Influences on the nonlinear dynamics of human running stride time series

by

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Dedication

Dedicated to the glory of God.

The heavens declare the glory of God; and the firmament sheweth his handywork

Psalm 19:1

Acknowledgements

It is May 2013 and difficult to believe that I am finally writing these acknowledgements. Five years ago, I arrived in Cape Town, a place that for me was simultaneously a new city, a new country, a new continent, and a new hemisphere. With that arrival began an amazingly memorable time in my life. Although I left Cape Town over a year ago, many memories are still vivid. To this day, I still find that *mal d'Afrique*[*] is a recurring ailment. May I never recover.

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[*] *Mal d'Afrique* is a French description of the longing to return to Africa after experiencing the wonders of her people and lands.

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Timothy Lindsay

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Abstract

High temporal resolution of inter-stride time series from human running demonstrates non-trivial fluctuations with a meaningful structure of variability. Nonlinear analyses can quantify this structure by describing scale invariance, serial correlations, and regularity. Stride timing shares many mathematical properties with other complex integrative physical systems. Accordingly, the output provides information about the locomotor control system that produced it.

The strength of persistent correlations in stride timing is altered with certain changes to the task, organism, and environment. However, evidence for this often comes from only a single nonlinear analysis and the influence of many interventions have not been fully investigated for running. Thus, we aimed to confirm effects due to running speed, prolonged strenuous running, and to provide the first direct comparison of treadmill and overground running. These three interventions provide an opportunity to apply the task, organismic, and environmental model of constraints.

Stride time series were generated from the peak vertical accelerations obtained from a shoe-mounted accelerometer. Nonlinear dynamics were quantified using the complementary methods of detrended fluctuation (DFA), power spectral density (PSD), and multiscale entropy analyses (MSE). These analyses identify behavior that generally corresponds to the characteristic of complexity.

In Study 1, eleven trained runners completed six 4-min treadmill running bouts at 40-90% of peak treadmill running speed. There were no significant differences for DFA and PSD but MSE values for 80 and 90% peak speed were significantly lower than at 70% ($p<0.05$). This difference represents greater order and

constraint at the highest speeds, perhaps due to the environmental constraint of the treadmill, or the physiological challenge of fast running, or a combination of both.

In Study 2, ten trained runners completed paced treadmill and track trials at 80, 100, and 120% of their preferred running speed. Treadmill running demonstrated higher DFA ($p=0.0024$), lower PSD ($p=0.0056$), and lower MSE values ($p<0.0001$). Together, these differences indicate increased correlations, increased regularity, and therefore increased constraint with treadmill running. This constraint may arise due to the visual, afferent, or kinematic changes present with treadmill running that may modify the underlying gait rhythm. These changes appear more pronounced for running faster and slower than preferred, pointing to a likely dual influence from the task and environment.

In Study 3, ten trained runners completed five 2000 m high intensity track intervals (~75% peak running speed, reaching ~95% HR_{max}) and the same protocol at an easy intensity (~55% peak running speed, ~73% HR_{max}). DFA and PSD did not show any significant time or intensity effects. MSE was lower for the easy condition ($p<0.0001$), but did not change with accumulated distance. Evidently, physiological constraint from strenuous intermittent running exerts a relatively minor influence compared to the influence of running speed.

Taken together, these three studies add to a growing body of literature which indicates that running speed exerts a major effect upon system control, and represents a constraining influence arising from the task and organism. The locomotor system is evidently able to maintain robust control throughout strenuous intermittent running, but the effect of higher speed is apparently accentuated due to the environmental

influence of the treadmill. These conclusions provide a more careful understanding of the myriad of factors that interact to influence dynamics.

List of presentations associated with this dissertation

1. Lindsay, T.R., and Martin-Gonzalez, J.M. Detrended fluctuation analysis of foot contacts during high-speed running: Evidence for crossover phenomena. 3rd International Congress Complex Systems in Medicine and Sport, Kaunas, Lithuania, September, 2010.

2. Lindsay, T.R., McGregor, S.J., and Noakes, T.D. Multiscale entropy is sensitive to speed constraint but not fatigue In high-intensity running intervals. American College of Sports Medicine annual meeting, San Francisco, CA, May, 2012.

3. Lindsay, T.R.., Noakes, T.D., and McGregor, S.J. Decreased complexity of stride timing dynamics with increasing speed during treadmill running. American College of Sports Medicine annual meeting, Indianapolis, IN, May, 2013.

4. Lindsay, T.R., Noakes, T.D., and McGregor, S.J. Effect of treadmill versus overground running on the structure of variability of stride timing. American Society of Biomechanics annual meeting, Omaha, NE, September, 2013.

List of abbreviations

ACF	Autocorrelation function
ANOVA	Analysis of variance
ApEn	Approximate entropy
CLR	Cerebellar locomotor region
CNS	Central nervous system
COP	Center of pressure
CPG	Central pattern generator
DFA	Detrended fluctuation analysis
EF	Executive function
EMG	Electromyogram
fBm	Fractional Brownian motion
fGn	Fraction Gaussian noise
H	Hurst exponent
HR	Heart rate
HRV	Heart rate variability
MLR	Mesencephalic locomotor region
MMG	Mechanomyogram
MSE	Multiscale entropy
OF	Optic flow
PAR-Q	Physical activity readiness questionnaire
PD	Parkinson's disease
PN	Peripheral neuropathy
PP	Preferred pace (of running)
PSD	Power spectral density
RPE	Rating of perceived exertion
SampEn or S_E	Sample entropy
SCPG	Super central pattern generator
VGRF	Vertical ground reaction force
α	Scaling exponent alpha (DFA)
β	Scaling exponent beta (PSD)

Chapter 1

Introduction

Introduction

The modeling of physiology and performance in the sport and exercise sciences often depends upon the fundamental assumption of the relationship between form and function. This relationship is bi-directional, in that an understanding of form can provide insight regarding function. For example, the rigidity of bones (form) points to load bearing (function)[1]. In the opposite direction, information about function allows us to infer the form that produced it. This dissertation will employ the latter approach to modeling by recognizing that the output of the central nervous system (CNS) provides insight into the goals and strategies that produced that output[2]. Specifically, we will examine the behavior of human running gait with a view to understanding the characteristics of the locomotor control system and thus move conceptually from function to form.

The task (or function) of running involves the coordination of a multitude of dynamical degrees of freedom to maintain forward movement that is stable and regular over the long term, yet reasonably resilient to any perturbation that interferes with movement and increases the challenge of that task. Kinematically speaking, running movement must be described in four dimensions: three of space and one of time. The distance vector of the stride represents the three spatial dimensions and the frequency of the stride represents the time dimension. Kinetically, this movement arises from muscle function brought about by the neuromuscular control system acting to generate the coordination required to produce running gait. There is much value in the simultaneous monitoring of multiple channels to measure gait, but here we focus on the stride interval time series, that is, a sequence of data points that represents the time between each stride of the same foot. Indeed, because the timing of strides has been suggested to be the "final output" of the neuromuscular control system[3],

understanding of this variable has been often pursued in gait literature for what it indicates about system control.

When we use the term *form* with regard to the human body, we have in view a system of systems; a whole that is comprised of many parts and interactions responsible for the neuromuscular control mentioned above. While deep investigation into the characteristics of a single part is useful in many cases, this approach often suffers from the problems associated with reductionism because the influence of other parts is often overlooked. Accordingly, the approach of this dissertation is decidedly holistic because we wish to consider how the different parts of the body work together to produce a function of the whole. Even more, we wish to view the function of the whole in light of the environment and the task that is undertaken. These three aspects: organism, task, and environment form the framework proposed by Newell[4]. Newell's understanding of motor control was that each component depends on the other. Thus, only when we account for all three can we come to a comprehensive and complete understanding of human exercise function. This requires: 1) an understanding of concepts in complex nonlinear dynamics that may used to describe the behavior of gait timing, 2) analyses that can quantify these dynamics, 3) an ability to move from the analysis output to biological meaning, and 4) knowledge of how and why this biological function changes with certain alterations in task, organismic, or environmental variables (Figure 1).

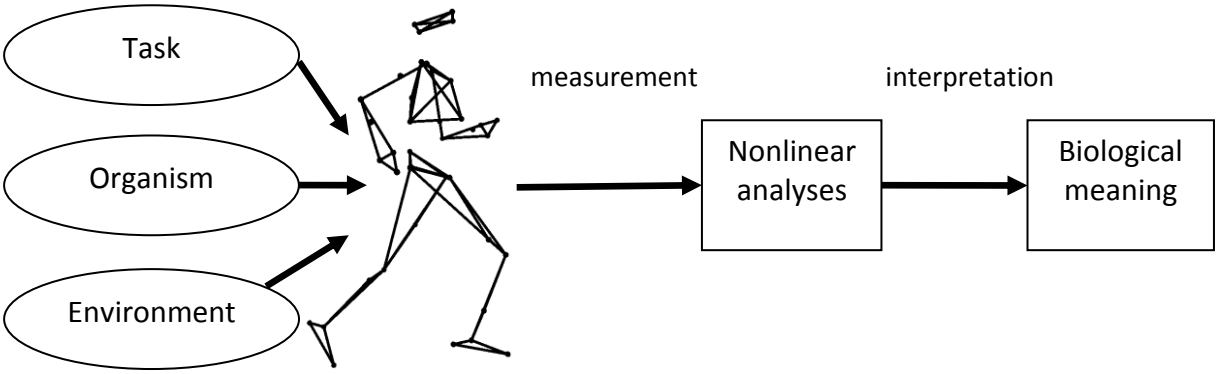

Figure 1. Conceptual path from gait behavior to the output of nonlinear analyses to interpretation to form an understanding of biological meaning. Gait output is understood to be influenced by considerations of the task, organism, and environment.

Major themes of the dissertation

Nonlinear concepts

Over the past century of sport and exercise science research, different explanations of human performance have likely been influenced by the most popular methodologies of each time period. The first measurements of oxygen consumption and exercise metabolism occurred in the early twentieth century (e.g., reference[5]); by the 1970s and 1980s, sophisticated analysis of metabolic variables was possible, perhaps influencing researchers to believe that metabolic variables were the "last word" in performance. Lately, however, emphasis has returned to aspects of integrated systems and complex function. One feature of this conceptual thrust is measuring and modeling changes in a variable or group of variables and inference of the mechanisms that act to produce that change. When variables are measured too infrequently, or are only presented as mean values of seconds to minutes, the resultant picture can be termed a "fuzzy snapshot". This is suitable to understand average function during exercise, but it ignores behavior *within* those several minutes of data. A

framework devoted to the precise measurement of change therefore requires frequent and continuous measurement of a given variable, generating large data sets. Fortunately, modern computing power is sufficient and accessible for this task.

Given the framework described above, the methodological aspect of this dissertation depends on the monitoring strides with high temporal resolution. This involves continuous measurement throughout the entire gait cycle but is also sufficient to provide an annotated data set, where specific and discrete events are identified and described over time. In the studies of this dissertation, we use shoe-mounted accelerometers.

Measurement and nonlinear analysis

Better technology increases the possibility of measuring behavior that requires difficult or elaborate descriptions. Fortunately, current mathematical and statistical theory can accommodate this, but the application of such analytic tools within the exercise sciences is not yet common; analysis still predominantly occurs according to traditional assumption that physiological variables behave in a linear fashion. According to this modeling paradigm, any deviation from linearity in these variables is considered to be error, thus to eliminate that "error", it is a common practice to present only average values. However, recent work has demonstrated that measured variability is not totally comprised of erroneous data. Rather, at least a portion of that variability represents real changes in the data that are physiologically meaningful.

Quantification of this variability requires complex systems analysis and there is a growing emphasis on such approaches. Over the past century, the emphasis of exercise science research has shifted between systems and reductionism. The recent resurgence systems thinking[6–10] has encouraged a holistic understanding of human performance. In the

same way that reductionism tends to isolate certain parts of a system, there has also been a tendency to isolate certain events during an exercise session from other events. While there instances for which it is appropriate to focus on one part in isolation, we will employ an approach that sees a physiological time series as the output of a complex integrative system. On way to understand how the different parts of a system work in concert to generate an output is to make high resolution measurements of the temporal evolution of the measured variable. That is, how does the variable fluctuate?

Fluctuations in stride parameters can be analyzed for not only magnitude of variability (such as mean and standard deviation that describe the size of the fluctuations), but also the structure of variability, which refers to the ordering of each data point in the time series. The sequence of data points represents a "biological language", analogous to letters, words, sentences, and paragraphs that are used to organize literary expression. Words are small and frequent, while paragraphs are relatively large and less frequent. Similarly, there are small and frequent fluctuations in gait timing as well as large and less frequent fluctuations in gait timing. Yet, each kind of fluctuation is related to the other and the system must be understood as a whole to gain the true meaning. In literature, this is the meaning of the author; in gait studies, this is the meaning of the neuromuscular system.

Now within a nonlinear framework, this variability can be analyzed to quantify the fractal dimension, the level of entropy, or information content of the signal. These concepts will be discussed later in Chapter 3, but for the time being, it is sufficient to state that this allows us to infer the properties of the biological control systems that generated the output. The ultimate goal is then to classify the signal in a way that is often not possible with conventional analyses. For example, in some cases, it is only nonlinear analyses that are able

to discern certain disease states, the presence of strong influences upon behavior (constraint), or to distinguish a robust system from one that is failing. This broad family of analyses originated in physics, mathematics, and statistics (c. 1940s to 1970s, see references[11–15]) , and then began to be applied in medicine, among other disciplines (c. 1980s and 1990s, see references[16–19]). Use in exercise science is still relatively novel, but growing (c. 2000s onward, see references[20–22]).

Finding biological meaning

The output of nonlinear analyses must then be interpreted. Just as the written word must be interpreted according to the rules of that particular language, gait time series must be interpreted according to the rules of nonlinear mathematical analyses. As will be demonstrated, looking beyond the seemingly consistent rhythms reveals a meaningful structure. By this we mean that there is an intrinsic pattern to the data that is information-rich and non-trivial. This information must be interpreted by translating the observed patterns into biological meaning.

A holistic view of influences: task, organism, and environment

Finally, just as words form sentences, sentences form paragraphs, and paragraphs form an entire essay, the interpretation of each level of organization must occur within its own context. We view functioning during exercise performance as occurring within an immediate as well as general context extending to the environmental, psychological, and physiological settings of an exercise bout. An understanding of these descriptions informs the interpretation of events that occur during that time and in that setting.

In subsequent chapters of this dissertation, we will show that the use of nonlinear complex systems analysis has still not been extensively applied to the stride dynamics of running gait. We will also discuss the current understanding of the nonlinear dynamics of running stride time series and mention the need to confirm recently-suggested hypotheses as well as the need for what question requires a first direct test.

Purpose of thesis, format & research questions

The purpose of this thesis is to use several complementary nonlinear analyses to describe the dynamics of running stride time series and how these dynamics change with speed, surface, and throughout intermittent strenuous running. The first part of this dissertation is comprised of three literature reviews. Neuromuscular control involves the dynamic organization of movement that must be described mathematically and statistically. We review general concepts relating to this nonlinear behavior in the first review chapter (Chapter 2). We then introduce several nonlinear analyses to be used and will discuss them in light of a broader family of analyses that exist that are sufficient to address these patterns (Chapter 3). Since the dynamics of the human stride time series are subject to various influences coming from the task, the organism, the environment, and the interaction among all these variables, we review current literature on these effects and offer discussion as to their biological origin and meaning of the dynamics (Chapter 4).

The second part of the dissertation reports original experimental research on the structure of gait timing variability, as it depends on running speed, surface/environment, and fatigue. These three interventions address considerations coming from the task-organism-environment model of Newell[4]. To this end, the following questions are addressed:

1. How does structure of variability of stride time series during treadmill running change over a broad range of speeds? (Chapter 5)

2. How does the structure variability of stride time series differ between treadmill and over-ground running at slow, preferred, and fast speeds? (Chapter 6)

3. Does the accumulation of high intensity running intervals lead to a different structure of variability of stride time series compared to the same intervals run at a lower intensity? (Chapter 7)

Finally, an integrative model to explain exercise function with respect to complexity and possible future research will be offered (Chapter 8).

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Chapter 2

Concepts in complexity:

Towards a nonlinear systems view of data analysis and modeling in the sport and exercise sciences

Introduction

With the progress of measurement in human biology comes a new a new set of challenges. With our increasing technical abilities, we are provided with information about human structure and function that is ever more detailed. Yet, more and better information must be first processed, and then interpreted if it is to be useful. One example of this in the exercise sciences is the measurement of human gait rhythm. If stride timing data is presented as mean values of several seconds to minutes, stride timing will appear to be a constant and monotonous process. However, if measurement is made of every single stride, a different story is told. The time series will contain small but apparently meaningful fluctuations: this variability often houses a clear structure and betrays any expectation of a perfectly constant system of control. Thus, the challenge is to select the best way to describe these fluctuations and suggest what they mean for biological modeling.

The advent of accessible and powerful computing in previous decades has accelerated the sophistication with which this modeling occurs. Traditional mathematical and statistical analyses, while relatively simple in concept, were rather tedious in earlier times and have been aided greatly by technology. Yet, the benefits go far beyond traditional analyses. Novel approaches, put forward only in the 20th century, such as fractal analysis, are also widely accessible today. These help us understand intricate patterns in data and explain behavior that is otherwise unexpected. Such analyses are already being used in the exercise sciences, but are still not a common part of the analysis toolkit[1] of most researchers. As these methods are gradually established in our field, we see an increasingly clear mandate to use novel analyses in our work. These approaches help uncover previously ignored information in the data set, encourage "systems thinking", and help improve modeling sophistication.

Distinct mathematical patterns that are often termed *complex* can be found in phenomena from a multitude of scientific disciplines such as astronomy, geology, and meteorology. It is difficult to define complexity and definitions must often be specific to the scientific sub-discipline. Since these patterns are also found in the human structures and functions that are commonly studied in the exercise sciences, our first task in this paper will be to introduce and describe these mathematical behaviors. Second, we will provide a brief overview of where this behavior is seen in human biology. Third, we will offer some explanations regarding the biological meaning. The second review chapter of this dissertation describes some of the most common analyses that are used to uncover each kind of behavior, along with the requisite considerations for each method. The third review chapter focuses on the complex behavior of human stride timing and how it is modified in various configurations of task, organism, and environment.

The nonlinear paradigm

To describe complexity in human biology, we first introduce the concept of nonlinearity. We will presently be describing systems that produce nonlinear output, as a background to nonlinearity, and a more complete description of nonlinear behavior, but we will first provide a brief statement of what is meant by nonlinearity. Nonlinearity arises when the response is not linearly proportional to the strength of the stimulus[2].

Biological systems are highly integrative, naturally dynamic, and often nonlinear[3]. A system is simply the name given to an object of interest that is being studied[4]. Systems are mainly described by their parts and the laws that govern the relationships between those parts. Together, these two descriptions will determine how we view and describe the nature and behavior of a given system. A system is considered to be simple if it has only a few parts that

relate to one another according to simple laws. The system is more complicated if it has many parts, however these parts may still be governed by simple laws. A complex system generates a feature-rich output arising from the collective behavior of many parts, even though the interactions may be (but are not necessarily) simple[5]. An example of a complex system is the human brain, with its vast network of neurons and capability for creativity[5]. At this point, we distinguish between spatial and temporal complex systems. Spatial complex systems possess complexity because of their *physical architecture.* On the other hand, temporal complexity is a characteristic of the time series of the signal produced by a system. Both spatial and temporal complex systems may be described with regard to parts, patterns, and relations, but these terms refer to physical connections in the former and mathematical characteristics and regions of measured data in the latter. While we will sometimes make use of spatial examples later in this chapter, our focus for the rest of the chapter will be on descriptions of temporal complexity.

We will employ a mathematical paradigm with the purpose of formalizing (as much as possible) many of these system properties and the key characteristics of their functions. Paradigms serve a useful purpose by aligning concepts and researchers through a shared understanding or mental model (see, e.g., Kuhn[6]). In order to clearly define the nonlinear paradigm, we will contrast it with the traditional, incumbent paradigm, that is subscribed to (perhaps by default) by many scientists working with sport and exercise applications.

The human body is comprised of many interacting systems and subsystems that often generate complex output. The purpose of complexity science is therefore to study systems that have many interdependent components, the behavior of each, and the interactions among those components[7–10]. In fact, the focus is often placed on the patterns and relationships,

rather than the parts themselves[11]. Prior to the development of formal mathematical descriptions and analyses, this task was most challenging because even experts were unable to discern and describe subtle and complex patterns of output, despite their training to identify patterns visually[12].

Complex patterns are very often seen in the rhythmic processes that the human body uses to organize biological function[13]. West[14] proposed six traits of complexity. We will describe complexity in more detail later, but it is presently important to understand the structure of a complex system and the output it can generate. First, a complex system has many elements that change with time. Second, there are many relations among the elements of the system. These relations are interdependent and dynamic. Third, the relations themselves are generally nonlinear. Fourth, the relations are subject to environmental constraints. Fifth, there is both order and randomness in the system. Sixth, the system is not dominated by one or a few characteristic scales.

Examples of complex rhythmic output includes the beating of the heart, respiratory rhythm, and gait; yet these examples rarely follow a purely periodic function[15]. That is, the time period between each cycle is not perfectly constant but rather varies over time. For example, Goldberger[2] stressed that "normal sinus rhythm" does not mean "regular sinus rhythm", for the heart beat is not perfectly regular, but possesses intrinsic variability. This variability has traditionally been considered to be noise or measurement error and thus devoid of meaning. According to this tacit assumption, the variability was, in effect, ignored through the use of averaging, smoothing, or filtering techniques[16,17], perhaps because the coefficient of variation was deemed too small to provide useful information[18]. While the relative *magnitude* of variability (i.e., relative dispersion) of an output indicates an accurate and reliable control

system[19], there is another aspect of variability that requires examination. This is the *structure* of variability – how the variability of data points is ordered in time. For a particular series of data points, knowledge of structure answers the question of whether there are certain values that are more likely to follow. This kind of examination often yields information not present in the mean and standard deviation. For example, two heart rate time series with near-identical mean and standard deviation can sometimes only be distinguished between healthy and diseased subjects by examining the structure of variability with the application of nonlinear analyses[20].

The reason for the traditional treatment of data may stem from conceptions of biological control systems. The traditional notion of homeostasis (e.g., Cannon[21,22]) suggests that physiological mechanisms aim to reduce variability and maintain a constant value[23,24]. Any failure to do so in the face of external perturbations[25], and any deviations from the "desired" value are therefore considered to be noise arising from the apparent inability of the physiological system to accomplish its goal, or perhaps, the ability of the measurement device to capture the "true" value[23]. Thus, the traditional understanding of homeostasis asks the question: "what is typical?"[24,26].

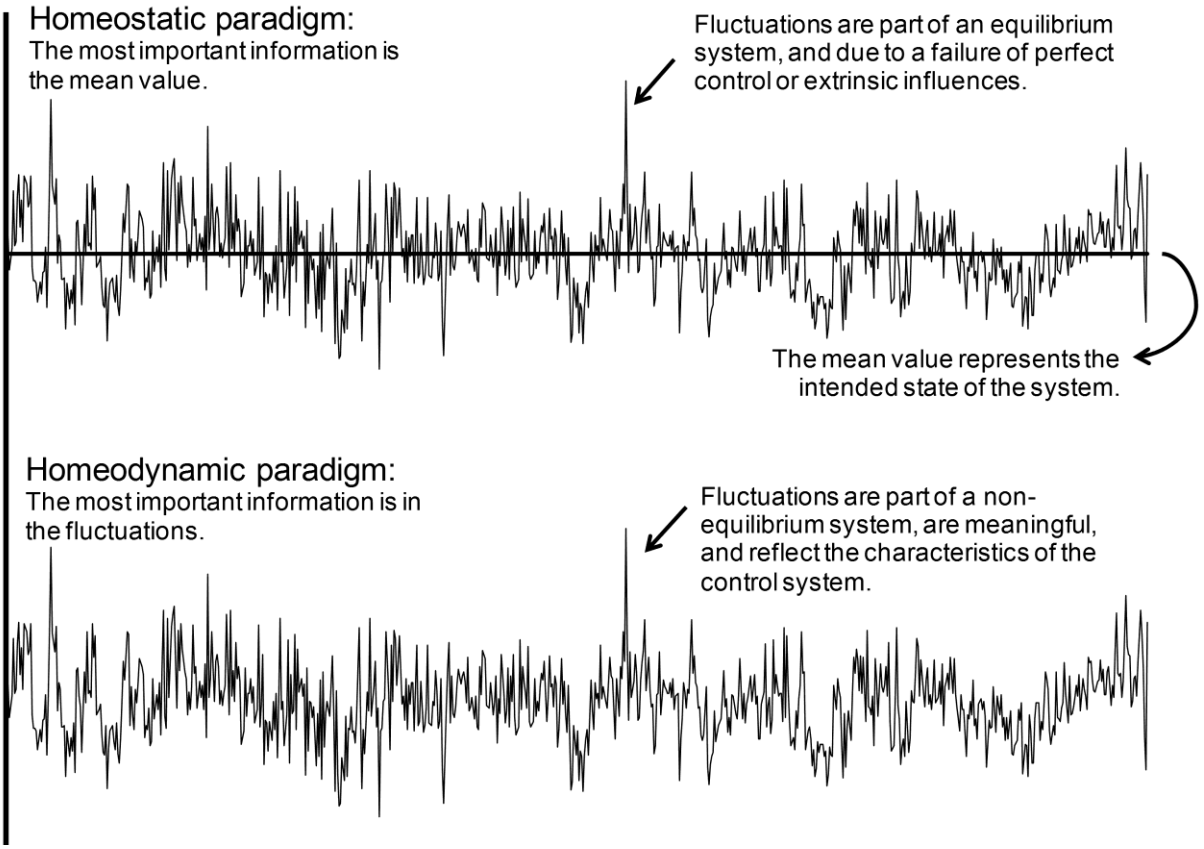

Figure 1. Illustration of homeostatic and homeodynamic paradigms. For the homeostatic paradigm (top), the thick black line indicates the mean value of a random system; fluctuations presumably caused by external perturbations to the system. In a homeodynamic paradigm (bottom), fluctuations are seen to be meaningful expressions of a complex system operating far from equilibrium.

At this point, we contrast the "classical" view of physiology with another view because a close look at many data sets indicates that supposedly homeostatic processes are not really "static"[3]. As Goldberger et al.[24] argue: "maintaining constancy is not the goal of physiologic control". Thus, the alternative *homeodynamic*[14*] viewpoint suggests that a certain degree and kind of variability is the physiological goal. This viewpoint is actually not new. Heraclitus (6th century B.C.) stated, "Everything flows and nothing abides; everything gives way and nothing stays fixed"[27]. Indeed, describing physiological behavior with the

[*] Also termed *homeorrhesis*[25,121].

homeostatic model is insufficient to describe the dynamic fluctuations commonly seen in most processes[14]. According to this behavior, the organism organizes the internal environment such that fluctuations are bounded within acceptable limits to create a sense of equilibrium, even though the external environment is variable[3]. At this point, the most appropriate question is not "what is typical?" but "what do these patterns mean?" According to the systems-thinking paradigm mentioned above, the answer will illuminate the nature of the relationships between the parts of the system[28] by "cracking the homeokinetic code"[29]. Figure 1 contrasts the homeostatic paradigm with the homeokinetic paradigm.

Understanding fluctuations: moving from a linear to a nonlinear model

To understand the aforementioned patterns of variability one needs to employ a nonlinear dynamical approach. Nonlinear systems are dynamic, which means they change over time. The pattern of this temporal evolution is of prime interest[30], however adequate descriptions of change in physiological systems can often be a challenge. The output of physiological systems can take several forms. These include behavior that is consistent with equilibrium, periodic or quasi-periodic, random (Brownian motion and white noise), and deterministic chaos systems[31,32]. Equilibrium systems behave according to the traditional view of homeostasis and can be described using linear reductionist methods. Periodic or orderly systems tend towards a fixed-point attractor (i.e., a tendency toward a stable, consistent value) or periodic attractor (i.e., follows an attractor that itself undergoes regular and consistent fluctuations)[9]. Random (also called stochastic) systems can be described according to a probability distribution and thus are predictable over the long term but not from

one data point to the next. These above systems are said to have minimal input from deterministic functions[9].

While periodic and random systems can be described in the same way as equilibrium systems, behavior arising from deterministic chaos cannot because linear approaches are not sufficient to completely describe nonlinear behavior[9,32]. Many physiological systems display this sort of behavior, and the experimental chapters of this dissertation will be devoted this function as it is found in the human running stride time series. We will describe chaos more fully later, but it is first necessary to describe nonlinear dynamics, which is part of the larger field of chaos theory[33]. The reader is referred to a good basic review of nonlinear terms and concepts in reference[9].

Describing nonlinear dynamics

Reductionism and the assumptions of linear systems

It is commonly assumed that systems can be reduced to their constituent components, which, when studied in isolation, exhibit the secrets of the system as a whole. This is known as reductionism. Although this approach is good for understanding simple parts of a system[7], nonreductionist approaches are needed to assess the system a whole and to appreciate the *emergent* behavior occurring at higher levels. Emergent behavior is not predictable by observing individual lower-level elements and behaviors[5,30]. This is what is meant by the popular saying, "the whole is greater than the sum of the parts"[7], which is often applied to the function of living organisms from a systems biology perspective[34]. Indeed, as Joyner and Saltin[35] suggest regarding sport and exercise science: "the main regulatory and adaptive responses to acute and chronic exercise defy simple reductionist explanations". Full understanding of that part can only be realized when it is viewed in terms of its relationships

to other parts. The multitude of local level interactions eventually produce order on the global level[36]. Thus, the output of biological systems should be viewed as an emergent property of the network itself, rather than from the sum of the function of each individual element[34].

Newtonian assumptions of reductionism and linearity require the properties of *proportionality* and *superposition*[9]. Proportionality means that the sum or product of a collection of variables is proportional to the size of each of those variables. This assumption holds for linear systems but fails when dealing with nonlinear systems because the outcome is often greater than the proportional impact expected based on the input. Nonlinear behavior is thus found in all physiological systems for which the strength of an applied stimulus does not elicit a linearly proportional response[2]. Further, unlike linear systems, which are *additive* in nature, nonlinear systems tend to be *multiplicative*, where the product or sum of two variables is *greater* than what is expected given the initial size of the input variables. In simple reductionist systems, one needs only to measure the dynamics of the parts in isolation. If the behavior of each element is understood, these may be added to each other to describe the overall output[20,37]. One may then account for observed overall performance by integrating the behaviors of these parts according to the principles of superposition[16,38]. In contrast, the principle of superposition does not apply to nonlinear systems because the components interact in a non-additive way[10,38,39].

Normal distribution

Traditional mathematics, statistics and science in general have tended to overlook such descriptions of behavior, preferring instead to focus on linear descriptions that are more familiar and tractable, by virtue of their discretely described parameters. Another popular characteristic that has been widely invoked to describe such systems is the "normal

distribution" or "bell curve". The assumption of normality underlies much research, with deviations from the mean being treated as outliers, and thus not worthy of prolonged scrutiny. While a normal distribution may underlie certain types of data such as biometrics like height and weight, this is not the case for most dynamic systems. Consequently, the parametric assumptions required by such distributions are violated for a wide range of research questions. While the assumption of normality is often convenient because it allows the use of descriptors such as mean and median measures, such descriptors are often less valid for nonlinear systems.

Finally, there is the belief that systems can be best understood by isolating the signal from the noise. While the output of linear systems is easy to predict via extrapolation, the output of nonlinear systems is not easily predicted in that same manner. Biological function is in a state of constant change across the many systems that integrate to maintain life. Thus, observed behavior must be described and prediction made based on those observed patterns. This framework holds that the output of a particular system contains information about the underlying dynamics of that system[40]. By discretizing systems and the modeling thereof, conventional biostatistics and reductionist modeling may be less adequate to model phenomena that is essentially nonlinear. Thus, the appreciation of the underlying dynamics is lost.

By way of example, traditional analytical methods often analyze data only at discrete points or present data as the mean of perhaps several minutes of collection (Figure 2). The generally unstated purpose of this practice is to eliminate much of the analysis problems arising from noise and measurement error. In a purely linear system, noise is easily identified

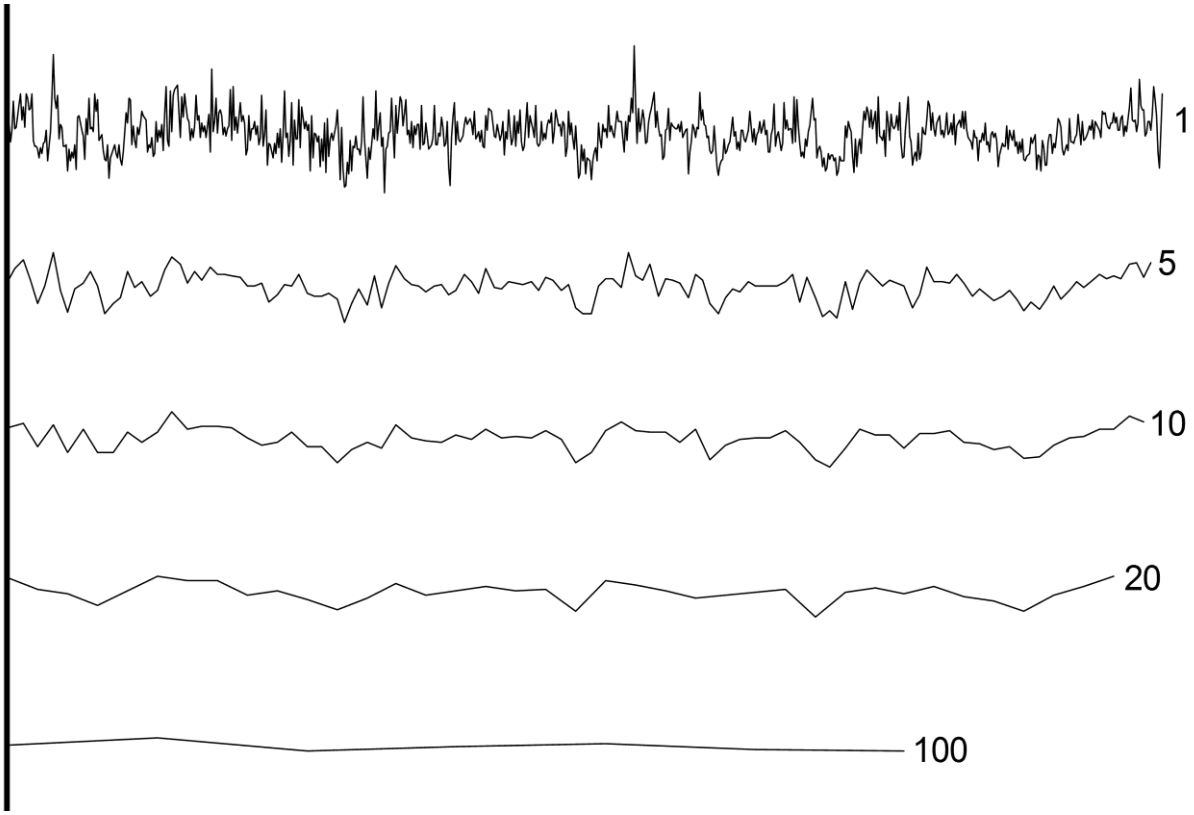

Figure 2. Stride time series (approximately 550 sec) presented as the original series as well as average values for every 5, 10, 20, and 100 data points. Lines are shifted vertically for visual clarity, but the vertical scale is consistent. The top 4 lines (original and average of 5-20 data points) retains some display of meaningful fluctuations but the bottom line (average of 100 data points representing approximately 70 sec of data) has lost its structure to the point that it resembles a constant, linear system.

as a departure from a straight-line. While random noise in nonlinear systems is not dismissed as a source of measurement variability, analyses have made it clear that at least *some* portion of the fluctuations from data point-to-data point is due to non-random processes[41,42]. Put another way, we argue that variability when measuring even steady-state function is not merely due to noise-error superimposed on a basically-constant time series. This can be seen when visually inspecting the difference between an original physiological time series and a surrogate time series generated by randomly shuffling the original data points (Figure 3).

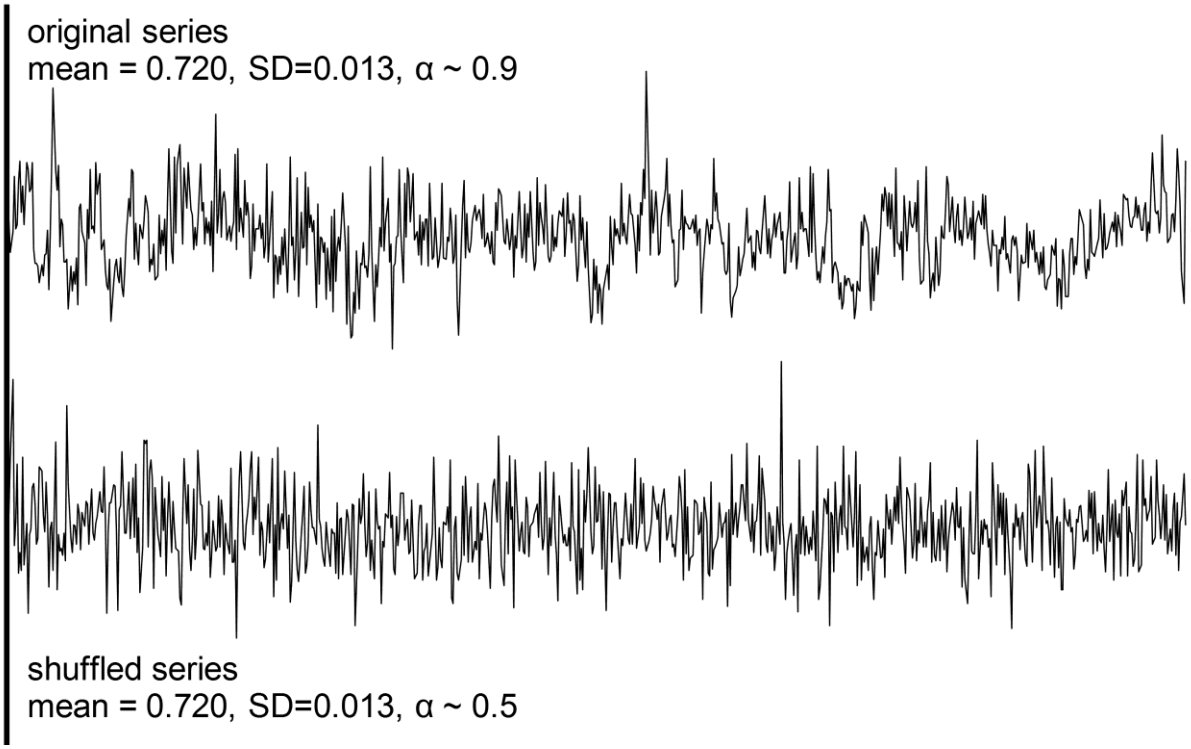

Figure 3. A stride interval time series presented as the original series (top) and the same series, randomly shuffled to destroy the temporal order (bottom). Lines have been shifted vertically for visual clarity, but the scale remains the same for both. Note that the mean and standard deviation are identical for both lines. However, the lines are distinguished well with the DFA scaling exponent α (described in the subsequent chapter).

Chaos

The special class of chaotic behavior is a subtype of nonlinear dynamics and is studied as part of a larger field of applied mathematics called *chaos theory*, or *dynamical instability*[43]. Not every nonlinear system is chaotic, but every chaotic system is nonlinear[38]. Chaos refers to the seemingly (but not actual) chaotic behavior of a deterministic system. It is important that chaos (in the colloquial sense of the word) only *seems* to be present because it points to the difficulty in describing a system that appears to be disordered. The term "chaos" conjures up striking images of anarchy and disorder, but this is not the scientific meaning of the word[38]. Rather, a chaotic system refers to one in which the system's macro behavior appears,

at least initially, counter-intuitive given the system's often simple inputs. Behavior *appears* irregular and random (because it is so complex) but it in fact is not random[32,38]. Rules of causality still hold in chaotic systems. That is, chaotic systems are still 100% deterministic, and thus display "chaotic determinism".

Early work on chaos, and more specifically, *sensitivity to initial conditions*, was put forward by Maxwell[44], Poincare[45], and was even seen in Ray Bradbury's 1952 short story about time travel[46]! Edward Lorenz later solidified the concept with his talk to the American Association for the Advancement of Science entitled *"Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?"*[47], thus bringing in to common parlance the term *butterfly effect*. Building upon ideas first published in 1963,[48] Lorenz[49] proposed simply that chaos is defined by sensitive dependence. Sensitive dependence describes evolution of a time series that is sensitive to the initial conditions of that system[43]. In his work, Lorenz used the metaphor of a butterfly flapping its wings to illustrate how exceedingly small differences in initial starting conditions can lead to vastly differing outcomes as the small difference snowballs over time into a real, large difference. Sensitivity to initial conditions thus represents the hallmark characteristic of chaotic behavior[9,38].

The classic example of weather systems, which humanity has attempted to predict for millennia, are often wrong, despite the best efforts of meteorologists, especially if the horizon is pushed beyond seven or eight days. From a Newtonian perspective, this presents us with a paradox – surely if we know the starting conditions of a weather system down to the smallest detail, as we are able measure with today's advanced satellite and land and sea sensor arrays, we should be able to predict the outcome of a weather system. We can contrast this perspective with the "Einsteinian" perspective, which does not view system mechanics as

100% predictable. Rather, description can occur only generally, in probabilistic terms at best[30], never with complete certainty, and definitely not possible with low frequency measurement that is commonly used for the purpose of describing the mean and standard deviation over long periods of time. It would be extremely unlikely that prediction would be precise because knowledge of initial conditions is usually imprecise[*], which increases uncertainty about future states[5].

The connection between sensitive dependence and long-term predictability makes a link between the sub-disciplines of complexity and information theory[5]. A fundamental question, then, is whether fluctuations in a system are noise or chaos[38]. A system comprised purely of noise contains no information, while a chaotic system is information-rich because the evolution of the system provides information about what previously could only be predicted in general terms. The trajectory of a chaotic system is not periodic or convergent toward fixed points, but is rather deterministic and obeys rules[9,12].

Biological systems are thought to contain both deterministic and stochastic components[40]. As mentioned above, deterministic means that particular states may be predicted both forward and backward in time, as well as behavior that arises from unpredictable (i.e., random) functions[11]. In contrast, in stochastic systems, behavior at a given time is independent of previous behavior[11]. One major theme of this dissertation is that behavior of biological systems (particularly the locomotor control of stride timing), being both deterministic and stochastic, occupy a domain between order and randomness[9]. This has been termed "the edge of chaos"[50], and mention of the concept helps to transition discussion from chaotic systems to complex systems.

[*] Even with modern technology, we must admit that we have limited measurement precision.

Complex systems

General features of complex systems

Having established the general concept of nonlinearity and chaos, we now turn to the description of complexity and complex systems. Chaotic behavior has been said to be "predictably unpredictable", while complex behavior is "unpredictably unpredictable"[9]. Thus, according to Higgins[9], complexity theory extends chaos theory by describing the emergence of the general and specific features described below.

Emergence describes the tendency for complex systems to behave in a way that is not implicit or predicable based on a knowledge of the parts and interactions within the system and with the environment[5,16,30]. MacKay[10] has suggested that emergence be defined as "non-unique statistical behavior". Emergence should be distinguished from chaos because in chaotic systems, sensitive dependence on initial conditions leads to trajectories that are non-unique[10].

A simple schematic of a biological system, as with any system, includes an input, an output, and some intermediate process or mechanism that receives input and generates output. Our understanding of the *construction* of human biological systems and their behavior will guide the analyses we employ to investigate such systems. We make the following points to introduce the structure and behavior of complex systems in general. As with many other complex systems, human biological systems are thought to possess these characteristics:

1. System interactions are not additive but often multiplicative in nature. Data are best described by non-parametric, skewed distributions such as power laws and exponential functions. Systems are best understood holistically.

2. Order (structure, organization, information) is a latent, endogenous characteristic of the system, emerging through time from the interactions of component parts. It is not externally controlled by a "third-party" system.
3. Systems exist as nested hierarchies, with each scale of the system recognizable as a qualitatively unique, emergent level.
4. System elements resemble each other across scales (self-similarity).
5. Feedback and iteration are essential parts of the system.
6. Systems are adaptive over time.
7. Healthy systems contain an inherent amount of noise, randomness or mutation.

Discussion of this measurement paradigm requires the use of several terms that may not be familiar to exercise scientists (Table 1). Some of the terms in the table have meanings different from those used in everyday speech. The terms are not necessarily mutually exclusive.

Nonlinearity is a natural behavior of a complex system. All physiological systems can be considered to occupy this category.[2] However, while nonlinearity is relatively simple to define, complexity is a concept that is difficult to define and the term varies widely depending on the specific scientific sub-discipline. In 1948, Weaver described complexity as the degree of difficulty one faces in predicting a system's properties given the system's components. In other words, a system's degree of complexity refers to a system's intractability[51]. This is often a relative estimation, making it a subjective analysis and, thus, a difficult term to define with empirical rigor. According to economist and psychologist Herbert Simon, a pioneer in the field of systems science, a complex system is "made up of a large number of parts that

Table 1. Common terms used in analysis of the structure of variability.

Linear	A mathematical system for which there is the property of proportionality and superposition. As opposed to nonlinear.
Dynamic	A process that is characterized by change. As opposed to static.
Complex	A process that is difficult to predict mathematically. A scale-free or scale-sparse system that contains both order and randomness, and has a plurality of elements and nonlinear relations that are constrained by the environment.
Chaos	An apparently random or disorderly behavior that is actually deterministic. The necessary equation to describe the system exists but is not ordinarily discoverable. Chaotic systems are sensitively dependent to initial conditions.
Fractal	A geometrical object or mathematical sequence that displays spatial or temporal self-similarity across scales. The self-similarity may be sequential or statistical. The part resembles the whole.
Power law	A class of skewed distributions that describe individual observations within a complex system characterized by long-term correlations or persistence. The slope (steepness) of the distribution is described by a scaling exponent that represents the fractal dimension of the data. Power law curves exhibit the property of scale invariance. The magnitude of fluctuation is inversely proportional to the frequency.
Entropy	Quantification of the state of disorder. Increasing entropy signifies increasing disorder. Decreasing entropy signifies increasing order and regularity

interact in a non-simple way…the whole is more than the sum of the parts…[such that] it is not a trivial matter to infer the properties of the whole"[52]. Simon noted that complex systems are hierarchical, with systems being composed of subsystems, and so on, until an elementary subsystem is reached[52]. While still lacking a formal definition over half a century later, Diniz, et al.[16] highlighted several key features of complex systems: "Complex systems are systems that consist of a set of interrelated and interdependent parts with an almost infinite amount of degrees-of-freedom that cohere into a coordinated functional system." Other suggestions are that complexity refers to a system that has "meaningful structural richness"[53], high

Table 2. Types of systems and their structure, interaction, and behavior. Based on Burggren & Montecino[5].

System	Elements	Interactions	Predictability
Simple	Few	Little	Easy
Complicated	Many	Possibly more	Not necessarily easy, but possible
Complex	Many	Many	Difficult

information content[54], and is "a system or whole consisting of an extremely large and variable number of component parts, where the individual components display marked variability over time, and are characterized by a high degree of connectivity or interdependence between variables"[55]. Whatever the definition, we may say that it is difficult to predict the outcome of complex systems with good accuracy and precision. Even when the properties of the elements of the system are known, the higher the level of complexity, the more difficult it will be to predict the behavior of the system[51]. Table 2 demonstrates the different categories of systems: simple, complicated, and complex[5]. In complex systems, interaction occurs in a nonsimple way and forms a rich collective output that feeds back to affect the behavior each individual element[4,52]. However, complex behaviors may still be modeled by systems with only a few elements that have mostly short-range but some long range connections[56]. Complex systems have an element of randomness (stochastic behavior) that is bounded or constrained by some sort of selectivity. The output consists of highly variable fluctuations that resemble chaos[57]. Too much randomness breaks down any organization, and too much rigidity removes the dynamic nature that makes the system complex in the first place. Thus, complexity exists at the "sweet spot" between structure and randomness that is thought to be

ideal for biological function[58]. In time series analysis, this is described by "pink noise" where the interplay between order and randomness results in a system that reaches an energy efficient and stable arrangement often with qualitatively unique characteristics, distinct from those of its subsystems. However, as appealing as are these ideas, there is still a need of empirical verification. For example, one research study did not show a relationship between metabolic/energy optimization and the stride dynamics of healthy children[59].

Specific features of complex systems

Stability

The distinction between normal distributions and their associated descriptive measures and non-parametric distributions is the key to the differing mindsets, or paradigms, of linear and nonlinear science. Linear science sees most systems as gravitating to an inherent point of stability as characterized by the mean of a normally distributed dataset. Conversely, nonlinear science assumes that whatever point of stability exists in the data is captured by the observations at the head of the distribution (the so-called 'outliers' from a linear perspective) and these regions of stability are only temporal in nature at best, for all points of stability are eventually lost over time (and often, a new region of stability is reached).

These dynamics may be reconstructed in *phase space*[38]. Phase space is a multidimensional geometric space that represents all the possible states of each key parameter of the system[4,32]. If three dimensions are used, then the phase space may be represented visually. If more dimensions are needed, then the space requires an abstract representation. The state of the system at a given time point is described with the value of each variable at that point. The temporal evolution of the system is represented by the path through phase space, called a *trajectory*. Simply put, this allows us to trace the path of a process from

beginning to end. The "movement" of the trajectory depends upon 1) the initial condition of the system, and 2) some rule that governs the evolution[4]. In *deterministic* systems, forward and backward prediction of behavior is possible if the initial and present state are known[4]. If the system tends toward a particular set of points or pattern (i.e., a state) in phase space, it is said to have an attractor[9,30,32]. The set of points that tend to move towards an attractor are called the basin of attraction[4]. The behavior leads to emergence, which is a form of order that "emerges" from behavior that is, at first, apparently disorderly[9]. Fixed attractors lead to a steady state for the system. Attractors can also be oscillatory or display fractal-like characteristics.[60] In this case, the behavior of the system still operates under a definite regulation, but the rule of regulation will be dynamic rather than static.

Entropy

Entropy is a characteristic of chaotic systems[43]. Measurement of entropy quantifies system disorder, unpredictability, or randomness. In a physiological time series, this entails how readily one can predict an upcoming pattern of fluctuation. However, entropy does not directly correspond with complexity[61]. For example, we can quantify the entropy of a physiological time series before and after randomly shuffling the data to create a surrogate time series (thus destroying the temporal structure of the data). Entropy can be higher in the surrogate time series, even though any complex patterns in the data have been eliminated.[4] As such, this higher entropy may reflect an increased unpredictability due to randomness rather than actual complexity in the physiological signal. In simple systems, for which outcomes may be predicted with perfect certainty, entropy is zero[5].

Fractals

In our mention of systems, we have so far discussed how organization of behavior might occur. We now discuss a specific pattern known as a fractal. Fractals are spatial or temporal self-similar patterns. They are ubiquitous in both non-living processes such as mountains and coastlines and the biological systems of plants and animals. The aperiodic fluctuations found in many physiologic processes seem to be best described by fractal models[37]. Early investigations into the relationship between scale, size, and shape were conducted by Thompson[62]. However, Thompson evidently did not conceive of the irregularity in form as did Benoit Mandelbrot several decades later[63]. Mandelbrot described the fractal phenomenon in his seminal paper of 1967, when investigating the measurement of coastline lengths[64]. Low-resolution measurements of the British coastline (i.e., using a longer ruler) showed a jagged structure. Instead of expected smoothness, higher-resolution measurement (i.e., with a shorter ruler, providing a "closer look") showed the same jagged appearance, albeit on a smaller measurement scale. Mandelbrot coined the term fractal from the Latin term *fractus*, which means broken or fractured[65].

Two main characteristics of fractals are self-similarity and power law scaling behavior. Fractals can come in several forms: 1) geometrical as with branching structures, 2) statistical as when applying the rules of geometry to a curve, and 3) correlational[63]. Fractals are prevalent across many scientific sub-disciplines, from physical, chemical, biological, psychological, and social systems[66].

The self-similarity of fractals means that the smaller parts of the structure resemble the larger[33]. In physical structures, this is called *spatial self-similarity*. This independence of the measurement scale from the object's form is termed *scale invariance* and such systems lack a

single characteristic scale of length[24,37]. Scale invariant temporal systems lack a single characteristic scale of time[24,37]. By way of example, it is not possible to properly describe scale-free systems such as the human respiratory anatomy by referring to their mean length or diameter since our lungs contain few very large bronchi and many smaller bronchioles. The measurements of the few bronchi would skew the mean, making it less representative of the many smaller bronchioles which make up the bulk of the population and would be best represented by an accurate mean. Similarly, a median measure would fail to capture the many orders of magnitude difference between the smallest bronchioles and the largest bronchus. Instead, nonlinear distributions are better described by skewed distributions such as power laws and exponential functions, where a large proportion of one's data falls within "the long tail", while what would traditionally be considered outlier observations make up the head of the distribution, indicating the important role they play in the system - a role that normal distributions might marginalize. Examples of non-normal distributions include gait time series[67] and neuronal activity[68]. In temporal self-similarity (also called temporal dependency or memory) fluctuations at a given moment are either identical or at least statistically related to fluctuations that occur over different timescales or orders of magnitude[11,16,19]. With prominent features at many different time scales, such a system cannot be suitably described by the behavior that occurs on one particular scale.

Power law scaling (also called $1/f$ noise, $1/f$ scaling, or pink noise)[4] means that the magnitude of the fluctuation is inversely proportional to the frequency of that fluctuation. In $1/f$ noise, the power of the fluctuations is distributed across the entire spectrum. These fluctuations are the output of relatively independent underlying processes operating on different scales. It has been suggested that this power distribution renders the entire system

particularly resilient to local perturbations because a disturbance at one time scale does not necessarily alter the global stability[69].

Fractal analysis does not dismiss fluctuations as random noise but seeks to quantify the series with regard to how it evolves in time and the relationships between the data points in the series[69]. In the case of fractals, the irregularity that is found has an underlying self-similar pattern[57]. Thus, fractals are an example of an organized complex system[36]. In non-fractal objects, the measurement converges with decreasing measurement scale (i.e., small units of measurement, whereas in fractal systems, the quantity does not converge[37]. Put another way, the measurement of fractal systems is dependent on the resolution (i.e., ruler length)[14]. The relationship between the resolution and the measurement is the scaling relationship or index[32]. This quantifies the coupling of the different scales for the purpose of understanding and interpreting the underlying dynamics of the system that produced that output[14]. The common fractal output of $1/f$ scaling represents a flexible and adaptable, yet stable system[70,71]. The breakdown of this scaling relationship is thought to create a rigid and less adaptable system, with behavior that moves away from pink noise towards highly regular or highly disordered behavior[70]. Figure 4 demonstrates pink noise in relation to behavior that is either completely ordered or completely disordered. This is also further described in Table 3.

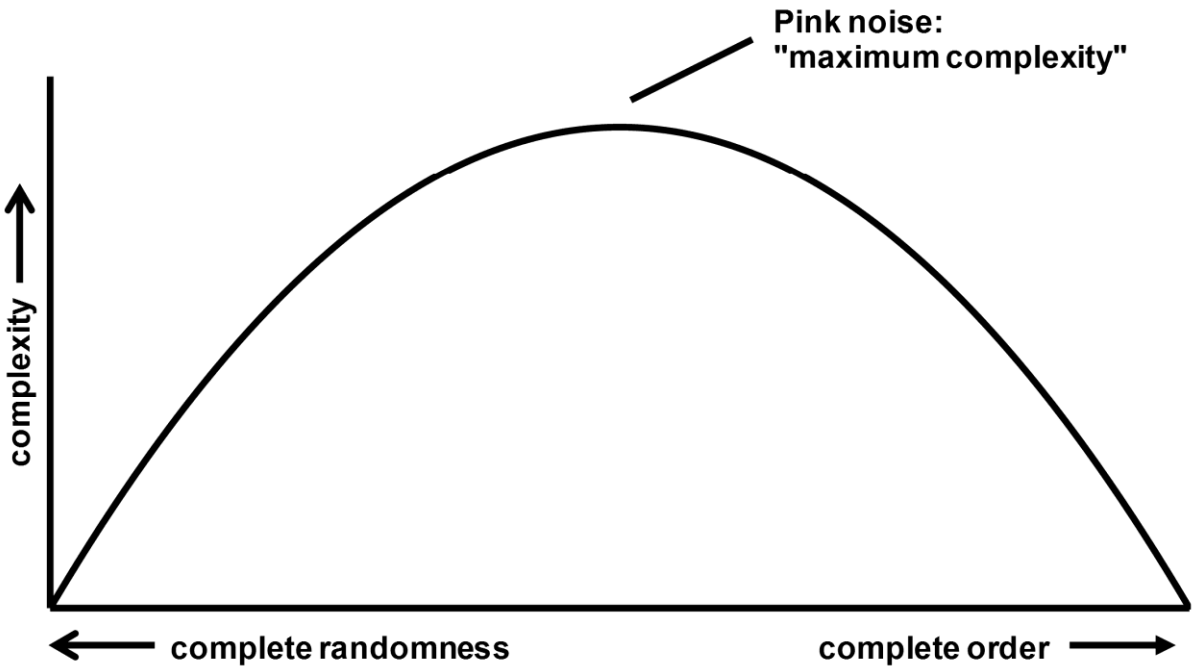

Figure 4. Pink noise resides between complete randomness and complete order. It has been suggested that pink noise represents maximum complexity.

The basic quantification of a fractal is the fractal dimension. In tradition Euclidean geometry, the dimension of an object is 1, 2, or 3. In fractals, however, the dimension of the object is not a whole number, but rather fractional. The fractal dimension provides an index of the space-filling properties and the ratio of the number of features at one scale to the number of features at another scale[32,57,72]. In exact fractals, the regression slope of a log-log plot between the size of the fluctuation and the measurement scale is a perfectly straight line. This is not always the case in nature, where fractals are more likely to be statistical, meaning that the self-similarity is not perfect but approximate. In this case, data points on the log-log regression are scattered around the line with a reasonably high correlation coefficient[37]. In another way, the statistical self-similarity can mean that the statistical properties of the part are proportional to the statistical properties of the whole[32]. The scaling range may still be

Table 3: The domains between complete order and complete disorder.

Anti-correlated	Smaller values are more likely to follow the large values occurring in the remote past. This gives rise to a "flip-flop" effect (long-term or anti-correlations or anti-persistence). Corresponds to a DFA-derived α value of less than 0.5 and β value of less than 0.
Random (white noise)	A process in which any value of each subsequent data point is independent of all previous values and therefore equally likely to occur. A random time series can still operate within bounds of certain limits. Corresponds to a DFA α value of 0.5 and a spectral analysis β value of 0. Disorder.
1/f scaling Correlated (pink noise)	A time series with long-term correlations or persistence indicating non-random behavior or order in the data. The magnitude of fluctuations is inversely proportional to the frequency of oscillation. Particularly large values are more likely to be followed by large values (long-term or persistent correlation). Corresponds to a DFA-derived α value of 1.0 and spectral analysis-derived β value of 1.0.
Brown noise	The integration of white noise, corresponding to a DFA-derived α value of 1.5 and a spectral analysis-derived β value of 2. Overly ordered (regular).

finite, with real upper and lower bounds to the behavior[20,24]. This is the case for natural fractals. This subclass of systems found in nature is called prefractal[73]. Fractals are related to, but are not the same thing as chaotic systems[74]. Rather, it has been said that a fractal is a specific form of chaos[70,72].

Complex nonlinear dynamics in human biological function

Structural and temporal biological system hierarchies

Complexity is frequently seen in the form of hierarchical systems[52]. A biological hierarchy is a system that includes subsystems that are related to one another[52]. This results in structure and function on many different levels of scale. Biological systems exhibit

behavior over multiple spatial and temporal scales[40]. However, functional hierarchies do not necessarily correspond with the structural hierarchies[75].

The spatial hierarchy reflected in human anatomy includes the "upward" relationship of the levels from cell, tissue, organ, organ system, and whole system. The "downward" progression moves from the cell to sub-cellular organelles, membranes, biochemistry. Whereas spatial self-similarity allows us to describe the patterns arising in human anatomy, temporal self-similarity allows us to properly describe how a time series on a micro-level resembles the (entire) time series on a macro-level. Temporal biological fluctuations reside on a continuum that extends from the order of milliseconds to ultradian (shorter than 24 hour), circadian (24 hour), and infradian (longer than 24 hour) timescales. Examples on this continuum include the rapid fluctuations of cell flickering, motor unit rotation, the familiar rhythms of human gait, the well-recognized circadian sleep-wake cycle, the weekly (circaceptan) cycling in hemostatic factors[76], the monthly (circatrigintan) hormonal cycling[77], and the yearly (circannual) cycling of hormones. The entire human biological system is complex in its output of exercise performance, and requires the integration of multiple physiological and psychological processes[3]. Just as the whole biological system is complex, so it is that the individual physiological processes are complex, because of the multitude of connections that must cooperate to produce that output[3]. Hence, the complexity operating over a wide range of spatial and temporal scales[39]. We will now briefly describe the presence of complex structures and functions of the human body from organ level upward.

Autonomic/involuntary function

The following descriptions are only intended to be brief, and to provide cursory evidence for the ubiquity of complex nonlinear function at the different levels of organization in human biology.

Organ/organ system level

Cardiovascular anatomy and function

The timing of the heart beat interval is, by far, the most studied nonlinear function in human biology. An examination of the beat-to-beat variability in heart rate in high resolution can identify seemly random variations in the beat-to-beat timing that is actually deterministic and varies in a complex fashion[70,78]. There seems to be good agreement that it is a fractal process[79], even multifractal[80–82]. There is also good agreement that the heart rate (HR) represents a nonequilibrium system, meaning that following a perturbation, the system does not return to a single state of equilibrium[82]. For example, in an ECG time series, fluctuations in the timing between successive heart beats over a small time scale can resemble the fluctuations of the same time series over a longer time scale. This self-similarity may be quantified as the degree of fractal scaling in that data set.

While there is no dispute that the human HR exhibits complex, nonlinear dynamics, there is some debate as to the precise behavior. Indeed, the difficult question is whether the HR is *chaotic*. Earlier work suggested that the healthy heartbeat demonstrates chaotic dynamics[2], while Hu[83] concluded that heart rate variability (HRV) is mostly stochastic (as opposed to deterministic, which is a necessary characteristic of chaotic systems). Yet later opinion has been equivocal as to whether HRV is chaotic and deterministic[81,82,84,85].

Other views on the dynamics of HR show that complexity can be shown through entropy measures[86]. The fractal characteristics in HRV are thought to arise through the complex interaction between the vagal and sympathetic modulation of the rhythm[72]. Indeed, it is thought that when these two branches of the ANS interact, they do so in a nonlinear fashion and for this reason are capable of generating these specific output.[40]

Billat et al.[87] reported that HR during running exercise maintained a scaling exponent close to long-term correlated 1/*f* noise in both constant-speed and freely-paced runs. When comparing the scaling exponents over time by investigating each quarter of the exercise bout, the scaling exponent for HR maintained its complexity (ranging from approximately 1.0 to 1.5, corresponding to from 1/*f* to Brownian noise). Other cardiovascular function shown to be complex and nonlinear includes blood pressure dynamics[86].

Respiratory anatomy and function

Respiration also exhibits complex patterns. Breath-to-breath variability in respiration is analogous to HRV, and tidal volume is analogous to stroke volume. Donaldson[88] and Hughson at al.[89] suggest that it is likely that respiration demonstrates chaotic patterns of breathing, perhaps to facilitate rapid and flexible responses to sudden perturbations[88]. The fractal nature of the inter-breath interval has also been established[90]. Angelini et al.[86] used multiscale entropy measures to demonstrate complexity in continuous lung volume measurement. It has been suggested that complexity in the respiratory rhythm arises from two coupled nonlinear oscillators in the brainstem[91].

Oxygen consumption

Billat et al.[87] measured behavior of oxygen consumption VO_2 during time trials of 10 km. It was shown that VO_2 demonstrated evidence for non-trivial fluctuations in the signals.

VO_2 values demonstrated a scaling exponent close to long-term correlated 1/*f* noise for both constant-speed and freely-paced runs. The scaling exponent for VO_2 declined throughout both conditions, from 1/*f* behavior to strongly anti-correlated values, indicating that the control mechanism may change throughout the duration of the exercise.

Muscle function

Electromyogram (EMG) and mechanomyogram (MMG) provide continuous data that may be analyzed for its nonlinear structure. Control entropy analysis indicated a complex structure to both measures, and that the complexity in these two measures is altered together with fatigue during short-term high-intensity cycling exercise[92]. This complexity may also be measured during a fatiguing isometric contraction, but the control entropy of EMG and MMG is altered in the opposite direction[93], indicating a possibly different mechanism of control between high-intensity cycling and an isometric contraction.

Somatic/Voluntary function

Postural control and balance

Force plate measurement of the center of pressure (COP) during quiet standing tasks demonstrates a correlated structure. For example, body fluctuations during quiet standing have DFA scaling exponents between 0.5 and 1.0[94]. Indeed, COP trajectories have been modeled as a one- and two-dimensional random walk (fractional Brownian motion)[95,96]. A closer investigation distinguishing short- and long-range correlations in COP data indicated negative correlations over the long-range and positive correlations over the short-range[97].

Reports regarding changes in complexity during postural control tasks with fatigue vary, perhaps because of different analysis methods. Corbeil et al.[98] found that the long-term scaling exponent during fatigue was decreased so that it represented a less stochastic and

more anti-persistent behavior. Another report indicated that there was increased complexity of single-legged postural control with fatigue, as demonstrated by control entropy[99].

Fine motor control

Finger tapping is a simple, but useful task for testing the control of rhythm during fine motor tasks. There is evidence for 1/*f* scaling in finger tapping tasks[16,100]. This 1/*f* noise is present in both self-paced and synchronized finger tapping[101]. This has also been shown in forearm oscillation tasks[16,102]. Other examples of 1/*f* noise in motor control include synchronization to a metronome[101,103], bimanual coordination[104], serial force production[105], and circle drawing[106].

Self-paced exercise

Terblanche et al.[107] used frequency distribution analyses to analyze work rate during freely paced exercise on a cycle ergometer. Power spectral density and fractal analyses indicated non-Gaussian distributions. The output followed a power-law behavior pattern generally associated with fractals and complex dynamical systems, with power spectral exponent β ranging from approximately 0.5 to 0.8. The authors suggested that this type of power spectra should be considered to be the usual physiological response to freely paced exercise.

Billat et al.[87] showed that speed fluctuations measured during running exercise demonstrated evidence of a significant non-random structure. However, the scaling exponent for speed declined throughout the exercise bout from 1/*f*-like behavior to white noise or slightly anti-correlated.

Tucker et al.[42] investigated fluctuations in power output during freely-paced cycling exercise that consisted of a 20 kilometer time trial. Spectral analysis revealed 1/*f*-like scaling

such that higher power outputs occurred less frequently and lower power outputs occurred more frequently, according to a power law. The fractal dimension varied between 1.56 and 1.9 for the entire trial. The authors concluded that these fluctuations stem from a control process that was intrinsically biological, rather than being an artifact of the environment, perhaps brought about by multiple feedback loops contained in various regulatory systems in the body operating over different time scales. Further, the study concluded that different individuals evidently employed similar system control mechanisms, even though their performance abilities were varied.

Activities of daily living

In activities of daily living, fluctuations in forearm movement over the 16 waking hours varies throughout a daily or weekly period occur according to a pattern that is temporally self-similar. Hu et al.[108] measured forearm motion as a way of quantifying activity during one's daily routine. Forearm motion appears random, but in fact behaves with scale-invariant and nonlinear properties. This dynamical structure was stable across subjects and was independent of known extrinsic factors (such as random and scheduled events) as well as intrinsic factors with a single timescale such as found with circadian or ultradian rhythms. Fluctuations did not only occur on a single scale, but provided evidence for a higher-order process in which a multi-scale mechanism regulates activity[108].

Cognitive function and psychology

Kello et al.[66] investigated the temporal structure of reaction time in key-press tasks. It was found that intrinsic fluctuations in the response time contained significant 1/f noise structure. According to van Orden et al.[109], 1/*f* scaling in human cognitive function represents the mind-body connection and self-organization. 1/*f* scaling has also been shown for

cognitive activities such as mental rotation, lexical decision, or visual search[110] and simple reaction time[111]. Day-to-day measures of self-esteem also contain 1/*f*-scaled fluctuations[112].

Gait

Complex dynamics in human gait is a widely studied area of research. The reader is directed to the subsequent chapter devoted entirely to this area.

The meaning of complex nonlinear dynamics

The dynamic signature

A complex signal arising from a biological system contains information (that may be called a "biomarker") that points to the dynamical state of that system. These complex signals may take one of several distinct classes or "styles" of nonlinear interactions. Perhaps best termed a "dynamic signature", each specific sequence or pattern of physiological signals can perhaps identify categories of possible physiological states of that system[113], and help discriminate time series of different systems or the same system under different conditions[3]. From information theory, the domain occupied by complex systems resides between "the extrema of perfect regularity and complete randomness"[40] (Figure 4), representing a balance between adaptability and regularity[26]. The breakdown of normal fractal function leads to the possible dynamical end-states that can ultimately take place: 1) highly periodic (predictable) behavior; 2) random walk (brown noise); and 3) completely uncorrelated (white) noise[39]. There is extensive and growing literature on the theory and evidence regarding the dynamics of pathological systems, but we will focus our discussion on normal physiological function.

The mechanism of organization

Non-equilibrium dynamics have been suggested as an essential characteristic of healthy biological systems[114]. Seely & Macklem[3] suggest that healthy states of the human body occur when the system operates far from thermodynamic equilibrium. In healthy heart function, for example, neuroautonomic control evidently keeps the system operating away from a single equilibrium position[31]. This behavior requires organization that may be achieved through the presence of long-range correlations, and the scaling exponent may quantify the precise balance of the many timescales that are represented in the system[115].

Perhaps the most convincing explanation of the source of these fractal fluctuations is the "iteration-dominant" view[66]. This view holds that long-range correlations arise because of complex interdependence in the system[17,24,39]. These long-range correlations and scale invariance may be a mechanism of self-organization for the structure and function of complex systems whose output includes fluctuations operating over a wide range of time scales[24]. If this were not the case, then having one characteristic scale would tend toward dominant periodicity (mode-locking) which would hinder the responsiveness of the system to only a limited scaling region[24,39]. There are other cases of physiological function in diseased individuals that show a flat power spectrum (scaling exponent of zero) in which there is little temporal correlation. In this behavior also, there is a loss of adaptive behavior[20,24,31,115].

In addition, all complex systems contain some level of inherent randomness, noise or mutation that is both endogenously produced as a by-product of component interactions. In particular, *in vivo* biologic signals are generated from a system with both stochastic and deterministic behavior[12]. Examples of stochastic behavior are replication errors in DNA mutations and energy released by chemical reactions. Random behavior can arise due to interference from overlapping systems, such as noise from other parts of the body or other

systems. Despite what one may think, such inherent system noise is precisely what makes these systems so robust and adaptive. By allowing for some level of randomized change, the systems are always probing for new, more energy efficient and stable organizations. This makes the systems resilient and adaptive. We call such adaptive systems 'stochastic systems' if they randomize their arrangements such that performance is increased.

Healthy and robust function as the consequence of a complex system

Adaptability, variability, and redundancy

1/*f* systems are generally thought to represent the healthy, stable, flexible, adaptable, and unperturbed function of a complex system[16,17]. Perhaps the most important feature of biological health is the ability to adapt to a wide variety of unexpected stimuli, perturbations, and stress[24], and this remains the most popular explanation and benefit of complex behavior. Flexibility and adaptability are two characteristics commonly attributed to chaotic systems and critical neural network systems[72,116]. Systems like this are said to be robust because they are also stable under small changes to its variables. This may also improve over time through the process of self-organization within a given environment[4].

A healthy human system is able to generate a multitude of integrated outputs spanning the functions of every body system including nervous system control of muscular movement and posture, cardiovascular, and mental health/cognitive function[19]. Each of these functions needs to interact with the internal and external environment according to the requirements of life. In doing so, the parts of the body, along with corresponding regulatory feedback loops, conduct their functions over the full breadth of temporal and structural scales[39,40]. The lack of characteristic scale in physical structures and the lack of a characteristic period in temporal processes affords good tolerance to perturbations[63]. This tolerance may extend to both

internal changes and changes in the environment. Indeed, fractal models are highly tolerant and largely unresponsive to error and environmental variability[63]. The redundancy in such systems provides a multitude of degrees of freedom, which affords several options by which tasks may be accomplished and also permits different task outcomes in different contexts or environments[117,118]. The proof of the accuracy and reliability of these many systems comes from an examination of the variability in these processes: fluctuations ordinarily occur within a coefficient of variation of only a few percent[19].

Variability may also be seen as exploratory behavior that may increase or decrease with skill acquisition[119]. It represents a search for stable and functional states of coordination[120]. A decrease in 1/*f* noise is thought to indicate a maladaptive system[17], perhaps because of the presence of additional, superimposed processes operating over short time scales only[17].

Implications for the concept of homeostasis

The classical notion of homeostasis maintains that a state of constancy typifies ideal functioning[24]. Homeostasis has been considered to be the result of multiple bodily systems seeking to minimize the variability in physiologic signals. The hallmark of this biological function was the achievement of an equilibrium-like status, whether dynamic or not. According to this traditional view, variability represents the deviation of a variable from a fixed-point attractor in a state of equilibrium, with fluctuations occurring because of disturbances from the internal and external environments that interact with the control mechanisms employed to maintain equilibrium[37]. The strength of the system is measured by how tightly this oscillation is regulated, such that a perfect homeostatic system would generate flat line outputs of every physiological variable and that this is the truly desired

situation for the body. Low-resolution measurement of a variable would seem to confirm the rigidity of this hypothetical value, providing evidence for a homeostatic set point or steady state. However, more in line with the principle of homeodynamicity, recent work has made it clear that the statistical properties of many physiological variables actually demonstrate the properties of a system that is operating far from equilibrium, shows complex fluctuations, and power law scaling[24,114].

Earlier in this paper, we described the perspective of *homeodynamicity* that may more correctly represent biological function. According to this view, biological function operates in a state that is far from equilibrium and aims to bring the system into organization so that fluctuations occur within acceptable limits. The attractor is probably not fixed but varies according to a complex pattern. In fact, it is likely that a stability of this "fixed point" attractor occurs not in health but in severe disease states.[42] Thus, variability likely indicates robust function, flexible, yet structured homeodynamicity is more desirable and a truer representation of what the body aims to achieve with its regulatory mechanisms.

Summary and conclusions

This paper introduced the need to view biological systems as complex systems with nonlinear outputs displaying distinct classes of behavior, produced according to rules that we have roughly defined. The use of high-resolution measurement when investigating problems in exercise science allows one to analyze the data with regard to complex temporal patterns, structures, and characteristics. Finding these properties provides information that is not available through traditional measures and corresponding statistics. This information may provide a more comprehensive description of physiological phenomena and enhance our ability to classify and predict different states of function during exercise. This classification

was explored by introducing the different qualities and behaviors of complex function such as nonlinearity, complexity, chaos, entropy, and fractal concepts. Understanding these concepts is crucial to provide a comprehensive interpretation and discussion of the results of the studies of this dissertation. Indeed, simply knowing that these patterns may exist in a data set is the first step in uncovering meaningful information in one's data with a view to eventually classifying the dynamics of any biological system. The complex dynamics that are observed indicate flexible, adaptable, and robust systems and serve to define the expected behavior of biological function.

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Chapter 3

Considerations of data collection and analysis of nonlinear systems

Data Collection

The measurement of nonlinear properties in a physiological system allows us to categorize the behavior of that system according to various dynamical categories such as those described in the previous chapter. Keeping with this purpose, it is important that our measurement practices reflect our adopted framework. Because even deterministic systems are likely affected by some portion of dynamic noise, a purely deterministic approach may not be appropriate[1]. Rather, it is important to employ a stochastic approach to analyze biological systems that most likely contain both deterministic and stochastic components[1].

The following descriptions are of analysis methods commonly used in recent clinical and applied studies investigating the dynamics of human physiology and movement and will represent the analytical approach used in the experimental chapters of this dissertation. These methods have been used more extensively in clinical research, although researchers in the applied exercise sciences have been giving these methods more attention of late. This review is not exhaustive and the reader is encouraged to refer to works such as Eke et al.[2] that provide a more detailed discussion on the methods introduced in this paper. We will be describing analyses conducted in both the time and the frequency domain.

Time domain analyses describe how a particular data set behaves across a spectrum of time, that is, from beginning to end. In a time domain presentation, the value of a particular variable is presented at equal time intervals. In a slightly different approach, a time series presents data from rhythmic processes as a sequence of values that are not separated by a precise time interval but rather each data point (rhythmic event) is presented in time whenever it occurs. This approach can sometimes be used interchangeably with the time domain, for example, a heart rate time series consisting of a series of intervals between each beat. Before

introducing the several analysis methods used to describe fluctuations and patterns in a time series, it is necessary to briefly review the concept of variability itself.

We can describe variability in terms of its magnitude and structure. The magnitude of variability, is expressed by the first and second statistical moments of mean and standard deviation. In the exercise sciences, the magnitude of variability is commonly reported. Yet, an examination of the mean and standard deviation is insufficient to understand the structure and dynamics of variability. Instead, we will present several complementary nonlinear methods to provide a comprehensive analysis. Many such analyses are described below can be performed using freely downloadable software available via the 'PhysioNet' internet resource (www.physionet.org)[3]. According to Goldberger et al.[4], there a danger in relying on a single statistical measure to assess the level of complexity in physiological systems. Rather, they suggest that a "tool kit" of many analysis methods be used to investigate and quantify the nature of complex biological function. This approach, later reinforced and applied by other researchers[5,6] represents the framework from which we operate in this dissertation.

Sampling

We will consider the issues of sampling, stationarity, artifact, and standardization of technique. Data must be collected in a manner that permits a thorough analysis of the signal of interest and is sufficient for the requirements of the statistical calculations to which the signal will be subjected. This means that data collection must provide a close enough examination to identify salient features of the fluctuations, and it must provide the information that is required for each mathematical approach. However, although much variability is interesting and meaningful, there still may be true error in the signal and care must be taken to identify artifacts that are unwanted.

Some features are only observable when measured in high resolution, but we first need to define more specifically what is considered *high* resolution. Intrinsic rhythmic variables such as heart rate and walking gait can be represented as a time series of intervals representing a certain frequency[7]. If there is no obvious intrinsic rhythm, the data should be analyzed for its frequency components (see the next section for an overview of this method). In either case, according to the Nyquist-Shannon sampling theorem, the data requires collection with a resolution at least double the highest frequency present significantly in the time series[2,7,8].

It is also important to consider the number of data points in the series. One aspect of time series length that is often overlooked is rooted in the understanding of the mathematical behavior of nonlinear systems. The traditional linear view holds that larger data sets are more reliable because they provide a better estimate of the mean value of the system, with a consistent error variance between short and long series. In contrast is the view that longer data sets can possess more extreme values and variability that would be missed in shorter data sets[9]. Thus, the dataset must be long enough to identify extreme values that are only noticeable in light of a long series of which they are a part.

However this must be balanced with practical considerations because the reliability of an analysis algorithm varies. It has been suggested that fractal methods require 2^{12} (i.e., 4096) data points for reliable results[2,10]. However, the practical experimental issues associated with exercise intensity sometimes prevent the acquisition of this length of series, series of length 2^9 (i.e., 512) or 2^{10} (i.e., 1024) may be an acceptable compromise[11]. In entropy measures, for example, Costa et al.[1] suggested that 1000 data points is the minimum requirement for MSE,

but others have reported reliable results, depending on the algorithm parameters, with as few as 512 data points[6].

Strictly speaking, many analyses such as DFA require uniform sampling intervals. This means that a traditional variable time series that contains a series of inter-point time durations must be resampled so that there is the same amount of time in between consecutive points. However, this requirement is often relaxed because many analyses work well with both practices[2].

Nonlinearity

An autocorrelation function (ACF) is useful to test for nonlinearity in the time series. An initial examination of shape of the autocorrelation function can indicate either non-stationarity or nonlinearity if there is a slow decrease in the ACF. Further comparison of the shape of the square of the ACF with the square of the samples can indicate the same thing[12].

Stationarity

Many analysis methods in the time and frequency domain require stationarity in the signals of interest. Stationary systems have a consistent mean and standard deviation throughout the entire length of the dataset.* The signal may vary within the recording period, but the behavior of this variance must not change significantly[2,7]. This is an obvious problem for free-running physiological systems, in which there is significant change in the statistical properties of the signal as it evolves with time. Fortunately, many analyses, such as detrended fluctuation analysis (DFA) do not assume stationarity. Additionally, although fractional Brownian motion (fBm) processes may not be appropriately analyzed with some methods

* This stationarity is more properly called *wide-sense* or *weak-sense stationarity* because only the mean and standard deviation (the first two statistical moments) are time invariant. If all statistical moments have this property, it is considered to be *strict* or *strong-sense stationarity.*

because they are nonstationary[2], many physiological processes are instead fractional Gaussian noise (fGn)[*] systems, which are stationary. If changes in the properties of the data set violate the assumption of stationarity, the time spectrum analysis can evaluate the power spectral density function for shorter periods of time because *within* these periods, stationarity may be assumed.

Artifacts

Care should always be taken so that the noise:signal ratio is as low as possible, so it is important to remove artifacts prior to analysis[7]. This can be done visually[7], or via filters. For example, a time series analysis of heart rate variability may first employ a cut-off filter set at a frequency less than 0.005/s (i.e., above 200 bpm)[13,14].

Standardized technique

It is important to ensure that all factors that may influence the variability in measurement are consistent (but not minimized lest an inherent real variability in the system is eliminated). For example, orthostatic considerations mean that body position can alter cardio-respiratory function. Control of breathing can also affect HR variability and it is thus prudent to control these influences during testing[7].

Post collection analysis methods

This section outlines the mathematical/statistical methods used to identify the properties of scale invariance and long-term dependence and to generally classify system behavior. The reader is referred to Eke et al.[2] for an extensive review of the methods used to

[*] Fractional Brownian motion and fractional Gaussian noise processes will be described later.

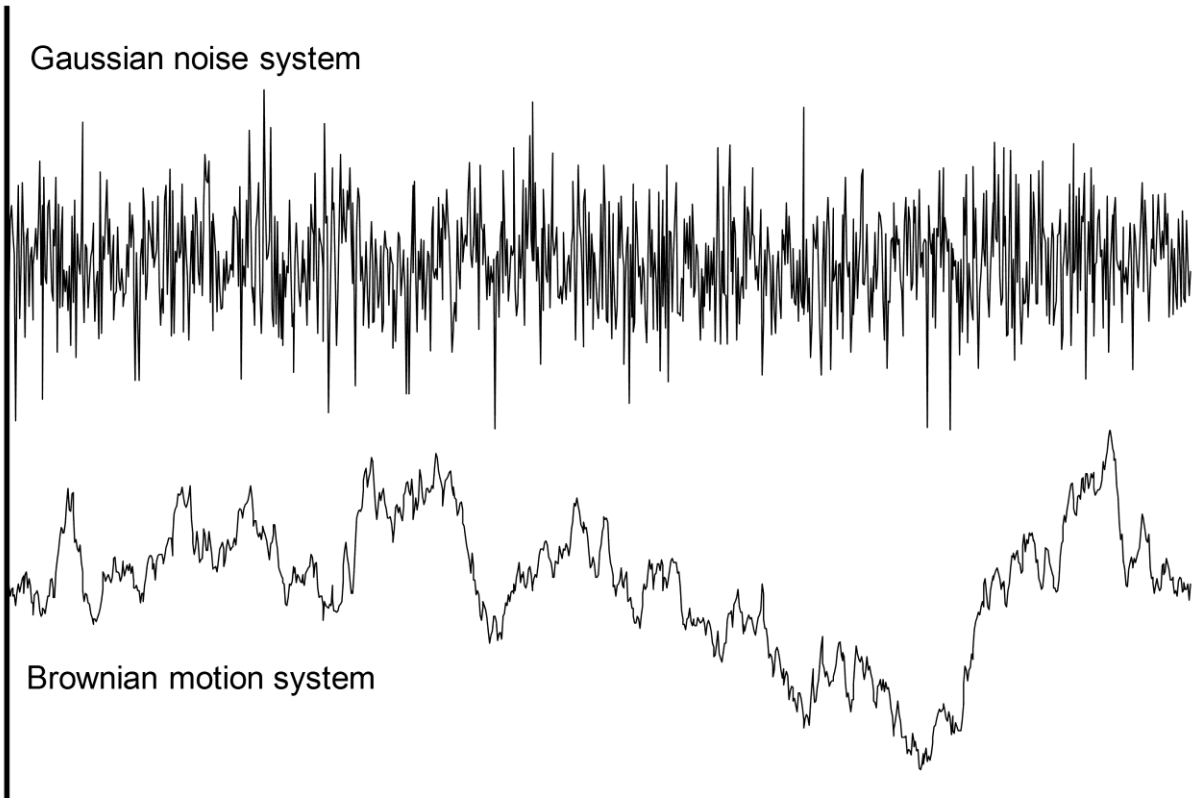

Figure 1. Synthetic time series demonstrating Gaussian noise (top) and Brownian motion (bottom). The Gaussian system is stationary, while the Brownian system is not.

classify fractal dynamics. These methods are executed in the time and frequency domains. The selection of analyses that will be described generally follows the suggestion of Crevecoeur et al.[6]. These form the suggested collection of complementary analyses to identify long term correlations in physiological time series. Many studies employ a single analysis only and it is thus difficult to compare results from one study to another if different analyses are used. It can also be difficult to conclusively identify long-term correlations from only one analysis. A comprehensive and complementary set of analyses serves to increase the confidence in interpreting the results.

This complementary aspect is possible because of the theoretical relationship between the outcomes of several analyses, usually identified by asymptotic behavior in the outcome

variables. Specifically, this involves results from autocorrelation, power spectral analysis, and estimation of the Hurst exponent. We will first describe these analyses and their relationships, and then describe the use of another method, namely multiscale entropy analysis. Finally, we will discuss the use of surrogate data and simulations as a way to test the results of experiments against artificially generated time series with known dynamics.

Identifying the model

Variability may be understood generally to follow either a fGn or a fBm model[2,11]. The assignment of one model to a particular process does not mean that behavior is purely Gaussian or Brownian, but only that it has certain properties that are defined by these labels. fGn is a stationary process consisting of successive increments that are uncorrelated. In these systems, the average value quickly converges because no new structures are displayed on larger scales[1]. In fBm (the integration of fGn), the successive increments are correlated and represents the random movement of a single particle along a straight line[11]. With certain analyses, it can be difficult to distinguish between the two processes when the behavior is close to 1/*f* noise, however, certain analyses such as DFA are not sensitive to this problem[11]. The two models are illustrated in Figure 1.

Analyzing in the time-domain

Time-domain analysis is a near-universal way of presenting data in the exercise science literature. This category includes the linear measures of the magnitude of variability: mean, standard deviation, coefficient of variation, and frequency distribution. Standard deviation shows the magnitude of dispersion of the values from the mean. Coefficient of variation goes one step further and relates this dispersion relative to the mean value. A

frequency distribution (not to be confused with frequency domain analyses) provides a picture of the entire data set by plotting the number of occurrences of each value as it falls into a particular range of values, displaying the symmetry of the data set. Common findings from frequency distributions are a normal distribution and a log-normal distribution, where the log of the dependent variable is normally distributed[7]. Nonlinear analyses in the time domain are able to account for the structure of variability by quantifying some aspect of time dependency in the data set. These include analyses of autocorrelation, rate of moment convergence, and estimates of the Hurst exponent (H). Some time domain measures are susceptible to bias arising from non-stationary signals[7], but there are some nonlinear analyses that are robust with regard to nonstationarity (e.g., ref[15]).

Autocorrelation

In systems with significant structure of variability, the sequence can be described with regard to the association between one data point and subsequent data points (system memory). The autocorrelation function quantifies correlations between data points separated by lag τ (reference[2]). System memory means that later data points are dependent to some extent upon earlier data points. These correlations decrease over time, at different rates, depending on the nature of the system. A finite sum of correlations (i.e., they are convergent), indicates short term memory. If the sum is infinite, the system is said to have long term memory because the correlations decay so slowly that they sum to an infinite number. In systems with long-term correlations, particularly large values are more likely to be followed by large values, and vice versa. In an anti-correlated data set, a large value is more likely to be followed by a small value, giving rise to a flip-flop effect.

Our interest is first to identify the presence of significant memory in the system, indicated by a non-zero autocorrelation value. This would indicate two possible phenomena[16], determined by examining the decay in memory according to the following equation: $C(\tau) \sim \tau^{-\beta}$. In this case, $\beta > 0$. Finite memory is determined if $\beta > 1$ and infinite memory is the case when $0 < \beta \leq 1$. For example, in the measurement of running strides, finite memory means that the autocorrelations extend only over a short number of strides, such that each stride is only influenced by a few previous strides[16]. This is the most intuitive possibility, but early work has instead suggested that there can be significant correlations up to a lag of 1000 strides in walking trials[17]. This represents approximately 1000 seconds (~16 minutes), which theoretically means that the timing of the 1000th stride is influenced in some way by the very first stride. While infinite memory is difficult to show in the typically short time series obtained from human subjects, a system with memory this long can at least be considered long term. A sample output of an autocorrelation analysis is presented in Figure 2.

Rate of convergence of statistical moments

Another useful measure is the rate of convergence of the mean and variance (or standard deviation). Rate of moment convergence is calculated by comparing the mean and variance of the original series and that same series randomly shuffled at each truncated length of that series. Over time, the order of the original time series will not be significantly different from the surrogate time series. If the rate of convergence is significantly slow, it suggests that the ordering of the original time series is meaningful[6]. One drawback of this method is that it only permits visual inspection of the graphical output. There is no single output value that indicates the criterion of meaningful nonlinear structure. Figure 3 provides examples of systems with a relatively slow convergence.

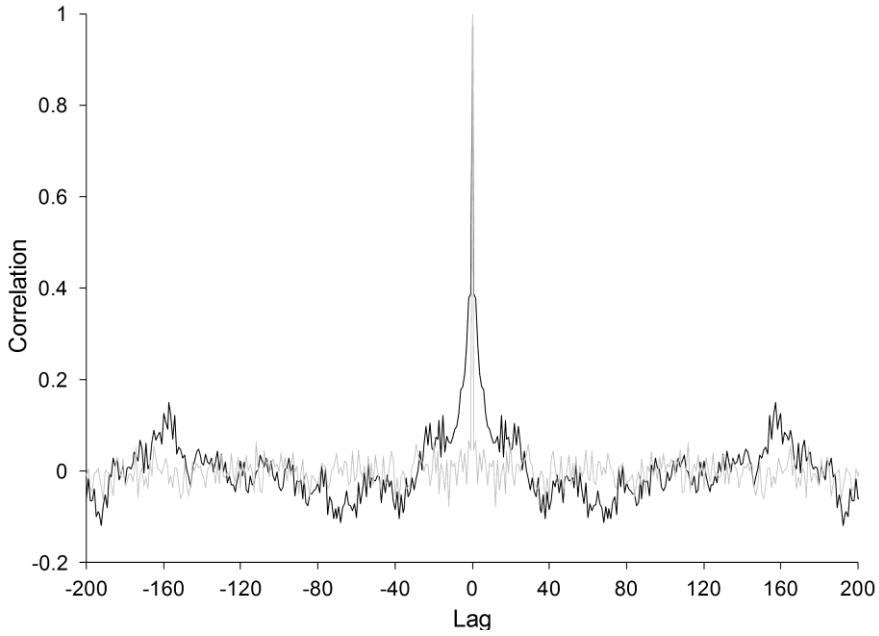

Figure 2. An example of an autocorrelation function showing values for both positive (forward) and negative (backward) lags in the time series. In this instance, correlations between the first 200 data points of an original time series are shown (black). Also shown are the correlations for the same time series randomly shuffled (grey). The original time series demonstrates a relatively slow decay in correlation from lag 0 to lag ~40. There are also prominent regions of correlation and anti-correlation at higher lags. In contrast, the shuffled time series rapidly decays and remains at a roughly 0 correlation, indicating no serial dependence in the system.

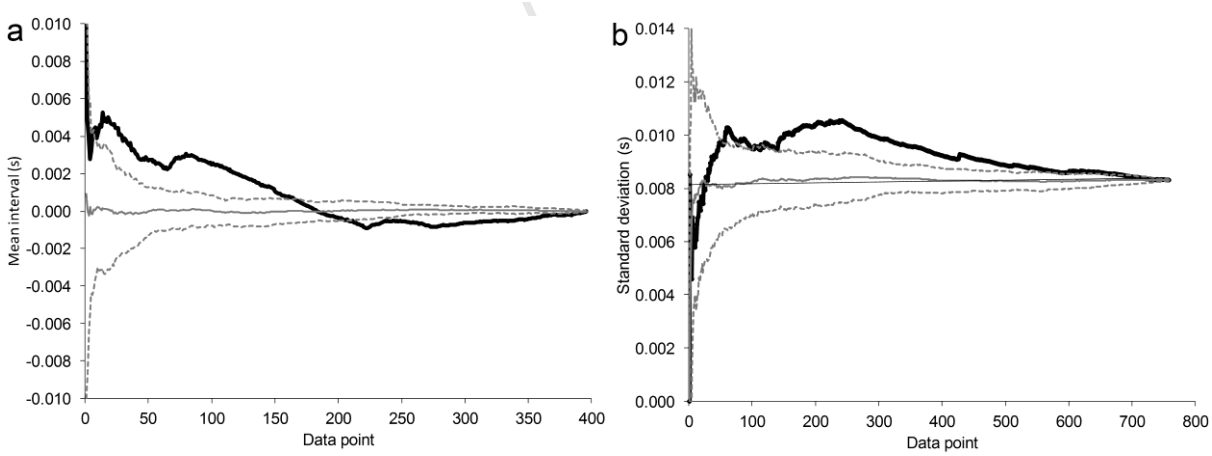

Figure 3. Demonstration of a relatively slow rate of convergence of the mean and standard deviation for two separate time series. In (a), the mean value remains outside the 1 standard deviation bounds for most of the 400 data points in the set. In (b), the standard deviation also remains outside the bounds from the region of data point 100 to 800. Thin solid and dotted lines = mean ± standard deviation of the 20 shuffled series at each truncation length. Thick solid line = mean value for the original series at each truncation length.

Estimates of the Hurst exponent

We now discuss how to measure scaling in a time series. Scaling refers to magnitude of fluctuations that are displayed when the time series is considered over small or large sections. Self-similarity is a common property of complex systems. This means that, either visually or statistically, a data set has a similar appearance with both a macro- and microscopic view. The scaling exponent of a time series can be estimated by taking the slope of a log-log plot, in which the log of the fluctuation size is plotted against the log of the window used for fluctuation determination. The most common such exponent is the Hurst exponent. This analysis is able to distinguish between long-term correlations and white noise[6]. More specifically, it can distinguish between white noise processes ($H = 0.5$), long-term correlated processes ($0.5 > H > 1$), and anti-correlated processes ($H < 0.5$).

Detrended fluctuation analysis

To deal with the problem of common nonstationary data sets, Peng et al.[18] developed detrended fluctuation analysis (DFA) to provide an estimate of the Hurst exponent[*], which, in turn, is related to the fractal dimension. DFA is a modified RMS analysis of a random walk that quantifies long-term correlations and is robust with regard to non-stationary processes because it subtracts local trends that likely are due to external stimuli[7,15,19–21]. It evaluates trends in the data occurring across multiple timescales, and because it is detrended, it thus addresses the requirement of stationarity in correlations present in the data. In other words, DFA evaluates the tendency for high and low trends in the data to persist. DFA is a mono-fractal analysis technique, which means that it investigates fractals occurring on a single time scale only.

[*] The value of the Hurst exponent H may be used interchangeably with DFA scaling exponent α.

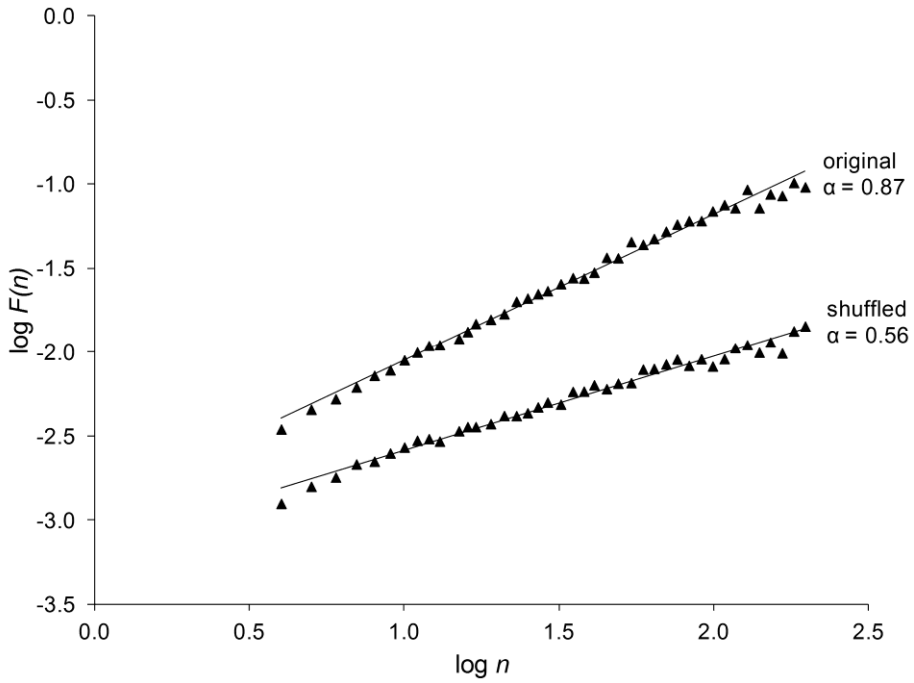

Figure 4. A sample output from detrended fluctuation analysis. The log-log relationship between the fluctuations and the box size has been plotted for an original gait time series and the same series randomly shuffled. Each output is fitted with a linear line, of which the slope is scaling exponent α. The lower dataset has been vertically shifted for visual clarity. The original dataset demonstrates a scaling exponent relatively close to pink noise (α = 1.0), while the shuffled dataset demonstrates a scaling exponent close to the expected α = 0.5 for white noise systems.

The algorithm generates a self-similarity parameter or scaling exponent (α), which reflects the rate of decay of the series autocorrelation function[22], and how the variability increases with the size of the box used to identify each region of the time series[23]. The speed of the decay of the autocorrelation function reflects the stochastic memory of the process. A slow decay reflects long-term memory and self-similarity that characteristic 1/*f* noise systems[24,25]. In fact, in such systems, the decay of the autocorrelation does not converge to a finite number[25]. A sample output for DFA is presented in Figure 4.

α distinguishes anticorrelated processes (α < 0.05) from uncorrelated processes (α = 0.5), pink noise (1/f noise) processes (α = 1.0), and Brownian motion (α = 1.5). Exponents below 1.0 are fGn processes, whereas exponents above 1.0 are fBm processes. There are still

correlations in the latter, but they do not follow a power law[15]. The higher the value of the scaling exponent, the more smooth the series becomes[15]. In contrast, the more stochastic (random) influence in a series, the more changes in direction will occur in the output. Such a series will appear rougher[26].

The steps in this algorithm are well described in references[18,19,21,22] and we provide them below:

1. Integrate the series (form a cumulative sum);
2. Divide the series into non-overlapping boxes of equal length *n*;
3. Use a least squares fit to define the local trend in each box;
4. Calculate the average fluctuation *F(n)* around the trend for each box according to the equation, where y(k) is the integrated time series and $y_n(k)$ is the local trend in each box:

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

5. Repeat for all box sizes;
6. Plot the log fluctuation *F(n)* versus log *n.*
7. The slope of this relationship, scaling exponent α, is an estimate of the self-similarity parameter. The slope is estimated in log-log space, so the box sizes commonly are set to increase by a factor of $2^{1/8}$, according to Peng et al.[18].

The two main considerations in the use of this algorithm are the range of box sizes and the series length. DFA is thought to be sensitive to window sizes[27]. There have been different suggestions as to the ideal scaling range (box size)[16,17,22,28–31], and several studies have used 4-N/4[18,32,33] and it is useful to follow the latter for the sake of consistency and

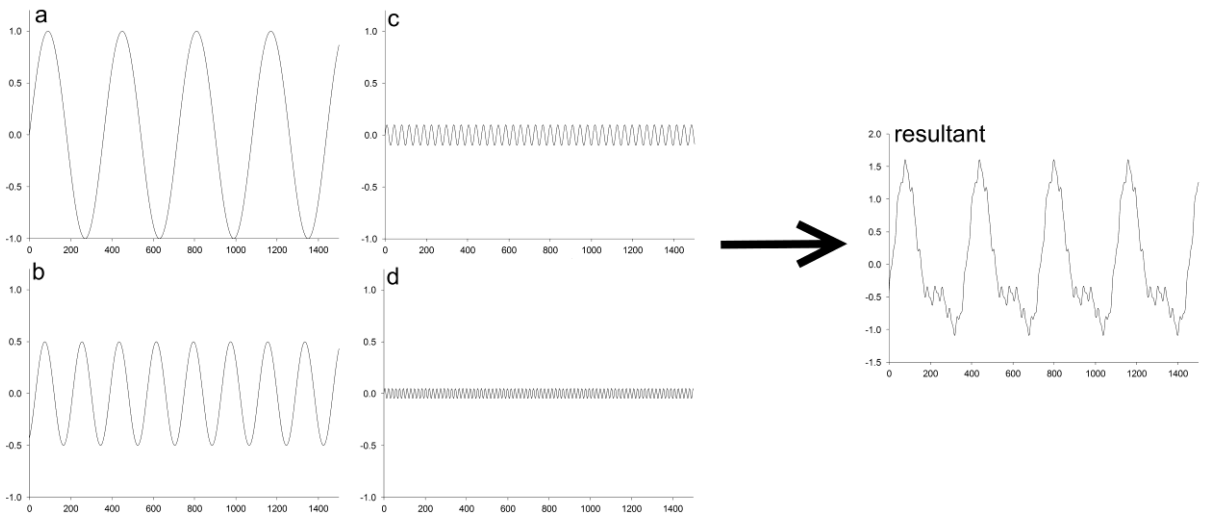

Figure 5. Example of the combination of sinusoidal fluctuations with different frequency and amplitude. Curves (a) – (d) on the left, when summed produce the resultant curve on the right that is beginning to show a more complex structure.

comparison*. DFA is also thought to be sensitive to data set length. Damouras et al.[22] suggest a minimum of 600 data points. However, as with the box sizes, there is varying practice regarding this issue. Some studies have demonstrated reliable data with as little as 2 minutes of walking data[29].

Analyzing in the frequency domain

Rhythmic biological processes can also be presented in the frequency domain[34]. With this approach, the series value is plotted on the ordinate, just as with the time domain, but instead of increasing time on the abscissa, the scale is comprised of a range of frequencies. Frequency domain analysis facilitates the reconstruction of a data set by using the sum of several sinusoidal oscillations with different frequencies and thus decomposes the signal into its constituent frequencies. An example of how different frequencies combine is given in

* We will use this scaling range for the DFA analyses in this dissertation.

Table 1. Corresponding values from different nonlinear analyses

H or DFA α	β	MSE	Interpretation
< 0.5	< 0		Anti-correlated
0.5	0	Entropy decreased over longer timescales	Random, Gaussian, White, disorder
0.5-1.0	0-1.0		Correlated, fGn
1.0	1.0	Entropy maintained over longer timescales	Pink noise, self-similarity, order
1.0-1.5	1.0-2.0		fBm
1.5	2.0		Brownian, "smooth landscape"

Figure 5. A perfectly periodic signal (such as a sine wave) has only one frequency component[35]. The power spectral density analysis assumes signal stationarity[19].

The earliest and most common method of this analysis is by Fourier transformation, which transforms the data from the time domain to the frequency domain and vice versa. A Fourier transformation is a way to describe a second-order linear characteristic of the time series and separates contributions of each oscillatory wave as a function of its frequency[7].This also requires periodicity, which means that the signal must be the product of recurrent oscillations[7], and thus a Fourier analysis is not suitable for all time series. Power spectral density is a quantification of the dominance of different frequencies (i.e., low, high) in a dataset. According to the Wiener-Khintchine theorem, the power spectral density of a stationary random process is the Fourier transform of the corresponding AC function[5]. Power spectral analysis (also called periodogram) generates an output (spectral index) signified by scaling exponent β. β indicates the "power" of different frequencies such that each of the

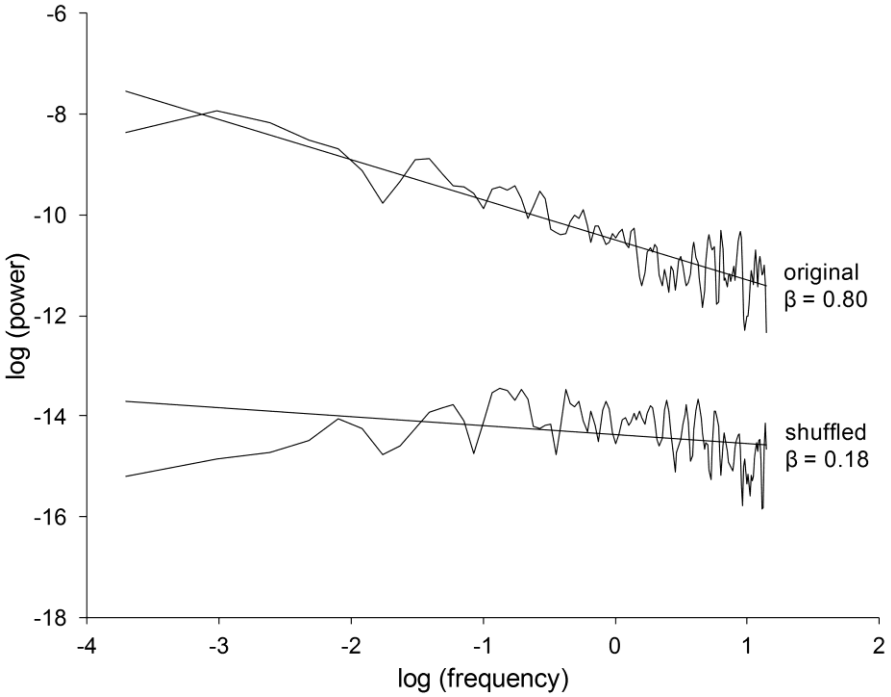

Figure 6. Sample output of Welch's method of power spectral density analysis. Output is presented for an original gait time series and the same dataset randomly shuffled. The slope of the fitted linear line is the scaling exponent expressed in positive terms. The original dataset shows an exponent close to the expected value of 1.0 seen for pink noise systems, while the shuffled dataset shows a near-zero slope that is expected for white noise systems.

dominant frequencies of oscillation in the time series as a peak in the amplitude-frequency plot. A sample output from power spectral density analysis is provided in Figure 6. The original data set (top) in this figure is dominated by low frequency. Given the relationship between the power spectrum and the autocorrelation via the Fourier transform, this mathematically corresponds with a slowly decaying autocorrelation function. Both presentations of a given dataset will represent the same statistical behavior.

Relationship between Hurst exponent and power spectrum

The confidence with which systems can be classified is increased when a good agreement between the different quantities is demonstrated. We note that these relationships

are reached asymptotically, and thus, may not be achieved in the typically short time series collected from human subjects. As such, the following relationships represent the theoretical ideal, and caution is needed in interpretation*. Confidence in results can be improved following the suggestion of Rangarajan[36] to consider the correspondence between the scaling exponent generated by the Hurst analysis (H) (or α) and the slope of the power spectral density (β), according to the equation: $H = (1 + \beta)/2$. Calculating the relationship d between the Hurst exponent and the PSD scaling exponent may put a value on the strength of the relationship. Bollens et al. suggested that $d \leq 0.1$ indicates a reasonable consistency between the two parameters[5]. We may then construct a table indicating the relations between the various quantities as well as what each range indicates mathematically. The DFA and PSD scaling exponents that correspond with different dynamical systems are presented in Figure 7 and Table 1.

Special case of a power law

A power law can be demonstrated by plotting the log of the power of the variable of interest against the log of its frequency distribution. A power law is actually an *inverse* power law[4] that is expressed in the frequency domain. It is described thus[23]: $P = Cf^{\beta}$, where P is the power spectral density, f is frequency, β is a negative exponent, and C is proportionality constant. Power refers to the level of variance or amplitude that is demonstrated for each frequency[37]. In a $1/f$ noise system, the squared power is the inverse power function of the frequency[38]. If the plot produces a linear line, this indicates scale invariant (fractal) self-

* We caution the reader to take care to understand the meaning of each Greek character presented in these equations. Some of the papers cited use alternate characters to express the same mathematical quantity. We have adopted our conventions so that they are consistent with the bulk of the research cited in this dissertation. Thus, some equations in this dissertation may not read precisely as they are found in the cited papers.

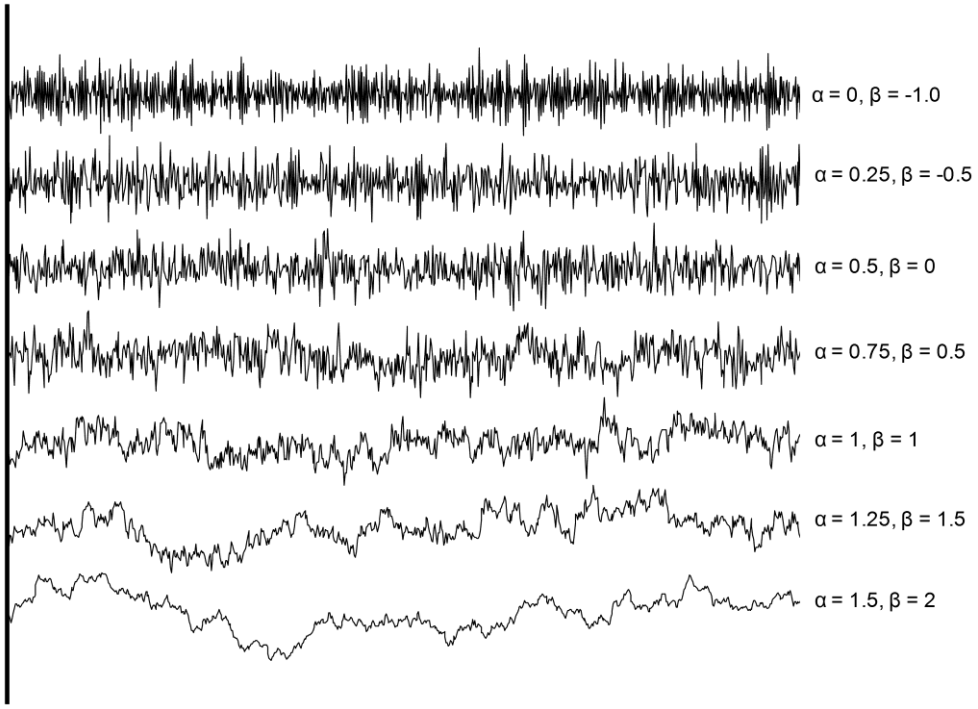

Figure 7. Synthetic systems to demonstrate different DFA (α) and PSD (β) scaling exponents. The systems range from highly anti-correlated (typical "flip-flop" overcorrection) at the top to Brownian motion (smooth random-walk landscape) at the bottom.

similarity. Scale invariant means that there is no characteristic scale[39,40]. The power law analysis is different from a spectral analysis because the former refers to the nature of the correlations that occur across the frequency spectrum, as opposed to simply quantifying the relative importance of frequencies that comprise the signal.

A broad, 1/*f*-like pattern indicates a fractal system. This pattern of distribution has a dominance of low frequency oscillations and progressively less dominance with higher frequency oscillations, hence the term 1/*f* pattern. For example, the power is doubled at double the frequency[2]. A total loss of significant variability will result in a flat pattern on the amplitude-frequency plot of a spectral analysis[41]. Systems that behave according to 1/*f* noise or a power law display complex behavior across multiple scales[1]. If the autocorrelation function satisfies the power law, the system is said to contain the main characteristics of long-

term memory and self-similarity[24,37]. 1/*f* noise is widely regarded as a signature of complexity and strongly emergent coordination[24].

Entropy and information content

An alternative and complementary index of complexity comes from the field of information theory. All data sets contain information but the amount of information gained varies with the properties of the data set and its generating system. For example, a constant output provides no new information with the addition of each data point, since it is already certain what the next value will be. This is also true for a system that strictly follows a sinusoidal oscillation. The data points change, but we know exactly what the next one will be, according to the sinusoidal equation that describes the system. In contrast, complex systems produce outputs that are difficult to predict. In this way, each subsequently measured data point brings with it varying levels of information, according to the certainty of prediction.

Entropy analyses provide a way to quantify the state of disorder, randomness, uncertainty, or irregularity in a dataset[1,7]. Outputs can span the continuum from completely ordered to completely random[42]. The understanding of this concept is rooted in the Second Law of Thermodynamics. A more disordered dataset is more difficult to predict, so the information content of each data point is higher such that maximum entropy occurs for system outputs that are completely random – uncorrelated random signals (white noise) are highly unpredictable, but not structurally complex[1].

Many physiological states have a tendency to move from ordered to disordered (complex) states. The former are less likely, statistically speaking; the latter are more likely[7].

With higher entropy values, and hence more uncertainty (more unpredictable), the system is said to be more complex because more information is required to predict future system states[1,35]. The difficulty with this understanding in human biology is that there is no straightforward relationship between entropy and complexity[1,43]. For example, many measures of entropy report a maximum value for a completely uncorrelated dataset[43]. Intuitively, however, such a dataset cannot be said to be complex or information-rich. Thus, while the benefits of entropy measurement include that it often requires the fewest data points, it should be used alongside other complementary analysis techniques[7].

Approximate entropy

One such measure of entropy is approximate entropy (ApEn)[42,44,45], which quantifies the degree of regularity or randomness in the data series. It provides a measure of system complexity (smaller values correspond with greater regularity and less complexity; greater values correspond with more disorder and higher complexity), although Goldberger et al.[4] have cautioned that it primarily quantifies regularity and not physiological complexity *per se*. ApEn can provide a measure of the feedback between different sub-systems in the human body or a measure of the degree of isolation between the various systems.[26]

In principle, greater nonlinearity manifests itself as more "undershooting" and "overshooting" of the mean expected trend. This will lead to the output of a greater ApEn[26]. There have been some serious concerns about the applicability of ApEn to real-world datasets. For example, ApEn provides a higher entropy value to randomly shuffled[4,46]. It is very sensitive to the length of the time series and gives lower values for shorter record lengths, and also lacks relative consistency[7,47].

To quantify the degree of regularity in a dataset, the ApEn algorithm searches for recurring patterns. A measure of the prevalence is calculated as the natural logarithm of the conditional probability. The ApEn calculation measures the difference between the logarithmic frequencies of similar runs of length *m* and runs with length *m + 1*. The algorithm returns the likelihood that this specific sequence is would show up in the dataset later. The frequency with which these repetitive runs in the data set occur is then calculated. A small value of ApEn indicates that the difference between *m* and *m+1* is small (i.e., the data set has a high degree of regularity)[7].

Sample entropy.

Sample entropy (SampEn) was developed to improve upon ApEn because it is less sensitive to the record length and is more consistent[7,43,47]. It excludes self-matching in the analysis and may also be less sensitive also to the number of data points in the series. SampEn outputs the negative natural logarithm of the probability that similar sequences remain similar at the next point. Lower values indicate greater self-similiarity[47].

Multiscale entropy

Because temporal complexity in biological signals exists on multiple timescales, Multiscale entropy analysis (MSE) was developed by Costa et al.46 to measure entropy over multiple timescales to account for the interrelationship of entropy and scale. MSE quantifies regularity or order over distinct series of different lengths. It is based on the ApEn family of

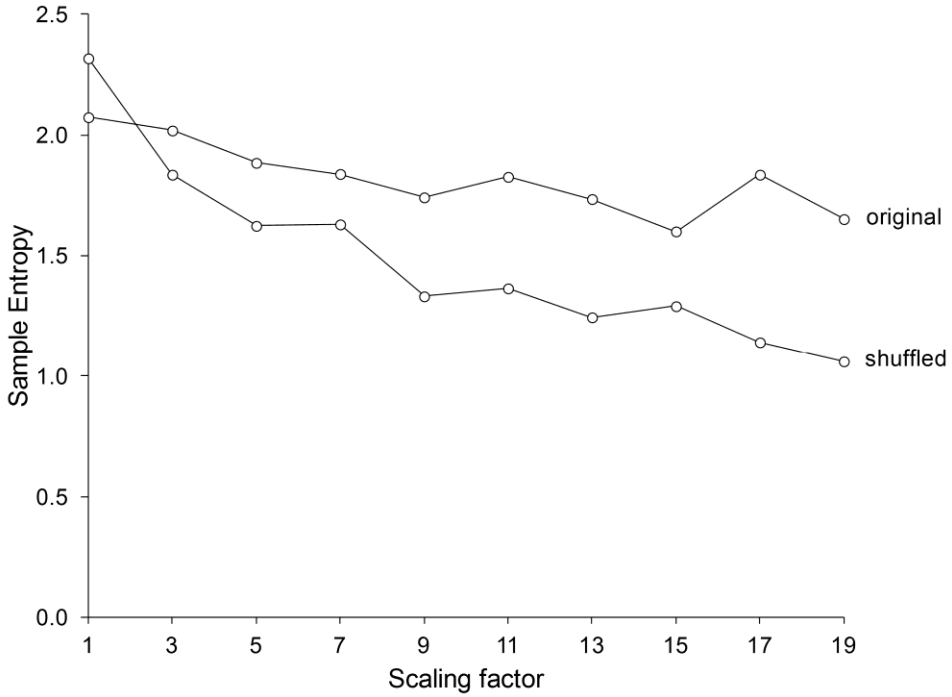

Figure 8. Multiscale entropy output for an original gait time series (top) and the same dataset randomly shuffled (bottom). The original time series maintains sample entropy over higher scaling factors, while the entropy for the surrogate dataset undergoes a more rapid decay.

analyses first developed by Pincus[44] and more specifically, the SampEn measure of Richman & Moorman[47]. Costa et al.[46] applied SampEn to distinct series composed of first the original time series, then the mean of every two values, then the mean of every three values, etc. Generally, this method is capable of discerning differences in the information content of different physiological time series. Specifically, it can distinguish white noise processes from processes with long-term memory. White noise processes demonstrate a monotonically decaying entropy with increasing scale, while long-term correlated processes demonstrate roughly equivalent irregularly across the time scales[6]. MSE is not susceptible to misidentification where there is a particularly noisy time series caused by noisy pathologic signals. One of the abilities of MSE analysis is it is able to deal with complex structures in the data set that function across multiple time scales[46]. A complex system will continue to

demonstrate greater amounts of information throughout the entire time series. The presence of pathologies seems to indicate a decrease in the amount of information of the system and the greater the amount of information in the system indicates a condition of robustness to be able to deal with perturbations to the body's internal environment. Additionally, noisy data or data that is non-stationary may introduce other challenges[45].

Multiscale entropy (MSE) applies SampEn to behavior on multiple timescales by calculating SampEn of each coarse-grained time series[1]. As with ApEn, and SampEn, MSE analysis operates based on two input parameters: the sequence length *m* and tolerance level *r*. The output of the algorithm is the likelihood that two sequences of length *m* are close within tolerance level *r* at the next point[48]. The procedure is as follows[1,43]:

1. Construct consecutive coarse-grained time series corresponding to scaling factor τ;
2. The original time series is divided into non-overlapping windows of length τ;
3. The mean value of the data points in each window is calculated;
4. Each element is calculated according to the equation:

$$y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i,\ 1 \le j \le \frac{N}{\tau}. \quad (2)$$

5. SampEn is calculated for each coarse-grained time series;
6. SampEn is then plotted as a function of the scale factor.

Tolerance level *r* is usually set at 0.15, which means 0.15 time the standard deviation[48]. MSE is able to distinguish colored noise from white noise[1]. A sample output is provided in Figure 8. In this dissertation, differences between two MSE outputs will be quantified by reporting the mean sample entropy value across all time scales.

Simulations and surrogate data generation

Another way of confirming a significant structure of variability is to create a surrogate dataset by randomly shuffling the original series in the time or frequency domain. Surrogates may be generated by a random shuffle or phase-randomization of the data[5]. A random shuffle preserves the mean and variance of the series, but destroys the temporal order and thus destroys any complexity and information that is present in that time series. A phase randomization permits the testing of the hypothesis that the variability structure in the series is totally accounted for by the autocorrelation function (> 2 SD different)[5]. That an experimentally-derived stride time series contains non-trivial fluctuations is visually demonstrated by contrasting the original time series with that same time series randomly shuffled.

When using simulations, previous work in the field has run twenty[49,50] or even one hundred[5,6] generated surrogates containing the same length of the original series. These surrogates together created a mean value bounded by a confidence interval. Bollens et al.[5] consider 2 SD (i.e., roughly 95% confidence interval) to be significantly different from a surrogate time series.

Summary and conclusion

This paper discussed an approach to quantifying distinct classes of nonlinear behavior in biological time series. This approach requires an adequate sampling approach to measure salient features in the data as well as provide sufficient information for each mathematical analysis. We then recommended a comprehensive selection of analyses that complement each other and serve to increase the confidence with which dynamics are quantified. Although the

concept of complexity is not one that can be precisely quantified, the concept itself being abstract, there are several features of the structure of variability in a data set that can be expressed. While this behavior can be classified with confidence, it is the interpretation of this behavior that is of crucial importance if meaningful statements are to be made about how human biology works. The following chapter discusses the phenomenon of $1/f$ noise in human gait time series and offers interpretation of this underlying behavior and how it is affected by internal and external perturbations to the system.

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Chapter 4

The origin and influences of 1/f scaling behavior in the gait of healthy humans

Introduction

The two previous chapters of this dissertation introduced the notion of viewing human biological function as the output of a complex system and classified as 1/*f* scaling. 1/*f* scaling systems contain fluctuations for which the amplitude is inversely proportional to the frequency, as well as having high and low values that persist according to the memory in the system (long-term correlations). This behavior can be expressed by a scaling exponent that quantifies the strength of memory in the system, and further confirmed by complementary approaches such as those based on entropy.

This chapter provides an in-depth description and interpretation of the phenomenon of 1/*f* scaling in human gait. While the three experimental studies of this dissertation focus on running gait, many (perhaps most) studies examining 1/*f* noise in gait use walking. There are some important differences in walking and running gait; for example, running includes greater impact loading and a flight phase. Measured differences include a higher stride rate[1], a higher metabolic cost[1], and an increased sense of effort or stretch in the ankle, knee, and hip extensors[2] during running. Nevertheless, walking and running likely use the same neural circuitry and control mechanisms[3–5], so we will make use of findings from both modes of exercise when discussing locomotor control.

We will first establish that normal stride timing may be generally classified as 1/*f* behavior, with long-term correlations in the time series. Second, we will describe the putative biological mechanisms by which this variability is produced. Third, we will discuss the effects that various internal and external influences have upon this behavior. To do so, we will employ the task-organism-environment of Newell[6] to show that these various influences may be placed in one of the three categories of constraint sources, and, in many cases, are

inter-related to other influences. We will demonstrate that although 1/*f* noise is dominant in human gait, this may be modified under certain conditions, sometimes so that this class of behavior is apparently lost and another is adopted.

The 1881 work of Vierordt[7] provided perhaps the first measurements and reports of human stride timing. Vierordt observed long-term stability in the timing of the gait cycle but he also recognized that the pattern was not perfectly constant. Modern work on stride variability began in the early 1990s and research has flourished since then. In 1992, Pailhous and Bonnard[8] noted that gait cycle timing varied in a complex fashion, and Hausdorff et al.[9] eventually provided evidence that fluctuations in gait timing are not random but rather demonstrate a meaningful structure of variability.

The coefficient of variation of stride durations is relatively low and typically ranges from 2 to 4%[9–13]. However, neither the magnitude of variability nor variables such as stride length and frequency[14] appear to be related to the structure of variability as expressed in nonlinear measures. Thus, for the evaluation of gait dysfunction and for the purpose of uncovering the control mechanisms of locomotion, dynamical changes (the structure of variability) provide a unique measure that may be more sensitive to changes in the functional status of the individual, as compared to more traditional statistical measures of dispersion[15–17]. Accordingly, research subsequent to the first reports of a meaningful non-random structure of gait timing have operated under the belief that descriptions of stride interval variability point to the characteristics of the biological control system that produced that variability. As Winter[18] has commented, gait kinetics provide a window into the control strategies of the central nervous system (CNS). Winter stressed that researchers must focus on total limb and total body movement to gain a complete picture of CNS strategies. Although a complete

description includes both spatial and temporal dynamics, much may still be gained by looking to a series of stride intervals (i.e., just temporal dynamics), which may be considered to be the "final output" of the neuromuscular control system[19]. The understanding of the state of a biological system with fractal outputs can provide information with which to classify functional status, as in health, disease, and performance ability. In this way, it is useful to view the output variables that indicate the state of the system act as a *homeokinetic code*[20]. According to this framework, the most important question is not, "what is the typical or average stride?", but rather "how do the strides fluctuate"?[19].

Normal stride dynamics in healthy individuals during walking and running

The control of gait is usually considered to be under voluntary control, but there is a more precise level of control that would not be possible to exert consciously. Timing is generally stable over long durations, but high resolution measurement reveals a non-trivial variability in both walking and running. This gait control is thought to depend on both central and peripheral sites[32] that are involved in the production of long-range self-similar correlations[26 27 30-34]. Table 1 presents relevant studies reporting the nonlinear dynamics of the stride cycle during walking. Most studies used detrended fluctuation analysis (DFA), although some present data from power spectral and multiscale entropy analysis. The first identifications of a meaningful structure of gait timing variability were done for overground walking and showed inter-stride correlations over timescales of up to 1000 strides (~16 min)[9,21]. The DFA scaling exponent α (or in some cases, the Hurst exponent from rescaled range analysis) for healthy adults without any neurological conditions (~0.8-0.9) is consistent

with (non-random) 1/*f* noise systems operating far from equilibrium. Subsequent work[13,15,16,22–28] confirmed this behavior in both treadmill and overground walking trials of 6-60 min length, with an overall range of DFA α of ~0.7-1.0. This general agreement is sufficient to establish adult human walking dynamics as behaving according to a fractional Gaussian noise system, significantly different from random systems and close to a "perfect" pink (1/*f* noise) behavior that would elicit a DFA α of 1.0. Of the studies cited above, some also used additional complementary nonlinear measures such as power spectral, maximal Lyapunov exponent, approximate entropy, multiscale entropy analyses[21–23,25]. These additional measures help to confirm the behavior demonstrated by the DFA output and strengthen the conclusions of the study, although these measures are not mathematically identical and thus indicate slightly different aspects of the output.

The first studies into inter-stride dynamics during running were performed on a treadmill. Jordan et al.[17,29] reported DFA α of approximately 0.7-0.9. Subsequent studies reported similar values ($0.7 < \alpha < 1.0$) for treadmill and overground running[30,31]. While there is some discussion as to the exact interpretation of these reported values, and the confidence with which interpretations are made, the above reports demonstrate that stride timing demonstrates a specific class of dynamic behavior in healthy adults during both walking and running. The following sections will discuss the origin and meaning of this behavior and how it is modified in various experimental interventions.

Nomothetic and mechanistic perspectives on explaining 1/f noise

Torre & Wagenmakers[32] and Diniz et al.[33] describe two approaches to explaining 1/*f* noise: the nomothetic and mechanistic. The nomothetic* perspective appreciates the ubiquity of 1/*f* noise in nature and seeks general explanations for behavior. The myriad of appearances of 1/*f* noise across many scientific disciplines such as biology, geology, and physics has led researchers to seek general principles to explain this phenomenon. The general laws suggested by the nomothetic perspective refer to the dynamic, self-organizing characteristics of a complex system. When applied to the human function, 1/*f* noise is a natural outcome of the self-organization in the human neuro-mechanical function, resulting from a self-organized critical system or perhaps the aggregation of short-range processes, each operating on different time scales[32,34]. However, noting the similarity between 1/*f* noise in human biological function and other physical systems does not point to a specific mechanism. Thus, subsequent discussion will adopt a primarily mechanistic approach, set firmly in the human exercise sciences. According to the mechanistic view each individual system possesses an idiosyncratic source of 1/*f* behavior and thus the researcher works toward domain-specific explanations of observed behavior[34]. This requires modeling of the specific biological processes responsible for serial correlations in human stride time series[32].

Intrinsic origins of 1/f noise in gait

Bipedal locomotion is inherently unstable, as evidenced by toddlers learning to walk[35]. This instability therefore requires that motor control be regulated in a compensatory fashion

* *Nomo* is derived from the Greek root "law"

by the cerebellum, motor cortex, basal ganglia, along with feedback from proprioceptive, visual, and vestibular sensors[12,16,19,36,37]. The integration of afferent and efferent components of this system leads to a stable and consistent coordinated movement[19,38]. Yet, within the same process, there remains a meaningful variability, indicative not of dysfunction, or a response to a nonstationary environment, but of normal and healthy neurological, metabolic, and musculoskeletal function that contains both deterministic and stochastic components[9,39–44]. Thus, meaningful fluctuations in the stride interval are thought to arise from the rhythm generated by the locomotor system[45]. Further, the serial dependence of this output may help inform us about the dynamics and key operating characteristics of the system that produced that output[19,32].

Putative biological structures

Some hypothesized sources of system dynamics include supraspinal[21], correlated CPG output[9,39,41], integration of information from visual, auditory, vestibular, proprioceptive, and kinesthetic inputs occurring on multiple time scales[21,46]. We will describe these processes later, but will first seek to establish the specific neural structures responsible for the initiation of gait and the regulation of speed via pacemakers. These locations include the interfastigial cerebellum and bilateral midbrain tegmentum of the cerebellar (CLR) and mesencephalic locomotor (MLR) regions, the descending target regions in the pontine reticular formation, and the rhythm generators in the cerebellar vermis and paravermal cortex[47]. The cortical aspects of locomotor control are thought to involve the frontal and parahippocampal gyri and include the sending of signals via the basal ganglia to the gait initiation centers in the dorsal brainstem. The midbrain tegmentum around the pedunculopontine and cuneiform nuclei (MLR) receives input from the cerebellar vermal and paravermal cortex via the fastigial

nuclei and the CLR. The vermis integrates incoming proprioceptive, exteroceptive, visual, and vestibular afferent information originating from various sources. The CLR regulates the speed of locomotion. The MLR output projects to the pontine reticular formation, which is connected to the spinal cord[47].

Hausdorff et al.[21] provided evidence for supraspinal neuromuscular control. After noting that long-range correlations break down as a result of metronomic walking they postulated that supra-spinal influences can override and possibly are responsible for the generation of long-term correlations in stride-to-stride timing. Further evidence for this hypothesis comes from the Parkinson's disease model, where the primarily supraspinal neurological impairment seems to obliterate much of the long-term correlations observed in healthy individuals[48]. The basal ganglia is also thought to have a role in the generation of fractal structures because fractality is also lost with the impairment of basal ganglia function[19].

Central pattern generation

In addition to the supraspinal influences, other elements of the biological system may generate the long-term correlations[21]. A central pattern generator (CPG) is a hypothesized functional network of neurons located in various regions of the CNS and may be coupled with other biorhythms[21,49]. It is thought to provide nonlinear oscillation for each limb involved in walking and a single central synchronized nonlinear dynamical network to regulate the overall rhythm of muscular activity[38] that is perhaps overseen by structures at supraspinal levels to either initiate or cease the function of the rhythm generators[49].

Evidence for the CPG in humans comes from studies showing that epidural spinal cord stimulation can lead to EMG activity and organized locomotor-like activity in

paraplegics[50]. The hypothesized action of classic CPG models is oscillatory neural activity that arises through the interaction of neural centers to regulate gait dynamics. However, this is not a fractal output[40] and correlations are not well explained by traditional CPG models[51]. Earlier theory on CPG function suggested that there was a single nonlinear oscillator operating for each limb. However, more recent work that recognized the synchronization present in nonlinear dynamical systems suggested that neurons in both limbs followed the set syncopated rhythmic activity arising from a single CPG[41,52]. A correlated CPG model has been proposed that produce fractal dynamics[9]. Transitions between modes may be driven by sensory, environmental, muscle state, and supraspinal inputs to encourage switching in the model[9]. Other thoughts include a hypothesized super-CPG (SPCG), which suggests that the CNS is linked to the motocontrol system and through this synergy, locomotion is controlled[41].

The SCPG is a stochastic correlated CPG, coupled to a van der Pol nonlinear oscillator that is capable of producing an output with fractal properties[38,40]. The model involves random walk dynamics along a chain of excitable neural centers, of which each provides impulses of its own characteristic frequency, and they are mutually correlated[32,38,40]. With increasing complexity of the system and therefore increasing interconnectedness, the size of jump from one neural node to another increases, and this, in turn, increases the correlations in the output[40].

This spinal pattern generator is able to produce a rhythm without input from supraspinal sources[53]. However, afferent input regarding the load and hip joint is still useful in the production of the locomotor pattern[53]. Such afferent input includes proprioceptive feedback from the extensor muscles, or mechanoreceptors in the foot, in the case of information about the load[54]. These signals are thought to be integrated into the polysynaptic

spinal reflex pathway at spinal and supraspinal levels, so that the system controller may modify the programmed locomotor pattern according to the specific environmental demands of that gait[49,53]. For example, three main sensory sources may provide input to the CPG in cats. Proprioceptive afferents in the extensor muscles and exteroceptive afferents from the foot mechanoreceptors provide information about the load. Also, afferent signals providing hip muscle information toward information about the position of the hip[55].

Some neuroanatomical locations of interest include the brainstem, suggested after research on mesencephalic cats (brainstem sectioned rostral to the superior colliculus) demonstrated that near-normal walking may take place with electrical stimulation of a particular section of the midbrain[56]. The caudal cholinergic nucleus (mesencephalic locomotion center) is also believed to control the CPG[19].

Other sources of 1/f noise

The hypothesis that long-term correlations arise from CPG activity has had some significant attention. However, it has also been suggested that 1/*f* noise can be generated by a simple biomechanical model employing a minimal level of feedback control such as spinal reflexes[57]. Gates et al.[57] modeled a system with varying levels of sensory noise, motor noise, and feedback gain. It was possible to model long-range correlations even without any feedback control. Thus, it may be that correlations may be present in the absence of supraspinal generation of rhythm and arise mostly from interactions between noisy sensory and motor signals as the system aims to control a highly nonlinear biomechanical structure. It was also suggested that this mechanism could operate in addition to CPG mechanisms.

Other possibilities include the operation of coupled nonlinear oscillator networks containing multiple components and feedback loops that couple centrally and peripherally

located neural nodes such that each node acts over a specific range of timescales[19,58]. According to the mode-switching model of Griffin et al.[37], the locomotor system is adaptive and contains many interdependent subsystems that possess their own characteristic frequencies[37]. Principle control randomly switches from one subsystem to another in order to create stability. Persistence arises from the switching action such that behavior persists for a while and then switches to another regime of control[37].

Intrinsic influences of 1/f noise in gait

In addition to understanding how 1/*f* noise arises in human gait, there is a second question: how might this behavior change in various experimental conditions? According to Torre et al.[32], the intensity of 1/*f* noise does change in certain circumstances. We will relate what is known on this topic as a prelude to the following three chapters detailing the results of three original experiments. Tables 1 and 2 summarize current research on the influences of gait dynamics during walking and running, respectively, with a desire to highlight task and environmental influences.

Speed

Speed is a common example of a task-based constraint upon movement, but it is easy to see that modification of speed may potentially affect organismic considerations. Several studies have shown that long-term correlations in stride time series are speed-dependent, in both walking and running applications. Early research investigated walking dynamics over

Table 1. Influences on nonlinear dynamics of inter-stride time series during walking by healthy subjects. Included studies report DFA, PSD, or MSE results.

Conditions	Sample	Task	Results	Difference	Reference
-	10 ♂ h y a	9 min walk @ preferred pace, overground	$\alpha = 0.86$	-	Hausdorff et al.[9]
1. Slow 2. Preferred 3. Fast 1. Free 2. Metronome	10 ♂ h y a	60 min walk, overground	Free (slow, pref., fast): $\alpha = 1.00, 0.84, 0.90$; $\beta = 0.91, 0.68, 0.98$ Metronome: nr	Free: minimum @ preferred; Metronome: correlations break down	Hausdorff et al.[21]
1. Free 2. Metronome	7 ♂♀ h y a	30 min walk @ preferred pace, overground	Free: $\alpha = 0.79$ Metronome: $\alpha = 0.21$	Free = persistent; Metronome = anti-persistent	Terrier et al.[13]
-	12 ♂♀ overweight h o a	10 min walk @ preferred, overground	$\alpha = 0.88$; $\beta = 0.60$	-	Gates & Dingwell[22]
5 different speeds: 80-120% preferred 5 different speeds: 60-140% preferred	Experiment 1 11 ♀ h y a Experiment 2 10 y h a	12 min walk, treadmill 6 min walk, treadmill	$\alpha = 0.78 – 0.92$ $\alpha = 0.71 – 0.80$	U-shaped relationship, minima @ 100-110% preferred	Jordan et al.[16]
1. Overground 2. Treadmill (no rail-holding) 3. Treadmill (rail-holding)[28]	16 ♂♀ h y a	15 min walk @ preferred pace	Overground: $\alpha = 0.83$ Treadmill (no rail): $\alpha = 0.82$ Treadmill (rail): $\alpha = 0.92$	↑ α for rail	Chang et al.[15]
1. Overground 2. Treadmill	10 ♂♀ h y a	15 min walk @ preferred pace	Overground: $H = 0.79$; $\beta = 0.47$ Treadmill: $H = 0.79$; $\beta = 0.44$	ns	Bollens et al.[23]

Table 1 (continued).

Conditions	Sample	Task	Results	Difference	Reference
1. Track 2. Compliant surface	14 ♂♀ h y a	15 min walk @ preferred pace, overground	Track: $\alpha = 0.97$ Compliant surface $\alpha = 0.92$	↓ α for compliant surface	Chang et al.[24]
-	6 h	15 min walk @ preferred pace, overground	$H = 0.78$; $\beta = 0.54$	-	Crevecoeur et al.[25]
5 different speeds: 80-120% preferred	17 ♂♀ h y a	5 min walk, treadmill	$\alpha = 0.80 – 0.87$	-	Dingwell & Cusumano[26]
1. Virtual optic flow (fast) 2. Virtual OF (normal) 3. Virtual OF (slow) 4. No OF	10 ♂♀ h y a	15 min walk @ preferred pace, treadmill	nr	ns	Katsavelis et al.[27]
1. Overground 2. Treadmill	20 ♂ h y a	10 min walk @ 1.25 m/s	Overground: $\alpha = 0.81$ Treadmill: $\alpha = 0.72$	↓ α for treadmill	Terrier et al.[28]

h, healthy; y, young; o, obese; a, adult; ♂, male; ♀, female; H, Hurst exponent from rescaled range analysis; α, DFA scaling exponent alpha; PSD scaling exponent beta; ns, no significant difference; nr, specific values not reported in text or not possible to discern from figure; N.B. "preferred pace" was variously termed "self-selected", "comfortable", "usual", etc.

Table 2. Influences on nonlinear dynamics of inter-stride time series during running

Conditions	Sample	Task	Results	Difference	Reference
5 different speeds: 80-120% preferred	8 ♀ y h a recreational runners	8 min run, treadmill	α = 0.73-0.86	U-shaped relationship, minimum @ preferred	Jordan et al.[17]
5 different speeds: 80-120% preferred	11 ♀ y h a recreational runners	8 min run, treadmill	α = 0.78 – 0.88	U-shaped relationship, minimum @ preferred	Jordan et al.[29]
3 different speeds: 80-120% preferred	♂ y a 7 trained runners 7 non-runners	10 min run, treadmill	nr	no significant difference with speed ↓ α for trained runners close to statistical significance	Nakayama et al.[30]
1. Effect of time (each 1/3 duration	♂♀ recreational runners	Run to exhaustion @ ~5km race pace, overground	1/3: α = 1.05 2/3: α = 0.77 3/3: α = 0.81	↓ α from first 1/3 to second 1/3 duration	Meardon et al.[31]
2. Effect of injury history	9 injury history 9 no injury history		Injured: α = 0.79 Non-injured: α = 0.96	↓ α for injury history	

h, healthy; y, young; a, adult; ♂, male; ♀, female; H, Hurst exponent from rescaled range analysis; α, DFA scaling exponent alpha; PSD scaling exponent beta; ns, no significant difference; nr, specific values not reported in text or not possible to discern from figure.

level ground at self-selected, and faster and slower speeds[21]. Long-term correlations were the lowest at preferred speed and somewhat higher at speeds faster and slower than preferred. This research was later confirmed in both treadmill and overground walking[16,26] and running[17,29], although one study on running did not show a significant speed effect[30]. In studies using more than three speeds, the relationship between speed and strength of correlations was modeled with a quadric equation (U-shaped relationship), with the minimum values for DFA α centered on or close to the preferred walking or running speed[16,17,29]. In these descriptions, behavior at all speeds was still considered persistent (significantly different from random), but the strength of the long-term correlations was lower at preferred speeds. This relationship has been found not only for the stride interval of running but also for other variables such as ground reaction force and stride length[29].

It has been suggested that preferred behavior is the most stable and exists close to an attractor, with movement occurring with the greatest number of dynamical degrees of freedom. Conversely, when movement must occur in non-preferred conditions, the behavior is drawn away from the attractor and there is a loss of stability[17,29]. The more regular dynamics seen at non-preferred speeds may reflect the reduced availability of dynamical degrees of freedom, which means that there are fewer options for solving Bernstein's problem (see reference[59]) of how to coordinate movement when there are a multitude of dynamical options to accomplish the task of running[16,29,31]. Movement at non-preferred speeds has been proposed to be indicative of increased biological stress or a psychological stress because of the constraint imposed by an externally imposed signal[56]. Physically speaking, for example, this may involve increased muscular stress on the dorsi- and plantar-flexors[60,61], and saturation of stride length[62].

This biological stress may increase the strength of correlation between the different neuronal centers[38,41]. Indeed, walking at stride rates away from the resonance frequency (that is naturally selected) increases dynamical instability and the strength of correlations[16]. The major constraints of running come from the interaction between metabolic power generation, the elastic spring characteristics of the limbs, and the biomechanical coupling of the involved joints[63,64]. Forward movement is more subject to organismic or task oriented constraints stemming from biomechanical and metabolic aspects of function, whereas vertical movement subject to the environmental constraint of gravity[65]. The selection of a specific pattern of movement may reflect the seeking of an energetically favorable pattern[4,66–69], or an optimal level of musculoskeletal forces[67,70].

Chronic changes to exercise capacity (age, disease, injury, fitness)

Maturation and aging

This dissertation does not contain experiments on the effects of maturation, aging, disease, injury, or fitness, but we will briefly describe some changes in nonlinear gait dynamics in children and the elderly, since this will point to some of the mechanisms involved in the production of 1/*f* scaling output.

Gait time series in children has a higher magnitude of variability than in adults, presumably since children lack fully mature neural systems for integrating information and generating a stable locomotor pattern[71]. Power spectral analysis of stride-to-stride variability indicates that older children show more high frequency power and less low frequency power[72]. System memory (autocorrelation) decays more rapidly in the youngest children (3-4 years old). DFA α is also higher in children 3-4 and 6-7 years old, as compared to 11-14 year olds[72]. Some findings for younger children, such as magnitude of stride variability are similar

to those found for elderly individuals and those with neurological dysfunction. However, other findings suggest that the DFA α might decrease monotonically throughout the lifespan such that correlations are the highest for the young and the lowest for older individuals[72]. Even healthy elderly individuals demonstrate lower persistence in stride intervals, as compared to healthy young adults.[73] Suggested factors that may contribute to this difference include age-related changes in striatal dopamine mechanisms or central processing[73].

Disease

Seely & Macklem[74] suggest that healthy states of the human body operate far from a state of thermodynamic equilibrium. It is thought that in healthy subjects, for whom there is an intact supraspinal locomotor center, supraspinal input is predominant over the spinal/mechanical reflex pathways and represents an intrinsic source of correlated gait patterns[15]. In contrast, neurodegenerative diseases are associated with alterations in the nonlinear dynamics of gait[38]. Long term correlations and scaling in stride time series are altered with the advancement of conditions such as Parkinson's disease (PD). The stride-to-stride fluctuations of PD patients have been well-studied. For example, Bartsch et al.[75] found that PD patients exhibit a fluctuations that are significantly less persistent (i.e., closer to random dynamics) than healthy controls. Similarly, Hausdorff[48] reported that stride dynamics in PD patients were virtually indistinguishable from randomly shuffled time series.

The traditional explanation of this loss of correlations is the degeneration of CNS mechanisms. However, another question may be asked as to the role that the peripheral nervous system plays in influencing correlations[22]. This is an appropriate question because sensory feedback from the periphery, such as from muscle and load receptors, is thought to contribute to the regulation of gait timing and patterning[76]. Patients with peripheral

neuropathy (peripheral sensory loss, PN) do not demonstrate altered long-term correlations; output is the same between healthy and neuropathic patients. However, PN patients have functioning proximal somatosensory inputs, visual, and vestibular feedback that may play an adaptive role in dealing with the challenges of the condition[22]. Nevertheless, while this research does not rule out a role for the peripheral nervous system, it does shift the strength of the evidence toward the view that the CNS is the prime influence of long-term correlations[22].

Injury

The effect of injury on 1/*f* scaling in human gait has not been extensively researched. To date, only one study[31] has investigated the effect of injury history on this parameter. Injuries can affect musculoskeletal strength, energy system support, perceptual, and balance mechanisms, and these may still be compromised long after the acute state of injury has passed. Accordingly, these components, and their respective interactions, are potentially affected, thus altering the complexity of the system and altering stride dynamics. The above thinking is consistent with the findings of Meardon et al.[31], who found that those with an injury history had less persistent stride fluctuations than those without an injury history. According to Meardon et al.[31], these effects may arise due to changes in strength, motor recruitment, the coupling between the joints of the lower extremity, and balance. This dynamical change is in the same direction as found for walking gait in the elderly, who also would have detrimental changes in functional status[73].

Fitness and training status

Highly trained individuals may provide the best example of an optimized system, with optimal consistency and stability and variability of movement patterns[65,77–82]. Some optimization changes in locomotion with practice may include improved running economy[83],

and flexible coupling between the nervous system, the musculoskeletal system, and the task environment[84,85]. Specific motor skill training likely improves the ability to utilize and integrate sensory and proprioceptive information[86]. Hence, the decreased long range correlations seen in trained runners may reflect their enhanced ability to perceive visual, tactile, or proprioceptive information about the movement[30]. Higher entropy values have been found for trained runners versus untrained individuals, suggesting that trained were less constrained[87]. Because untrained runners are less practiced at running, they may require a higher contribution of executive function to the task[87].

According to Davids et al.[77], those with a higher skill level exhibit higher levels of variability. This indicates a freedom to explore options to the solution of Bernstein's problem[87]. Those who lack skill at a particular task tend to deal with the problem by rigidly restricting segmental movements such that general variability is reduced, resulting, in this case, a lower entropy, likely due to increased constraints[77]. Entropy in the vertical and mediolateral axes during running is lower for trained runners compared to untrained individuals, which is interpreted as lower complexity and more constraint[88]. Thus, in trained individuals, although capable of performing optimally at higher running speeds, lower entropy may actually indicated a lesser ability to perform optimally at lower speeds because these are outside their normal training regime[88]. The above descriptions regarding maturation, aging, disease, injury, and training status highlight the organismic status of the locomotor system that renders it more or less able to execute the specific task of walking or running.

Acute impairments to exercise capacity (fatigue)

Fatigue is an example of an organismic source of constraint. It is well established that gait patterns change under conditions of fatigue[78,89–93]. However, the effect of fatigue on nonlinear stride dynamics has not been well studied. Costa et al.[94,95] hypothesized that stressful conditions cause healthy systems to generate outputs that are less complex and "working under a tighter regime" with dynamics limited to a subset of state space. This, in comparison to healthy, "free running" systems that are adaptable. It would seem that in addition to exercise at severe intensities, fatigue states brought about by prolonged exercise could also represent this kind of stressful condition.

A few studies using more conventional measures demonstrate some of the differences with fatigue. Le Bris[91] showed that fatigue elicits a more regular running pattern, according to an autocorrelation-based regularity index. The authors concluded that changes in the regularity index provided an early indication of more drastic alterations in running stride pattern that were to come later. Although stride regularity was affected, stride frequency and stride symmetry (between the right and left foot) did not change. Other research has shown that the variance of linear spatial and temporal measures of the stride during treadmill running changes during fatigue situations[96].

To the knowledge of the author, no studies have assessed the effect of walking-induced fatigue using the nonlinear analyses mentioned in the previous chapter. Yoshino et al.[97] found that prolonged walking increased the magnitude of variation of the stride duration and decreased the local dynamic stability of the vertical acceleration of the back-waist, as indicated by Lyapunov exponent analysis. They suggested that local dynamic stability decreased with fatigue, which led to the individuals selecting a lower walking speed to increase local dynamic stability. Individuals who developed greater fatigue demonstrated

decreased mean power frequency of EMG of TA, increased gait rhythm variability, and decreased dynamic stability. This may be because the musculoskeletal system is less able to deal with the shock associated with foot strike, resulting in increased acceleration at the shank and sacrum[98–100].

Meardon et al.[31] used DFA to demonstrate changes in the dynamics of the running stride interval over a continuous exhausting run at approximately 5 km race pace. The running bout was divided for analysis into three sections of equal duration. DFA α decreased from the first to second section, but not from the second to third section. It was suggested that in fatigue states, there is a greater need to make adjustments to maintain the appropriate running speed. The greater emphasis on the adjustment of stride timing would have lessened the tendency for long and short duration strides to persist, with more immediate correction instead taking place. However if this explanation is correct, it is unknown why these dynamics would not change further from the second to the third interval.

These dynamical changes that occur with fatigue may also come from altered afferent feedback that influences rhythm generation. For example, in a quiet standing experiment, Corbeil et al.[101] showed that fatigued ankle plantar flexors leads to less correlated center of pressure (COP) trajectories. Gates et al.[102] showed that neuromuscular fatigue during a seated goal directed repetitive task for the upper extremity elicited timing errors and movement speeds with decreased correlations. The proposed reason for these changes in the two papers was an increase in the use of corrective strategies[101,102]. A stiffening strategy via agonist recruitment may also be involved, along with centrally- or peripherally-mediated reductions in force development[101]. There may also be decreased motor unit firing, force production, and more variable motor unit firing with fatigue[103–105].

Extrinsic influences of 1/f noise

This section discusses several influences of gait variability that may be considered to be part of the environment with which the individual interacts. Each environmental configuration has a unique assembly of characteristics that must be negotiated by the individual during gait tasks. These include characteristics that affect touch sensations such as the nature of the ground surface, the physical space in which movement occurs, the visual field (whether it remains the same as on a treadmill, or is moving as with overground locomotion), and various other cues, instructional and otherwise, that may compete for the attention of the individual. As with the above organismic- and task-associated factors, the individual will also select a movement pattern based on the environment. Understanding potential influences from these factors is important because much laboratory research uses a treadmill, which has different characteristics than found in everyday life. If the characteristics of treadmills (or any other research settings that are not common to locomotion in everyday life) affect the outcome of stride fluctuation measures, then treadmill-based assessment may not accurately reflect the coordinative processes of an individual running overground. Thus, there is a need for the comprehensive investigation of these possible influences.

Treadmill and the exercise environment

Environmental differences. The treadmill is a popular piece of laboratory equipment and many studies cited in this chapter have been performed on a treadmill. However, there are some important differences between treadmill and overground settings that have not been fully investigated as to their effect on nonlinear gait measures. Apparent differences between the treadmill and overground environment include the long-term constancy of the treadmill belt speed and direction, the size and compliance of the belt

surface, optic flow, and vestibular perceptual information[28,106,107]. A treadmill may also act as a simple external cue to direct attention to the task of locomotion[107]. These factors potentially influence factors such as neuromuscular control, mechanical constraints, or both[108]. For example, the physical constraint imposed by the treadmill from the constant speed and the dimensions of the treadmill belt may increase stability by reducing the number of available degrees of freedom[28]. As well, although treadmill control boxes will display a constant speed, the belt does not necessarily maintain a perfectly constant speed because the motor cannot exert perfect control with changes in load that occur from stride to stride. Measurements of belt speed indicate possible small step-to-step fluctuations in speed[109], which could affect stride dynamics.

Experimental differences. Differences in locomotor patterns between treadmill and overground gait can be discussed in the categories of kinematics, kinetics, and energetics[28]. With regard to kinematic changes, treadmill walking has been shown to elicit increased step frequency, decreased stance time, and decreased stride length[71], and also leads to a lower self-selected gait speed[15]. Kinetic changes during walking have also been demonstrated, with different vertical ground reaction force (VGRF) during certain parts of the stance phase and have lower breaking GRF at heel contact[110], although peak VGRF and mediolateral GRF are similar[111]. Treadmill walking has also been shown to elicit decreased dorsiflexor and knee extensor moments, and greater hip extensor moments[111]. Regarding energetic differences, according to Dingwell et al.[112], individuals employ a hierarchy of goals which, on the short term involve the maintenance of stride-to-stride walking speed, and on the long term seek to minimize average energy cost of movement[112].

With regard to linear dynamics, treadmill walking has a lower magnitude of variability. Some nonlinear data indicates that treadmill walking is less correlated (DFA) and more dynamically stable (Lyapunov exponent), as compared to overground walking[28,107,108]. Suggestions reasons for this include perceptual changes[28], and the treadmill acting as an external cue[107]. Yet, other studies using the same measures in the experimental chapters of this dissertation indicate that there are no differences between treadmill and overground walking, as measured by DFA, PSD, and MSE analyses[15,23]. Overall, it appears that the locomotor system is able to maintain variability similarly in both conditions because stabilizing factors may override destabilizing factors[28]. As well, care must be taken to navigate the different nonlinear measures, as some may show differences where others do not. Furthermore, there has not yet been a test of differences between treadmill and overground running.

Entrainment and sensory feedback. It was initially thought that since metronomic walking lowers stride timing correlations by disturbing natural rhythms and decreasing adaptability to the environment[21], a treadmill may also entrain the supraspinal locomotor clock to produce an external rhythm[113]. However, metronomic walking and treadmill walking are different tasks and recent research suggests that a treadmill does not alter the long-term correlations found in overground walking gait[15,23].

During treadmill walking, afferent information is first relayed to the spinal neuronal circuits[114–116]. This sensory input sufficient to activate or regulate spinal locomotor neural structures because afferent information can help to modify locomotor patterning[55,117]. Indeed, peripheral feedback from legs can modify locomotor activity of the hypothesized CPG to provide appropriate movement according to external demands[118–120]. The moving belt

appears to accentuate hip extension, which may activate the spinal and mechanical reflexive response to elicit the swing phase (hip flexion) of the walking movement, and thus lead to changes in stride timing[15,121]. In humans, the effect that load has on eliciting stepping movements is seen in paralyzed individuals when the load is shifted onto a fully extended leg during the stance phase of walking[122]. As well, Dobkin et al.[123] showed that if the hip joint is moved toward extension a few degrees at the end of the stance phase, an initiation of the swing phase occurs. The effect of treadmill has also been shown in spinal cord injured patients to affect pressure sensitive nerves in the lower limbs that then relay afferent information to the spinal pattern generator to produce muscle activity independent of supraspinal input[53].

Surface. The characteristics of the walking or running surface *per se* may also affect the rhythms of gait. Indeed, Menz et al.[124] showed that walking surface is an external source of variability. The tactile response from the surface, along with the energy return and ground reaction force all potentially alter affective responses from the soles of the feet. The size of the surface may also be relevant, especially for treadmill situations where the size of the treadmill belt is relatively small, and individuals must endeavor to stay roughly in the middle of the belt and try to avoid falling off the edge of the belt.

Optic flow. One main way that stability of gait and body position is maintained is through the use of visual information[125]. Optic flow (OF), which provides information about the speed and direction of movement, may influence locomotion kinematics and desired speed of locomotion, whereas somatosensory input may only influence kinetic control[126–128]. The manipulation of OF via visual patterns projected on a screen alters step time[129], speed, stride length, frequency, drift[130]. OF while on a treadmill increases stride variability and leads to a

higher approximate entropy (ApEn) of the stride interval at comfortable walking speeds[27]. Whereas there are no differences in the CV of hip, ankle, ROM, and stride interval, there are differences in the ApEn of hip ROM, ankle ROM, and the stride interval[27]. There was also a lower DFA α for hip ROM during OF on treadmill[27]. Mismatch between "leg velocity" and "optic flow velocity" represents conflicting information leading to a destabilizing effect such that there is increased variation in step-cycle parameters[126,127]. Visual information processed by supraspinal processes represents feedforward control of locomotion and helps to modulate walking velocity via stride length and may influence CPG activity[126].

Rhythmic auditory stimulation

Audible cues from a metronome have been used to influence persistence in stride intervals[13,38]. In most cases, walking according to a metronomic signal (no running studies have yet used this intervention) destroys gait persistence, perhaps because the signal constrains supraspinal regions responsible for keeping pace or time[25]. It is thought that auditory input causes the individual to adopt a more centralized control of rhythm such that discrepancies between planned movement set at supraspinal levels, and sensory inputs elicit a continuous loop of control causing oscillation of stride timing around the mean externally set value, with a low CV of under 3%[13]. An alternative view holds that when strides are constrained to the external rhythm of a metronome, there is a psychophysical stress present that leads to altered dynamics[38,41].

Torre & Delignieres[52,131] suggest that although tasks involving synchronization to an external signal generate an antipersistent behavior, they still depend on a central timekeeper with fractal properties – it is just that an autoregressive correction process is also present[52]. Since both metronomic and free walking use the same lower motor neurons, actuators, and

feedback, it may be that different supraspinal control (i.e., the brain) is responsible for the different dynamical/correlated behavior[40].

Metronomic walking is thought to enhance the supraspinal control of stride times such that stride timing reflects anti-persistent behavior, while speed and length of the stride remain persistent[13,26]. Thus, only those variables that must be tightly controlled demonstrate uncorrelated or anti-persistent dynamics. From this perspective, subjects for whom neural control is impaired in some way may be dealing with this deficiency by exerting enhanced control such that their gait patterns become more cautious[26]. Further, it may be that during conditions of severe running intensity, patterns of movement also reflect caution, albeit for reason not of disease but of exercise-induced biological stress.

Attention and executive function

There are both autonomic and attention-demanding aspects to walking[10]. Tasks that are achieved primarily via autonomic control show a low magnitude of variability, while tasks requiring significant attention tend to be more variable[10]. Some studies regarding executive function (see reference[132] for a review) suggest that the addition of cognitive tasks to locomotion alter gait characteristics[10,133,134]. For example, strenuous running is an example for which executive function is required to provide a focus on accelerating forward in the plane of movement[65]. If the addition of an attention-demanding task to walking (dual-task protocol) increases stride variability magnitude, this would be seen as evidence that walking requires some attention in addition to autonomic function. Some experiments such as requiring walking plus counting backwards, show that for college students, stride variability is unchanged, inferring that walking requires minimal attentional demand[10]. However, other experiments such as those involving the holding of a cup and saucer[135] and finger tapping[136]

demonstrate increased stride variability, an indication that a proportion of the attention requirement of walking was reallocated to second task. Additionally, the decline of executive function is associated with an increase in the magnitude of stride variability in both healthy and demented older adults[137,138].

Imaging studies show that regulation of rhythmic activity such as walking[139] and tapping[140] depend primarily on the basal ganglia, supplementary motor area, and cerebellum[138]. However, there is a question of whether walking also requires input of executive function and higher level cognition[138]. Locomotion requires the integration of a multitude of sensory and conscious input that must be assessed and integrated according to the task that perhaps includes competing objectives such as in a dual or multi-task[138]. Thus, there is the suggestion that walking requires both complex cognition and executive function to accomplish the aspects of that task that require such things as estimation, planning, and ongoing adjustment and error correction – "real time control"[138].

Integrated model

We now construct an overall framework to model human gait function. This model consists of a control system that receives information from both internal and external sources. Internal sources of information concern the status and functioning of the different systems of the body and are relevant for organismic sources of constraint. In our research setting, it is primarily the vestibular and somatosensory systems (such as information regarding balance, proprioception, and fatigue states) that provide necessary feedback for nervous system control. Changes monitored by these systems may be part of the exercise response to some external event, but still are considered to have arisen internally. External sources of

information include those coming from each of the five senses, particularly from visual and auditory sources. All such influences can exert a constraint upon the controller so that it is more likely to respond in a certain way. These inputs are thought to modulate the spinal pattern generator on a supraspinal level and in an integrated fashion. Thus, there is a multitude of influences acting upon gait control mechanisms on different timescales. According to the iteration-dominant view[34], a multiscale system is necessary to organize complex function. In the case of gait output, the synthesis of these inputs may contribute to and be consistent with a hypothesized mode-hopping spinal pattern generator[38,40].

Acknowledging the multitude of sources of inputs that are operating on different timescales is important. According to Davids & Araújo[141], explanations of constraint are often biased toward internal mechanisms and away from the performer-environment relationship. Yet, in Newell's task-organism-environment model of constraint[6], the environment plays a key role in influencing movement patterns as it interacts with the neurobiological systems. We will take treadmill running as an example to explain the action of constraining influences. Task-based constraints include the specific parameters and instructions for the particular task. In our example, this would be to run (the mode) on the treadmill at a set speed (the parameter). The treadmill is part of the environmental influences (i.e., the physical dimensions of the belt and the properties of the running surface), along with the environmental conditions of the room in which the treadmill is situated. The individual also has organismic sources of constraint because of the physical state of his own body. His anthropometric measures, physical fitness, fatigue, and disability may all influence the selected movement.

Constraint does not imply a strict cause of a particular pattern of movement. Rather, the human neuromusculoskeletal system operates within boundaries defined by constraints influencing the patterns of coordination and control that emerge[142]. Structural and functional constraints (both organismic) such as those arising from physical and psychological processes tend to fluctuate more rapidly than do the characteristics of the surrounding environment[142]. The resultant movement variability reflects adaptation to the constant changes in all constraints[142]. According to the principle of constrained optimization, the system will always select the best approach possible for a certain task[143]. If a variable is influential, the individual adopts (or is more likely to adopt) a particular pattern of movement as a direct or indirect consequence.

Feedback systems oversee the interaction between different physiological processes and between those processes and the environment[144]. Because this interaction is continual, it is impossible to separate internal and external dynamics because each depends on the other[144]. Yet, extrinsic and intrinsic factors may influence motor behavior differently. Unexpected extrinsic factors requiring a response likely account for apparently random fluctuations over short time scales, while intrinsic physiological factors may account for the underlying regularity seen over longer timescales[145]. For example, to minimize the energy cost of walking by choosing an ideal step frequency[4,146–149], a slow optimization process over longer timescales[150] uses feedback from chemoreceptors (medulla oblongata, carotid/aortic bodies, group III and IV muscle afferents), and requires at least 5 sec to produce physiological response to stimulus[151,152]. The energy expenditure sensed at one particular step frequency, does not provide information about whether other frequencies will be optimal[150].

Patterns of force generating movement are brought about actively via the nervous system and passively by the mechanical properties of the musculoskeletal system as well as the environment[153]. One of the guiding constraints to bipedal locomotion is aspect of not falling[153]. The presence of constraints reduces the number of available degrees of freedom[154], yet the remaining degrees of freedom are still multitudinous and may still employ some redundancy to properly execute the movement task[59]. According to Bernstein, coordination is the problem of organizing the multitude of degrees of freedom and reducing the number of dependent variables that need to be controlled[56]. This requires the organization of multiple parts over many different spatial and temporal scales[56]. When these different subsystems work in concert, muscles working over multiple joints can functionally linked to behave as a single unit (hence reducing the degrees of freedom)[56].

Thus, a suitable neuromechanical model for probing the mechanisms of gait includes the leg functioning as a spring-mass, a source of rhythm generation (i.e., CPG), proprioceptive feedback, and a perturbation or source of external influence[155]. The internal control (CPG) functions as a feedforward system, while the proprioceptive influence represents feedback control[156]. Feedback control may be the primary means by which stability is achieved[156]. According to this hypothesis, the limbs may function as a peripheral pattern generator, which provides feedback signals that are necessary for energy supply and the maintenance of rhythm[156]. According to the modeling of Kuo[156], ideal systems may function rhythmically with either feedforward or feedback control, yet there are disadvantages when either type of control is absent. Systems operating purely on feedforward mechanisms are unable to respond properly to perturbations, while purely feedback systems are disadvantaged with sensory error[156]. Thus, the ideal system employs both mechanisms.

According to Goldberger[67] this ideal adaptive ability requires a complex mechanism that needs to be organized and long-term correlations serve to help this organization. The mechanism has more than one specific time-scale for fluctuations may prevent the emergence of a dominant periodicity in the signal that would inhibit the ability to respond to perturbations of any scale[36]. The human locomotor system is an example of a pleiotropic system, which means that it has the capacity to use the multiple degrees of freedom in different ways such that there may be a multitude of methods for accomplishing a specific movement task[142]. This redundancy provides back up and metastability[142]. Such systems are open systems – they are stable, yet operate far from equilibrium[142]. When the task requires a reduction of the number of biomechanical degrees of freedom, this can be accomplished by forming muscle synergies[59,157] or coordinative structures[158] so that certain aspects of function occur via the action of a single unit[142].

During running, both the musculoskeletal and neuromuscular systems interact with the environment to produce motion with a relatively low magnitude of variability, indicating stability. However, within this variability is a pattern of fluctuation that is not random but rather contains long-term correlations indicative of robust function[31]. Variability may permit the exploration of successful movement patterns for the task, the distribution of tissue stresses, and responsiveness and adaptability to a changeable environment[159,160].

1/*f* noise appears to be ubiquitous in human biological function. Nevertheless, such patterned behavior highlights the underlying intrinsic rhythms of gait that can apparently be modified under various experimental interventions. These interventions, interacting with the locomotor system give evidence of a significant perturbation to the control scheme. Yet, evidently, the human gait system demonstrates a remarkable ability to maintain overall

stability, with the different behavior providing evidence of successful control, rather than a failure in the control regime.

Summary and conclusions

The human stride typically demonstrates 1/*f* behavior and contains long-term correlations in the stride time series. This dynamic behavior is thought to represent a balance between flexible and rigid control. By way of general explanation, 1/*f* noise is considered to be the natural outcome of the human neuro-mechanical control system. A more domain-specific explanation is that these dynamic fluctuations in human gait rhythm are the output of a complex system that integrates intrinsic and extrinsic influences upon control. These influences form a triad of constraint sources from the task, organism, and environment. The system employs both feedforward and feedback control to deal with this myriad of influences and consequently maintain an overall stability of movement.

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Chapter 5

Decreased complexity of stride timing dynamics with increasing speed during treadmill running

Abstract

Human running gait is characterized by consistent and apparently irregular fluctuations. Previous work suggests that these dynamics are speed-dependent, but evidence is equivocal and most studies have not used complementary analyses to increase confidence in the results. **Purpose:** To determine the relationship between inter-stride dynamics and speed using detrended fluctuation (DFA), power spectral density (PSD), and multiscale entropy (MSE) analysis, upon a wider range of speeds than used previously. **Methods:** Eleven distance runners completed six 4-min bouts at 40-90% of peak treadmill running speed, in random order. We used shoe-mounted accelerometers to generate stride time series. We compared DFA, PSD, and MSE outputs using ANOVA and a Bonferroni post hoc test, when necessary. **Results:** 88% of α values and 82% of β values were significantly different from random, reflecting statistical persistence. α ranged 0.79-0.88 and β ranged 0.42-0.53. There was no speed effect for α or β ($p>0.05$), but there was for MSE ($p<0.0001$). MSE values for 80 and 90% of peak speed were significantly lower than at 70% ($p<0.05$). **Conclusion:** Lower entropy represents greater order and constraint. The underlying intrinsic gait rhythm may be modified due to environmental and/or physiological constraints. This modification may help control the strides when the required movement is more challenging (e.g., not falling off the treadmill at high speeds). Alternatively, this may indicate a neuromuscular constraint present whenever there is a physiological challenge. The precise mechanism for this remains unclear but it is plausible that physiologically or biomechanically strenuous activities elicit changes in motor control to deal with the challenge.

Introduction

The timing of human running gait is comprised of irregular fluctuations. These fluctuations were once thought to represent undesirable noise but, to some extent, may actually be part of the signal of interest. This approach to the temporal modeling of running gait is still relatively new, but has potential to uncover previously obscured but important information about neuro-mechanical function[1,2]. To date, several studies have demonstrated that stride interval time series contain fractal characteristics that can be quantified as persistent correlations over multiple timescales[3–6]. In a data set containing gait timing persistence, particularly long or short stride intervals are more likely to be followed by strides that are also particularly long or short. This persistence can extend over several minutes and decays according to a power law[4,7]. One of the features of persistence is the presence of 1/*f*-like scaling, for which the power of the fluctuations is roughly proportional to the inverse of the frequency. In contrast, in anti-persistent systems, particularly long stride intervals are not as likely to be followed by long intervals, and vice versa.

To identify speed-related changes in the persistence of gait dynamics, we used several analysis methods: detrended fluctuation analysis (DFA)[8,9], power spectral density (PSD)[10], and multiscale entropy (MSE)[11–13]. DFA is robust with regard to non-stationary data and generates a scaling exponent (α) to distinguish anti-persistent (anti-correlated), uncorrelated, and persistent (correlated) behavior[3,14–18]. PSD and MSE potentially provide a quantitative confirmation of persistent correlations and thus all of the analyses are complementary[6].

There is some evidence that α varies with the speed of locomotion, according to a U-shaped relationship[3,14,15,19], exhibiting minimal values at subject-identified preferred speeds, whether walking[7,14], or running[3,15,19]. In two papers by Jordan et al.[3,15] female recreational

runners completed 8-minute trials of treadmill running at 80-120% of preferred speed. The higher α found for slower and faster speeds was interpreted as evidence for increased constraint due to a reduction in the availability of dynamical degrees of freedom. However, more recent work on running at comparable intensities did not confirm this relationship but rather demonstrated a similar α at all speeds in both trained and untrained runners[20]. Nakayama et al.[20] did not find a speed effect for 10-minute trials treadmill running at 80-120% of preferred speed. Persistent correlations are thought to indicate levels of constraint, which, with the manipulation of running speed, most likely arise from organismic and task sources[21]. PSD and MSE have been used to confirm the presence of persistent correlations in a descriptive paper on running gait[6] and in an experimental study on walking stride time series[22], but these complementary analyses have not yet been used to investigate differences between experimental conditions in running.

The concept of a preferred speed of running is familiar to individuals who participate in an athletic context. Previous authors have described preferred speed in terms of individual perception[3,15], but it may also depend on factors such as energy cost, heart rate (HR), rating of perceived exertion (RPE), and biomechanical factors[23]. Therefore, we sought to set the range of speeds in relation to fitness level and further describe these intensities by reporting HR and RPE. Two studies have suggested that a higher range of speeds be used to confirm the U-shaped relationship[15,20], so we aimed to test this hypothesis with the maximum range possible given the requirements of the DFA algorithm[*]. Thus, the purpose of this study was to describe changes in nonlinear dynamics of inter-stride time series during treadmill running at a broad range of speeds quantified relative to fitness level.

[*] The DFA algorithm requires an *approximate* minimum of 300 data points. For faster running speeds, there eventually comes a speed that is so strenuous that subjects are unable to maintain this for the duration needed to measure 300 strides.

Table 1. Subject characteristics.

	Mean	SD	Range
Age (yr)	27.5	5.2	21-36
Height (m)	1.78	0.08	1.64-1.89
Mass (kg)	71.6	11.8	55-95
Peak treadmill running speed (km/h)[a]	19.3	1.6	16.5-21.5
VO_{2peak} (ml/kg/min)	59.0	6.4	49.3-72.1
Years' training (yr)	7.3	5.2	1.5-18
Weekly running volume (km)[b]	41.9	27.7	17.5-120

[a] during maximal incremental running test to exhaustion; [b] reported mean km run per week over the previous 3 months.

Methods

Participants

Eleven healthy distance runners (9 male, 2 female) participated in the study (mean (SD) age = 27.5 (5.2) yrs; height = 1.78 (0.08) m; mass = 71.6 (11.8) kg. All performed high intensity training at least once per week. The characteristics of the sample were 7.3 (5.2) yrs experience and weekly running volume was 41.9 (27.7) km. Participants were informed of potential risks and provided informed consent prior to participation. The protocols of this study were approved by the Human Research Ethics Committee of the Faculty of Health Sciences at the University of Cape Town. Subject characteristics are presented in Table 1.

Procedures

We established peak treadmill running speed in session 1 and measured stride timing during treadmill running in session 2. The sessions were separated by at least 48 hr and participants refrained from heavy exercise for 48 hr before each session. Sessions occurred at approximately the same time of day.

The incremental treadmill test began at 10 km/h and increased by 0.5 km/h every 30 sec until volitional exhaustion. Peak running speed was defined as the highest speed run for 30 sec. The experimental session included six 4-min running stages at 40, 50, 60, 70, 80, and 90% of peak speed. Speeds were presented in random order. Participants were permitted at least 2 min rest between runs. The treadmill was set at 1% grade[24] and a fan was provided for thermal comfort.

Stride time series have previously been generated using footswitches[25], force-sensitive shoe inserts[26,27], treadmill force plates[3,14,15], and GPS satellite technology[28]. We have found footswitch durability to be insufficient for fast or long duration running. We selected shoe-mounted accelerometers suitable for both treadmill and field testing and durable because they are not subjected to direct impact. Two-dimensional accelerometers were mounted on the top of each running shoe by the laces (316-10G, Noraxon, Phoenix, AZ; mass ~20 g each). The accelerometers recorded accelerations roughly in the anterior-posterior and vertical axes (the superior surface of the foot/shoe is not perfectly aligned with the global axes). Data were captured at 1500Hz by a device worn on the participant's lower back (TeleMyo 2400T G2, Noraxon; mass ~535 g), and were transmitted to a notebook computer. To quantify running intensity, we recorded HR throughout each trial (Polar Vantage XL, Polar Electro Oy, Kempele, Finland), and RPE[29] in the last 30 seconds of each trial.

Data Analysis

Accelerometer data was analyzed with custom-written software in a Matlab environment (Matlab R2009a, Mathworks, Natick, MA). The right stride time series were generated by first applying a 4th order Butterworth filter to the raw accelerometer data in the vertical axis, allowing a band pass between 0.9 and 50 Hz[30]. Peak accelerations in the vertical axis (threshold = 1.5g) corresponding with heel strike were identified and the stride and step time series were generated. Values greater than 2 SD from the mean (rare) were deemed erroneous and were omitted from the series.

To identify correlations in the time series, we applied the complementary analyses suggested by Crevecoeur et al.[6]: Hurst exponent, PSD, MSE, and surrogate generation. As argued by Rangarajan & Ding[31], finding an expected agreement between the scaling exponents of the Hurst and PSD strengthens the conclusions that may be drawn. We presently provide a brief description of these analyses.

The Hurst exponent may be estimated by detrended fluctuation analysis (DFA)[8,9]. DFA has been widely used in stride interval analysis, particularly because it is robust toward non-stationary processes[32]. The DFA algorithm first calculates an accumulated sum of the time series, to which the mean is subtracted, and then sections it into boxes of a specified range (described below). The log of the average fluctuation around the fitted linear line for each box of size n (log F(n)) is plotted against the log of the box size (log n). Following Jordan et al.[3,14,15] we used a range of box sizes of 4 toN/4, where N is the total number of data points in the series. Scaling exponent α is the slope of the linear line, which is an estimate of the rate of decay of the series' autocorrelation function. Behavior ranges from persistent anti-correlations ($\alpha < 0.5$) to white noise ($\alpha = 0.5$), persistent correlations ($\alpha > 0.5$), and Brownian motion ($\alpha = 1.5$).

PSD is the Fourier transform of the autocorrelation function. The PSD of systems composed solely of white noise is the same over all frequencies, whereas systems with long-term memory demonstrate a function that scales according to $1/f^{\beta}$. This $1/f$ scaling may be considered to be the "hallmark" of complexity[33]. A plot of log(power) versus log(frequency) can be fitted according to a linear model, the slope of which provides an estimate of the scaling exponent β. We used the Welch method of calculating PSD[10]. The scaling exponent generated by the Hurst analysis (i.e., α) is related to the slope of the power spectral density (β), according to the equation

$$\alpha = (1 + \beta)/2. \quad (1)$$

Instances where these two measures agree according to the expected theoretical relationship serve to strengthen a classification of long-term correlations. A difference $-0.1 < d < 0.1$ indicates good agreement[6].

Statistical entropy is a measure of system disorder or irregularity (increased entropy indicates increased disorder). MSE analysis[11–13] is able to distinguish between white noise processes and processes with long-term memory. The method calculates sample entropy (S_E)[34] for distinct series composed of, first, the original time series, then the mean of every two values, then the mean of every three values, etc. White noise processes demonstrate a monotonically decaying entropy with increasing scale, while long-term correlated processes demonstrate roughly equivalent irregularly across the time scales[6]. We ran the analysis for scale factors 1 to 19, and set parameters m and r at 1 and 0.15, respectively, which is appropriate for short time series[6].

To test the results of the experiments, we generated twenty randomly shuffled surrogate time series[5,28] for each original dataset. This process preserves the mean and

variance of the series, but destroys the temporal order. We calculated the mean and SD of the surrogate series. In the case of DFA and PSD, we considered value from an original time series to be significantly different if it was more than 3 SD (i.e., roughly 99% confidence interval) away from the mean of the surrogate datasets[28].

For performance variables (HR, $\%HR_{max}$, and RPE), measures of distributional variability (mean, SD, and CV%), DFA, and PSD, differences across speed were tested with an analysis of variance (ANOVA). MSE outputs were tested with a 6 (speed) ×10 (scaling factor) ANOVA. In case of significant difference, a Bonferroni post hoc test was used to determine the source of the difference. Statistical significance was set at $p < 0.05$.

Results

Physiological and subjective measures of intensity for each run trial are presented in Table 2. Mean reported RPE for each speed ranged from 9.3 (40%) to 17.5 (90%). Percentage of maximum HR ranged from 70 to 97%. The lowest speed was 7.7 km/h on average, which is close to a common walk-run transition. Mean stride interval decreased with increasing running speed ($p<0.0001$) (Table 3, Figure 1). There were no other significant effects due to speed on the distributional measures of variability.

Table 2. Mean (SD) values describing running intensity during the experimental intervention.

	Percent peak treadmill running speed					
	40	50	60	70	80	90
Speed (km/h)	7.7 (0.7)	9.7 (0.8)	11.6 (1.0)	13.5 (1.1)	15.5 (1.3)	17.4 (1.5)
RPE units (6-20)	9.3 (1.3)	10.9 (1.1)	11.9 (0.9)	13.4 (1.3)	15.2 (1.5)	17.5 (1.3)
HR (bpm)	135.8 (6.5)	147.1 (9.0)	161.1 (11.3)	171.8 (9.4)	180.8 (7.7)	187.7 (7.3)
% HR_{max}	70 (3)	75 (5)	82 (6)	88 (4)	93 (3)	97 (3)

Table 3. Effect of speed on mean, SD, CV%, DFA, and PSD of stride interval series.

Variable	*df*	df_{error}	$F(5,60)$	*p*	η^2
Mean	5	60	23.66	<0.0001*	0.66
SD	5	60	1.37	0.2487	0.10
CV%	5	60	1.44	0.2225	0.11
α	5	60	1.15	0.3442	0.09
β	5	60	0.34	0.889	0.03

*significant effect at $p<0.05$.

α and β provided an initial confirmation of a significant non-random structure of variability (Figure 2). Mean α for each speed ranged from 0.79 to 0.88 for the stride series and 58/66 (88%) of datasets had a value >3 SD from random (α = 0.5). β ranged from 0.42 to 0.53 and 54/66 (82%) of these datasets were >3 SD from random (β = 0). α and β showed difference $|d|<0.1$ in 51/66 (77%) of datasets, according to equation (1). As expected, the

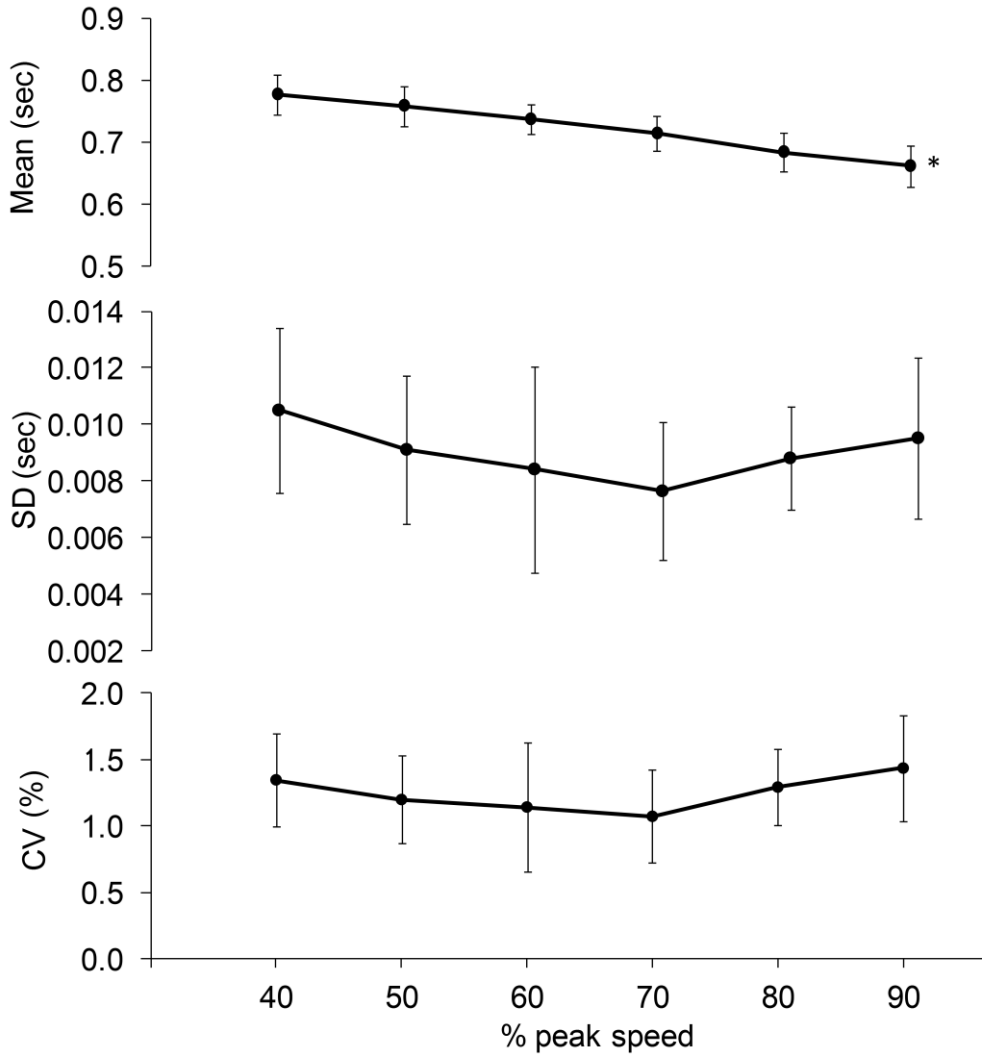

Figure 1. Distributional measures of variability: mean (top), standard deviation (middle), and coefficient of variation (bottom). Error bars represent SD. *significant speed effect $p<0.0001$.

output of the MSE analysis was significantly different whenever the effect of random shuffling was tested.

Neither DFA nor PSD (Table 3, Figure 2) showed any main effects due to running speed. However, MSE analysis (Table 4, Figure 3) did show a significant speed effect ($p<0.0001$). Mean S_E at 90% peak speed was significantly lower than S_E at 40-70% peak speed, while mean S_E at 80% peak speed was significantly lower than S_E at 40, 50, and 70% peak speed (Bonferroni post hoc test, $p<0.05$). The lack of a significant interaction between

Table 4. Effects upon the output of multiscale entropy analysis.

Effect	*df*	df_{error}	*F*	*p*	η^2
Speed	5	600	8.58	<0.0001*	0.04
Scaling factor	9	600	39.53	<0.0001*	0.34
Speed × scaling factor	45	600	0.88	0.7021	0.04

*significant effect at $p<0.05$.

speed and scaling factor indicated the pattern of change with speed is similar for all scaling factors. Accordingly, any changes due to the speed effect indicated that S_E at all scaling factors was reduced at the highest speeds, indicating a lower S_E at each scaling factor (i.e., the entire output line was shifted vertically).

Discussion

We tested the hypothesis that persistence in running stride time series would vary with speed, according to a U-shaped relationship. Previous studies investigating this relationship[3,15,20] have used DFA only, so we used several complementary analyses to provide insight that was perhaps not previously available. The other novel aspects of this study were that running speed was quantified relative to subject fitness and the range of speeds was likely the greatest possible given the data set length requirements for the DFA algorithm (faster speeds can only be maintained for a shorter time). In most cases, tests revealed a significant non-random structure of the data sets, which confirms previous work in human walking and running gait[3,7,14,15,19]. We did not find a significant speed effect with DFA or PSD, but we were able to show that MSE is able to discriminate an effect at the highest running speeds. MSE may be more sensitive to identify differences, especially given datasets that are somewhat shorter than previous work[3,15,20].

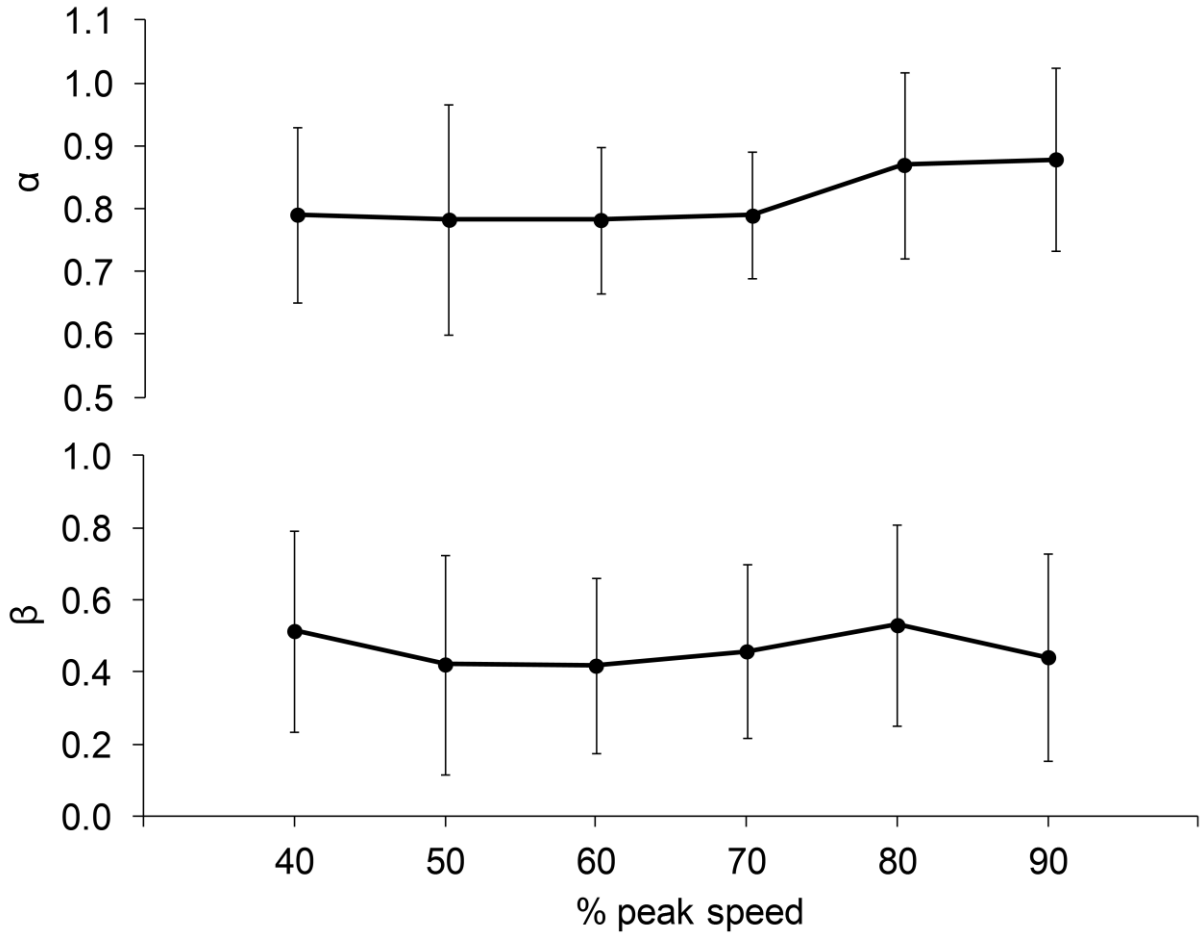

Figure 2. Effect of speed on DFA (top) and PSD (bottom) scaling exponent. Error bars represent SD. There were no significant effects at $p<0.05$.

α values were similar to previous reports (0.79-0.88), generally indicating a non-equilibrium system. Previous work has reported on stride intervals reported α =0.74-0.86[15] and α=0.78-0.89[3]. Jordan et al.[3] reported a range of α=0.69-0.78 for step intervals. Nakayama et al.[20] reported α values of between approximately 0.7 and 0.8 for trained runners. These values indicate significant correlations because the scaling exponent is between that expected for systems composed of white noise (α = 0) and pink noise (α = 1.0). These values correspond also to the region of PSD scaling exponents between white (β = 0) and pink noise (β = 1.0).

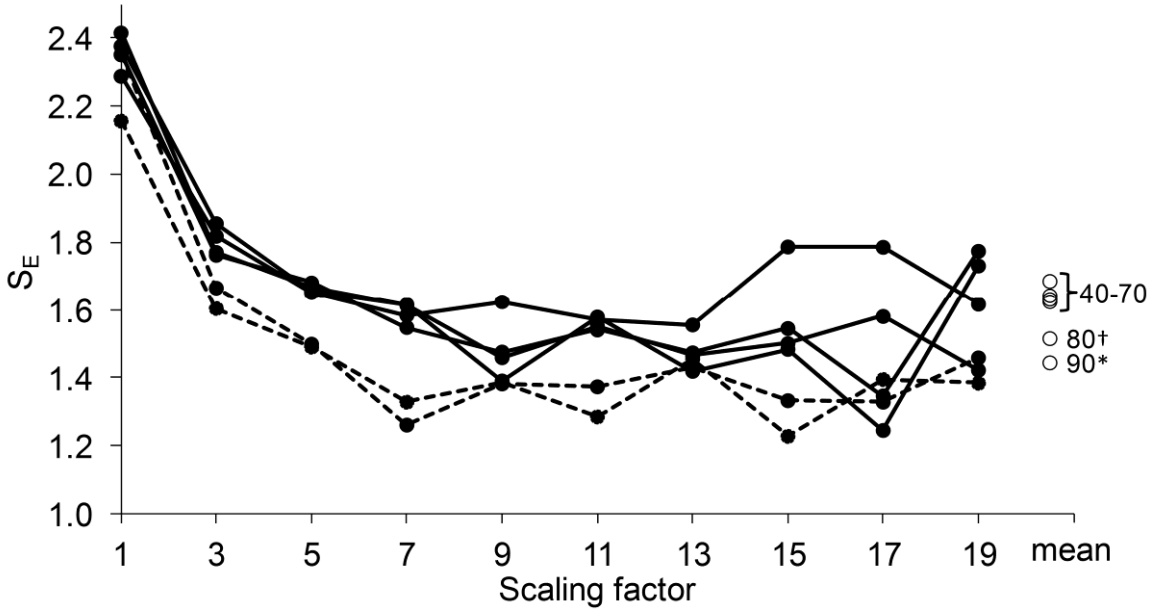

Figure 3. Demonstration of the effect of speed and scaling factor on MSE. †S_E at 80% peak speed significantly different from S_E at 40, 50, and 70% peak speed ($p<0.05$). *S_E at 90% peak speed significantly different from S_E at 40-70% peak speed ($p<0.05$). Solid lines are speeds 40-70%; dotted lines are speeds 80-90%.

Previous work in both walking and running has demonstrated a U-shaped relationship between DFA scaling exponent and speed, and this has remained the working hypothesis in the literature. There were no significant trends due to speed for either DFA or PSD. The DFA results were consistent with Nakayama et al.[20] but not Jordan et al.[3,15]. However, where DFA and PSD did not demonstrate significant effects, MSE was sensitive to changes in speed. Indeed, the mean S_E across all scaling factors was significantly lower for the stride time series at 80 and 90% peak speed, as compared to 70%. Decreased entropy in gait time series suggests less disorder and more constraint in stride timing. In situations of higher intensity, then, the response of the individual seems to be that stride timing (as one of the two factors that regulates running speed) is more tightly controlled or corrected. Statistically speaking, the timing between one particular stride and those in the near and distant future is more

predictable. Movement timing is thus less "free" and more regulated and the result of this is that the probability of predicting the timing of subsequent strides is greater.

To discuss possible contributors to tighter regulation of stride timing, we employ the model of Newell[21], which suggests three categories of sources of constraint: organism, task, and environment. Newell[21] recognized that the status of the exercising individual, such as the physiological or psychological ability to perform a given task, may give rise to constraints upon their movement. Increasing running speed increased the energy requirement during the task and elicited considerable physiological strain at the highest speeds. Indeed, subjects ran to up to 90% of their peak treadmill running speed, at up to 97% of maximum HR (on average) and reported an average RPE of 17.5 units at the highest speed. The two highest speeds (80 and 90%) would be associated with prominent afferent feedback from exertion, such as breathing, muscle tension, and proprioceptive feedback, and an internal milieu consistent with significant physiological strain. These measures of exercise intensity may reflect internal (organismic) sources of constraint. This notion is supported by the work of McGregor et al.[35] and Parshad et al.[36], who used an entropy-based measure to demonstrate evidence for increasing constraint with increasing running speed. In those studies, individuals who undertook an incremental running test to exhaustion had steadily decreasing entropy (increasing constraint) as speed increased, providing evidence that subject exerted increased control[37] over their stride timing during periods of exercise stress.

The other source of constraint (which may act in combination to organismic constraints) is the task, which in this case, requires the individual to run while remaining roughly in the center of the treadmill belt. This skill, presumably more challenging at higher intensities, may involve changes in executive function (EF) devoted to the successful

execution of the task. There are many studies investigating the link between EF and gait, but gait variability generally does not change with the addition to walking of additional tasks requiring EF[38]. However, there is some evidence showing changes in the linear characteristics of stride length, stride frequency, and speed[39–41] and there are no studies investigating running exercise or nonlinear measures of variability. Thus, the role of EF in complex fluctuations in gait timing is presently unknown, but remains a reasonable hypothesis. Future research is needed to determine how aspects of the organism task may work together to influence constraint. For example, is part of the challenge that influences constraint of running at high speeds simply that it is undertaken on a treadmill?

Conclusions

The data for this study did not support previous work demonstrating a significant speed effect upon the Hurst-based scaling exponent[3,15,19], but we observed that MSE analysis is sensitive to changes in entropy at higher speeds, which agrees with previous studies using entropy measures[35,36]. We characterized system behavior for a wide range of running speeds. The persistence commonly seen in these data sets likely represents the already-established dynamical behavior arising from an integrative system, regardless of whatever mechanism is accepted as the source of the patterning. Likely causes of this alteration at high speeds are the environmental constraint imposed by the treadmill that requires skill at higher speeds and physiological changes manifest in the exercising individual. Further temporal modeling of human gait in various situations and with participants of varying experience would add to our understanding of neuro-mechanical control systems. A logical next question is whether similar behavior is present during unconstrained over-ground running.

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Chapter 6

Effect of treadmill versus overground running on the structure of variability of stride timing

Abstract

Previous research into the nonlinear dynamics of walking stride timing has demonstrated some similarities and some differences between treadmill and overground, depending on the selected analyses that point to mechanisms of gait control. Both treadmill and overground running are often used in research, but there has not yet been a direct comparison of these two conditions for running. Thus, this study compared nonlinear gait timing dynamics of paced treadmill and overground running using a complementary set of nonlinear analyses. Ten trained runners ran for 8 min on a track at preferred pace (PP). They then ran paced treadmill and track trials at 80, 100, and 120% PP for 8 min each. We applied detrended fluctuation analysis (DFA), power spectral density analysis (PSD), and multiscale entropy (MSE) analysis. Treadmill had a higher DFA scaling exponent (0.94 vs. 0.86, p = 0.0024), lower PSD scaling exponent (0.62 vs. 0.75, p = 0.0056), and lower MSE ($p<0.0001$), compared to overground. There was no effect of speed for DFA and PSD, but MSE at 80 and 120% PP was significantly different between conditions ($p<0.05$). A higher DFA scaling exponent for treadmill running and lower MSE for treadmill running at speeds slower and faster than preferred suggests increased constraint. Higher constraint during treadmill running may manifest itself via visual, afferent, or kinematic changes that modify the intrinsic persistent gait rhythm. That these changes may be more pronounced during running at speeds slower and faster than preferred suggests that the task and environment combine to elicit especially constrained behavior.

Introduction

The presence of persistent correlations in human gait is well established for walking[1–4] and running[5,6]. The earliest studies showing evidence for statistical persistence in stride time series comes from overground walking[1,3,4,7,8]. Later work confirmed this finding for treadmill walking[9,10]. In contrast to walking studies, the earliest running studies on gait persistence were conducted on treadmills[5,6] and to date, only one study has investigated and demonstrated persistence in stride time series during overground running[11]. There has not yet been a direct comparison between treadmill and overground running. Statistical persistence in gait timing is thought to represent the underlying rhythm of a complex and integrative biological control system. This persistence can be modified according to various experimental interventions and this change can indicate subtle modifications to the regime of control (see chapter 4 of this dissertation). Given the popularity of both modes in exercise and research settings, there is a need to understand any potential differences resulting from these different running environments.

In any gait task, individuals must select a movement pattern given characteristics pertaining to the environment, as well as task itself, such as speed of locomotion[2,5–7,12–14]. The coupling of these perceptual sources and consequent movement coordination[15] reflects *constraint.* There are several differences between treadmill and overground locomotion that may affect the movement constraints of the individual. Newell[16] recognized the contributions from the task, organism, and environment. Putative environmental or external considerations including treadmill belt stiffness and compliance properties[17,18], belt speed regulation[9,17,18], belt dimensions[9,18], straight path of the belt[18], and differing visual field[18] may affect the afferent information from somatosensory sources[19–21] as well as visual and vestibular inputs[21].

Evidence that treadmill walking elicits different movement coordination from overground walking includes differences in average values of preferred speed[22], stride length[22,23], stance phase timing[22–24], step frequency[23], and vertical ground reaction force[25]. These may point to altered afferent input causing different modulation of central pattern generators (CPG) during walking[23]. In running, reported differences include knee kinematics, ground reaction force, and joint moment[17].

Despite these mean differences, it is often not the *magnitude* of kinematic variability that is altered, but rather the *structure* of variability. The difference between the dynamical structure of treadmill and overground locomotion has only been studied for walking and evidence is equivocal. Chang et al.[26] reported that the detrended fluctuation analysis (DFA) scaling exponent (α) was not significantly different between treadmill and overground walking. Bollens et al.[27] confirmed this finding by showing that the Hurst exponent (comparable to DFA α) and power spectral analysis (scaling exponent β) were not significantly different between treadmill and overground walking. However, local dynamic stability has been shown to be significantly higher during treadmill walking[18]. This finding was confirmed by Terrier & Dériaz[9], who also reported a significantly lower α with treadmill walking, as compared to overground.

Even if evidence were not equivocal, it is inappropriate to assume that walking results can explain running locomotion. Running is different from walking because it is more physiologically strenuous and is much different from walking from the perspective of task execution, such that the two gaits are modeled differently[28]. Previous work involving high intensity treadmill running showed decreased entropy (increased regularity) at the highest running speeds[29,30]. Unfortunately, from the designs of these studies, it was not possible to

determine whether it was the treadmill itself (environmental constraint) or the physiological stress (organismic constraint) that was the major contribution to changes in dynamics. Thus, the purpose of this study was to investigate the effect of treadmill versus overground running at different speeds. We hypothesized that treadmill running will result in more constrained gait time series, as compared to overground running, and that this effect will be more pronounced at faster speeds.

Methods

Participants

Ten trained male distance runners participated in the study (mean ± SD age = 28.8 ± 7.1 yr., height = 1.76 ± 0.04 m; mass = 70.9 ± 8.3 kg). All performed high intensity training at least once per week and participated in endurance competitions. The average weekly running volume was 48.5 ± 23.3 km. Participants were informed of potential risks and provided informed consent prior to participation. Subject characteristics are presented in Table 1. The protocols of this study were approved by the Research and Ethics Committee of the Faculty of Health Sciences at the University of Cape Town.

Protocols

This study consisted of one session to identify peak treadmill running speed, and two experimental sessions during which stride intervals were measured during 8 minute runs on a track and treadmill. Sessions were separated by at least 48 hours and participants refrained from heavy exercise in the 48 hours before each session. Sessions occurred at approximately the same time of day.

Table 1. Subject characteristics.

	Mean	SD	Range
Age (years)	28.8	7.1	20-42
Height (m)	1.76	0.04	170-182.5
Weight (kg)	70.9	8.3	57.1-84.7
Peak treadmill running speed (km/h)[a]	19.8	1.4	18-22
VO_{2peak} (ml/kg/min)	62.3	8.2	49-73
Years' training	8.8	7.7	0.75-25
Weekly running volume (km)[b]	48.5	23.3	25-110

[a]during maximal incremental running test to exhaustion; [b]mean over previous 3 months.

Session one consisted of a modified peak treadmill running test[31]. In this test, participants began running at 12 km/h. The speed was increased by 0.5 km/h every 30 seconds until volitional fatigue. The treadmill grade was set at 0 %. Sessions two and three both included a 10 minute track warm-up at a self-selected running pace and an 8 minute freely paced run on the track. This freely paced run was at the subjects' preferred pace (PP), described to the subjects as "a pace at which you would be comfortable to run for about 45 min., and represents a pace that is usual, common, or normal". This description generally corresponds with the methods of Jordan et al.[5,6]. Participants then completed three 8-minute runs at 80, 100, and 120% PP, in random order. These runs were on either the running track or treadmill, depending on the session, which was also in random order. In the second session, the freely paced run was only included to ensure both sessions were balanced with regard to volume.

Running speed was controlled either on the treadmill or by a series of pacing lights installed around the running track. For the latter, subjects were instructed to run behind the pacing lights at a constant distance (subjects ran ~1-2 m behind lights). Speeds were controlled to 0.1 km/h precision. The running track was 141.4 m long in the lane used by the subjects. Subjects were provided with at least 2 minutes rest between runs and a fan was provided for thermal comfort during treadmill running. To help monitor running intensity, we recorded HR (Polar Vantage XL, Polar Electro Oy, Kempele, Finland), and RPE in the last 30 seconds of each bout.

Accelerometry measurement and contact identification

Foot contact was identified using telemetric 3-D accelerometers mounted on the top of the running shoe (316-10G, Noraxon, Phoenix, AZ; mass ~ 20 g each). Data were captured at 2000 Hz by a device worn on the lower back (TeleMyo 2400T G2, Noraxon; mass ~ 535 g). We first applied a 4^{th} order Butterworth filter to the raw acceleration data, with band pass between 0.9 and 50 Hz. Peak vertical accelerations (threshold = 3g) corresponding with heel strike were identified to generate the stride time series. Values greater than 2 SD from the mean (rare) were deemed erroneous and were omitted from the series.

Non linear analyses

To identify persistent correlations, we applied the analyses suggested by Crevecoeur et al.[32]: Hurst exponent, power spectral density analysis, multiscale entropy analysis, and surrogate generation. We will briefly describe these analyses. The data set consisted of approximately 700 strides on average.

Detrended fluctuation analysis. DFA scaling exponent α provides an estimate of the Hurst exponent[33,34]. DFA is appropriate for stride interval analysis because it is robust toward non-stationary processes [35]. The algorithm first integrates the series and divides it into non-overlapping boxes of equal length *n*. A least squares fit is used to define the local trend in each box. The log of the average fluctuation for each box (log F(*n*)) is plotted against the log of the box size (log *n*). α is the slope of the linear line of the log-log plot. DFA distinguishes behavior that is classified as anti-persistent (α < 0.5), white noise (α = 0.5), persistent (α > 0.5), and Brownian motion (α = 1.5). We used a range of box sizes of 4-N/4, where N is the series length[2,5,6].

Power spectrum. Power spectral density (PSD) is the Fourier transform of the autocorrelation function. Pure white noise datasets demonstrate equal power at all frequencies, but functions with serial dependence scale according to $1/f^{\beta}$. 1/f scaling is considered an essential characteristic of complexity[36]. Scaling exponent β is estimated from the slope of the linear fitted line of a plot of log(power) versus log(frequency). We calculated PSD according to the Welch method[37]. α (or Hurst exponent) is related to the PSD scaling exponent β, according to the equation

$$\alpha = (1 + \beta)/2 \quad (1)$$

According to the expected theoretical relationship, an agreement between these two exponents strengthens the confidence with which datasets may be classified[38].

Multiscale entropy. System disorder is quantified by measures of entropy (increased entropy indicates increased disorder). Multiscale entropy analysis (MSE)[39–41], distinguishes between white noise and long-term memory processes. The MSE algorithm first constructs distinct coarse-grained series comprised of the mean values for each non-

overlapping window of specified scale. For example, the first series consists of the original dataset. The second series consists of the mean of every two values, and so on. Sample entropy (S_E)[42] is then calculated for each distinct series. The entropy of white noise processes decays monotonically with increasing scale, while long-term correlated processes maintain irregularity at larger scales[32]. We used scaling factors 1-19 and set parameters *m* and *r* at 1 and 0.15, respectively, which is appropriate for shorter time series[32].

Hypothesis tests

Performance data and distributional variability. Performance variables (HR, %HR_{max}, and RPE) and measures of distributional variability of stride intervals (mean, SD, and CV%) were tested with a 3 (condition) × 2 (speed) ANOVA.

DFA and PSD. To establish a non-random structure of variability in the DFA and PSD analyses, we generated twenty randomly shuffled surrogate time series for each original dataset[8,9]. This preserves the length, mean, and variance of the original dataset, but destroys the temporal order. We applied each analysis above to the surrogate time series for each grouping of twenty and calculated the mean and standard deviation. Original time series values more than 3 SD away (i.e., outside 99% confidence interval) from the mean surrogate value were considered to be significantly different[8]. DFA and PSD for treadmill and overground running were compared at 80, 100, and 120% PP using a two-factor (speed×condition) ANOVA.

Table 2. Mean (SD) running intensity variables for each condition.

	80% PP		PP		120% PP	
Variable	Treadmill	Overground	Treadmill	Overground	Treadmill	Overground
Speed, km/h.	9.9 (1.0)		12.4 (1.2)		14.9 (1.4)	
Speed, % max[a]	49 (4.9)		61 (6.0)		74 (7.3)	
HR, bpm	136 (12)	137 (12)	154 (14)	157 (15)	171 (15)	174 (14)
HR, % max	70 (5.8)	71 (5.4)	80 (6.3)	81 (6.7)	88 (6.8)	90 (5.7)
RPE	10 (1.2)	10 (1.0)	13 (1.6)	13 (1.3)	15 (2.0)	16 (2.0)

[a]percent peak treadmill running speed.

MSE. A non-random structure of variability was first established with original and surrogate data with a four-factor (speed×condition×scaling factor×surrogate) ANOVA. To test the experimental hypothesis, the above ANOVA was run again on the original datasets only, without the surrogate factor. Statistical significance for all tests was set at $p<0.05$. In case of significant difference, a Bonferroni post hoc test was used to determine the source of the difference. All of the above analyses were performed with custom-written software in a Matlab environment (Matlab R2009a, Mathworks, Natick, MA).

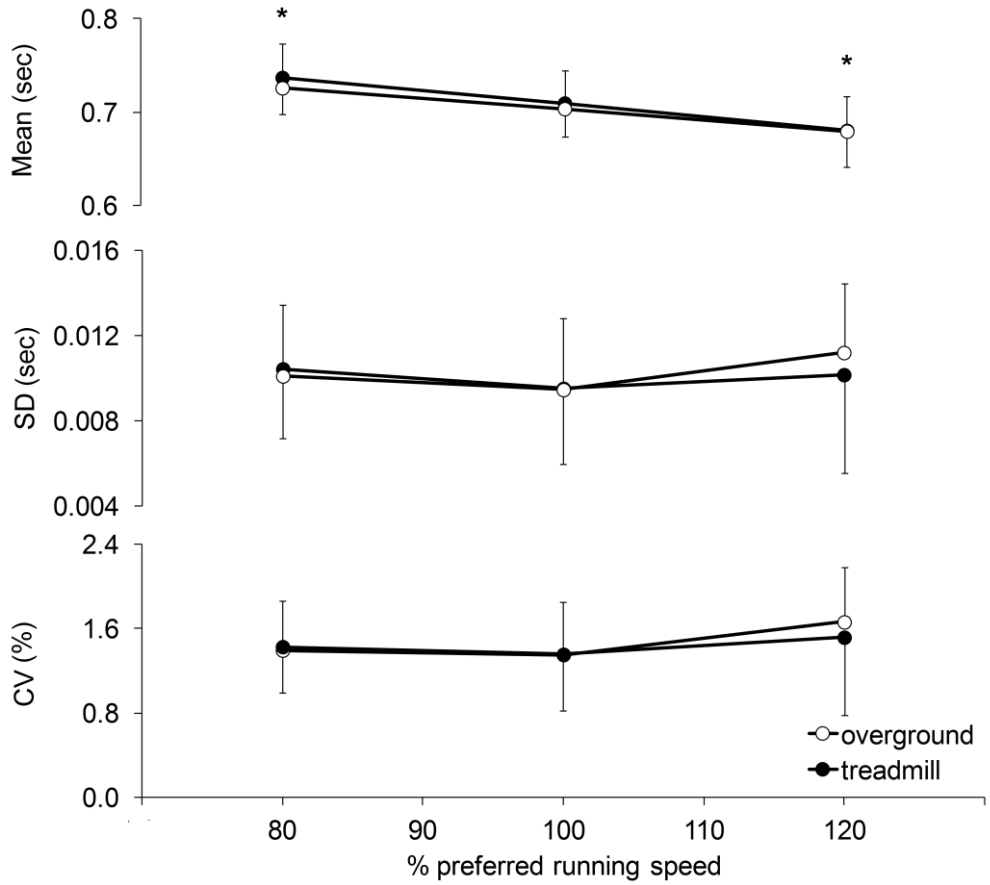

Figure 1. Descriptive statistics: mean (top), SD (middle), CV% (bottom) for treadmill and overground running. *significantly different from each other ($p<0.05$).

Results

Performance data and distributional variability

Running speed, HR, and RPE for each condition and speed are presented in Table 2. HR ($F_{2,56}=35.49$, $p<0.0001$, $\eta^2=0.56$), $\%HR_{max}$ ($F_{2,56}=47.41$, $p<0.0001$, $\eta^2=0.63$), and RPE ($F_{2,56}=64.45$, $p<0.0001$, $\eta^2=0.70$) all increased significantly with speed. Values for each speed were all significantly different from each other, according to the post hoc test. There were no significant condition effects. The descriptive statistics for the time series are provided in Table 3 and Figure 1. Mean stride interval decreased significantly with increasing

Table 3. ANOVA results for DFA and PSD.

		DFA				PSD			
Main effect	*df*	MS	*F*	*p*	η^2	MS	*F*	*p*	η^2
Condition	1	0.09098	10.11	0.0024*	0.16	0.26024	8.34	0.0056*	0.13
Speed	2	0.00169	0.19	0.8292	0.01	0.01318	0.42	0.6577	0.01
Condition × speed	2	0.00118	0.13	0.8772	<0.01	0.05194	1.66	0.1989	0.05
Error	54	0.00921	-	-	-	0.03121	-	-	-

*significant effect at p<0.05.

Table 4. ANOVA results for MSE analysis.

Main effect or interaction	*df*	MS	*F*	*p*	η^2
Condition	1	2.7808	42.72	<0.0001*	0.04
Speed	2	0.26779	4.11	0.0168*	0.01
Scaling factor	9	3.15232	48.43	<0.0001*	0.41
Condition × speed	2	0.25792	3.96	0.0196*	0.01
Condition × scaling factor	9	0.07374	1.13	0.3372	0.01
Speed × scaling factor	18	0.01629	0.25	0.9994	<0.01
Error	558	0.06509	-	-	-

*significant effect at p<0.05.

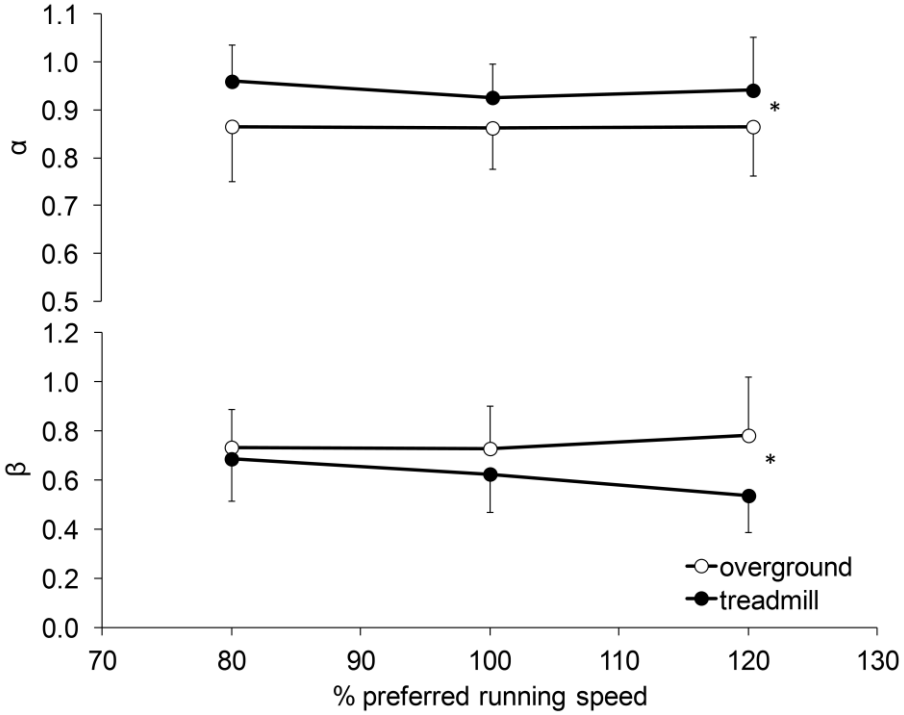

Figure 2. DFA (top) and PSD (bottom) for treadmill and overground running. *significant difference between conditions ($p<0.01$).

speed ($F_{2,54}$=11.25, p=0.0001, η^2=0.29) and each value was significantly different from the rest, according to the post hoc test. There were no other significant main effects or interactions for SD or CV%.

DFA and PSD results are presented in Table 3 and Figure 2. DFA for treadmill was significantly higher than for overground running ($F_{1,54}$=10.11, p=0.0024, η^2=0.16). Mean α across all speeds was 0.94 and 0.86 for treadmill and overground, respectively. β for treadmill was significantly lower than overground with mean values of 0.62 and 0.75, respectively ($F_{1,54}$=8.34, p=0.0056, η^2=0.13).

MSE results are presented in Table 4 and Figure 3. There were significant main effects for speed, condition, and scaling factor and a significant speed×condition interaction. S_E across all scaling factors for treadmill was significantly lower than overground

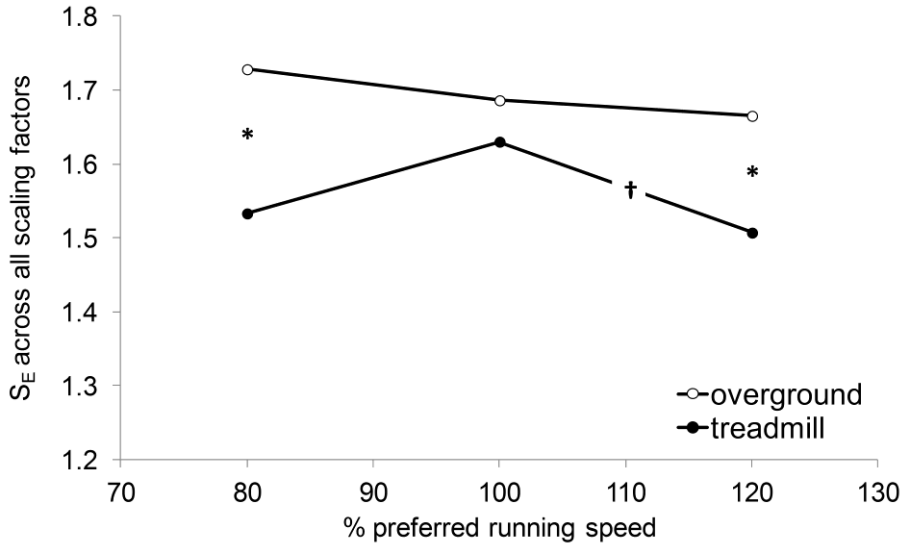

Figure 3. MSE for treadmill and overground running. *significant difference at this particular speed and condition ($p<0.05$), †significantly different between adjacent speeds for that condition ($p<0.05$).

($F_{1,558}=2.7808$, $p<0.0001$, $\eta^2=0.04$). For overground running, PP had the highest S_E across all scaling factors, and decreased significantly from PP to 120% PP ($p<0.05$). S_E at 80 and 120% PP were significantly different between overground and treadmill ($p<0.05$).

Discussion

We tested the hypothesis that statistical persistence in stride timing is different between overground and treadmill running. We confirmed previous research showing a DFA scaling exponent for different speeds and surfaces is significantly different from random. Yet, by using several complementary analyses, we provide an outlook that is not possible with DFA alone. In the first comparison, we found that across all three speeds, treadmill running had a higher α and a lower β, as compared to paced overground running.

A higher scaling exponent α means that the strength of correlations in the dataset increased and moved in a direction away from random dynamics toward more ordered

behavior. Further, treadmill running showed lower MSE values than overground at 80 and 120 % of preferred pace, meaning that stride timing was more regular and suggesting increased constraint. The range of values for α were consistent with several previous studies on treadmill[6] and overground running[4,11], ranging between approximately 0.7 and 1.1. β ranged between approximately 0.1 and 1.2.

The PSD results were not consistent with DFA and MSE, but the latter two measures are complementary and may be interpreted in a manner consistent with previous research. Although relationships between linear correlations and entropy measures should be made with caution because the two measures are not mathematically equivalent, the results of these two analyses suggest similar dynamics. The increased long term correlations and increased regularity, as demonstrated by DFA and MSE, both correspond with the notion of increased constraint. Increased strength of correlations mean that a particularly long or short stride is more likely to be followed by a stride of similar length. Decreased entropy means that subsequent strides are more regular and predictable. This regularity was significantly different for treadmill, as compared to overground, at speeds slower and faster than preferred.

Evidently the treadmill leads to reduced availability of dynamical degrees of freedom and therefore increased constraint. This interpretation is consistent with Jordan et al.[2,5,6], who interpreted increased long-term correlations at speeds slower and faster than preferred as indicative of increased constraint. That significantly decreased entropy indicates increased constraint is also consistent with previous research. For example, Borg & Laxåback[43] interpreted decreased entropy during a postural control task as increased constraint. As well, McGregor et al.[30] interpreted reduced entropy during slow and fast running as increased constraint.

The DFA results suggest that treadmill running is a source of environmental constraint. The MSE results permit a more specific suggestion that a combination of environmental and task factors, in this case, treadmill and speed, contribute to constraint during treadmill running at speeds higher and lower than preferred. In both cases, a loss of available dynamical degrees of freedom would provide fewer modes for a spinal pattern generator. There are several putative mechanical differences between overground and treadmill locomotion that may influence kinematic, kinetic, and muscle activation variables[17,23,44]. However, research is equivocal as to how these may lead to different levels of constraint between the two conditions and how this influences resultant motor output patterns that are required to execute the task within that specific environmental configuration. The most relevant possible changes include a higher cadence and lower stance time during treadmill walking, perhaps because individuals feel a greater sense of urgency to move their swing limb forward as the supporting limb is carried backward on the treadmill belt [24]. These altered gait mechanics may lead to a modification of afferent feedback. Any prolonged stride duration is likely to be corrected more rapidly, leading to: 1) a loss of long-term persistence in which particularly long duration strides are corrected in subsequent strides; and, 2) a loss of disorder (entropy), such that stride durations are more predictable from one stride to the next.

The agreement between afferent feedback and visual input may also influence operant constraints. The relationship between the two is "normal" during overground locomotion, but during treadmill running there may be a conflict between the forward speed that the eye sees and the speed that is sensed by the legs and feet[45]. Using treadmill walking simulations with virtual reality, Katsavelis et al.[46] found lower Approximate Entropy (ApEn) values and a higher α without a moving visual field (similar to normal treadmill locomotion) as compared

to with a moving visual field (similar to overground locomotion). These findings are consistent with the MSE results of the present study. According to Procop et al.[47], treadmill walking without optic flow is more stable than with optic flow. However, it was also concluded that alterations in visual flow primarily affect the stride length modulation of the individual, rather than the stride frequency. Thus, it may be that changes in stride temporal dynamics in the present study are unaffected by visual flow that would be different between treadmill and overground running.

The influence of the motor driving the treadmill belt is as yet unknown. The motor is consistently subjected to fluctuating forces and may not maintain a perfectly constant belt speed, which may affect stride timing[48]. Second, the mechanical compliance between the synthetic track surface and the treadmill belt is not the same. Wright et al.[49] showed that different walking surfaces can affect dynamic stability. Future research should investigate any influences posed by these mechanical aspects of the treadmill.

There are a few limitations to our study relevant to this discussion. First, familiarization and habituation of the subjects was not addressed. Subjects who are more familiar with fast treadmill running may be better able to deal with the mismatch between physical effort and visual stimuli during treadmill running. Second, although our time series were similar in length (>700 data points) to previous work[2,5,6], the size of dataset may influence the output values. Theoretical tests of the DFA-PSD relationship have used much longer datasets[38] but Crevecoeur et al.[32] showed that the agreement could be reliably shown with only 512 data points. A similar point may be made concerning the box sizes used in the DFA algorithm. Reported practices vary[2,5,6,8,50], but preliminary analysis in our lab indicated that for randomly shuffled datasets, a box size range of 4-N/4 generated scaling exponents

closest to the expected value of 0.5. Therefore, for purposes of comparing with the bulk of previous research[5,6], we selected 4 to N/4 for our analyses in the present study. Third, the size and shape of the running track may have influenced stride timing dynamics. Because the track was relatively small, there may have been some systematic changes to stride frequency at the curves, during which it is slightly more difficult to maintain speed. At present, there is no data regarding potential differences due to the size of the track.

In conclusion, we found that treadmill running resulted in increased strength of correlations across all speeds and more regular temporal stride dynamics compared to overground running at speeds slower and faster than preferred. These dynamics are indicative of a condition of higher constraint for treadmill running and a more regular temporal pattern for treadmill at higher and lower speeds. There is still general evidence for persistent correlations in all conditions of this study, perhaps due to underlying intrinsic gait rhythms. However, this underlying rhythm is likely influenced by the exercise setting, particularly due a combination of task and environmental constraints. These constraints may arise from interactions between mechanical, afferent, and visual phenomena. The resultant temporal patterns in the strides are indicative of the locomotor control system that operates to maintain a dynamic stability during running gait.

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Chapter 7

The entropy of stride timing dynamics is higher for strenuous running intervals compared to slower running but is not affected by accumulated distance

Abstract

Persistent correlations in stride timing are well established for running. Previous research suggests that these decrease non-monotonically over time in a bout of intense running. We aimed to confirm this in a series of high-intensity intermittent runs by applying several complementary nonlinear analyses. Ten trained runners completed two track sessions of 5×2000m. HI was at ~75% of peak incremental test speed, mean final rating of perceived exertion (RPE) = 16.8. LO was at < 75% maximum HR and < RPE 13 (mean speed = 56% of peak, mean final RPE = 11.1). Stride time series were generated from peak accelerations of each gait cycle, measured by foot-mounted accelerometers. We used detrended fluctuation analysis (DFA), power spectral density (PSD), multiscale entropy (MSE), and surrogate analysis. Outputs of nonlinear analyses were compared with an ANOVA. Most datasets showed DFA and PSD scaling exponents corresponding with significant statistical persistence (>3 SD from random). There were no intensity or interval effects for DFA or PSD ($p>0.05$). With MSE, HI had higher sample entropy across all scaling factors, compared with LO (1.77 vs. 1.71, $p<0.0001$). MSE was sensitive to intensity, but did not change with accumulated distance. Higher entropy suggests decreased order and decreased constraint. Evidently, organismic/physiological constraint changing with time and exertion exerted a minor influence compared to task/speed constraint, which was highest when subjects ran slower than preferred. A lack of a distance effect suggests that robust control is maintained for prolonged running at this range of intensities.

Introduction

The acute effect over time of strenuous exercise exerts profound influences on the kinematic and kinetic characteristics of running gait such as stride rate, stride length, joint angles, ground reaction force, EMG, and muscle fiber force generation capabilities[1–15]. The neuromuscular control system manages these aspects of gait in a coordinated fashion and alters them accordingly when one or more of these functions is compromised due to the effects of fatigue[4,5,10,14]. Movement is generally stable over long durations, but the finding of different gait characteristics before and after exercise, as well as at points in between, suggests that there is an alteration in neuromuscular control strategy associated with the progression of the exercise bout.

The dynamics of stride timing appears to exhibit an important aspect of movement control[16]. In healthy individuals, stride intervals are not perfectly constant, but, in fact, exhibit substantial variability. As with a multitude of natural phenomena, the inter-stride time series can be modeled as a persistent system containing long-term correlations that decay over time according to a power law[17,18]. In correlated systems, longer duration strides are more likely to be followed by longer duration strides, over multiple timescales, and vice versa. It has been argued that this variability is not an artifact of the measurement signal, but rather a characteristic of the system of interest and that higher variability is indicative of a robust and healthy system[19].

The nonlinear properties of running likely depend on task and environmental constraints that interact with the effects arising from the speed of movement[20–22]. Changes to the state of the individual occur with the accumulated duration of exercise at high intensities that is generally associated with terms such as fatigue and exhaustion. The overall (total-

body) severity of this stress is reflected in simple measures such as heart rate (HR) and rating of perceived exertion (RPE)[23]. This stress is thought to progressively alter the functional ability of neuromuscular mechanisms and therefore impose an organismic constraint[24] to movement that may in turn affect the persistent stride rhythm.

Muscle fatigue has been shown to influence the variability and timing of movements[25–27]. For example, Gates et al.[26] showed that statistical persistence of movement timing decreased with fatigue in a sawing motion task that required movement according to a metronome. However, to date, only one investigation has examined the effect of fatigue upon running stride dynamics. Meardon et al.[28] quantified statistical persistence in stride time series using detrended fluctuation analysis (DFA). The researchers analyzed data for each third duration of a run to exhaustion at 5 km race pace. They found that the DFA scaling exponent for the second section was significantly lower than the first, indicative of increased use of corrective strategies. However, the second scaling exponent was not significantly different from the third, indicating that this strategy did not increase further, as the run to exhaustion progressed.

The aforementioned study[28] applied only one nonlinear measure, but it has been argued by Crevecoeur et al.[29] that a "gold-standard" approach consisting of a more expansive list of analyses including multiscale entropy (MSE), DFA, and power spectral density (PSD) analyses be applied to assess long range correlations in physiological time series. Due to the paucity of data regarding nonlinear aspects of the effects of prolonged strenuous exercise on stride timing dynamics, we used this approach for running bouts at different intensities to investigate the effects of 1) intensity, and 2) the cumulative effects of high and low intensity over long durations on nonlinear measures of statistical persistence. To do this, we mounted a

small accelerometer on the top the running shoe and analyzed stride timing dynamics generated from low and high intensity running intervals performed by trained runners. We hypothesized that statistical persistence would decrease across intervals in the high intensity condition due to increasing organismic constraint (from increased exercise stress) present with each additional interval.

Methods

Subjects

Ten trained male distance runners participated in this study (mean ± SD age = 28.4 ± 9.0; height = 177.8 ± 6.7 cm; weight = 68.7 ± 6.6 kg). All subjects participated in regular distance running (≥4 times per week) for at least 2 years, performed at least 1 interval training session per week over the previous three months, during which at least 5000m was accumulated at 10 km race pace or faster. Subjects were capable of achieving a race time of 40 min for 10 km (or an equivalent performance). The average weekly running volume of the sample was 61.7 ± 19.2 km. Subject characteristics are presented in Table 1. Subjects were screened for any medical contraindications to participation using the Physical Activity Readiness Questionnaire (PAR-Q)[30]. Subjects were informed of potential risks and provided informed consent prior to participation. The protocols of this study were approved by the Research and Ethics Committee of the Faculty of Health Sciences at the University of Cape Town.

Table 1. Subject characteristics.

	Mean	SD	Range
Age (yr)	28.4	9.0	18-41
Height (m)	1.78	0.07	165-190
Weight (kg)	68.7	6.6	53.2-77.1
Peak treadmill running speed (km/h)*	21.4	0.7	20.5-23.0
VO_{2peak} (ml/kg/min)	67.0	2.1	64.4-71.0
Years' training (yr)	8.0	6.5	2-21
Weekly running volume (km)†	61.7	19.2	45-110

* during maximal incremental running test to exhaustion; † mean over previous 3 months.

Experimental protocol

This study included three sessions. A modified peak treadmill running speed test[31] was done in the first session. The second and third sessions involved the high and low intensity sessions, done in random order. All sessions were separated by at least 48 hours and subjects refrained from heavy exercise for 48 hours before each session. Sessions occurred at approximately the same time of day.

The incremental treadmill test began at 12 km/h and increased by 0.5 km/h every 30 seconds until volitional exhaustion[31]. Peak running speed was defined as the highest speed run for 30 seconds and VO_{2peak} was defined as the peak oxygen consumption occurring over a 30-second period. A fan was provided for thermal comfort.

To test for intensity and distance effects, we used an intermittent running protocol performed on a 141.4 m indoor athletics track. Subjects completed a 10 minute warm-up at self-selected pace, and were familiarized with the operation of the pacing lights around the

track. The pacing lights were illuminated in sequence and subjects followed these lights according to the speed set by the researcher. Subjects were also given time to perform their own chosen muscle stretches and any other desired warm-up activities. The high intensity session (HI) consisted of five 2000 m intervals at 70-80% of peak treadmill running speed, with 3 minutes rest between each interval. The low intensity session (LO) consisted of the same warm-up and intervals, but the intensity was limited to 75% of maximum HR and an RPE of 13. HR was monitored throughout the session using a wristwatch and chest strap (Polar Vantage XL, Polar Electro Oy, Kempele, Finland). RPE[23] was solicited immediately upon the completion of each interval. In the case of the LO session, the watch was set to beep if the HR limit was exceeded. Subjects were also instructed beforehand on the RPE limit, which was verbally checked periodically throughout the session by the experimenter to ensure that the maximum RPE was not exceeded.

Stride measurement

We mounted telemetric 3-D accelerometers mounted on the top of the running shoe (316-10G, Noraxon, Phoenix, AZ; mass ~ 20 g each). Data were captured at 2000 Hz by a device worn on the subject's lower back (TeleMyo 2400T G2 Telemetry System, Noraxon; mass ~ 535 g), and were subsequently exported for processing. Data were analyzed with custom-written software in a Matlab environment (Matlab R2009a, Mathworks, Natick, MA). Foot contact was identified with accelerations roughly corresponding to the vertical axis (the superior surface of the foot/shoe is not aligned perfectly with the global axes). We first applied a 4th order Butterworth filter to the raw acceleration data, with a band pass between 0.9 and 50 Hz[28]. Peak accelerations (threshold = 3 g) corresponding with heel strike were

identified and the stride time series were generated. Inter-stride durations greater than 2 SD from the mean (rare) were deemed erroneous and were omitted from the series.

Nonlinear analyses

Persistent correlations were quantified with the complementary analyses suggested by Crevecoeur et al.[29]: Hurst exponent, PSD, MSE, and surrogate generation, which are described briefly below.

DFA generates an estimate of the Hurst exponent[32,33] and is common in nonlinear analysis of stride time series, particularly because it is not sensitive to nonstationary processes[34]. DFA first integrates the time series and calculates the least squares trend for each set of non-overlapping boxes of a specified range[32,33]. The log of the average fluctuation around the trend for each box of size *n* (log F(*n*)) is plotted against the log of the box size (log *n*). Scaling exponent α is the slope of the linear trend. The DFA output quantifies behavior ranging from anti-persistent ($\alpha < 0.5$) to white noise ($\alpha = 0.5$), persistent ($\alpha > 0.5$), and Brownian motion ($\alpha = 1.5$). To aid interpretation, those original time series for which α was at least three SD away (i.e., $p<0.01$) from α_{mean} of the 20 surrogate data sets ($\alpha \sim 0.5$) were considered to be significantly different from random, possessing persistent properties[35].

PSD is the Fourier transform of the autocorrelation function. The PSD of datasets comprised of white noise demonstrates similar power over all frequencies, whereas functions containing significant memory scale according to $1/f^{\beta}$. This scaling behavior is considered to be the "hallmark" of complexity[36]. A log-log plot of power vs. frequency can be fitted according to a linear model, the slope of which provides an estimate of PSD scaling exponent β. We used the Welch method of calculating PSD[37]. α (or Hurst analysis) is related to the slope of the power spectral density (β), according to the equation:

$$\alpha=(1+\beta)/2 \quad (1)$$

Agreement between these two measures within distance $d < 1.0$ increases the confidence with which the series may be classified as possessing significant long-term correlations[38].

Entropy quantifies the level of system disorder. We applied MSE[39–41], which can distinguish between white noise processes and processes with long-term memory. The method calculates sample entropy (S_E)[42] for distinct series composed of first the original time series, then the mean of every two values, then the mean of every three values, etc. Through this coarse-graining procedure, we quantified entropy for scaling values 1 to 19, for pattern length *m* of 1 and similarity criterion *r* of 0.15[29]. With increasing scale, white noise processes demonstrate a monotonically decaying entropy, while long-term correlated processes demonstrate similar irregularly[29].

Hypothesis testing

Performance variables (HR, $\%HR_{max}$, and RPE) and measures of distributional variability of stride intervals (mean, SD, and CV%) were tested with a 2 (intensity) × 3 (interval) ANOVA.

To establish a significantly non-random structure of variability for DFA and PSD, we generated twenty randomly shuffled surrogate time series for each original dataset[18,35]. These surrogate series have identical length, mean, and variance as the original, but the order of data points is destroyed. The mean and SD of α and β were calculated for each group of twenty surrogate time series. DFA and PSD outputs for each original series values that were more than 3 SD away (i.e., outside 99% confidence interval) from the corresponding mean surrogate value were considered to be significantly different[35]. DFA and PSD outputs were compared using a 2 (intensity) × 3 (interval) ANOVA.

A non-random structure of variability for the MSE output was first established with original and surrogate data with a four-factor 4 (intensity) × 5 (interval) × 10 (scaling factor) × 2 (original or surrogate) ANOVA. To test the experimental hypothesis, the above ANOVA was run again on the original datasets only, without the surrogate factor. Statistical significance for all tests was set at $p<0.05$. In case of significant difference, a Bonferroni post hoc test was used to determine the source of the difference.

Results

Performance characteristics describing the intensity for each interval are presented in Table 2. Mean relative speed was 56 and 76% of peak treadmill running speed, for LO and HI, respectively. Mean RPE was from 10.2 to 11.1 for LO and from 14.5 to 16.8 for HI. Mean HR across all subjects reached 95.2% of HRmax for the fifth interval in HI. RPE, HR, and $\%HR_{max}$ values were significantly different between intensities ($p<0.0001$), but there were no significant effects due to interval. Tests on descriptive statistics (mean, SD, CV%) are presented in Table 3 and Figure 1. The mean stride interval was significantly lower in HI ($p<0.0001$). There were no significant effects or interactions over the five intervals for either condition.

Table 2. Performance characteristics of the easy and fast intervals.

	Interval									
	1		2		3		4		5	
Variable	LO	HI	LO	HI	LO	HI	LO	HI	LO	HI
Absolute speed (km/h)	12.0	16.2	11.8	16.2	11.7	16.2	11.6	16.2	12.0	16.2
Relative speed (%)*	56.4	76.0	55.1	76.0	54.7	76.0	54.4	76.0	55.9	76.0
HR (bpm)†	135.3	172.1	136.8	174.9	135.9	175.9	136.0	177.1	137.5	177.3
% HR_{max}†	72.6	92.4	73.4	93.9	72.9	94.4	73.0	95.1	73.8	95.2
RPE†	10.5	14.5	10.2	14.9	10.5	15.6	10.6	16.2	11.1	16.8

* percentage of running speed attained during the peak treadmill running speed test; † significantly different between intensity ($p<0.0001$).

Table 3. ANOVA results for measures of distributional variability, DFA, and PSD.

	Mean		SD		CV		DFA		PSD	
Effect	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*p*	*F*	*P*
Intensity*	48.47	<0.0001‡	5.09	0.0265‡	1.37	0.2243	0.45	0.506	1.01	0.3171
Interval†	0.11	0.9776	0.14	0.9655	0.15	0.9611	0.13	0.9691	0.47	0.7555
Intensity× interval†	0.1	0.9819	0.15	0.9627	0.18	0.9499	0.06	0.9934	0.33	0.8543

* F(1,90); †F(4,90); ‡*significant main effect.

Establishing a nonlinear structure of variability

We first sought to establish the presence of a structure of variability that is significantly different from randomly ordered datasets. DFA and PSD provided preliminary

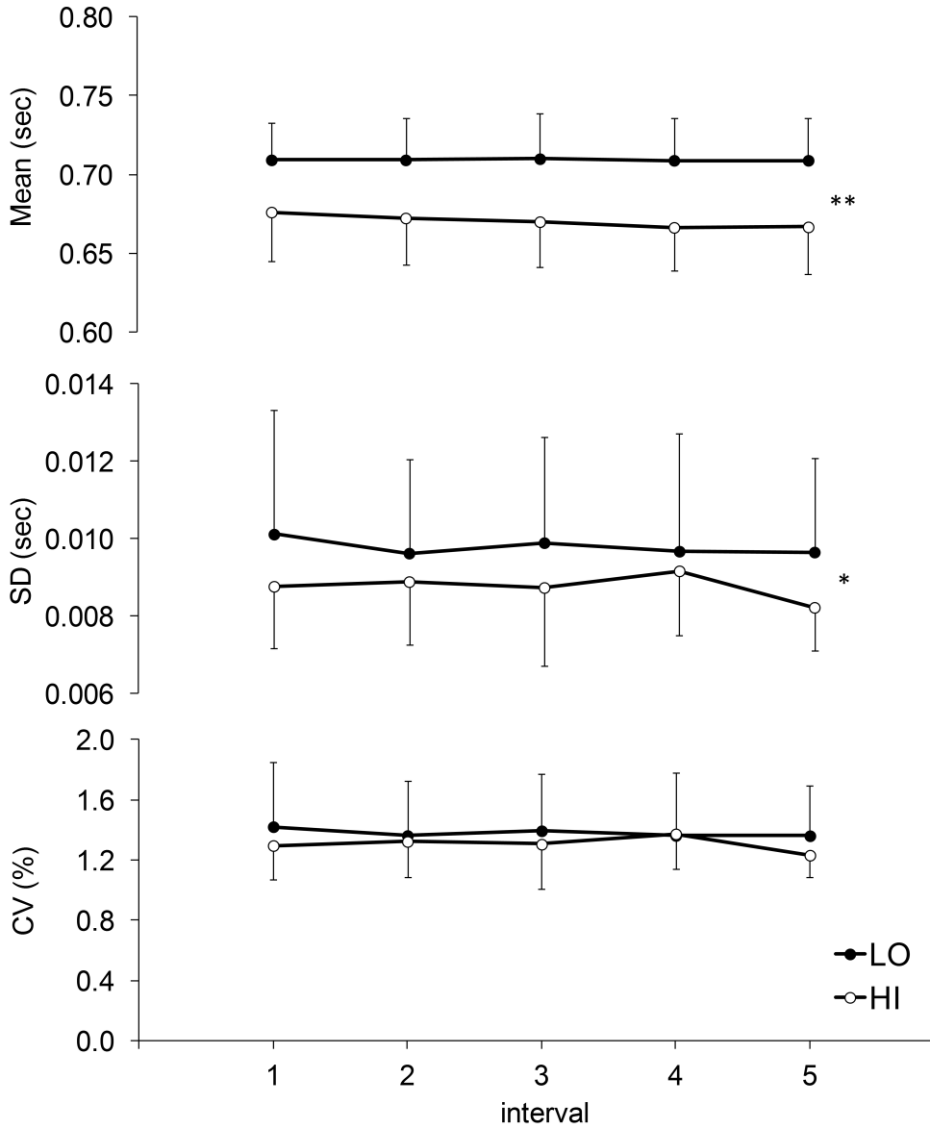

Figure 1. Descriptive statistics of the stride and step interval over the five intervals for each intensity: mean (top), standard deviation (middle), and coefficient of variation (bottom). **significant intensity effect ($p<0.0001$); *significant intensity effect ($p<0.05$).

confirmation of these findings. Of the 100 unique stride time series, 98 time series had α and β >3 SD from random ($\alpha = 0.5$, $\beta = 0$). α and β agreed according to equation (1) for 46 datasets. We also examined whether the MSE analysis was affected by random shuffling of the data sets. There was a significant shuffling effect, which interacted significantly with the intensity, interval, and scaling factor ($p<0.01$).

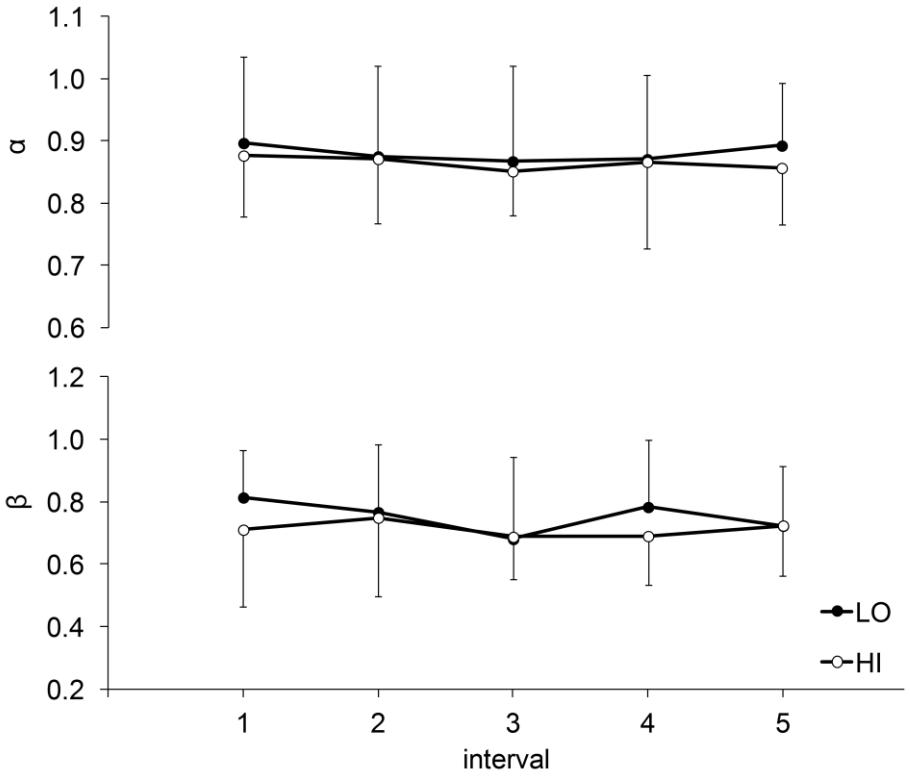

Figure 2. Results of DFA (top) and PSD (bottom) analysis. There were no significant effects at $p<0.05$.

Experimental hypothesis testing

There were no significant effects or interactions for DFA or PSD (Table 3 and Figure 2). Results for the MSE analysis are presented in Table 4. There were significant main effects due to intensity and scaling factor ($p<0.0001$). There was also a significant intensity × interval ($p=0.0001$) and intensity × scaling factor ($p=0.0057$) interaction. A post hoc test indicated that mean S_E was significantly lower for the LO condition at the third interval ($p<0.05$). Figure 3 presents the data to highlight the effects of intensity and interval, and the interaction between the two. Figure 4 depicts the $S_{E,}$ interval, and scaling factor data in three dimensions.

Table 4. ANOVA results for MSE.

Main effect or interaction	*F*	*p*
Intensity[a]	18.22	<0.0001[e]
Interval[b]	1.38	0.2404
Scaling factor[c]	98.29	<0.0001[e]
Intensity × interval[b]	5.76	0.0001[e]
Intensity × scaling factor[c]	2.61	0.0057[e]
Interval × scaling factor[d]	0.42	0.999

[a]F(1,936); [b]F(4,936); [c]F(9,936); [d]F(36,936); [e]significant effect or interaction.

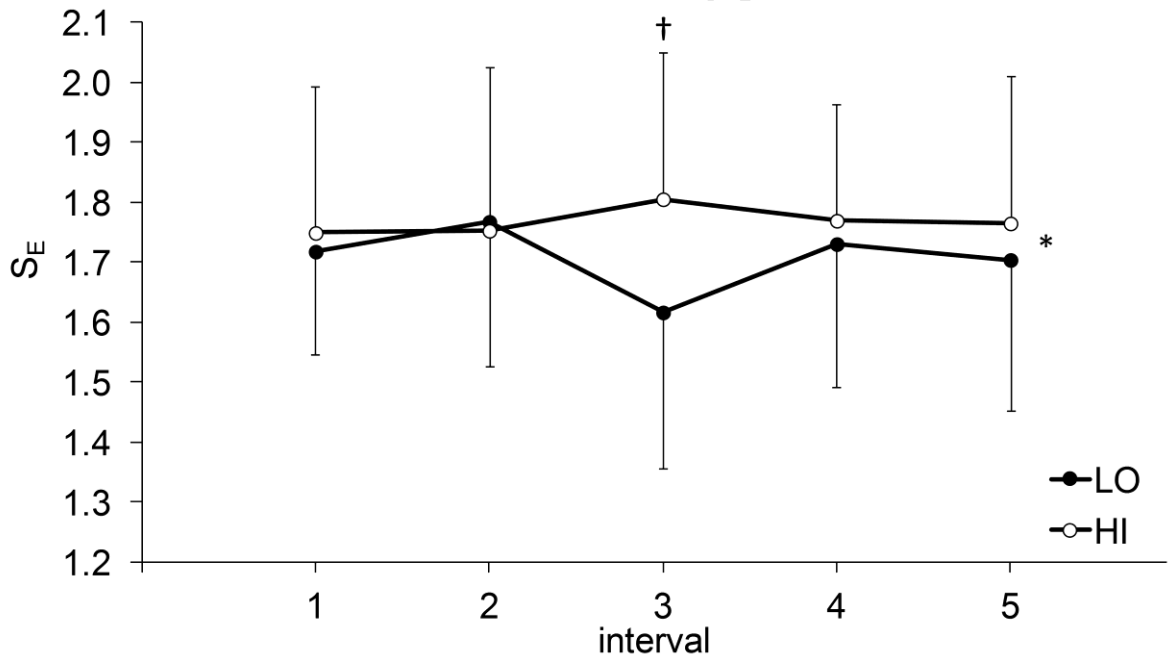

Figure 3. Results of MSE analysis that demonstrate the intensity and intensity × interval effects. The mean S_E across all scaling factors is presented for each intensity and interval. *significant intensity effect ($p<0.0001$). †significantly different between intensities at that interval ($p<0.05$).

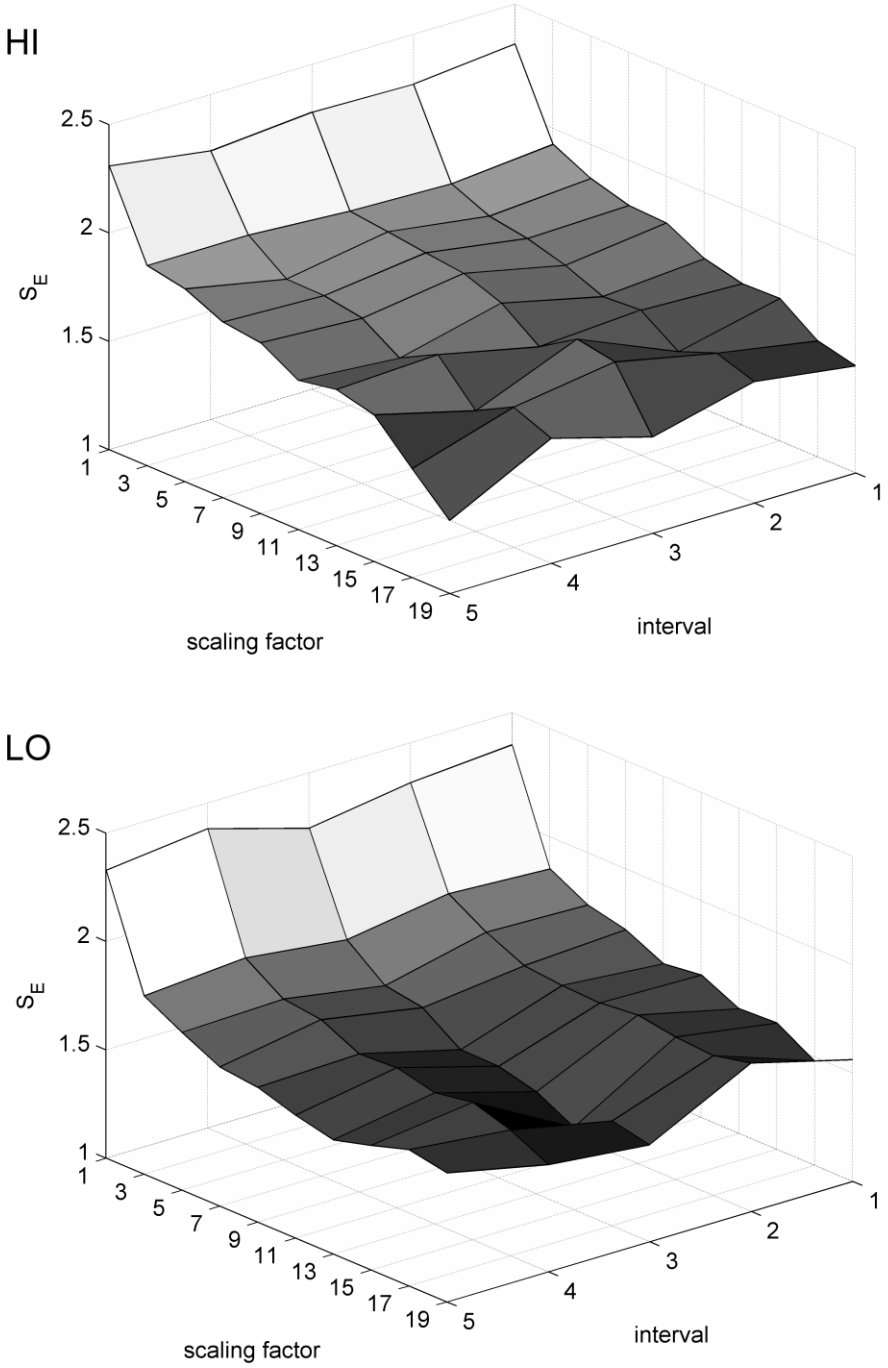

Figure 4. MSE analysis for high (top) and low intensity (bottom). Note that the interval axis increases from right to left. The mean S_E value for each scaling factor is presented for each intensity and interval.

Discussion

The primary finding of this study was that MSE analysis identified speed-associated alterations in the dynamics of stride interval timing. Specifically, results indicated lower overall entropy with low intensity running, indicative of increased regularity and therefore a more predictable sequence of stride patterns. That there was only an intensity effect and no interval effect suggests that the constraints on nonlinear stride dynamics are affected by the kinematic requirements to maintain a set absolute running speed (task-associated constraint), rather than by influences due to accumulated physiological or neural stress (organismic constraint) .

Decreased statistical entropy is generally associated with increased system constraint[43]. Because there was no significant intensity×interval interaction, though, we interpret that constraints of stride timing dynamics arise due to the speed of running *per se*, and not the changes in physiological milieu, accelerated cardiovascular function, altered muscle fiber function, and increased RPE that commonly signal the progression of fatigue. Thus, the timing of strides was more predictable and ordered in LO, and less predictable and more disordered in HI. There were some significant differences in mean entropy between some of the intervals for the LO condition (intensity×interval interaction), but the first and fifth interval were not significantly different from each other. Thus, there does not appear to be any constraining influence from the accumulation of running distance at this intensity.

The above evidence points to a model in which increasing organismic or physiological contributions to constraint exert a relatively minor influence, if any, on gait timing dynamics. Since entropy was lower in the LO condition, constraints were apparently the highest when subjects were required to run at a low intensity. To ensure a low relative intensity for each

subject we instructed the subjects to not exceed an RPE of 13 or a HR over 75% of their HR_{max}. Table 2 confirms that the group as a whole ran within this limitation. Our limiting of the running speed in this manner was designed so that there would be minimal fatigue development due to metabolite accumulation, prolonged high perceived exertion, or extreme musculoskeletal stress. Anecdotally, many subjects indicated that they felt they needed to hold back and that this imposed running intensity was lower than what they would normally choose. Thus, the speed was below the "preferred speed" that has been used in previous research[20,21,44] and at which some have reported a minimum in persistent correlations[20,21]. Constraint is thought to increase at speeds faster and slower than preferred, where there are fewer available dynamical degrees of freedom[20]. Evidently, the increased constraint elicited by the requirement of low intensity was greater than the constraint elicited by the high intensity.

Our results differ in some ways to other roughly similar study designs that have used different analyses. Le Bris et al.[10] had subjects run to exhaustion at maximal aerobic speed. Strides were less regular at the end, as compared to the beginning of the running test, based on an autocorrelation-related measure of regularity. The most similar study to ours was conducted by Meardon et al.[28], who demonstrated a decreased α from 1/3 to 2/3 of the duration of running at about 5000 m time trial pace. However, α did not change from the second to the last third of the duration when, presumably fatigue would be the greatest. Subjects ran at a faster speed in the study of Meardon et al.[28], but the subjects in the current study ran farther and longer, albeit intermittently. Both studies are similar in that there was no change in statistical persistence during the portion of exercise in which there was the greatest fatigue.

Changes in motor coordination have been suggested to be a way to deal with developing muscle fatigue[45]. For example, Yoshino et al.[46] showed that prolonged walking elicits local muscle fatigue in the tibialis anterior, followed by gait rhythm instability (measured by Lyapunov exponent), and a consequent slowing of gait to compensate for the instability. However, the results of the current study suggest that not all movement variables will show fatigue-associated alterations. Indeed, the consistent temporal structure over five 2000 m intervals, whether at a high or low running intensity indicates stable kinematic patterns even though it would be assumed that changes in neuromuscular function over the course of the bout would be greater at high intensity. Some support for this consistency comes from Chapman et al.[47], who reported that triathletes who cycled for 20 min prior to a 30 min run preserved their running kinematic patterns, even though the muscle activity of the tibialis anterior was altered. It was suggested that redundancy in the motor control system allows kinematic processes (output) to be maintained despite evident alterations in muscle activity. The stability of muscular output during fatiguing running has also been shown by Cottin et al.[48], who found that variations in velocity (measured every 20 m) did not change with accumulated distance run at 90% the velocity at VO_{2max}. Thus, it is possible that despite biological stress during fatiguing exercise, muscle activation patterns are preserved so that athletes may maintain a given motor program in their movements, perhaps by adopting a scaled template to maintain coordinated movement where performance is impaired[49,50].

Another argument in favor of maintained persistence of movement patterns in the face of encroaching fatigue is also plausible because the perception of fatigue has been shown to be disassociated from gait variability. Morris et al.[51] reported that multiple sclerosis patients demonstrated that subjective rating of fatigue did not relate to gait variability, suggesting that

the mechanisms relating to neuromuscular control are separate from those that regulate perceived fatigue. Some aspects of the neuromuscular control of gait, such as the maintenance of gait rhythms might originate from central pattern generators (CPG)[52]. Putative stimuli thought to elicit this motor response and contribute to pattern generation includes muscle stretching, electrostimulation of the peripheral nerve afferents, and cutaneous stimulation, perhaps arising in the lumbar-sacral network[52,53]. The continuously present afferent feedback during running may provide the requisite stimulation for this mechanism to maintain coordination throughout an entire bout of running.

It is possible that a higher intensity is necessary to observe alterations in movement patterns over time or distance. Although this study involved extensive running at what would be considered a high intensity, which elicited high RPE values at the end, the intensity was still low enough to allow the accumulation of about 40 min of running. Although we didn't test for muscular fatigue with approaches such as examining the Fourier transform of EMG[54], or other nonlinear methods[55,56], RPE provided a simple alternative and average values for the fifth interval were above the "very hard" verbal anchor. It is also possible that the rest period between each interval was sufficient to recover from any internal source of constraint that potentially affects nonlinear dynamics. Thus, continuous running may be required to elicit measureable changes with accumulation of distance. Nevertheless, we have recently found that control entropy[43] is stable over the course of a 10 km time trial with university cross-country runners (unpublished results), so there is some support for the finding of consistent dynamics over time.

In summary, this study demonstrated the sensitivity of MSE to changes in nonlinear dynamics arising from running speed, with lower entropy at a lower running intensity. This is

consistent with the notion of increased constraint during the slower condition, likely because of the limits to intensity imposed upon the subjects. Consistent with findings from the last third of a high intensity running bout[28], we did not find evidence of increased constraint with the accumulation of prolonged stressful running. Rather, the nonlinear dynamics of stride timing were maintained over the 10 km of running at each intensity. We suggest, therefore, that slow running leads to significantly lower entropy in stride interval timing. This leads to the conclusion that the task parameters can be a more significant source of constraint than the physiological and neural status of the body during stressful exercise. The apparent stability of movement patterns provides evidence that the operant motor control system is robust during conditions of prolonged running at this range of intensities, and reflects adjustment to the task itself, not the acute neurophysiological changes associated with strenuous intermittent running.

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Chapter 8

Summary and conclusions

This dissertation employed a nonlinear dynamical systems approach to the analysis of the behavior of stride time series in running exercise performed under various experimental interventions. Study 1 investigated the effect of running speed on the dynamics of stride time series during treadmill running. Study 2 compared these dynamics between treadmill and overground running. Study 3 investigated the effect of 10 km of strenuous intermittent running on these dynamics.

These three experimental interventions fit with the task-organism-environment model of constraints, proposed by Newell[1]. According to this model, the various influences upon coordination exert a constraint (but not strict control) upon coordinated movement patterns. Running gait requires the organization of a large number of dynamical degrees of freedom. In addition to spatial patterns of movement, some organization must also occur with regard to timing. The stride time series is considered to be an output variable that can indicate the nature of control employed by the locomotor control system. Explanations of behavior often are biased towards the organism and fail to consider the relationship between the individual and the exercise environment.[2] However, to study a biological system in isolation of its environment betrays the holistic model of Newell[1]. Instead, physical behavior must be studied in light of the status of the individual, the task being performed, and the environmental setting of that task. Accordingly, a complete description of the system extends beyond the person performing the task and includes a multitude of sources of constraint from the task, organism, and environment[3].

In brief, our experiments confirm statistical persistence as the normal behavior present in running stride time series in several conditions. We also showed that: 1) higher treadmill running speeds are more constrained, 2) overground running is more constrained than

treadmill, particularly at speeds slower and faster than preferred, and 3) constraint doesn't change over a series of strenuous track running intervals. These findings are reviewed in more detail below.

Novel findings

Nonlinear analysis demonstrates a speed effect upon the entropy of stride time series

Study 1 applied a comprehensive set of analyses to treadmill running at 40-90% of peak treadmill running speed. The range of speeds included perhaps that highest relative intensity possible given the data set length requirements of the DFA algorithm. Previous research demonstrated a U-shaped relationship between the scaling exponent and running speed. The present study did not confirm this relationship with DFA or PSD measures but did demonstrate decreased entropy at the two highest speeds with MSE measures. MSE had not yet been applied to this research question. Thus, there is the novel finding that MSE may be sensitive to changes where other measures such as DFA and PSD are not. The reduced sample entropy values across all time scales is consistent with the presence of a neuromuscular constraint during treadmill running that points to stress arising from the physiological intensity or skill requirements for running on a treadmill at high speeds. Given anecdotal evidence regarding the challenges of intense running on a treadmill, a logical next question is whether this effect is also present during overground running.

Treadmill running is more constrained than overground running, particularly at speeds slower and faster than preferred

Study 2 investigated possible differences between treadmill and overground (indoor) track running at 80, 100, and 120% of preferred running speed. DFA demonstrated an increased strength of correlations for treadmill running and MSE demonstrated increased regularity for treadmill, as compared to overground, at speeds slower and faster than preferred. These findings, consistent with each other point to the interpretation of increased constraint arising from a combination of treadmill-associated environmental constraint and speed-associated task constraint. This confirms the results found for study 1 (chapter 5) and also by Jordan et al.[4,5] This seems to demonstrate that the challenge of treadmill running is greater when the speed is high. This may be due to visual, afferent, or kinematic changes in that condition that add to the challenge. Previous studies investigating the differences between treadmill and overground walking indicate different dynamical stability (Lyapunov exponent) but no differences in the output of DFA or PSD analysis. The present study indicates that treadmill running is subject to challenges not present with walking exercise.

When testing running gait dynamics, the treadmill should be considered to be a unique environment for locomotion that may not reflect overground in every way. Indeed, the treadmill as environment modifies the task of running by confining movement to a specific space. Thus the two sources of constraint interact. To the extent that this interaction poses a psychological and physiological challenge, organismic sources of constraint must also be seen to be involved. Accordingly, it is necessary to recognize the limitations of treadmill testing, particularly if the subject sample is more likely to engage in overground rather than treadmill running.

Maintained stride timing dynamics throughout 10 km of high intensity running intervals

Study 3 investigated dynamical changes occurring over the course of five 2000m track running intervals. Results indicated no differences in the DFA, PSD, and MSE outputs across the five intervals. However, there were significant differences in the MSE values between the high intensity running speed and the control condition run at an easy pace. This points first to the notion that individuals in this study were able to maintain dynamically similar locomotor control despite accumulating 10 km of high intensity running. Second, it indicates again the possibility that MSE is a more sensitive measure of dynamical changes in stride time series due to speed, as compared to DFA and PSD analyses.

Additional main findings

Confirmation of statistical persistence in a variety of conditions

In addition to the differences between conditions found in some cases, and no differences found in other cases, the three studies of this dissertation also confirmed the general presence of 1/*f*-like scaling in almost all stride time series. Using the complementary approach suggested by Crevecoeur et al.[6], we employed three analyses that together serve to confirm and strengthen the conclusion of the general class of dynamics shown in stride time series. In every study, a high percentage of time series showed dynamics that were significantly different from random. As well, a good agreement between the DFA and PSD scaling exponents was often found. Although the percentage of time series for which this agreement was found according to the requirements proposed by Crevecoeur et al.[6] did not include all time series; this may be because the data sets were often shorter than the lengths

used to demonstrate theoretical relationships and simulation studies. This is often an inevitable aspect of applied research, especially when investigating the dynamics of high intensity exercise that cannot be performed long enough to generate data sets of "theoretically desirable" lengths. Nevertheless, we have performed experiments that share many of the design specifications published previously, and our data set lengths are within the ranges proposed previously[6,7].

Use of foot-mounted accelerometry to generate stride time series

This dissertation also employed a novel accelerometry method to generate the stride time series. Previous work has used footswitches, force plates, and GPS technology. We selected shoe-mounted accelerometers because they are not subject to any direct impact during running, are portable, and able to measure with a high capture rate. We believe this combination of characteristics is ideal for research applications that necessarily must include field measurement. The raw accelerometer data required only a simple analysis to generate the stride time series. Our findings showed similar outputs from the nonlinear analyses to data previously published using other methods of data collection. This work establishes the utility of foot-mounted accelerometers in this sub-discipline.

Proposed model of neuromuscular function, performance, and pacing during running exercise in different contexts

Taken together, our findings first confirm that normal running dynamics include long-term correlations. The strength of these correlations may be modified according to various experimental interventions, but this did not represent a change in dynamical classification in our experiments (such as dynamics found for metronomic walking or patients with

neurodegenerative diseases). Rather, results indicated a relatively slight, but significant change representing an alteration of the strength of persistent correlations. This is consistent with the available data regarding the stride dynamics of healthy individuals and shows that this dynamical behavior is ubiquitous in many locomotor tasks and settings.

Our data indicate that running speed is a major influence upon dynamics. In all three studies, there was a significant effect due to speed. In the first study, this occurred only for fast speeds, and not slow (significant effects have been shown for slow running in previous research). In the second study, this effect emerged for treadmill running at speeds slower and faster than preferred. In the third study, this distinguished easy from high intensity running, and in this case easy running was evidently more constrained because subjects had to "hold back".

In cases where constraint increased during faster running, we take this to mean that although athletes may find it quite challenging to perform the task of running when constrained by a treadmill environment or higher levels of physiological stress, they are still able to perform this task. Constraints influence the selected pattern of coordination and control[3]. The alteration of dynamics in these certain situations, then, seems to indicate the level of effort or intensity of control, but not the *failure* of the individual to coordinate movement in that task and setting. This confirms the findings of Jordan et al.[4,5] regarding the output of DFA, and the work of McGregor et al.[8]. In these studies, changes in dynamics in the direction of tighter control were interpreted as increased constraint.

In our studies, we apply the same framework to make the following statements: First, our subjects, when faced with the challenge of treadmill running at a physiologically challenging speed exerted a higher level of control due to the environmental constraint of the

treadmill. Lower entropy values indicate that the timing for each stride is more regular and predictable. This likely arises because the environment defines the region of movement and therefore the task in such a way that there is reduced availability of dynamical degrees of freedom. The constant feedback from multiple afferent sources allows the provides the individual with continuous updates on the success of the task execution. This allowed them to continue running in roughly the center of the belt (i.e., not falling off). Second, this same situation was evidently present in the second study when athletes presumably demonstrated an increased level of control from normal to fast treadmill running, but not from normal to fast overground running. The former case was evidently challenging, again because of the physical constraint of the treadmill. In the latter case, however, there was no danger of falling, and thus, there were no significant dynamical differences between the different speeds. Finally, even the presence of significant physiological strain, brought about by 10 km of high intensity running intervals was not sufficient to elicit dynamical changes. Since the speed and environmental constraints were consistent between each interval, it would make sense that the dynamics also remained consistent. Only the differences between the easy and fast running speeds in this protocol led to measureable differences in long-term correlations and in this situation, it was the easy running speeds that elicited more constrained dynamical behavior, likely because the prescribed speed was lower than the subjects would prefer.

Future research

Because of anticipated technological advances in the next few decades, we expect that it will be possible to measure gait variables (particularly those associated with timing, rather than spatial dynamics) in real time and with the smallest of interference to the exercising

individual, thus maintaining a high level of ecological validity. This technology will permit measurement of many gait characteristics in a many task and environmental scenarios.

This dissertation leads to several future research questions. First, there is a requirement to separate fully the influence of physiological strain and the difficulty of performing the movement *per se* of running exercise. That is, there is a need to separate considerations of bioenergetics from considerations of how to manage the dynamical degrees of freedom to form a coordinated movement output (Bernstein's problem). This will likely involve interventions that account for the conscious and voluntary effort given to movement as well as the decrement in autonomic functioning that occurs due to neuromuscular or bioenergetic decrements in performance ability due to exercise stress.

Second, whereas both overground and treadmill running represent individual performance, there is another research question involving the investigation of overground running in a group. It may be that gait timing becomes synchronized among the members of the group, much in the same way that synchronized clapping can occur in the concert hall[9]. It is unknown what sort of environmental constraint is caused by group running, and how this should be interpreted within the task-organism-environment relationship. Given the numerous studies to be found on the interaction dynamics of individuals in team sports settings, there is potential to apply this to endurance sports performed in group situations such as following a designated pacer or running while in a large pack. Results would illuminate additional considerations of constraint and the challenges (or performance) benefits when movement is undertaken in these other situations.

Third, given the difficulty with which fatigue is denominated and quantified, there is a need to investigate fully effects in various situations when exercise is used to induce acute

impairments to performance. Unfortunately, because nonlinear analyses require a minimal number of data points, enough running strides cannot be accumulated in bouts lasting less than approximately 3-4 minutes. However, some alternative analyses may be performed using continuous accelerometer or joint angle data, and thus provide a suitable alternative to a time series describing a series of discrete events. As well, there may be a fine level of difference between high intensity exercise done at slightly different intensities. For example, study 3 had subjects perform intermittent running at approximately 10km race pace, whereas subjects in the study of Meardon et al.[10] ran for about 6km in an exhaustive run. It is yet unknown whether the differences between these intensities are large enough to elicit different timing dynamics between the two protocols.

The ability to maintain coordination despite the presence of significant exercise stress may be natural output of an adult neuromuscular system since gait does not commonly become uncoordinated near the termination of exercise[11]. On the other hand, the subjects our study were all trained at high intensity distance running and could have demonstrated an enhanced ability to maintain coordination throughout the entire high intensity protocol. This has some precedent in the literature – a study on the differences between trained and untrained runners reported a lower DFA α (p=0.055) for trained runners. However, there has not yet been a study on the differences in the stride dynamics of trained and untrained individuals during a fatiguing/strenuous bout of running.

Finally, there is a growing need to consider distance running as a task that requires the execution of movement skill and not just bioenergetic ability. The subjects of the studies in this dissertation were all trained as distance runners. Although level of experience with treadmill running was not assessed in these studies, most athletes were quite comfortable with

treadmill running. It would be useful to study the dynamical behavior of individuals who are learning how to walk or run on a treadmill.

Conclusion

In conclusion, we demonstrate ubiquitous long-term persistence in stride time series in a variety of settings. The strength of these correlations is sensitive to speed, and this was particularly well identified by entropy measures. The alterations apparently indicate the operation of a neural control system that maintains a high level of consistency over time. Slight but significant alterations in the level of these correlations indicate a robust regime of control that is sufficient to maintain coordination in stressful task-environment combinations. Nonlinear dynamics evidently demonstrate something of the natural output and mechanisms of human neuromechanical control organized over multiple time scales. This dynamical behavior is necessary for the multitude of sub-systems involved in the control. As consistent as this control is over long durations, there are subtle changes that indicate varying levels of response to constraint that arises in different situations. Nonlinear dynamical analysis highlights overarching functional behavior that cannot be properly described using linear or reductionist methods. The application of such analyses in the field of exercise science should lead to some novel insights that are holistic and able to describe the many facets of human biological function during exercise tasks.

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