctuations in stride intervals under fractal auditory stimulation. *PLoS ONE, 9*, e91949. PubMed doi:10.1371/journal.pone.0091949

Miller, R.H., Meardon, S.A., Derrick, T.R., & Gillette, J.C. (2008). Continuous relative phase variability during an exhaustive run in runners with a history of illiotibial band syndrome. *Journal of Applied Biomechanics, 24*, 262–270. doi:10.1123/jab.24.3.262

Newell, K.M. (1986). Constraints on the development of coordination. In M.G. Wade, & H.T.A. Whiting (Eds.), *Motor development in children: Aspects of coordination and control* (pp. 341–360). Dordrecht, The Netherlands: Martinus Nijhoff.

Newell, K.M., & Corcos, D.M. (Eds.). (1993). *Variability and motor control.* Champaign, IL: Human Kinetics Publishers.

Newell, K.M., & Vaillancourt, D.E. (2001). Dimensional change in motor learning. *Human Movement Science, 20*, 695–715. PubMed doi:10.1016/S0167-9457(01)00073-2

Owings, T.M., & Grabiner, M.D. (2004a). Step width variability, but not step length variability or step time variability, discriminates gait

of healthy young and older adults during treadmill locomotion. *Journal of Biomechanics, 37*, 935–938. doi:10.1016/j.jbiomech.2003.11.012

Owings, T.M., & Grabiner, M.D. (2004b). Variability of step kinematics in young and older adults. *Gait & Posture, 20*, 26–29. doi:10.1016/S0966-6362(03)00088-2

Palmer, C.J., Van Emmerik, R.E.A., & Hamill, J. (2012). Ecological gait dynamics: Stability, variability and optimal design. *Footwear Science, 4*, 167–182. doi:10.1080/19424280.2012.666271

Peng, C.K., Buldyrev, S.V., Havlin, S., Simons, M., Stanley, H.E., & Goldberger, A.L. (1994). Mosaic organization of DNA nucleotides. *Physical Review E, 49*, 1685–1689. doi:10.1103/PhysRevE.49.1685

Peng, C.K., Havlin, S., Stanley, H.E., & Goldberger, A.L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos, 5*, 82–87. PubMed doi:10.1063/1.166141

Preotoni, E., Hamill, J., Harrison, A.J., Van Emmerik, R.E.A., Wilson, C., & Rodano, R. (2013). Movement variability and skills monitoring in sports. *Sports Biomechanics, 12*, 69–92. doi:10.1080/14763141.2012.738700

Rhea, C.K., & Kiefer, A.W. (2014). Patterned variability in gait behavior: How can it be measured and what does it mean? In L. Li, & M. Holmes (Eds.), *Gait biometrics: Basic patterns, role of neurological disorders and effects of physical activity* (pp. 17–43). Hauppauge, NY: Nova Science Pub, Inc.

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

Sapoval, B., Gobron, T., & Margolina, A. (1991). Vibrations of fractal drums. *Physical Review Letters, 67*, 2974–2977. PubMed doi:10.1103/PhysRevLett.67.2974

Scholz, J.P., & Schöner, G. (1999). The uncontrolled manifold concept: Identifying control variables for a functional task. *Experimental Brain Research, 126*, 289–306. PubMed doi:10.1007/s002210050738

Schroeder, M.R. (1991). *Fractals, chaos, power laws: Minutes from an infinite paradise.* New York, NY: W. H. Freeman and Company.

Seay, J.F., Van Emmerik, R.E., & Hamill, J. (2011). Low back pain status affects pelvis-trunk coordination and variability during walking and running. *Clinical Biomechanics, 26*, 572–578. doi:10.1016/j.clinbiomech.2010.11.012

Seely, A.J., & Macklem, P. (2012). Fractal variability: An emergent property of complex dissipative systems. *Chaos, 22*, 013108. doi:10.1063/1.3675622

Stergiou, N., & Decker, L.M. (2011). Human movement variability, nonlinear dynamics, and pathology: Is there a connection? *Human Movement Science, 30*, 869–888. PubMed doi:10.1016/j.humov.2011.06.002

Stergiou, N., Harbourne, R.T., & Cavanaugh, J.T. (2006). Optimal movement variability: A new theoretical perspective for neurological physical therapy. *Journal of Neurologic Physical Therapy, 30*, 120–129. doi:10.1097/01.NPT.0000281949.48193.d9

Terrier, P., & Deriaz, O. (2011). Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking. *Journal of Neuroengineering and Rehabilitation, 8*, 1–13. doi:10.1186/1743-0003-8-1

Van Emmerik, R.E.A., Ducharme, S.W., Amado, A.C., & Hamill, J. (2016). Comparing dynamical systems concepts and techniques for biomechanical analysis. *Journal of Sport and Health Science, 5*, 3–13. doi:10.1016/j.jshs.2016.01.013

Van Emmerik, R.E.A., Wagenaar, R.C., Winogrodzka, A., & Wolters, E.C. (1999). Identification of axial rigidity during locomotion in Parkinson disease. *Archives of Physical Medicine and Rehabilitation, 80*, 186–191. PubMed doi:10.1016/S0003-9993(99)90119-3

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

Verghese, J., Holtzer, R., Lipton, R.B., & Wang, C. (2009). Quantitative gait markers and incident fall risk in older adults. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences, 64*, 896–901. PubMed doi:10.1093/gerona/glp033

Von Holst, E. (1939/1973). *The behavioral physiology of animals and man: Selected papers of E. Von Holst* (Vol. *1*). Coral Gables, FL: University of Miami Press.

Wagenaar, R.C., & Van Emmerik, R.E.A. (1994). Dynamics of pathological gait. *Human Movement Science, 13*, 441–471. doi:10.1016/0167-9457(94)90049-3

West, B.J., & Shlesinger, M. (1990). The noise in natural phenomena. *American Scientist, 78*, 40–45.