# CHANGES IN RUNNING GAIT COMPLEXITY DURING A CROSS-COUNTRY SEASON IN COLLEGIATE RUNNERS

Jacob E. Vollmar

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

Master of Science

in the School of Public Health

Indiana University

Accepted by the Graduate Faculty, Indiana University,

in partial fulfillment of the requirements for the degree of Master of Science

Master's Thesis Committee

_____

Allison H. Gruber, PhD

Chairperson

_____

Robert F. Chapman, PhD

_____

Georgia C. Frey, PhD

_____

Max R. Paquette, PhD

**Abstract**

Center of mass (COM) acceleration complexity has been shown to decrease during a single fatiguing run. However, no studies have investigated how COM acceleration complexity changes over the course of a running training program and before the onset of a running related overuse injury (RROI). The purpose of the present study was to observe if the COM acceleration complexity of collegiate cross-country athletes over the course of their season training changed prior onset of a RROI. Thirty athletes wore a triaxial, research grade accelerometer secured over the posterior aspect of their pelvis during all continuous training runs. The accelerometers were worn for the entire cross-country season. Participants completed a daily online survey to report any musculoskeletal pain or injuries. An RROI was assessed by a trainer and defined as any musculoskeletal pain or problem that resulted in a reduction or stoppage of normal training. Control entropy (CE) analysis was used to assess the complexity of the resultant COM acceleration collected by the wearable accelerometer. Participants who developed a RROI and matched (by gender and age) uninjured controls were compared. Seven participants developed a RROI. No change in COM acceleration complexity was seen prior to the diagnosed RROI ($p$ = 0.64). The unchanged COM acceleration complexity may be explained by similar training workloads between start of the season and immediately prior to RROI onset ($p$ = 0.20).

TABLE OF CONTENTS

# CHAPTER I

# INTRODUCTION

Annual healthcare costs totaled $1.05 trillion over the past decade, with physically inactive adults paying $1,437 more per year in healthcare than physically active adults (Carlson et al., 2015). Running is an excellent way to become and remain physically active as it is easily modifiable to accommodate varying degrees of skill, has a low equipment cost, and can be either a social or individual activity. However, the risk of developing a running related overuse injury (RROI) is much greater than all other exercise-related injuries and risk is particularly high in novice runners (Requa et al., 1993, Vidabaek et al., 2015). RROI is a major concern because it can leave an individual unable to run, cause a loss in the desire to run, or loss in desire to be physically active all together. Between 26.0% and 92.4% of runners will experience a RROI each year (van Gent et al., 2007). Out of runners who experience a RROI, around half will stop running for at least one year and others may stop running or being physically active permanently (Fields et al., 2010). In order for running to be a successful tool to increase physical activity and health benefits while reducing healthcare costs, the risk of developing RROI must be reduced.

A current strategy proposed to reduce RROI risk is to target the gait characteristics identified previously to be intrinsic risk factors for RROI development (Duffey et al., 2000). The identification of these gait characteristics, such as excessive rearfoot eversion and knee abduction moments, has led to the development of gait retraining. Gait retraining aims to alter identified internal risk factors as a means to manipulate gait to a more favorable pattern (Cheung et al., 2011; Noehren et al., 2011). Gait training requires a biomechanical assessment to determine which gait characteristics should be targeted, requires a clinician or researcher to

instruct and oversee the gait retraining, and is most commonly utilized only after a runner has suffered a RROI. This form of treatment also involves changing a runner's "habitual movement pattern", which is the running form an individual has developed because of their specific anatomy. A deviation from the habitual movement pattern may result in irregular tissue stresses and could result in injury (Nigg, 2001). Therefore, gait retraining is subject specific, time-consuming, and more research is needed to clarify its effectiveness as a treatment for RROI (Heiderscheit, 2011).

An alternative to targeting internal risk factors of RROI through gait retraining is to focus on the foremost extrinsic risk factors which include: excessive weekly running mileage (Rauh, 2014), duration of a single run (Hespanhol Junior et al., 2013), running experience (Macera et al., 1989), and training intensity (Bovens et al., 1989). Progressive overload training is required to stress the body to stimulate the physiological processes to increase fitness and performance. However, overtraining occurs when repeated stresses occur without proper rest periods and leads to chronic detriments in performance (Kreher and Schwartz, 2012). Training volume and intensity (i.e. workload) that surpass a runner's fitness level and ability are major contributors to RROI (Videbaek et al., 2015) and strong correlations have been observed between increased running exposure and increased overuse injury incidence (Martinez-Silvan et al., 2017). While there are many running programs available for differing ability levels, runners are unique in the sense that two runners with the same skill or ability may not respond to a workload in the same way. That is, one runner may become injured while the other suffers no problems.

To prevent rather than simply treat RROI, a detection measure is needed to identify changes in running gait prior to the onset of an injury. Dynamical systems theory suggests that human movement is comprised of many co-dependent sub-systems, such as respiratory,

skeletomuscular, and nervous, that each contain their own continuously interacting sub-systems. Co-dependence between systems makes human movement both dynamic and complex (Glazier et al., 2003). Human movement that allows for more variability between sub-systems is thought to be more complex, more flexible, and more adaptive than movement with less variability (Glazier et al., 2003). When an individual's movement experiences a decrease in variability between sub-systems it becomes less adaptable and the individual may be at a greater risk of becoming injured (Hamill et al., 1999).

Statistical entropy are a classification of techniques used to measure the complexity of a physiological signal. Physiological signals that are more complex will have greater entropy values than less complex signals. The complexity of a signal is thought to represent the interactions between sub-systems that control movement. High entropy indicates that the sub-systems can respond to more input-variables, believed to be a characteristic of healthy systems with a higher adaptive capacity (Costa et al., 2002). Entropy analysis has been used to distinguish between populations and conditions such as young adults verses healthy and unhealthy older adults (Costa et al., 2002), trained and untrained runners (Parshad et al., 2012), and has been shown to decreases sharply just before a runner indicates that they are exhausted during a single fatiguing run (McGregor et al., 2009). Therefore, entropy analysis is a sensitive parameter to identify different states or conditions that could not be identified from comparing traditional variables, such as ankle pronation or foot-ground impact.

The relationship of overtraining with an increased risk of developing RROI is becoming well established. However, signs of overtraining often present too late to prevent injury development. We also tend to rely on self-reported fatigue levels, which are susceptible to bias. Therefore, a more objective tool to monitor fatigue would be beneficial. It is currently unknown

how running gait biomechanics change following a running training program, which could be thought of as a cumulative development of biological fatigue. An increase in running skill has been shown to increase center of mass complexity (Parshad et al., 2012). To better study the effects of a running training program on center of mass complexity it is beneficial to study collegiate cross-country runners who are less likely to undergo an increase in running skill during the running training program compared to a novice runner population. Previous studies have examined how the complexity of the center of mass acceleration signal changes in response to a single fatiguing run (McGregor et al., 2009, Parshad et al., 2012). However, no studies have used control entropy to examine how the complexity of the center of mass signal changes during a collegiate cross-country season.

### *Statement of the Problem*

RROI is a problem that has been shown to lead to physical inactivity (Fields et al., 2010) and increased healthcare costs (Carlson et al., 2015). Many studies have looked at kinematic and kinetics risk factors for RROI, however identifying which internal factors or combination of factors to target is difficult because two individuals can have a different response to the same intervention (Heiderscheit, 2011). Excessive running exposure, leading to excessive fatigue and overtraining, was shown to be strongly correlated with increased RROI incidence (Martinez-Silvan et al., 2017). During the cross-country season, collegiate cross-country runners adhere to a rigorous training program that similarly increases their running exposure from the off-season. Cross-country runners are also less likely to experience an increase in running skill in response to a running training program when compared to novice runners. Currently, no studies have investigated how the complexity of the center of mass motion changes in response to a collegiate

cross-country running training program and if complexity can be used to predict the onset of a RROI.

### *Purpose of the Study*

The purpose of this study was to determine if the complexity of the center of mass acceleration signal in collegiate cross-country runners decreased before reporting the onset of a RROI. The participants followed the same prescribed seasonal running training program and completed daily surveys to track the potential development of a RROI.

### *Specific Aim and Hypothesis*

**Specific Aim #1:** To determine if the complexity of the center of mass acceleration signal changed in collegiate runners before reporting the onset of a RROI.

Hypothesis #1: The complexity of the center of mass acceleration signal of collegiate runners will decrease before reporting the onset of a RROI.

### *Significance*

During the cross-country season, collegiate runners increase their workload and risk developing a RROI in an effort to increase performance. It is not adequately understood how the complexity of the center of mass acceleration signal changes in response to a collegiate cross-country running training program. A decrease in center of mass complexity just before a subject indicates exhaustion and lower center of mass complexity in unhealthy signals compared with healthy signals, suggest that changes in center of mass complexity could indicate when running training volume and intensity become excessive. If the complexity of the center of mass

continues to decrease in response to a running training program, the complexity measure could be used as a simple, noninvasive tool to monitor overtraining to prevent RROI and maintain physical activity.

### *Delimitations*

1. Subjects are healthy collegiate runners.
2. Adherence will be monitored by a coach, daily injury survey and a wearable tri-axial accelerometer.
3. Center of mass acceleration signal is representative of the coordinated motion of all body segments.

### *Limitations*

1. The results can only be generalized to collegiate runners.
2. Only studied one cross-country team with one training schedule.
3. Relatively small sample size.
4. Accelerometer only worn during easy and long runs.

### *Assumptions*

1. Subjects in this study are representative of collegiate distance runners.
2. Wearable tri-axial accelerometer placement will not affect running gait.
3. A decrease in control entropy values represents an overtaxed running gait.

## *Definition of Terms*

- *Control entropy:* statistical analysis that assesses the complexity of a physiological signal (Costa et al., 2002).

# CHAPTER II

# REVIEW OF LITERATURE

This study seeks to determine how the complexity of the center of mass acceleration signal in collegiate runners' changes over the course of a cross-country season and is related to onset of RROI. Center of mass complexity can be measured using a statistical entropy technique, like control entropy, and could be a way of monitoring risk for developing RROI. Therefore, this review will focus on: (1) the mechanics of running gait, (2) effects overtraining/fatigue on running gait, (3) the prevalence and causes of RROI, (4) how statistical entropy techniques can monitor changes in running gait, and (5) how RROI may be related to complexity of COM accleration.

## Running Gait

### *Mechanics of Running Gait*

Human locomotion is comprised of a repetitive gait cycle. The gait cycle starts when one foot makes initial contact with the ground and ends when that same foot contacts the ground again. The gait cycle can be divided into two main phases: a stance phase and a swing phase. The stance phase is defined as the portion of the gait cycle for which the foot is in contact with the ground. The swing phase is the portion of the gait cycle where the foot is not in contact with the ground (foot is "swinging" through the air) (Novacheck, 1998). A stride is one repetition of the gait cycle, stride length is the distance traveled during a stride, and stride frequency is the inverse of the time it took to complete a stride or the number of strides per unit time. Locomotion velocity is the product of stride length and stride frequency.

$$Velocity = Stride\ Length \times Stride\ Frequency$$

When running at a constant velocity, any increases in stride length must be coupled with a decrease in stride frequency, and vice versa (Derrick et al., 1998).

The running gait of terrestrial animals is modeled as a bouncing spring-mass system (Figure 2.1). This bouncing model is used to demonstrate the effective utilization of elastic energy of the animals' tissues, which can result in up to a 70% conservation of kinetic energy (Blickhan, 1989). The model includes a point mass bouncing on a massless spring. The massless spring represents the animal's musculoskeletal system, while the point mass represents the whole-body center of mass (Blickhan, 1989). The spring (representing the musculotendinous structures in the leg) is compressed during the first half of the stance phase of running, when the negative vertical acceleration of the center of mass pushes down on the leg and the vertical force of the impact with the ground pushes up on the leg. The spring lengthens during the second half of the stance phase, when the center of mass is experiencing positive vertical acceleration (Farley et al., 1998).

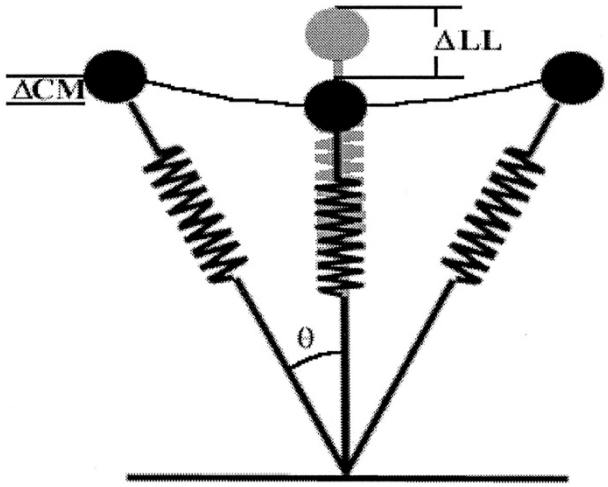



**Figure 2.1:** *Simple spring-mass model of running gait during stance phase. Point mass is attached to a massless spring. Adapted from (Dutto and Smith, 2002)*

The stiffness of the spring in the mass-spring model is an important concept in human locomotion. The properties of the spring will change with speed, surface hardness and fatigue among other environmental and physiological conditions. Changes in the properties of the spring will be reflected in the motion of the point mass (i.e. whole-body center of mass), therefore changes in running gait can be observed by monitoring changes in center of mass motion.

## Fatigue

### *Acute Fatigue*

Acute fatigue can be defined as being central or peripheral. Central fatigue refers to whole body feelings of weakness and energy deprivation whereas peripheral fatigue is localized to a specific muscle or muscle group that is impaired or unable to initiate a muscle contraction. The theories of central and peripheral fatigue are heavily debated, not fully understood, and achieving fatigue in its strictest definition is difficult in human subject research. Therefore, it is important for studies to state an operational definition for fatigue. Fatigue for the following discussion is referring to acute exhaustion resulting from an intense run, ending when the subject can no longer continue or when certain physiologic measurements of exhaustion have been reached (Enoka, 2015).

The physiological and cognitive symptoms of fatigue result in changes in running gait (Fischer et al., 2015, Morin et al., 2005, Schütte et al., 2015). When fatigued, runners tend to increase their stride frequency while decreasing their time spent in the flight phase and concomitantly increasing their contact time (Fischer et al., 2015, Morin et al., 2005). Fatigued runners also exhibit increased step width variability, hip range of motion, and trunk range of motion (Qu and Yeo, 2011). Ground reaction forces and tibial shock also increase with fatigue

(Clansey et al., 2012, Dierks et al., 2010). Researchers have presented mixed findings as to whether the center of mass movement changes in response to fatigue. Center of mass vertical displacement with fatigue, for example, has been found to increase, decrease, or have no vertical change whereas increased mediolateral and anteroposterior displacement is observed more consistently (Fischer et al., 2015, Morin et al., 2005, Schütte et al., 2015). Regardless of the specific findings, it is clear that fatigue to exhaustion can result in gait mechanic changes and a deviation from a runner's normal movement pattern. This deviation from the normal movement pattern has been proposed to induce abnormal stresses on the musculoskeletal systems that can have an injurious effect if appropriate rest is not taken (Nigg, 2001).

*Overtraining*

Individuals must progressively increase their workload in order to increase performance or improve fitness. Periods of high workloads should be followed by rest periods to prevent deleterious effects of training, or overtraining. When appropriate rest is not taken, the accumulation of high workloads can over stress the body and result in performance (i.e. ability to complete a task) decreases instead of increases (Kreher and Schwartz, 2012). This scenario is termed overreaching. Functional overreaching (i.e. lack of sufficient rest for days to weeks) results in short-term performance decrements and commonly produces a positive outcome (i.e. increase above the original performance level) after sufficient rest. Long-term overreaching (i.e. lack of sufficient rest for weeks to months) results in greater performance decreases, negative psychologic and neuroendocrinologic symptoms, and has a negative outcome (i.e. no performance increases). Full recovery from overreaching is possible after sufficient rest.

Overreaching that lasts months results in severe performance decreases and maladapted physiology. This is termed overtraining (Cardoos, 2015, Kreher and Schwartz, 2012).

As described previously, when a runner experiences fatigue from a single running bout to exhaustion, they can experience acute changes in gait mechanics or deviations in their habitual movement pattern. These acute changes in gait mechanics are thought to cause abnormal stresses to musculoskeletal structures (Clansey et al., 2012, Dierks et al., 2010, Nigg, 2001). With appropriate rest, this micro damage is repaired which can lead to increased strength of the affected musculoskeletal structures over time. When appropriate rest is not taken between acute fatiguing bouts of running over a prolonged period of time (overtraining), this micro damage can accumulate and increase the risk of developing a RROI (Nigg, 2001). While subjective ratings of perceived effort and fatigue may be beneficial, they can be susceptible to bias. Therefore, a potential avenue for RROI prevention is to objectively identify when a runner needs to undergo a period of rest during a training period.

*Running Related Overuse Injury*

Annual healthcare costs in the United States averaged around $1.05 trillion over the last decade with an estimated $131 billion associated with physical inactivity (Carlson et al., 2015). With more than 40 million people in the United States participating in running (Videbaek et al., 2015) and a RROI incidence rate of 26.0 – 92.4%, millions of people have had to cope with a RROI. The mean medical cost of RROI is over $700 per injury but the cost can increase to $10,000 per injury if factors associated with quality of life and lost wages are included (Knowles et al., 2007, Hespanhol Junior et al., 2013). When half of runners who experience a RROI stop

running for at least a year and some stop running or being physically active altogether, RROI can become a physically and finically costly problem (Fields et al., 2010).

When running, the foot repetitively collides with the ground. The contact with the ground results in an impact force that is transmitted from the point of contact, up the leg, and through the musculoskeletal structures. Multiple impacts over the course of a run imposes stress and strain on the musculoskeletal structures, causing micro damage. The motion of the body in response to these forces also contributes to the stresses experienced by the musculoskeletal structures. These motions including greater peak hip adduction angles, greater peak knee internal rotation angles, and greater rearfoot invertor moments during stance phase have all been retrospectively linked to RROI (Ferber et al., 2010). With appropriate rest between running bouts the micro damage will promote remodeling and adaptation making the musculoskeletal structures more resistant to future loading. Without appropriate rest, musculoskeletal micro damages can accumulate leading to weaker structures and or maladaptation (Warden et al., 2014).

One way to mitigate the accumulating micro damage cycle is to reduce the load applied to the tissues with each step through gait retraining (Heiderscheit, 2011). Both kimematic (Cheung and Davis., 2011, Heiderscheit et al., 2011, and Noehren et al., 2011) and kinetic (Crowell and Davis, 2011) factors have been identified as possible positive treatment targets. Gait retraining must be tailored to each runner individually and is most commonly used as an injury treatment, not a method of injury prevention (Heiderscheit, 2011). It is unclear if gait retraining is appropriate as an intervention to prevent injury prior to signs or symptoms because there is currently no consensus as to what gait patterns are injurious verses protective and this distinction is likely highly specific to the individual.

An alternative to reducing tissue load through gait modifications is to better utilize rest periods to allow the musculoskeletal system to repair micro damage and promote healthy remolding and adaptation. Planning appropriate rest periods can be difficult because there are often no signs or symptoms that overtraining is leading to an injury until after the initiation of pain and some damage is sustained. Additionally, planning rest periods too early or too infrequently will hinder gains in fitness and performance. Therefore, the feasibility of better utilizing rest periods as an alternative to gait modifications relies on a measure that can determine when the musculoskeletal system has been overstressed and needs rest.

**Dynamical Systems Theory**

Dynamical systems theory describes the approach to utilize multiple scales of analysis to quantify systems that are composed of co-dependent interacting parts and are nonlinear (Davids et al., 2003, Hamill et al., 1999). A list of important terms of dynamical systems theory with a detailed definition is provided in Appendix C. Human locomotion is the product of multiple physiological systems working together (nervous, musculoskeletal, etc.) (Glazier et al., 2003). When these physiological systems interact, there is a certain level of coordination (long-range correlations) and variability (adaptability) unique to the task being performed (Crevecoeur et al., 2010). Analysis tools based on dynamical systems theory enables one to measure changes in the coordination and variability of the task being performed that might not have been observable by examining the kinematics of the task alone (Hamill et al., 1999). This dynamical systems approach could provide a measurement tool that can determine when the physiological systems associated with running are being stressed to the point where a RROI is likely to occur.

*Complexity*

The dictionary definition of 'complex' is something that is hard to separate, analyze, or solve. When defining complexity, it is important to decide whether to define it perceptively or algorithmically. Algorithmically, complexity is a completely random or disordered system, while defining it perceptively, complexity is a system comprised of a mixture of order and disorder is the most complex (Figure 2.3). In this context, order refers to long-range correlations related to the interaction between physiological subsystems and disorder refers to the ability to adapt.

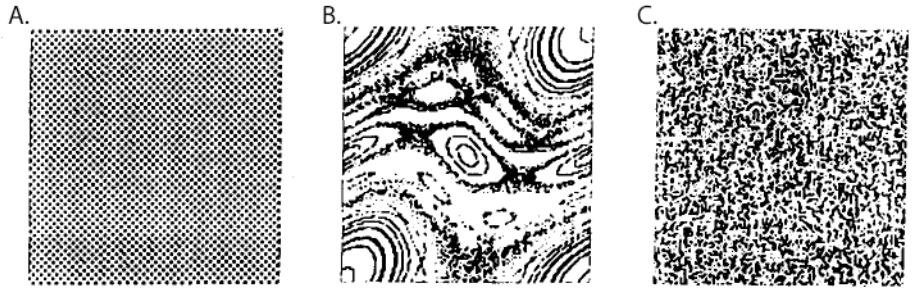



**Figure 2.2:** *A) Illustration of a pattern with no randomness (lowest algorithmic complexity). B) Illustration of a pattern with a mix of randomness and order. C) Illustration of a pattern with complete randomness (highest algorithmic complexity). Adapted from Wackerbauer et al., 1994.*

The perceptive view of complexity suggests that complexity is not linearly related to the randomness of the system, rather it has a more inverted U-shape. This U-shape indicates that complexity is both low for systems with no randomness and low for systems with complete randomness, whereas complexity is high for systems with a mixture of order and disorder (Wackerbauer et al., 1994). It is believed that a highly complex physiological signal will consist of a mixture of randomness and order (Costa et al., 2005). A symptom of a pathological system (injury, aging, disease, etc.) will result in a reduction in the system's ability to adapt and thus will present as a less complex system (Costa et al., 2002, Costa et al., 2005).

*Control Entropy*

Statistical entropy is an analytical technique used to quantify the complexity of a physiological signal (Costa et al., 2002). For stationary signals (i.e. signals collected during steady state conditions), several variations for statistical entropy have been used, including approximate, sample, and multiscale entropy.

Approximate entropy is a measure of the predictability of a time series. It is a calculation to determine the conditional probability that two similar consecutive sequences of *m* data points will remain similar when an additional consecutive data point is added. Whether two consecutive sequences of data are similar is determined by a predetermined threshold *r*, which is typically between 10% and 20% of the standard deviation of the original data set (Appendix D). Approximate entropy is biased in that it compares the sequence of *m* data points to itself. This self-matching overestimates the predictability of the time series, thus underestimating the degree of complexity of the signal.

Sample entropy is a variation of the approximate entropy method that was developed to account for this self-matching bias (Richman and Moorman, 2000). Multiscale entropy is a variation of sample entropy used to analyze the complexity of a stationary signal on different temporal scales (Costa et al., 2002). These temporal scales represent the varying levels of interactions between subsystems, such as, neural, musculoskeletal, sensory, etc. (Busa et al., 2016). For nonstationary signals (i.e. signals collected during non-steady state conditions), another variation of sample entropy has been developed termed, control entropy (McGregor and Bollt, 2012).

Sample entropy is the foundation for determining the complexity of both stationary and nonstationary signals. The equation for calculating the sample entropy of a set of time series data is as follows:

$$S_E(m, r, N) = ln \frac{\sum_{i=1}^{N-m} n_i'^m}{\sum_{i=1}^{N-m} n_i'^{m+1}}, 1 \leq i \leq N - m$$

where $n_i'^m$ is the number of vector matches for vectors with length *m* and $n_i'^{m+1}$ is the number of vector matches for vectors with length *m*+1 (Costa et al., 2005). More precisely, sample entropy is the negative natural logarithm of the probability that two sequences will be similar for *m* + 1 data points divided by the probability that two sequences will be similar for *m* data points. For two data points to match they need to be within a range of ± *r*, which is commonly between 10% and 20% of the standard deviation of the original data set (Appendix A). The inevitable match of the template sequence to itself is excluded in this calculation. The elimination of this self-matching is the distinction between sample entropy and approximate entropy (Richman and Moorman, 2000).

Multiscale entropy is a statistical entropy measure that has been employed to determine the complexity of physiological time series data over multiply temporal scales. It is an improved measure compared with previous entropy calculations (i.e. sample entropy, approximate entropy) in that multiscale entropy identifies both completely ordered and completely random data sets as not complex. This identification is important when dealing with physiological systems that pathologically can present as more ordered (less adaptable) or more random (loss of long-range correlations within the signal) (Costa et al., 2002, Costa et al., 2005). A detailed overview of the multiscale entropy analysis can be found in Appendix A.

Approximate, sample, and multiscale entropy calculations assume that the time series data being analyzed is stationary. Stationary data means that the data was collected under steady

state conditions (i.e. resting heart rate and constant speed when running/walking). To analyze nonstationary data a variation of the sample entropy analysis, termed control entropy, is used. To calculate control entropy, the time series data set of interest is broken down into small windows or partitions. An assumption of stationarity is made for each partition of the original data set and then the sample entropy of that partition is calculated (Bolt et al., 2008). Control entropy would allow one to determine the center of mass complexity during free runs when speed is not controlled.

The control entropy calculation has most notably been applied to gait signals measured by high resolution triaxial accelerometry to determine if the complexity of the center of mass signal differs between fatigued and non-fatigued conditions (McGregor et al., 2009). Subjects tasked with completing two continuous, incremental, exercise tests on a treadmill exercised to self-determined exhaustion with six days separating each testing session. Control entropy was used to analyze the center of mass acceleration, along the vertical axis, medial/lateral, and anterior/posterior axes. At the point of exhaustion, it was shown that the center of mass complexity was lower than the center of mass complexity measured during quiet stance before the start of the run. It is proposed that inducing fatigue increased the constraints on the physiological system, making it less adaptable, and that is reflected in a decrease in signal complexity (McGregor et al., 2009).

**Summary**

Overtraining, doing “too much, too soon”, or otherwise completing a running volume that exceeds a runner’s current fitness level and ability, are likely the predominate risk factors associated with RROI. Several changes in running gait resulting from an acute, exhaustive run

have been identified but the gait changes associated with a prolonged intense training period have not been identified. If overtraining is considered as a form of physiological fatigue, we may be able to identify when running gait mechanics change due to this overtraining and prior to the onset of RROI. Within dynamical systems theory, statistical entropy has been used to quantify the complexity of physiological time series data. The entropy analysis has successfully been used to analyze how the complexity of the center of mass acceleration signal changes during a single fatiguing run. However, continued research is needed to determine how center of mass acceleration complexity changes throughout a collegiate cross-country season and the relationship between the change in center of mass acceleration complexity and the development of a RROI.

# CHAPTER III

# EXPERIMENTAL PROCEDURES

## *Selection of Subjects*

Participants included collegiate cross-country runners who were currently uninjured or restricting training due to pain or prior injury (Table 3.1). Each participant signed a written informed consent document before testing procedures begin (Appendix B). The University of Memphis Institutional Review Board approved all documents and procedures used in this study.

An *a priori* power analysis was performed based on pilot data collected from an uninjured and an injured group following the same training protocol. This power analysis revealed that a total of 12 subjects would be required to establish 0.8 statistical power at an alpha scale of 0.05. Therefore, a conservative sample size of 30 participants were recruited from the University of Guelph campus. Unlike the pilot data, participants did not follow identical training schedules because they competed in different events and those who qualified for tournament or championship meets had a longer training period than those who did not. Therefore, participants who became injured (n = 7) were matched by gender and age to participants that did not sustain an injury (n = 7).

| | Male<br>(n = 18) | Female<br>(n = 12) |
|---|---|---|
| Age, yr | 19.17±1.01 | 19.58±1.44 |
| Height, m | 70.94±2.15 | 65.64±7.64 |
| Weight, kg | 66.09±4.99 | 55.04±7.33 |

**Table 3.1:** *Study population demographics.*

*Design*

Participants were given a wearable triaxial accelerometer (GT3XP-BTLE, ActiGraph Corp., Pensacola, FL) at the start of the collegiate cross-country season, September 7th, 2017. Participants wore the accelerometer during all continuous training runs throughout the entire cross-country season (approx. 14 weeks). The accelerometers were not worn during specialized runs, such as interval running or races. Participants wore the accelerometer over the posterior aspect of their pelvis to capture center of mass acceleration. The accelerometer was secured using an adjustable belt and captured data at the maximum sampling frequency of 100 Hz. Accelerometer data was downloaded from the wearable device every second Sunday following participants' long run. Total enrollment time was dependent on whether the subjects qualified for a tournament or championship that met outside of the regular season.

At the start of the study, all runners completed a baseline run, which was an easy run on a known cross-country route. The length of this run varied among runners given that they all trained at slightly different weekly running volumes. However, the relative intensity of the run was low and the same for all runners.

An example of a typical week of training is presented in Table 3.2 All participants followed a similar training strategy with respect to the following: timing and days of training sessions; the type of run for each training session (e.g. interval, tempo, easy run, long run, etc.); the intensity of a given training session (i.e. workouts were high relative intensity, continuous runs were low relative intensity); training routes and/or terrains; in-season racing schedule; and similar recovery strategies (e.g. massage, foam rolling, ice baths, etc.). Although the absolute time and or mileage for a given run or week of running was different between runners, the same relative training stimulus (intensity and miles or minutes) were prescribed across all participants.

There were three to four days per week of continuous runs in which the accelerometer was worn. These continuous runs were performed at a low relative intensity. The daily workload was calculated for each participant included in the analysis. Workload was calculated by taking a participant's run time multiplied by their rate of perceived exertion for that run (Hulin et al., 2014).

| | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday | Sunday |
|---|---|---|---|---|---|---|---|
| AM | | Easy run or cross training | | Easy run or cross training | | | Long run |
| PM | Workout + plyos | Easy run or cross training + strength | Workout + plyos | Easy run or cross training + strength | Workout + plyos or pre-race (if competing Saturday) | Race or easy run or cross training or rest | |

**Table 3.2:** *Example of a typical training week.*

Every day during the season, runners also completed an online survey to track injury or symptom onset and injury location and severity (Appendix C). An injury was defined as any pain or discomfort that resulted in a stop or reduction in the participant's current running training volume. When injuries were reported, the date of injury onset was recorded and accelerometer data during runs preceding injury onset were analyzed. Injuries were diagnosed by an athletic trainer. All diagnosed injures were chronic in nature.

Participants who became injured (i.e. "injured group") were matched by age and gender to a participant who remained uninjured during the course of the training season (i.e. "uninjured group"). Matching by age and gender accounted for any differences in relative training volume given that training volumes were based on class year (i.e. freshman, sophomore, junior, senior) and gender.

Acceleration data from the first run of the season (i.e. early September) was analyzed and served as the baseline COM acceleration complexity. For the injured group, acceleration data from the run performed just prior to the reported injury was also analyzed. This we termed the "pre-injury" run. For matched controls, acceleration data from a run taken from the same day as the pre-injury run for the injured group was analyzed.

*Data Reduction*

A Matlab program was used to perform the control entropy analysis (Costa et al., 2002, Costa et al., 2005, McGregor et al., 2009). Control entropy was calculated by determining the sample entropy of the center of mass acceleration signal within discrete overlapping windows of length α = 750 data points. Sample entropy calculated the conditional probability that two similar consecutive sequences of $m$ = 2 data points will remain similar when an additional consecutive data point is added. Whether two consecutive sequences of data were similar was determined by a predetermined threshold $r$, which is typically between 10% and 20% of the standard deviation of the data. Threshold $r$ was 15% of the standard deviation of the resultant acceleration signal for the complete run. If the sequence of data points is more similar, than the signal is considered less complex because there is a higher probability that two similar consecutive sequences of $m$ data points remain similar when an additional consecutive data point is added.

The sample entropy for each discrete window was calculated as follows:

$$S_E(m, r, N) = ln \frac{\sum_{i=1}^{N-m} n_i'^m}{\sum_{i=1}^{N-m} n_i'^{m+1}}, 1 \leq i \leq N - m$$

where $n_i'^m$ was the number of vector matches for vectors with length $m$ and $n_i'^{m+1}$ was the number of vector matches for vectors with length $m$+1 (Costa et al., 2005). A vector match was two consecutive sets of $m$ data points that were considered to be similar. Data points were

considered similar if their difference was within the ± *r* threshold. The calculation performed with the input parameters of a vector length of 2 (*m*), a tolerance of 0.15 times the signal standard deviation (*r*), and discrete overlapping windows of 750 data points, thus a single entropy value was calculated for each discrete window and an entropy vs. time series was generated for a single run.

*Statistical Analysis*

JMP (SAS Corp., Cary, NC) was used to conduct the statistical analysis. The Shapiro-Wilk test was used to assess the normality of the data. Paired student t-tests were used to determine if there were statistical differences between the average center of mass acceleration complexity between the following runs:

- Baseline run (i.e. first run) verses pre-injury run (i.e. last run before reported injury in injury group and a run from the same day in the matched control group) within groups
- Baseline run verses pre-injury run between groups

For all tests, the alpha for statistical significance was set at $p < 0.05$. Cohen's *d* effect sizes were used to assess meaningfulness of complexity differences. Cohen's $d$=0.2, $d$=0.5, and $d$=0.8 represent a small, medium, and large effect respectively.

CHAPTER IV

MANUSCRIPT

*Formatted for submission to Journal of Biomechanics*

# CHANGES IN RUNNING GAIT COMPLEXITY DURING A CROSS-COUNTRY SEASON IN COLLEGIATE RUNNERS


## Abstract

Center of mass (COM) acceleration complexity has been shown to decrease during a single fatiguing run. However, no studies have investigated how COM acceleration complexity changes over the course of a running training program and before the onset of a running related overuse injury (RROI). The purpose of the present study was to observe if the COM acceleration complexity of collegiate cross-country athletes over the course of their season training changed prior onset of a RROI. Thirty athletes wore a triaxial, research grade accelerometer secured over the posterior aspect of their pelvis during all continuous training runs. The accelerometers were worn for the entire cross-country season. Participants completed a daily online survey to report any musculoskeletal pain or injuries. An RROI was assessed by a trainer and defined as any musculoskeletal pain or problem that resulted in a reduction or stoppage of normal training. Control entropy (CE) analysis was used to assess the complexity of the resultant COM acceleration collected by the wearable accelerometer. Participants who developed a RROI and matched (by gender and age) uninjured controls were compared. Seven participants developed a RROI. No change in COM acceleration complexity was seen prior to the diagnosed RROI ($p$ = 0.64). The unchanged COM acceleration complexity may be explained by similar training workloads between start of the season and immediately prior to RROI onset ($p$ = 0.20).

## Introduction

Annual healthcare costs totaled $1.05 trillion over the past decade, with physically inactive adults paying $1,437 more per year in healthcare than physically active adults (Carlson et al., 2015). Running is an excellent way to become and remain physically active as it is easily modifiable to accommodate varying degrees of skill, has a low equipment cost, and can be either a social or individual activity. However, the risk of developing a running related overuse injury (RROI) is much greater than all other exercise-related injuries (Requa et al., 1993) with between 26.0% and 92.4% of runners experiencing a RROI each year (van Gent et al., 2007). Out of runners who experience a RROI, around half will stop running for at least one year and others may stop running or being physically active permanently (Fields et al., 2010). In order for running to be a successful tool to increase physical activity and health benefits while reducing healthcare costs, the risk of developing RROI must be reduced.

Several intrinsic risk factors for RROI are unmodifiable, such as gender, age, and previous injury. A current strategy proposed to reduce RROI risk is to target the gait characteristics identified previously to be intrinsic risk factors for RROI development (Duffey et al., 2000). Although gait retraining can be an effective tool for injury rehabilitation, researchers have yet to reach a consensus on the gait characteristics to retrain for injury prevention. This form of treatment also involves changing a runner's "habitual movement pattern", which is the running form an individual has developed because of their specific anatomy. A deviation from the habitual movement pattern may result in irregular tissue stresses and could result in injury (Nigg, 2001). Therefore, it is critically important to investigate other causes of RROI that could target and have a more pronounced impact on RROI prevention.

Targeting extrinsic risk factors rather than intrinsic risk factors of RROI may be a more advantageous strategy for RROI prevention. These extrinsic risk factors include: excessive weekly running mileage (Rauh, 2014), duration of a single run (Hespanhol Junior et al., 2013), running experience (Macera et al., 1989), and training intensity (Bovens et al., 1989). Any one or a combination of these extrinsic risk factors can subject the musculoskeletal system to an excessive workload can have a detrimental effect on performance. For example, training volume and intensity that surpass a runner's fitness level and ability (i.e. overtraining) are major contributors to RROI (Videbaek et al., 2015) and strong correlations have been observed between increased running weekly volume and increased overuse injury incidence (Martinez-Silvan et al., 2017). However, progressive overload training is required to stress the body to stimulate the adaptive physiological processes that increase fitness and performance. While there are many programs available for differing ability levels, runners are unique in the sense that two runners with the same skill or ability may not respond to a training load in the same way. That is, one runner may become injured while the other suffers no problems.

To prevent rather than simply treat RROI, a measure is needed that can identify changes in running gait prior to the onset of an injury. Dynamical systems theory suggests that human movement as a whole is comprised of many co-dependent sub-systems, such as respiratory, skeletomuscular, and nervous, that each contain their own continuously interacting sub-systems. Co-dependence between systems makes human movement both dynamic and complex (Glazier et al., 2003). Human movement that allows for more variability between sub-systems is thought to be more complex, more flexible, and more adaptive than movement with less variability (Glazier et al., 2003). When an individual's experiences a decrease in variability between sub-

systems, movement becomes less adaptable and the individual may be at a greater risk of becoming injured (Hamill et al., 1999).

Statistical entropy is a classification of techniques used to quantify the complexity of physiological signals. The complexity of a signal is thought to represent the interactions between sub-systems that control movement. Therefore, high entropy indicates that the sub-systems can respond to more perturbations, such as changing external environment and fatigue, which is believed to be a characteristic of healthy systems that possess a higher adaptive capacity (Costa et al., 2002). Entropy analysis has been used to distinguish between populations and conditions. Young adults have a higher entropy than healthy and unhealthy older adults (Costa et al., 2002), trained runners have a higher entropy than untrained runners (Parshad et al., 2012), and unfatigued runners have higher entropy than fatigued runners (McGregor et al., 2009). Therefore, a decrease or lower entropy value acts like the check engine light in an automobile, warning of a detrimental change in the signal before the change physically manifests.

The relationship of overtraining and an increased risk of developing RROI is becoming well established. However, signs of overtraining often present too late to prevent injury development. It is currently unknown how running gait biomechanics change following a progressive running training program, which could be thought of as a cumulative development of biological fatigue. Previous studies have examined how the complexity of the center of mass acceleration signal changes in response to a single fatiguing run (McGregor et al., 2009, Parshad et al., 2012), however no studies have used control entropy to examine how the complexity of the center of mass signal changes throughout an entire running training program. Specifically, a running training program that includes various types of runs (e.g., easy running, intensive intervals, and races). Trained runners have been shown to have higher COM acceleration

complexity compared to untrained runners, suggesting running skill acquisition has an effect on COM acceleration complexity (Parshad et al., 2012). By using experienced, higher level runners, such as collegiate runners, we could test a running population that was less likely to experience an increase in running skill in response to a running training program; allowing us to make a safer assumption that any changes observed in COM acceleration complexity were a result of cumulative loading of the musculoskeletal system and not skill acquisition.

The purpose of this study was to determine if center of mass (COM) acceleration complexity, measured using control entropy, in collegiate cross-country runners changed prior to the onset of a RRIOI. It was hypothesized that COM acceleration complexity would decrease during trainings runs leading up to the onset of a RROI in collegiate runners who developed an injury compared to matched controlled collegiate runners who did not develop an injury.

## Methods

### *Participants*

Thirty collegiate cross-country runners from the University of Guelph (Guelph, Ontario, Canada) participated in the study (Table 4.1). All participants were given a triaxial wearable activity monitor (GT3XP-BTLE, ActiGraph Corp, USA) at the beginning of their collegiate cross-country season (i.e. early September). All participants were informed of the potential risks and gave written informed consent prior to participation. The protocols of this study were approved by the University Institutional Review Board. Written support to participate in the study was provided by the University's cross-country/track and field head coach.

[Insert Table 4.1 Here]

*Protocol*

Raw tri-axial COM acceleration (g's) was measured with the accelerometer with the maximum sampling frequency of 100 Hz. The monitor was worn over the posterior aspect of the runner's pelvis and secured using an adjustable belt per company instruction (Figure 4.1).

[Insert Figure 4.1 Here]

The belt was tightened so the monitor would not bounce or rotate from its position over the pelvis.

Participants wore the monitor during all easy continuous training runs throughout the fall 2017 cross-country season (approx. 14 weeks) including their weekend long run. An easy continuous training run was a submaximal aerobic run performed on a familiar course at the athlete's preferred light pace for 30 to 60 minutes while the long run was performed at a similar effort but for a longer period: 65 to 110 minutes. The activity monitor was not worn during interval running sessions or races.

At the start of the study, all runners completed a baseline run, which was an easy run on a known cross-country loop. The baseline run occurred on September 7, 2017 for all but one participant. The length of this run varied among runners given that they all trained at slightly different weekly running volumes. However, the relative intensity of the run was low and similar between all runners.

An example of a typical week of training is presented in Table 3.2. All participants followed the same training program prescribed by the same coach with respect to the following: timing and days of training sessions; the type of run for each training session (e.g. interval, tempo, easy run, long run, etc.); the intensity of a given training session (i.e. workouts were high relative intensity, continuous runs were low relative intensity); training routes and/or terrains; in-

season racing schedule; and similar recovery strategies (e.g. massage, foam rolling, ice baths, etc.). Thus, although the absolute time and or mileage for a given run or week of running was different between runners, the same relative training stimulus (intensity and volume) were prescribed across all participants. There were three to four continuous easy runs per week during which the accelerometer was worn. The daily workload was calculated for each participant included in the analysis. Workload was calculated by taking a participant's run time (external load) multiplied by their rate of perceived exertion (internal load) for that run (Hulin et al., 2014).

[Insert Table 4.2 Here]

For the duration of the cross-country season, each participant logged the onset, location, and severity of any pain or discomfort after training in an online survey (Appendix C). If the participant reported experiencing pain or discomfort, an athletic trainer determined if the pain or discomfort was a RROI. For participants who experienced a RROI, the date of the injury was recorded and the run immediately preceding the onset of the injury (pre-injury) was analyzed. Participants who reported experiencing a RROI were matched based on age and gender to uninjured runners to compare COM acceleration complexity between groups. Matching by age and gender accounted for any differences in relative training volume given that training volumes were based on class year (i.e. freshman, sophomore, junior, senior) and gender.

*Data Analysis*

Of the thirty participants, one participant lost the accelerometer (stolen backpack containing the accelerometer) and seven participants developed a RROI. Seven uninjured control

participants were matched with the injured participants (Table 4.3). Data from these 14 athletes were analyzed.

[Insert Table 4.3 Here]

COM acceleration measured by the triaxial wearable accelerometer was truncated to isolate the data recorded during a participant's run. The resultant acceleration was calculated from the raw three-dimensional COM acceleration signal for each data point during the run by taking the square root of the sum of the components squared. A residual analysis was performed to determine the appropriate filtering cutoff frequency (Jackson, 1979, Winter, 2009). The resultant signal was filtered using a $4^{th}$ order Butterworth filter with a 12 Hz cutoff frequency. A custom Matlab program incorporating the Physionet Toolbox was used to perform the control entropy analysis on the filtered COM acceleration signal (Costa et al., 2002, Costa et al., 2005).

*Control Entropy*

Complexity of a physiological signal can be quantified using statistical entropy analysis techniques (Costa et al., 2002). For stationary signals (i.e. signals collected during steady state conditions), several variations for statistical entropy have been used, including approximate, sample, and multiscale entropy. Control entropy is a variation of sample entropy to quantify complexity of non-stationary signals (i.e. signals collected during non-steady state conditions) (McGregor and Bollt, 2012).

The control entropy calculation began by partitioning the original physiological signal into short overlapping portions using a moving window. Given the original time series of length N $[x_1, \dots, x_N]$, the moving window was:

$$x_j = [x_i, \dots, x_{i+\alpha}] |\, i = \{1, \dots, N - \alpha\} \in \mathbb{Z}$$

where $x_j$ was the partitioned data set, $N$ was the length of the original time series, and $\alpha$ was the chosen window length. For each partition of data, the sample entropy of the partition was calculated:

$$S_E(m, r, N) = ln \frac{\sum_{i=1}^{N-m} n_i'^m}{\sum_{i=1}^{N-m} n_i'^{m+1}}, 1 \leq i \leq N - m$$

where *N* was the number of data points in the partitioned time series, *r* was the tolerance for determining if two data points were similar, $n_i'^m$ was the number of vector matches for vectors with length *m*, and $n_i'^{m+1}$ was the number of vector matches for vectors with length $m$+1 (Costa et al., 2005, McGregor et al., 2009). The tolerance *r* was set to equal 15% of the standard deviation of the original time series. As a result, a series of sample entropies was generated as the moving window of 750 data points (i.e. α) extracted and analyzed successive partitions of data. The final product of the control entropy analysis was an entropy vs. time data series (i.e. the list of sample entropies generated by the moving window of 750 data points is the control entropy data series):

$$CE = SE(x_j), 1 \leq j \leq N - 750$$

The overall complexity value for each run was calculated by taking an average of the control entropy data series for that run:

$$Overall\ Complexity = \frac{1}{N - 750} \sum_{i=1}^{N-750} CE(i)$$

Overall complexity was calculated for the first run of the season (i.e. early September) and served as the baseline COM acceleration complexity. For the injured group, overall complexity was also calculated for the run performed just prior to the reported injury. This we termed the "pre-injury" run. For matched controls, overall complexity was also calculated for a run taken from the same day as the pre-injury run for the injured group.

*Statistical Analysis*

JMP (SAS Corp., Cary, NC) was used to conduct the statistical analysis. The Shapiro-Wilk test was used to assess the normality of the data. Paired student's t-tests were used to determine the statistical difference between the average COM acceleration complexity between the following runs:

- Baseline run (i.e. first run) verses pre-injury run (i.e. last run before reported injury in injury group and a run from the same day in the matched control group) within groups
- Baseline run verses pre-injury run between groups

For all tests, the alpha for statistical significance was $< 0.05$. Cohen's $d$ effect sizes were used to assess the meaningfulness of the differences in complexity. Cohen's $d$=0.2, $d$=0.5, and $d$=0.8 represent a small, medium, and large effect respectively.

**Results**

Within both the injured and uninjured control groups there was no difference in mean complexity between the baseline run and the pre-injury run (Table 4.4). With the injured group, average workload for the pre-injury run increased by 23% from baseline, for which the size of the effect was large but the difference was not statistically significant ($p = 0.20$, $d = 1.48$). A 4% change in workload between baseline and pre-injury runs in the control group was observed, but the change was not statistically significant ($p = 0.64$, $d = 0.11$) (Figure 4.2).

[Insert Figure 4.2 Here]

COM acceleration complexity was larger at baseline and pre-injury in the injured group compared with the control group ($d$ = 0.93 and $d$ = 0.91, respectively), but not statistically significant ($p$ = 0.14 and $p$ = 0.14, respectively). The workload at baseline was moderately greater in the control group than the injured group ($d$ = 0.51), but not statistically significant ($p$ = 0.48). No change was observed in the workload between injured and control groups at pre-injury ($d$ = 0.18, $p$ = 0.79) (Figure 4.3).

[Insert Figure 4.3 Here]

[Insert Table 4.4 Here]

A number of unknown transients were present in the control entropy data series even after filtering the acceleration data (Figure 4.4). These transients were removed using a median filter to calculate the mean complexity values as described in the methods. The data represented in Figure 4.5, Figure 4.6, and Table 4.6 show mean complexity without the transients removed from the control entropy data series.

[Insert Figure 4.4 Here]

[Insert Figure 4.5 Here]

[Insert Figure 4.6 Here]

[Insert Table 4.5 Here]

**Discussion**

The purpose of this study was to determine if change in COM acceleration complexity could be used to determine onset of a RROI. COM acceleration complexity during the run immediately preceding the report if a RROI was not different from the COM acceleration complexity measured during the baseline run in collegiate cross-country runners. This finding

was contrary to our hypothesis that COM acceleration complexity would decrease before the development of a RROI. Previous studies have shown that the constrained movement pattern resulted in a lower complexity measure (Lindsay et al., 2014, Busa et al., 2016). Fatigue during a single run has been shown to coincide with a lower complexity measure leading us to believe that fatigue results in a more constrained movement pattern (McGregor et al., 2009). Our results could mean that COM acceleration complexity changes differently depending on the environment. Perhaps when running gait is constrained by a treadmill complexity decreases with fatigue, while complexity increases with fatigue when unconstrained in over ground running.

In this study, for both the injured and control groups, we observed no statistical differences in the COM acceleration complexity during the baseline run and the run preceding the onset of a RROI. However, for both the baseline and pre-injury runs, the injured group, had greater complexity values compared with the control group and this difference had a large effect size. This finding could suggest that baseline complexity magnitude is associated with RROI rather than a change in complexity over the course of a training season. The higher complexity in the injured group may indicate that their running gait is too variable, resulting in maladaptive tissue loading and the development of a RROI.

Six out of the seven injured participants reported the onset of their RROI within three weeks of the baseline run. The lack of time between the baseline run and the onset of a RROI could mean that observation of the would-be injured participants did not begin early enough to capture a potential change in complexity. Future research should examine COM acceleration complexity analysis over to multiple runs throughout a training period to help identify when a theoretical injurious change in complexity could occur.

Another possibility for the unchanged complexity from baseline between groups prior to injury is that we simply do not end up having enough participants experience a RROI to tease out the association between RROI and COM acceleration complexity. Seven participants in the injured group may not provide enough statistical power to detect the expected trend that COM acceleration complexity would decrease before the development of a RROI. This is supported by the large effect sizes observed for the difference in complexity magnitude between the injured and control group at baseline and pre-injury. Our results suggest that the magnitude of the COM acceleration complexity at baseline could be a greater predictor of the development of a RROI than change in complexity. Future studies interested in observing the potential relationship between COM acceleration complexity and RROI should endeavor to recruit a larger subject pool and examine subjects who become injured at least a month following baseline testing.

*Limitations*

The current study had a few limitations. The first limitation is that when and how the triaxial accelerometer was worn was not strictly controlled. Participants were given the accelerometer and instructed to wear the device during all easy runs with the device positioned securely over the lower back however, study personnel were not at every practice to ensure that these procedures were consistently followed. As participants were cross-country runners during cross-country season many of their workouts were conducted as a team which may have mitigated this issue. If a participant was confused or unsure of how and when to wear the accelerometer, they could most likely speak to a teammate or coach and get the assistance they required immediately. For future studies, especially studies involving runners not associated with

a team or club, when the accelerometer is worn and its placement should be tightly controlled and recorded by study personnel.

A second limitation of this study is the low sampling frequency of the wearable accelerometer. Previous studies utilized high resolution accelerometer capable of capture data at a sampling frequency 6 – 10 times higher than the wearable accelerometers used in this study (McGregor et al., 2009). More investigation with using the control entropy analysis procedure with data collected at lower sampling frequencies is needed.

A final limitation of this study was it did not incorporate COM acceleration complexity data collected in a controlled environment (e.g. consistent terrain, constant running pace, consistent route for baseline and pre-injury runs). Participants performed all recorded runs outside the laboratory and thus, the terrain and pace of the baseline and pre-injury runs could have differed in this study. It is important to have participants train outside of the laboratory environment since that best mimics normal running training, however future studies could benefit from incorporating time, pace, and terrain into the selection of the pre-injury run to help ensure the run is similar to the baseline run.

## Conclusion

COM acceleration complexity did not change prior to onset of a RROI in collegiate cross-country runners, however it was higher in the injured group compared to the uninjured group at the baseline and pre-injury runs. The higher complexity in the injured group could indicate that the magnitude of the COM acceleration complexity is related to the onset of a RROI, rather than a change in complexity. COM acceleration complexity could still be a

potential tool in identifying when a runner needs to rest during their progressive running program to avoid developing a RROI.

**Acknowledgements**

This study was funded by the American Athletics Conference.

Thank you to the University of Guelph cross-country coaching staff and the athletes for taking part in this study.

**Conflicts of Interest**

None

REFERENCES

Blickhan, R. (1989). The spring-mass model for running and hopping. *Journal of Biomechanics, 22*(11–12), 1217–1227.

Bollt, E., Skufca, J., & McGregor, S. (2008). Control entropy: A complexity measure for nonstationary signals. *Mathematical Biosciences and Engineering*, *6*(1), 1–25. https://doi.org/10.3934/mbe.2009.6.1

Brund, R. B. K., Rasmussen, S., Nielsen, R. O., Kersting, U. G., Laessoe, U., & Voigt, M. (2017). Medial shoe-ground pressure and specific running injuries: A 1-year prospective cohort study. *Journal of Science and Medicine in Sport*. https://doi.org/10.1016/j.jsams.2017.04.001

Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *Journal of Sport and Health Science*, *5*(1), 44–51. https://doi.org/10.1016/j.jshs.2016.01.018

Butler, R. J., Crowell III, H. P., & Davis, I. M. (2003). Lower extremity stiffness: implications for performance and injury. *Clinical Biomechanics*, *18*(6), 511–517. https://doi.org/10.1016/S0268-0033(03)00071-8

Cardoos, N. (2015). Overtraining syndrome. *Current Sports Medicine Reports, 14*(3), 157–158. https://doi.org/10.1249/JSR.0000000000000145

Carlson, S. A., Fulton, J. E., Pratt, M., Yang, Z., & Adams, E. K. (2015). Inadequate Physical Activity and Health Care Expenditures in the United States. *Progress in Cardiovascular Diseases, 57*(4), 315–323. https://doi.org/10.1016/j.pcad.2014.08.002

Clansey, A. C., Hanlon, M., Wallace, E. S., & Lake, M. J. (2012). Effects of fatigue on running mechanics associated with tibial stress fracture risk. *Medicine and Science in Sports and Exercise*, *44*(10), 1917–1923. https://doi.org/10.1249/MSS.0b013e318259480d

Costa, M., & Goldberger, A. (2015). Generalized Multiscale Entropy Analysis: Application to Quantifying the Complex Volatility of Human Heartbeat Time Series. *Entropy*, *17*(3), 1197–1203. https://doi.org/10.3390/e17031197

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical Review Letters*, *89*(6), 068102/1-068102/4.

Costa, M., Goldberger, A. L., & Peng, C.-K. (2005). Multiscale entropy analysis of biological signals. *Physical Review E*, *71*(2). https://doi.org/10.1103/PhysRevE.71.021906

Costa, M., Peng, C.-K., L. Goldberger, A., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A: Statistical Mechanics and Its Applications*, *330*(1–2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Crevecoeur, F., Bollens, B., Detrembleur, C., & Lejeune, T. M. (2010). Towards a "gold-standard" approach to address the presence of long-range auto-correlation in physiological time series. *Journal of Neuroscience Methods*, *192*(1), 163–172. https://doi.org/10.1016/j.jneumeth.2010.07.017

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement Systems as Dynamical Systems. *Sports Medicine*, *33*(4), 245–260. https://doi.org/10.2165/00007256-200333040-00001

Derrick, T., Caldwell, G., & Hamill, J. (2000). Modelling the Stiffness Characteristics of the Human Body while Running with Various Stride Lengths. *Journal of Applied Biomechanics*, *16*(1), 36–51.

Derrick, T. R., Hamill, J., & Caldwell, G. E. (1998). Energy absorption of impacts during running at various stride lengths. *Medicine and Science in Sports and Exercise*, *30*(1), 128–135.

Dierks, T. A., Davis, I. S., & Hamill, J. (2010). The effects of running in an exerted state on lower extremity kinematics and joint timing. *Journal of Biomechanics*, *43*(15), 2993–2998. https://doi.org/10.1016/j.jbiomech.2010.07.001

Duffey, M. J., Martin, D. F., Cannon, D. W., Craven, T., & Messier, S. P. (2000). Etiologic factors associated with anterior knee pain in distance runners. *Medicine and Science in Sports and Exercise*, *32*(11), 1825–1832.

Dutto, D. J., & Smith, G. A. (2002). Changes in spring-mass characteristics during treadmill running to exhaustion. *Medicine and Science in Sports and Exercise*, *34*(8), 1324–1331.

Edwards, W. B., Taylor, D., Rudolphi, T. J., Gillette, J. C., & Derrick, T. R. (2009). Effects of stride length and running mileage on a probabilistic stress fracture model. *Medicine and Science in Sports and Exercise*, *41*(12), 2177–2184. https://doi.org/10.1249/MSS.0b013e3181a984c4

Farley, C. T., Houdijk, H. H. P., Strien, C. V., & Louie, M. (1998). Mechanism of leg stiffness adjustment for hopping on surfaces of different stiffnesses. *Journal of Applied Physiology*, *85*(3), 1044–1055.

Ferber, R., Noehren, B., Hamill, J., & Davis, I. (2010). Competitive female runners with a history of iliotibial band syndrome demonstrate atypical hip and knee kinematics. *Journal of Orthopaedic & Sports Physical Therapy*, *40*(2), 52–58.

Fischer, G., Storniolo J, L. L., & Peyré-Tartaruga, L. A. (2015). Effects of Fatigue on Running Mechanics: Spring-Mass Behavior in Recreational Runners After 60 Seconds of

Countermovement Jumps. *Journal of Applied Biomechanics*, *31*(6), 445–451. https://doi.org/10.1123/jab.2014-0235

Fourchet, F., Girard, O., Kelly, L., Horobeanu, C., & Millet, G. P. (2015). Changes in leg spring behaviour, plantar loading and foot mobility magnitude induced by an exhaustive treadmill run in adolescent middle-distance runners. *Journal of Science and Medicine in Sport*, *18*(2), 199–203. https://doi.org/10.1016/j.jsams.2014.01.007

Gent, R. N. van, Siem, D., Middelkoop, M. van, Os, A. G. van, Bierma-Zeinstra, S. M. A., & Koes, B. W. (2007). Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *British Journal of Sports Medicine*, *41*(8), 469–480. https://doi.org/10.1136/bjsm.2006.033548

Girard, O., Millet, G., Slawinski, J., Racinais, S., & Micallef, J.-P. (2010). Changes in leg-spring behavior during a 5000 m self-paced run in differently trained athletes. *Science & Sports*, *25*(2), 99–102. https://doi.org/10.1016/j.scispo.2009.10.001

Glazier, P., Davids, K., & Bartlett, R. (2003). Dynamical Systems Theory: a Relevant Framework for Perfromance-Oriented Sports Biomechanics Research. *Sportscience*, *7*. Retrieved from https://www.researchgate.net/publication/255735755_Dynamical_systems_theory_A_relevant_framework_for_performance-oriented_sports_biomechanics_research

Goldberger, A. L., Peng, C.-K., & Lipsitz, L. A. (2002). What is physiologic complexity and how does it change with aging and disease? *Neurobiology of Aging*, *23*(1), 23–26.

Gruber, A. H., Busa, M. A., Gorton, G. E., Van, E., Masso, P. D., & Hamill, J. (2011). Time-to-contact and multiscale entropy identify differences in postural control in adolescent

idiopathic scoliosis. *Gait and Posture*, *34*(1), 13–18. https://doi.org/10.1016/j.gaitpost.2011.02.015

Hamill, J., Palmer, C., & Van Emmerik, R. E. A. (2012). Coordinative variability and overuse injury. *Sports Medicine, Arthroscopy, Rehabilitation, Therapy & Technology*, *4*(1). https://doi.org/10.1186/1758-2555-4-45

Hamill, J., van Emmerik, R. E., Heiderscheit, B. C., & Li, L. (1999). A dynamical systems approach to lower extremity running injuries. *Clinical Biomechanics (Bristol, Avon)*, *14*(5), 297–308.

Heiderscheit, B. (2011). Gait Retraining for Runners: In Search of the Ideal. *Journal of Orthopaedic & Sports Physical Therapy*, *41*(12), 909–910. https://doi.org/10.2519/jospt.2011.0111

Hespanhol Junior, L. C., Pena Costa, L. O., & Lopes, A. D. (2013). Previous injuries and some training characteristics predict running-related injuries in recreational runners: a prospective cohort study. *Journal of Physiotherapy*, *59*(4), 263–269. https://doi.org/10.1016/S1836-9553(13)70203-0

Hobara, H., Hashizume, S., & Kobayashi, Y. (2017). Effects of prophylactic ankle and knee braces on leg stiffness during hopping. *Open Access Journal of Sports Medicine*, *8*, 107–112. https://doi.org/10.2147/OAJSM.S132275

Hulin, B. T., Gabbett, T. J., Blanch, P., Chapman, P., Bailey, D., & Orchard, J. W. (2014). Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *Br J Sports Med*, *48*(8), 708–712. https://doi.org/10.1136/bjsports-2013-092524

Humeau-Heurtier, A. (2015). The Multiscale Entropy Algorithm and Its Variants: A Review. *Entropy*, *17*(5), 3110–3123. https://doi.org/10.3390/e17053110

Knowles, S. B., Marshall, S. W., Miller, T., Spicer, R., Bowling, J. M., Loomis, D., … Mueller, F. O. (2007). Cost of injuries from a prospective cohort study of North Carolina high school athletes. *Injury Prevention: Journal of the International Society for Child and Adolescent Injury Prevention*, *13*(6), 416–421. https://doi.org/10.1136/ip.2006.014720

Kreher, J. B., & Schwartz, J. B. (2012). Overtraining syndrome: a practical guide. *Sports Health*, *4*(2), 128–138. https://doi.org/10.1177/1941738111434406

Lake, D. E., Richman, J. S., Griffin, M. P., & Moorman, J. R. (2002). Sample entropy analysis of neonatal heart rate variability. *American Journal of Physiology. Regulatory, Integrative and Comparative Physiology*, *283*(3), R789-797. https://doi.org/10.1152/ajpregu.00069.2002

Leverick, G., Szturm, T., & Wu, C. Q. (2014). Using Entropy Measures to Characterize Human Locomotion. *Journal of Biomechanical Engineering*, *136*(12), 121002. https://doi.org/10.1115/1.4028410

Lindsay, T. R., Noakes, T. D., & McGregor, S. J. (2014). Effect of Treadmill versus Overground Running on the Structure of Variability of Stride Timing. *Perceptual and Motor Skills*, *118*(2), 331–346. https://doi.org/10.2466/30.26.PMS.118k18w8

Lipsitz, L. A. (2002). Dynamics of StabilityThe Physiologic Basis of Functional Health and Frailty. *The Journals of Gerontology: Series A*, *57*(3), B115–B125. https://doi.org/10.1093/gerona/57.3.B115

Martínez-Silván, D., Díaz-Ocejo, J., & Murray, A. (2017). Predictive Indicators of Overuse Injuries in Adolescent Endurance Athletes. *International Journal of Sports Physiology and Performance*, *12*(Suppl 2), S2153–S2156. https://doi.org/10.1123/ijspp.2016-0316

McClay, I., & Manal, K. (1999). Three-dimensional kinetic analysis of running: significance of secondary planes of motion. *Medicine and Science in Sports and Exercise*, *31*(11), 1629–1637.

McGregor, S. J., & Bollt, E. (2012). Control entropy: What is it and what does it tell us? *Clinical Kinesiology*, *66*(1), 7–12.

McGregor, S. J., Busa, M. A., Skufca, J., Yaggie, J. A., & Bollt, E. M. (2009). Control entropy identifies differential changes in complexity of walking and running gait patterns with increasing speed in highly trained runners. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *19*(2), 26109. https://doi.org/10.1063/1.3147423

McMahon, T. A., & Cheng, G. C. (1990). The mechanics of running: how does stiffness couple with speed? *Journal of Biomechanics*, *23 Suppl 1*, 65–78.

Meardon, S. A., Hamill, J., & Derrick, T. R. (2011). Running injury and stride time variability over a prolonged run. *Gait and Posture*, *33*(1), 36–40. https://doi.org/10.1016/j.gaitpost.2010.09.020

Meeusen, R., Duclos, M., Foster, C., Fry, A., Gleeson, M., Nieman, D., … American College of Sports Medicine. (2013). Prevention, diagnosis, and treatment of the overtraining syndrome: joint consensus statement of the European College of Sport Science and the American College of Sports Medicine. *Medicine and Science in Sports and Exercise*, *45*(1), 186–205. https://doi.org/10.1249/MSS.0b013e318279a10a

Miller, R. H., Chang, R., Baird, J. L., Van Emmerik, R. E. A., & Hamill, J. (2010). Variability in kinematic coupling assessed by vector coding and continuous relative phase. *Journal of Biomechanics*, *43*(13), 2554–2560. https://doi.org/10.1016/j.jbiomech.2010.05.014

Morin, J. B., Jeannin, T., Chevallier, B., & Belli, A. (2005). Spring-Mass Model Characteristics During Sprint Running: Correlation with Performance and Fatigue-Indcued Changes. *International Journal of Sports Medicine*, *27*(2), 158–165.

Nielsen, R. O., Buist, I., Parner, E. T., Nohr, E. A., Sørensen, H., Lind, M., & Rasmussen, S. (2014). Foot pronation is not associated with increased injury risk in novice runners wearing a neutral shoe: a 1-year prospective cohort study. *British Journal of Sports Medicine*, *48*(6), 440–447. https://doi.org/10.1136/bjsports-2013-092202

Niemuth, P. E., Johnson, R. J., Myers, M. J., & Thieman, T. J. (2005). Hip muscle weakness and overuse injuries in recreational runners. *Clinical Journal of Sport Medicine: Official Journal of the Canadian Academy of Sport Medicine*, *15*(1), 14–21.

Nigg, B. M. (2001). The role of impact forces and foot pronation: a new paradigm. *Clinical Journal of Sport Medicine: Official Journal of the Canadian Academy of Sport Medicine*, *11*(1), 2–9.

Novacheck, null. (1998). The biomechanics of running. *Gait & Posture*, *7*(1), 77–95.

Parshad, R. D., McGregor, S. J., Busa, M. A., Skufca, J. D., & Bollt, E. (2012). A statistical approach to the use of control entropy identifies differences in constraints of gait in highly trained versus untrained runners. *Mathematical Biosciences and Engineering: MBE*, *9*(1), 123–145.

Pathria, R. K., & Beale, P. D. (2011). *Statistical Mechanics, Third Edition* (3 edition). Amsterdam ; Boston: Academic Press.

Qu, X., & Yeo, J. C. (2011). Effects of load carriage and fatigue on gait characteristics. *Journal of Biomechanics*, *44*(7), 1259–1263. https://doi.org/10.1016/j.jbiomech.2011.02.016

Requa, R. K., DeAvilla, L. N., & Garrick, J. G. (1993). Injuries in recreational adult fitness activities. *The American Journal of Sports Medicine*, *21*(3), 461–467. https://doi.org/10.1177/036354659302100323

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate and sample entropy. *American Journal of Physiology - Heart and Circulatory Physiology*, *278*(6 47-6), H2039–H2049.

Roger Enoka. (2015). *Neuromechanics of Human Movement* (5th ed.). Human Kinetics.

Schubert, A. G., Kempf, J., & Heiderscheit, B. C. (2014). Influence of stride frequency and length on running mechanics: a systematic review. *Sports Health*, *6*(3), 210–217. https://doi.org/10.1177/1941738113508544

Schütte, K. H., Maas, E. A., Exadaktylos, V., Berckmans, D., Venter, R. E., & Vanwanseele, B. (2015). Wireless Tri-Axial Trunk Accelerometry Detects Deviations in Dynamic Center of Mass Motion Due to Running-Induced Fatigue. *PLoS ONE*, *10*(10). https://doi.org/10.1371/journal.pone.0141957

Seyfarth, A., Geyer, H., Günther, M., & Blickhan, R. (2002). A movement criterion for running. *Journal of Biomechanics*, *35*(5), 649–655. https://doi.org/10.1016/S0021-9290(01)00245-7

Silva, L. E. V., Cabella, B. C. T., Neves, U. P. da C., & Murta Junior, L. O. (2015). Multiscale entropy-based methods for heart rate variability complexity analysis. *Physica A: Statistical Mechanics and Its Applications*, *422*, 143–152. https://doi.org/10.1016/j.physa.2014.12.011

Strogatz, S. H. (2014). *Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering* (2 edition). Boulder, CO: Westview Press.

Valencia, J. F., Porta, A., Vallverdu, M., Claria, F., Baranowski, R., Orlowska-Baranowska, E., & Caminal, P. (2009). Refined Multiscale Entropy: Application to 24-h Holter Recordings

of Heart Period Variability in Healthy and Aortic Stenosis Subjects. *IEEE Transactions on Biomedical Engineering*, *56*(9), 2202–2213. https://doi.org/10.1109/TBME.2009.2021986

Videbæk, S., Bueno, A. M., Nielsen, R. O., & Rasmussen, S. (2015). Incidence of Running-Related Injuries Per 1000 h of running in Different Types of Runners: A Systematic Review and Meta-Analysis. *Sports Medicine (Auckland, N.Z.)*, *45*(7), 1017–1026. https://doi.org/10.1007/s40279-015-0333-8

Wackerbauer, R., Witt, A., Atmanspacher, H., Kurths, J., & Scheingraber, H. (1994). A comparative classification of complexity measures. *Chaos, Solitons & Fractals*, *4*(1), 133–173. https://doi.org/10.1016/0960-0779(94)90023-X

Warden, S. J., Davis, I. S., & Fredericson, M. (2014). Management and prevention of bone stress injuries in long-distance runners. *The Journal of Orthopaedic and Sports Physical Therapy*, *44*(10), 749–765. https://doi.org/10.2519/jospt.2014.5334

Winter, D. A., Sidwall, H. G., & Hobson, D. A. (1974). Measurement and reduction of noise in kinematics of locomotion. *Journal of Biomechanics*, *7*(2), 157–159. https://doi.org/10.1016/0021-9290(74)90056-6

Wu, S.-D., Wu, C.-W., Lee, K.-Y., & Lin, S.-G. (2013). Modified multiscale entropy for short-term time series analysis. *Physica A: Statistical Mechanics and Its Applications*, *392*(23), 5865–5873. https://doi.org/10.1016/j.physa.2013.07.075

Zifchock, R. A., Davis, I., Higginson, J., McCaw, S., & Royer, T. (2008). Side-to-side differences in overuse running injury susceptibility: a retrospective study. *Human Movement Science*, *27*(6), 888–902. https://doi.org/10.1016/j.humov.2008.03.007

TABLES

| | Male (n = 18) | Female (n = 12) |
|---|---|---|
| Age, yr | 19.17±1.01 | 19.58±1.44 |
| Height, m | 70.94±2.15 | 65.64±7.64 |
| Mass, kg | 66.09±4.99 | 55.04±7.33 |

**Table 4.1:** *Study population demographics.*

| | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday | Sunday |
|---|---|---|---|---|---|---|---|
| AM | | Easy run or cross training | | Easy run or cross training | | | Long run |
| PM | Workout + plyos | Easy run or cross training + strength | Workout + plyos | Easy run or cross training + strength | Workout + plyos or pre-race (if competing Saturday) | Race or easy run or cross training or rest | |

**Table 4.2:** *Example of a typical training week.*

| | Injured | Control |
|---|---|---|
| Gender (M/F) | 3/4 | 3/4 |
| Age, yr | 18.71±0.88 | 18.71±1.03 |
| Height, m | 68.43±4.03 | 67.29±3.69 |
| Mass, kg | 59.61±8.68 | 58.64±9.64 |

**Table 4.3:** *Injured and control group demographics.*

| | Baseline Run | | Pre-Injury Run | |
|---|---|---|---|---|
| | Mean Complexity | Workload | Mean Complexity | Workload |
| Injured | $0.65\pm0.05^{\Phi}$ | 146.00±26.56 | $0.67\pm0.10^{\ddagger}$ | 180.00±18.71* |
| Control | 0.59±0.09 | $165.83\pm48.74^{\gamma}$ | 0.58±0.09 | 171.83±61.47 |

**Table 4.4:** *Injured and control groups' mean complexity and workload for baseline and pre-injury runs without transient data. No statistically significant differences ($p > 0.05$) in mean complexity or workload between time points for both injured and control groups. * indicates large effect size ($d = 1.48$) for increased workload between baseline and pre-injury runs for injured group. $\Phi$ indicates large effect size for higher mean complexity at baseline in injured group vs. control ($d = 0.93$). ‡ indicates large effect size for higher mean complexity in injured group at pre-injury vs. control ($d = 0.91$). $\gamma$ indicates moderate effect size for higher workload in control group vs. injured at baseline ($d = 0.51$).*

| | Baseline Run | | Pre-Injury Run | |
|---|---|---|---|---|
| | Mean Complexity | Workload | Mean Complexity | Workload |
| Injured | 0.76±0.23 | 146.00±26.56 | 0.94±0.45$^{\zeta\ddagger}$ | 180.00±18.71* |
| Control | 0.83±0.27 | 165.83±48.74$^{\gamma}$ | 0.83±0.23 | 171.83±61.47 |

**Table 4.5:** *Injured and control groups' mean complexity and workload for baseline and pre-injury runs with transient data. No statistically significant differences (p >0.05) in mean complexity or workload between time points for both injured and control groups. * indicates large effect size (d = 1.48) for increased workload between baseline and pre-injury runs for injured group. ζ indicates moderate effect size between baseline and pre-injury mean complexity for injured group (d = 0.51). ‡ indicates small effect size for higher mean complexity in injured group vs. control at pre-injury (d =0.32). γ indicates moderate effect size for higher workload in control group vs. injured at baseline (d = 0.51).*

FIGURES

**Figure 4.1:** *Example of accelerometer placement during easy and long training runs.*

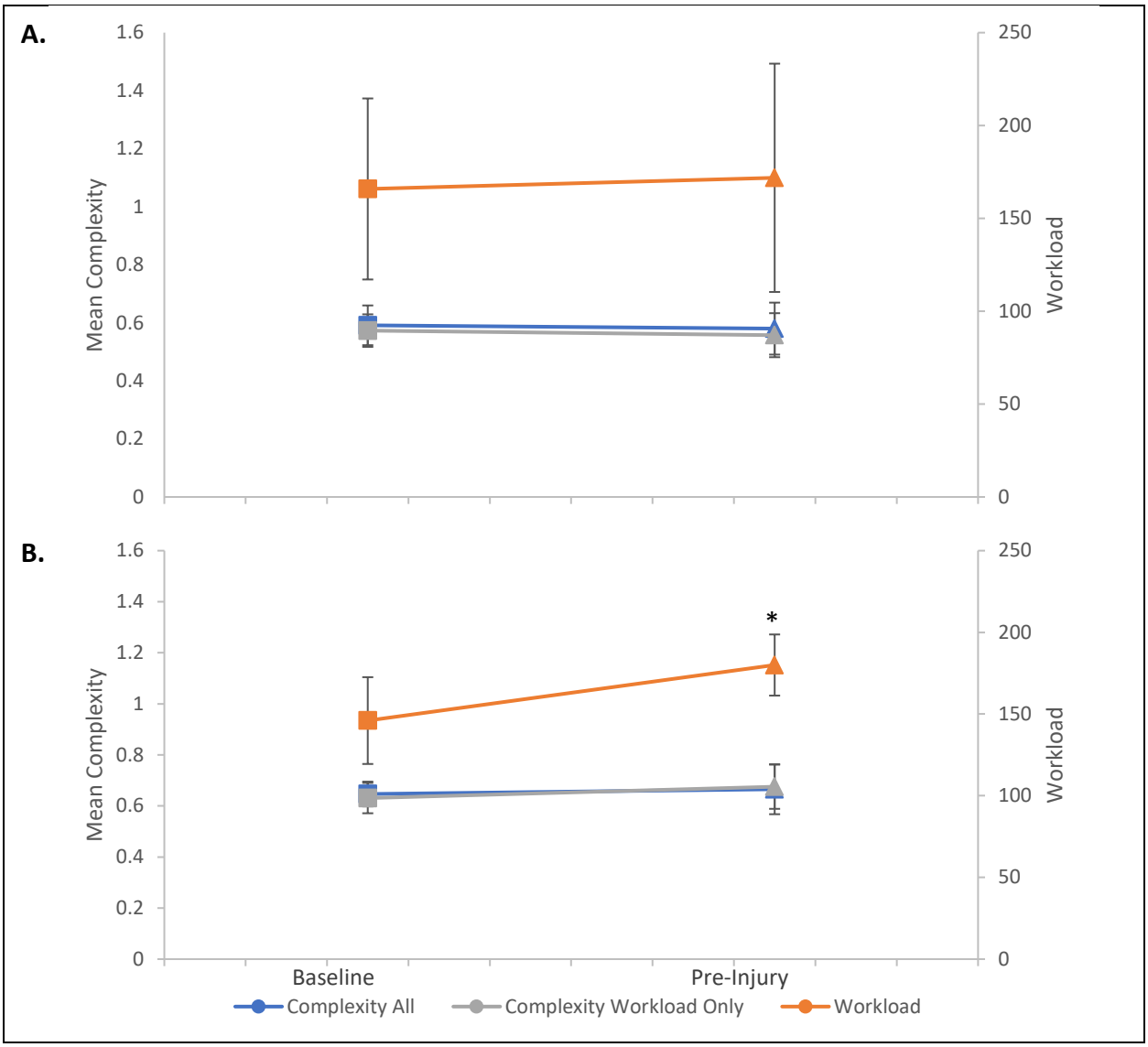



**Figure 4.2:** *A) Mean complexity and workload change from baseline run to pre-injury run for control group without transient data. B) Mean complexity and workload change from baseline run to pre-injury run for injured group. Error bars are ± 1 standard deviation. The differences in mean complexity and workload between time points within groups were not statistically significant (p >0.05). * indicated a large effect between baseline and pre-injury workload for the injured group (d = 1.48).*

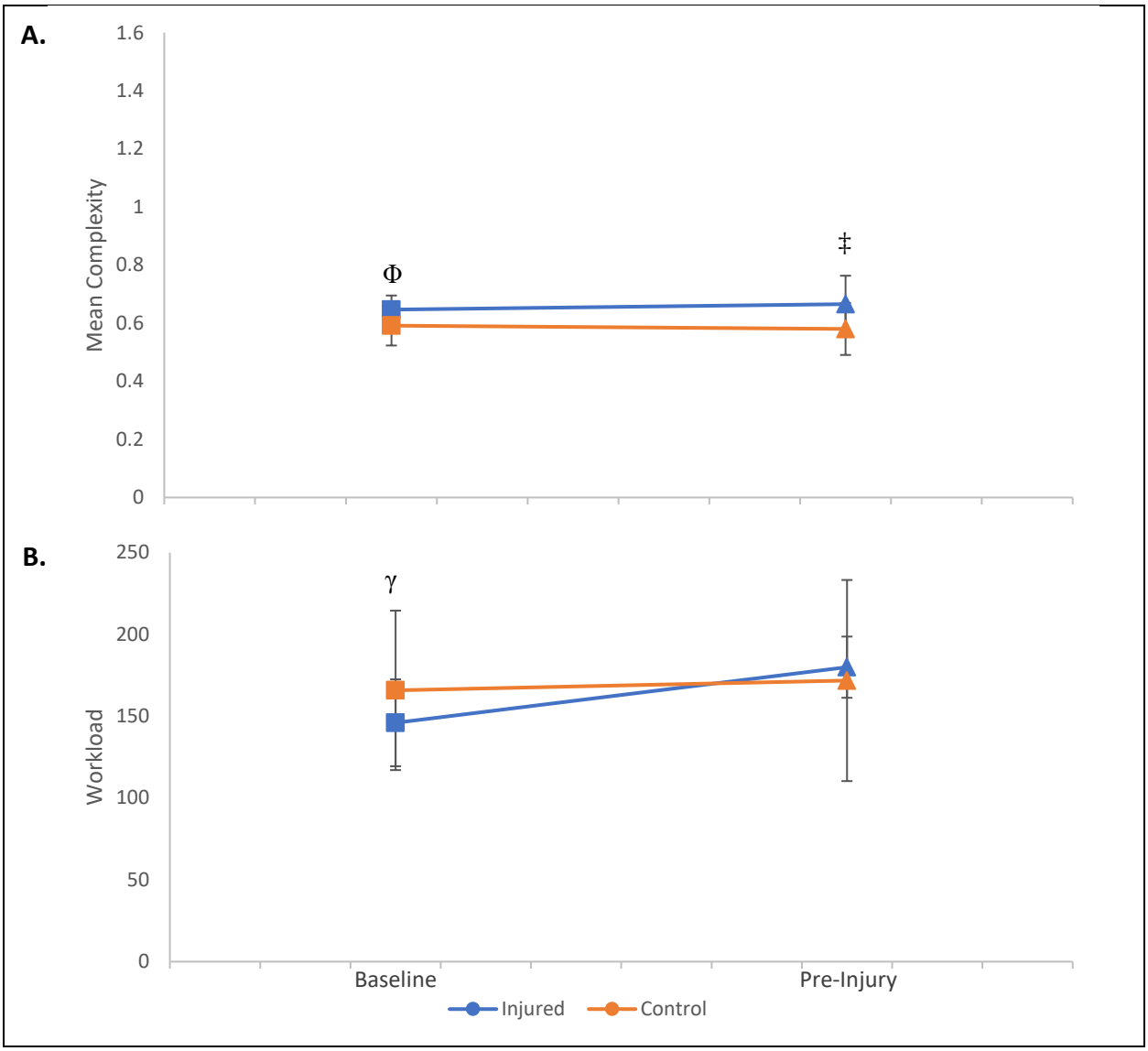



**Figure 4.3:** *A) Mean complexity change between baseline and pre-injury runs for injured and control groups without transient data. Φ indicates large effect size for higher mean complexity in injured group compared to control at baseline (d = 0.93). ‡ indicates large effect size for higher mean complexity in injured group compared to control at pre-injury (d =0.91). B) Workload change between baseline and pre-injury runs for injured and control groups. γ indicated moderate effect size for higher workload in control group compared to injured at baseline (d = 0.51). Error bars are ± 1 standard deviation.*

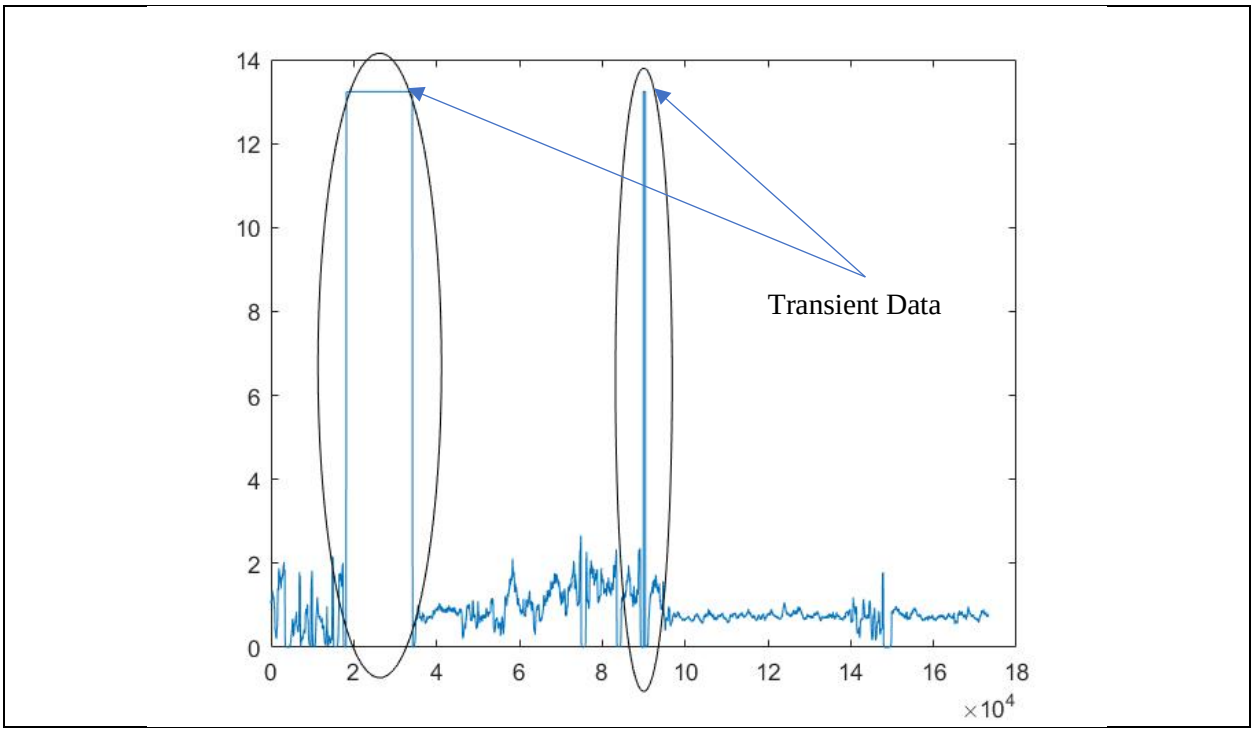



**Figure 4.4:** *Example of transient data in control entropy data series.*

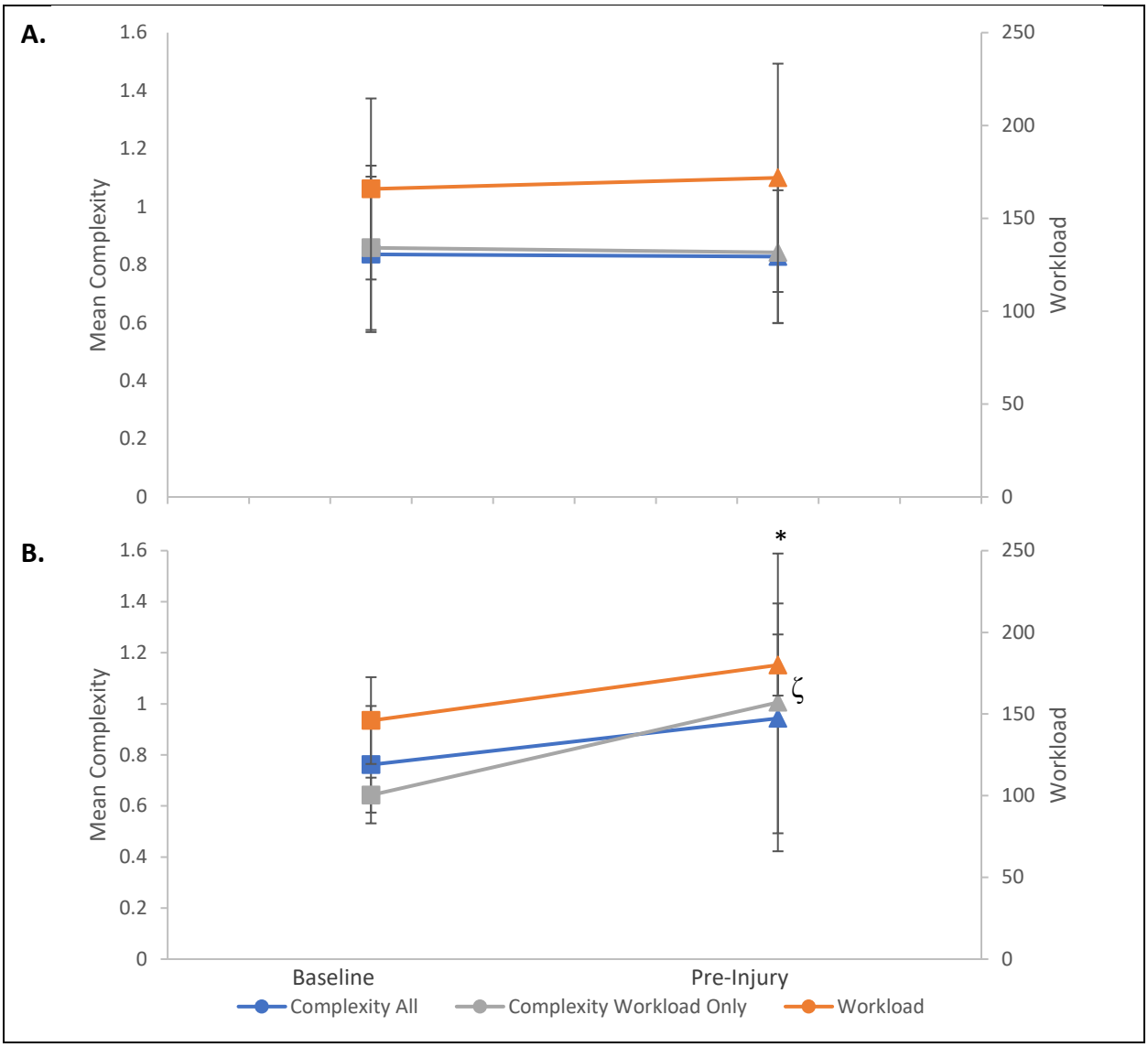



**Figure 4.5:** *A) Mean complexity and workload change from baseline run to pre-injury run for control group with transient data. B) Mean complexity and workload change from baseline run to pre-injury run for injured group. Error bars are ± 1 standard deviation. The differences in mean complexity and workload between time points within groups were not statistically significant ($p > 0.05$). ζ indicates moderate effect size between baseline and pre-injury mean complexity for injured group. * indicates a large effect between baseline and pre-injury workload for the injured group ($d = 1.48$).*

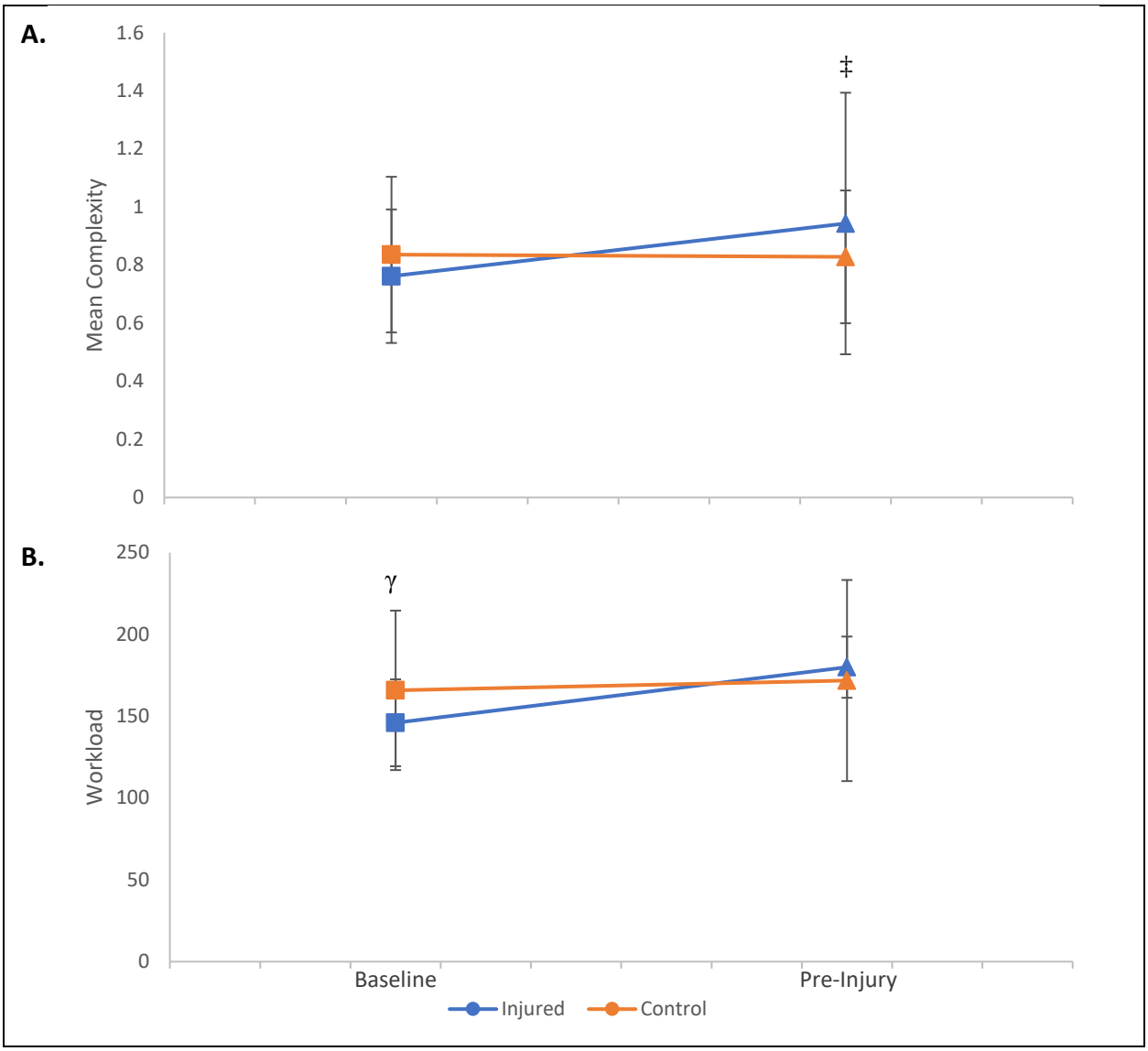



**Figure 4.6:** *A) Mean complexity change between baseline and pre-injury runs for injured and control groups with transient data. ‡ indicates small effect size for higher mean complexity in injured group vs. control at pre-injury (d =0.32). B) Workload change between baseline and pre-injury runs for injured and control groups. γ indicates moderate effect size for higher workload in control group compared to injured at baseline (d = 0.51). Error bars are ± 1 standard deviation.*

# APPENDIX A

# ENTROPY FORMULAS

## Sample Entropy

The sample entropy of a time series is calculated using the following equation:

$$\textbf{(1)} \qquad S_E(m, r, N) = ln \frac{\sum_{i=1}^{N-m} n_i'^m}{\sum_{i=1}^{N-m} n_i'^{m+1}} \, , 1 \leq i \leq N - m$$

where $N$ is the number of data points in the time series, $r$ is the tolerance for determining if two data points are similar (typically 15% of the standard deviation of the original time series), $n_i'^m$ is the number of vector matches for vectors with length $m$, and $n_i'^{m+1}$ is the number of vector matches for vectors with length $m$+1 (Costa et al., 2005).

The following is an example of calculating sample entropy on a simulated time series. Consider a fictional time series $x_1, \ldots, x_N$ with a chosen $m = 2$ and $r = 0.15$. Two data points will match if the absolute difference between them is $\leq r$. Points that match $x_1$ will be assigned a value of 1, points that match $x_2$ will be assigned a value of 2, and points that match $x_3$ will be assigned a value of 3. The sequence 1 – 2 will denote a match for vectors of length $m$ and the sequence 1 – 2 – 3 will denote a match for vectors of length $m$ + 1 (Figure D.1).

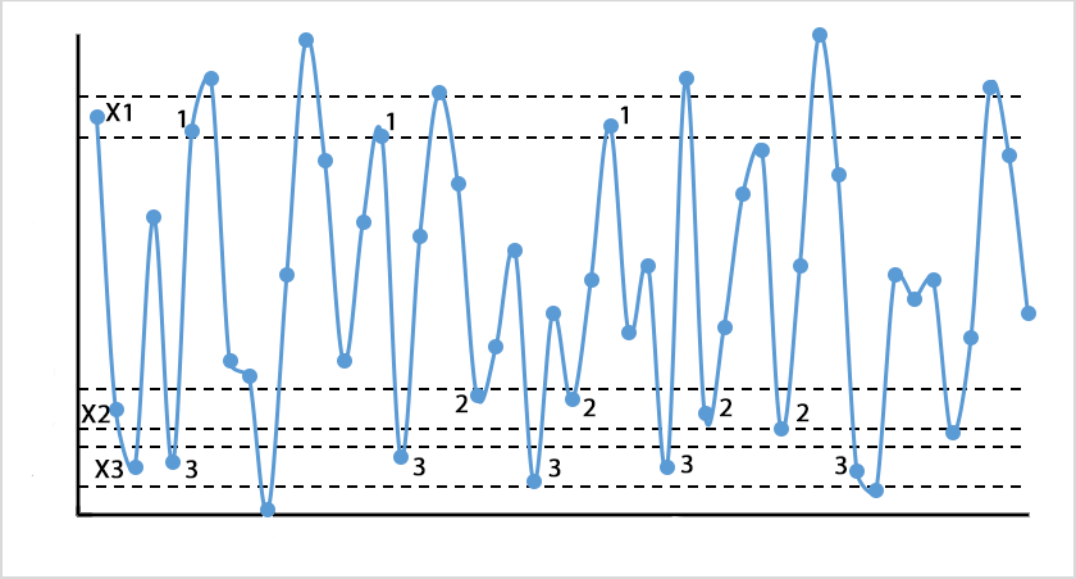



**Figure A.1:** *Illustration of procedure for vector matching in calculation of sample entropy. Adapted from Costa et al., 2005.*

This calculation will be repeated for the following two component sequence ($x_2$, $x_3$) and three component sequence ($x_2$, $x_3$, $x_4$). The two component and three component matches are then added to their respective component matches for the previous sequence template. This calculation is repeated for each successive template sequence. Once the total two component matches have been summed together and the total three component matches have been summed together, the natural logarithm of the ratio of two component matches to three component matches is taken and that value is equal to the sample entropy of that time series dataset (Equation 1) (Costa and Goldberger, 2015, Costa et al., 2002, Costa et al., 2005, Costa et al., 2003).

**Multiscale Entropy**

Calculating the multiscale entropy of a time series can be broken down into three major steps; 1) filtering the original time series into multiple temporal scales using a coarse-graining

procedure, 2) calculating the sample entropy of each temporal scale, and 3) plotting the calculated sample entropies vs. their respective temporal scales.

*Step 1: Coarse-graining Procedure*

The coarse-graining procedure for separating the original time series into multiple temporal scales follows the equation below:

$$\textbf{(2)} \qquad y_j^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i \,, 1 \le j \le {}^{N}/_{\tau}$$

where τ is the scale factor and *N* is the number of data points in original time series (Costa et al., 2002).

For example, the data set $\{x_1, x_2, x_3, x_4\}$ with a scale factor of 2 will be broken down into two sections; $\{x_1, x_2\}$ and $\{x_3, x_4\}$. Subsequently the data points within each section will be averaged to obtain a value for each specific section, resulting in a new data series with a length equal to the original length of the data series divided by the scale factor (i.e. $\{x_1, x_2, x_3, x_4\}$ becomes $\{\frac{x_1+x_2}{2}, \frac{x_3+x_4}{2}\}$ at scale 2).

*Step 2: Calculate Sample Entropy*

Once the original time series has been filtered into multiple temporal scales the sample entropy of each scale is calculated using Equation 1 (see sample entropy description above).

*Step 3: Plotting Sample Entropy vs. Time Scale*

Finally, after the sample entropy of each temporal scale is calculated, the calculated sample entropy of each scale is plotted on the y-axis with the scale (e.g. 1, 2, 3, 4, etc.) plotted on the x-axis (Figure D.2).

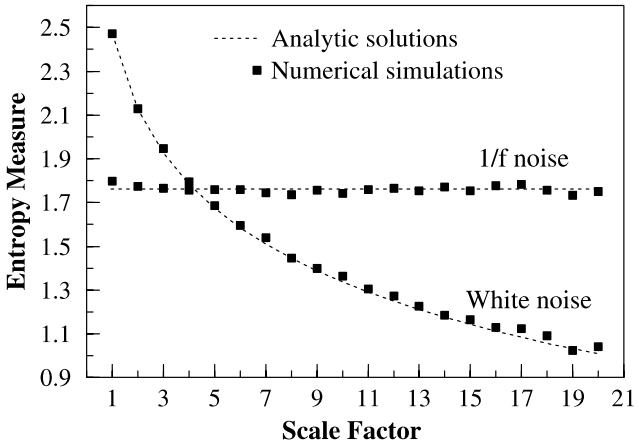



**Figure A.2:** *Example of an entropy vs. temporal scale plot (Costa et al., 2002).*

Plotting the entropy in this fashion allows you to observe how the entropy changes over multiple time scales and allows you to calculate the overall complexity of the signal using the complexity index. The complexity index is the area under the entropy vs. scale curve and is calculated using the following equation:

$$\textbf{(3)} \qquad C_I = \sum_{i=1}^{N} S_E(i)$$

where $S_E$ is the sample entropy at time scale $i$ and $N$ is the number of desired time scales used to calculated $C_I$ (Busa et al., 2016).

**Control Entropy**

Calculating control entropy, like multiscale entropy, consists of multiple steps; 1) develop a moving window that extracts out a partition of the original data set and 2) calculating the sample entropy of each partition of data.

*Step 1: Partitioning Original Time Series*

Given the original time series $[x_1, \dots, x_N]$, the equation for the moving window is as follows:

$$\textbf{(4)} \qquad x_j = [x_i, \dots, x_{i+\alpha}] \mid i = \{1, \dots, N-\alpha\} \in \mathbb{Z}$$

where $x_j$ is the partitioned data set, $N$ is the length of the original time series, and $\alpha$ is the chosen window length.

For example, if I chose a window length of 201 data points; the first partition would be $[x_1, \dots, x_{202}]$ and the second partition would be $[x_2, \dots, x_{203}]$. This trend would continue until the final partition, $[x_{N\text{-}201}, \dots, x_N]$, is reached.

*Step 2: Calculate Sample Entropy*

For each partition of data, the sample entropy of the partition is calculated using Equation 1. As a result, a series of sample entropies is listed as the moving window extracts successive partitions of data. The list of sample entropies is control entropy (Equation 5).

$$\textbf{(5)} \qquad CE = SE(x_j), 1 \leq j \leq N - \alpha$$

APPENDIX B

INFORMED CONSENT

**Consent to Participate in a Research Study**

**The use of wearable sensors to detect early signs of overtraining and running-related overuse injury during training**

**WHY ARE YOU BEING INVITED TO TAKE PART IN THIS RESEARCH?**

**You are being invited to take part in a research study in which we are examining the use of wearable sensors to detect early signs of overtraining and running-related overuse injury during training. You are being invited to take part in this research study because you are a cross country runner with no running injuries. If you volunteer to take part in this study, you will be one of up to 30 runners to do so.**

**WHO IS DOING THE STUDY?**

**The person directly in charge of this study is Dr. Max Paquette of the School of Health Studies at The University of Memphis.**

**WHAT IS THE PURPOSE OF THIS STUDY?**

**The overall purpose of the proposed study is to understand if we can identify periods of cumulative fatigue or injury risks following a prolonged training period using wearable sensor technology. The results from this study may provide beneficial information to coaches, athletes, athletic trainers and medical stuff to help track periods of overtraining and elevated injury risks in collegiate runners and ultimately, reduce injury risks.**

**ARE THERE REASONS WHY YOU SHOULD NOT TAKE PART IN THIS STUDY?**

**We will be recruiting collegiate cross-country runners who are not currently injured. If you do not fit the previous criteria, then we apologize, but you cannot participate in the study. Finally, if you are a woman and are currently pregnant, we apologize, but you cannot participate in the study.**

**WHERE IS THE STUDY GOING TO TAKE PLACE AND HOW LONG WILL IT LAST?**

**The research procedures will be conducted during your scheduled practice time in Guelph, Ontario.**

**WHAT WILL YOU BE ASKED TO DO?**

**At the start of the study at your schedule practice you will be informed of all procedures, potential risks, and benefits associated with the study through both verbal and written form and will be asked to complete your easy/aerobic run on a loop trail while wearing your sensor. You will be asked to wear your sensor during all easy/aerobic and long runs (not during workouts and races). At the end of your season, you will be asked to complete your easy/aerobic run on that same loop while wearing your sensor. About every two weeks, the sensor data will be downloaded following your Sunday long run. Finally, you will be asked to continue filling out your training volume and perceived effort log on your training App.**

**WHAT ARE THE POSSIBLE RISKS AND DISCOMFORTS?**

**Since you are a well-trained competitive cross country runners and you will be asked to wear a sensor on your pelvis during easy and long runs, there are minimal risks to conducting procedures listed above.**

**WILL YOU BENEFIT FROM TAKING PART IN THIS STUDY?**
**There is no guarantee that you will get any benefit from taking part in this study. However, the results from this study may provide beneficial information to coaches, athletes, athletic trainers and medical staff to help track periods of overtraining and elevated injury risks in runners. Thus, this study may ultimately help prevent or at least reduce the risk of overuse injuries in runners.**

**DO YOU HAVE TO TAKE PART IN THE STUDY?**

**If you decide to take part in the study, it should be because you really want to volunteer. You will not lose any benefits or rights you would normally have if you choose not to volunteer. You can stop at any time during the study and still keep the benefits and rights you had before volunteering. If you decide not to take part in this study, your decision will have no effect on the quality of care, services, etc., you receive from the University.**

**IF YOU DON'T WANT TO TAKE PART IN THE STUDY, ARE THERE OTHER CHOICES?**

**If you do not want to be in the study, there are no other choices except not to take part in the study.**

**WHAT WILL IT COST YOU TO PARTICIPATE?**

**There are no costs associated with taking part in the study.**

**WILL YOU RECEIVE ANY REWARDS FOR TAKING PART IN THIS STUDY?**

**There are no rewards for taking part in this study.**

**WHO WILL SEE THE INFORMATION THAT YOU GIVE?**

**We will make every effort to keep private all research records that identify you to the extent allowed by law. Your information will be combined with information from other people taking part in the study. When we write about the study to share it with other researchers, we will write about the combined information we have gathered. You will not be personally identified in these written materials. We may publish the results of this study; however, we will keep your name and other identifying information private. The information on the forms we will have you fill out will remain private, and only the study staff will see them.**

**We will make every effort to prevent anyone who is not on the research team from knowing that you gave us information, or what that information is. After the forms you will fill out are completed, they will be kept in a locked file cabinet at which my research team will be the only ones to be able to access it. Any information that gets transferred electronically will be stored on a computer with passcode entry that only the research team will know.**

**We will keep private all research records that identify you to the extent allowed by law. However, there are some circumstances in which we may have to show your information to other people. If any medical situation arises at which the paramedics or any other form of emergency care have to be called, we may be required to provide health history forms and or contact information. For example, the law may require us to show your information to a court or to tell authorities if you report information that could pose a danger to yourself or someone else. Also, we may be required to show information which identifies you to people who need to be sure we have done the research correctly; these would be people from such organizations as the University of Memphis or any other funding agencies that may have ties with our research study.**

**CAN YOUR TAKING PART IN THE STUDY END EARLY?**

**If you decide to take part in the study you still have the right to decide at any time that you no longer want to continue. You will not be treated differently if you decide to stop taking part in the study.**

**The individuals conducting the study may need to withdraw you from the study. This may occur if you are not able to follow the directions they give you, if they find that your being in the study is more risk than benefit to you, or if the agency funding the study decides to stop the study early for a variety of scientific reasons.**

**ARE YOU PARTICIPATING OR CAN YOU PARTICIPATE IN ANOTHER RESEARCH STUDY AT THE SAME TIME AS PARTICIPATING IN THIS ONE?**

**You may take part in this study if you are currently involved in another research study that does not require strenuous physical activity. It is important to let the investigator/your doctor know if you are in another research study. You should also discuss with the investigator before you agree to participate in another research study while you are enrolled in this study.**

**WHAT HAPPENS IF YOU GET HURT OR SICK DURING THE STUDY?**

**If you believe you are hurt or if you get sick because of something that is due to the study, you should call Dr. Max Paquette 865-310-7820 (mrpqette@memphis.edu) immediately. In case of illness or injury during participation in the study, you may reach Dr. Paquette on his mobile phone at 865-310-7820.**

**If any abnormal signs or symptoms are present during your participation, testing will be terminated and you will receive attention, following the Adverse Events plan of the Human Performance Laboratories. Otherwise, no treatment will be provided.**

**It is important for you to understand that the University of Memphis does not have funds set aside to pay for the cost of any care or treatment that might be necessary because you get hurt or sick while taking part in this study. Also, the University of Memphis will not pay for any wages you may lose if you are harmed by this study.**

**Medical costs that result from research related harm cannot be included as regular medical costs. Therefore, the medical costs related to your care and treatment because of research related harm will be your responsibility.**

**A co-payment/deductible from you may be required by your insurer or Medicare/Medicaid even if your insurer or Medicare/Medicaid has agreed to pay the costs. The amount of this co-payment/deductible may be substantial.**

**You do not give up your legal rights by signing this form.**

**WHAT IF YOU HAVE QUESTIONS, SUGGESTIONS, CONCERNS, OR COMPLAINTS?**

**Before you decide whether to accept this invitation to take part in the study, please ask any questions that might come to mind now. Later, if you have questions, suggestions, concerns, or complaints about the study, you can contact Dr. Max Paquette at 865-310-7820 (or mrpqette@memphis.edu), or come by the researcher's office located in Fieldhouse room 308 at The University of Memphis. If you have any questions about your rights as a volunteer in this research, contact the Institutional Review Board staff at the University of Memphis at 901-678-2705. We will give you a signed copy of this consent form to take with you.**

**WHAT IF NEW INFORMATION IS LEARNED DURING THE STUDY THAT MIGHT AFFECT YOUR DECISION TO PARTICIPATE?**

**If the researcher learns of new information in regards to this study, and it might change your willingness to stay in this study, the information will be provided to you. You may be asked to sign a new informed consent form if the information is provided to you after you have joined the study.**

**_____ ___ _____**

**Signature of person agreeing to take part in the study Date**

**_____**

**Printed name of person agreeing to take part in the study**

**_____ _____**

**Name of [authorized] person obtaining informed consent Date**

APPENDIX C

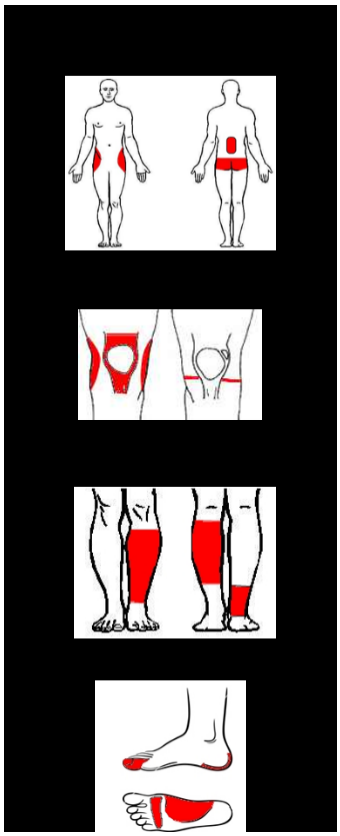
DATA COLLECTION MATERIALS

**Daily Running Injury Questionnaire**

Q1 Please enter your identification number as given to you by the primary investigator.

Q2 Did you have any pain or discomfort on your legs during or after your run today?
- ❍ Yes
- ❍ No

Q3 Where was your lower extremity pain or discomfort today? (Please specify an injury that does not appear on the list) (Diagram shown on survey, see image below)
- ❑ Lower back
- ❑ Right hip
- ❑ Left hip
- ❑ Pelvis
- ❑ Right thigh
- ❑ Left thigh
- ❑ Right knee
- ❑ Left knee
- ❑ Right lower leg
- ❑ Left lower leg
- ❑ Right ankle
- ❑ Left ankle
- ❑ Right foot
- ❑ Left foot
- ❑ Other location



Q4 Was this pain or discomfort assessed by your athletic trainer?
- ❍ Yes
- ❍ No

Q5 (IF YES) Did your trainer diagnose an injury from this pain or discomfort?
- ❍ Yes
- ❍ No

Q6 (IF YES) Which of the following injuries was diagnosed?
- ❑ Lower back (type specific injury) _____
- ❑ Pelvis-Gluteus Medius injury
- ❑ Pelvis-other (type specific injury) _____
- ❑ Foot-Metatarsal stress fracture (type specific metatarsal) _____
- ❑ Hip-Femoral neck stress fracture
- ❑ Hip-Other (type specific injury) _____
- ❑ Thigh (type specific injury) _____
- ❑ Knee-Patellofemoral Pain Syndrome
- ❑ Knee-Meniscal injury
- ❑ Knee-Patellar tendinitis
- ❑ Knee-other (type specific injury) _____
- ❑ Lower Leg-Tibial stress fracture
- ❑ Lower Leg-Tibial stress syndrome
- ❑ Lower Leg-Other (type specific injury) _____
- ❑ Ankle-Achilles tendinitis
- ❑ Ankle-Other (type specific injury) _____
- ❑ Foot-Plantar fasciitis
- ❑ Foot-Other (type specific injury) _____
- ❑ Knee-Iliotibial band syndrome

# APPENDIX D

## GLOSSARY OF DYNAMICAL SYSTEMS TERMS

(in alphabetical order)

- **Approximate entropy:** the probability that two sequences of *m* data points will remain similar when one more data point is added to the sequence, low matching probability (i.e. less predictability) is associated with higher complexity and vice versa. Contains an analytical bias of comparing the template sequence of *m* data points to itself (Richman and Moorman, 2000).
- **Complexity (i.e. a complex signal):** a system with a mixture of multiple degrees of freedom and long-range correlations (Hamill et al., 1999).
- **Control Entropy:** original data set is divided into discrete overlapping windows and the sample entropy of each window is calculated resulting in a entropy vs. time data series. To be used when physiological signal was not collected under steady state conditions (i.e. signal is non-stationary) (Bollt et al., 2008, McGregor et al., 2009).
- **Dynamic system:** a system whose state is variable over time (Strogatz, 2014).
- **Entropy:** the number of different microstates in a system given the macrostate (e.g. how many different ways can you arrange a pile of sand in order to create a specific sandcastle) (Pathria and Beale, 2011).
- **Nonlinear signal:** a signal that does not follow the principle of superposition. That is to say that system $F(x_1 + x_2) \neq F(x_1) + F(x_2)$ and $F(ax_1) \neq aF(x_1)$ (Strogatz, 2014).

- **Predictability:** the odds of a behavior or result being based on previous behaviors or results (e.g. value of data point three being based on the values of data points one and two).
- **Sample entropy:** same as approximate entropy absent the self-matching bias (Richman and Moorman, 2000).
- **Stationarity (i.e. a stationary signal):** signal mean is not time dependent. Commonly means that the signal was collected under steady state conditions (McGregor and Bollt, 2012).
- **Time series:** a series of data points that are listed in a time sequential order ($t_0, t_1, t_2, \ldots, t_n$).

REFERENCES

Blickhan, R. (1989). The spring-mass model for running and hopping. *Journal of Biomechanics, 22*(11–12), 1217–1227.

Bollt, E., Skufca, J., & McGregor, S. (2008). Control entropy: A complexity measure for nonstationary signals. *Mathematical Biosciences and Engineering*, *6*(1), 1–25. https://doi.org/10.3934/mbe.2009.6.1

Brund, R. B. K., Rasmussen, S., Nielsen, R. O., Kersting, U. G., Laessoe, U., & Voigt, M. (2017). Medial shoe-ground pressure and specific running injuries: A 1-year prospective cohort study. *Journal of Science and Medicine in Sport*. https://doi.org/10.1016/j.jsams.2017.04.001

Busa, M. A., & van Emmerik, R. E. A. (2016). Multiscale entropy: A tool for understanding the complexity of postural control. *Journal of Sport and Health Science, 5*(1), 44–51. https://doi.org/10.1016/j.jshs.2016.01.018

Butler, R. J., Crowell III, H. P., & Davis, I. M. (2003). Lower extremity stiffness: implications for performance and injury. *Clinical Biomechanics*, *18*(6), 511–517. https://doi.org/10.1016/S0268-0033(03)00071-8

Cardoos, N. (2015). Overtraining syndrome. *Current Sports Medicine Reports, 14*(3), 157–158. https://doi.org/10.1249/JSR.0000000000000145

Carlson, S. A., Fulton, J. E., Pratt, M., Yang, Z., & Adams, E. K. (2015). Inadequate Physical Activity and Health Care Expenditures in the United States. *Progress in Cardiovascular Diseases*, *57*(4), 315–323. https://doi.org/10.1016/j.pcad.2014.08.002

Clansey, A. C., Hanlon, M., Wallace, E. S., & Lake, M. J. (2012). Effects of fatigue on running mechanics associated with tibial stress fracture risk. *Medicine and Science in Sports and Exercise*, *44*(10), 1917–1923. https://doi.org/10.1249/MSS.0b013e318259480d

Costa, M., & Goldberger, A. (2015). Generalized Multiscale Entropy Analysis: Application to Quantifying the Complex Volatility of Human Heartbeat Time Series. *Entropy*, *17*(3), 1197–1203. https://doi.org/10.3390/e17031197

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical Review Letters*, *89*(6), 068102/1-068102/4.

Costa, M., Goldberger, A. L., & Peng, C.-K. (2005). Multiscale entropy analysis of biological signals. *Physical Review E*, *71*(2). https://doi.org/10.1103/PhysRevE.71.021906

Costa, M., Peng, C.-K., L. Goldberger, A., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A: Statistical Mechanics and Its Applications*, *330*(1–2), 53–60. https://doi.org/10.1016/j.physa.2003.08.022

Crevecoeur, F., Bollens, B., Detrembleur, C., & Lejeune, T. M. (2010). Towards a "gold-standard" approach to address the presence of long-range auto-correlation in physiological time series. *Journal of Neuroscience Methods*, *192*(1), 163–172. https://doi.org/10.1016/j.jneumeth.2010.07.017

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement Systems as Dynamical Systems. *Sports Medicine*, *33*(4), 245–260. https://doi.org/10.2165/00007256-200333040-00001

Derrick, T., Caldwell, G., & Hamill, J. (2000). Modelling the Stiffness Characteristics of the Human Body while Running with Various Stride Lengths. *Journal of Applied Biomechanics*, *16*(1), 36–51.

Derrick, T. R., Hamill, J., & Caldwell, G. E. (1998). Energy absorption of impacts during running at various stride lengths. *Medicine and Science in Sports and Exercise, 30*(1), 128–135.

Dierks, T. A., Davis, I. S., & Hamill, J. (2010). The effects of running in an exerted state on lower extremity kinematics and joint timing. *Journal of Biomechanics, 43*(15), 2993–2998. https://doi.org/10.1016/j.jbiomech.2010.07.001

Duffey, M. J., Martin, D. F., Cannon, D. W., Craven, T., & Messier, S. P. (2000). Etiologic factors associated with anterior knee pain in distance runners. *Medicine and Science in Sports and Exercise, 32*(11), 1825–1832.

Dutto, D. J., & Smith, G. A. (2002). Changes in spring-mass characteristics during treadmill running to exhaustion. *Medicine and Science in Sports and Exercise, 34*(8), 1324–1331.

Edwards, W. B., Taylor, D., Rudolphi, T. J., Gillette, J. C., & Derrick, T. R. (2009). Effects of stride length and running mileage on a probabilistic stress fracture model. *Medicine and Science in Sports and Exercise, 41*(12), 2177–2184. https://doi.org/10.1249/MSS.0b013e3181a984c4

Farley, C. T., Houdijk, H. H. P., Strien, C. V., & Louie, M. (1998). Mechanism of leg stiffness adjustment for hopping on surfaces of different stiffnesses. *Journal of Applied Physiology, 85*(3), 1044–1055.

Ferber, R., Noehren, B., Hamill, J., & Davis, I. (2010). Competitive female runners with a history of iliotibial band syndrome demonstrate atypical hip and knee kinematics. *Journal of Orthopaedic & Sports Physical Therapy, 40*(2), 52–58.

Fischer, G., Storniolo J, L. L., & Peyré-Tartaruga, L. A. (2015). Effects of Fatigue on Running Mechanics: Spring-Mass Behavior in Recreational Runners After 60 Seconds of

Countermovement Jumps. *Journal of Applied Biomechanics*, *31*(6), 445–451. https://doi.org/10.1123/jab.2014-0235

Fourchet, F., Girard, O., Kelly, L., Horobeanu, C., & Millet, G. P. (2015). Changes in leg spring behaviour, plantar loading and foot mobility magnitude induced by an exhaustive treadmill run in adolescent middle-distance runners. *Journal of Science and Medicine in Sport*, *18*(2), 199–203. https://doi.org/10.1016/j.jsams.2014.01.007

Gent, R. N. van, Siem, D., Middelkoop, M. van, Os, A. G. van, Bierma-Zeinstra, S. M. A., & Koes, B. W. (2007). Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *British Journal of Sports Medicine*, *41*(8), 469–480. https://doi.org/10.1136/bjsm.2006.033548

Girard, O., Millet, G., Slawinski, J., Racinais, S., & Micallef, J.-P. (2010). Changes in leg-spring behavior during a 5000 m self-paced run in differently trained athletes. *Science & Sports*, *25*(2), 99–102. https://doi.org/10.1016/j.scispo.2009.10.001

Glazier, P., Davids, K., & Bartlett, R. (2003). Dynamical Systems Theory: a Relevant Framework for Perfromance-Oriented Sports Biomechanics Research. *Sportscience*, *7*. Retrieved from https://www.researchgate.net/publication/255735755_Dynamical_systems_theory_A_relevant_framework_for_performance-oriented_sports_biomechanics_research

Goldberger, A. L., Peng, C.-K., & Lipsitz, L. A. (2002). What is physiologic complexity and how does it change with aging and disease? *Neurobiology of Aging*, *23*(1), 23–26.

Gruber, A. H., Busa, M. A., Gorton, G. E., Van, E., Masso, P. D., & Hamill, J. (2011). Time-to-contact and multiscale entropy identify differences in postural control in adolescent

idiopathic scoliosis. *Gait and Posture*, *34*(1), 13–18. https://doi.org/10.1016/j.gaitpost.2011.02.015

Hamill, J., Palmer, C., & Van Emmerik, R. E. A. (2012). Coordinative variability and overuse injury. *Sports Medicine, Arthroscopy, Rehabilitation, Therapy & Technology*, *4*(1). https://doi.org/10.1186/1758-2555-4-45

Hamill, J., van Emmerik, R. E., Heiderscheit, B. C., & Li, L. (1999). A dynamical systems approach to lower extremity running injuries. *Clinical Biomechanics (Bristol, Avon)*, *14*(5), 297–308.

Heiderscheit, B. (2011). Gait Retraining for Runners: In Search of the Ideal. *Journal of Orthopaedic & Sports Physical Therapy*, *41*(12), 909–910. https://doi.org/10.2519/jospt.2011.0111

Hespanhol Junior, L. C., Pena Costa, L. O., & Lopes, A. D. (2013). Previous injuries and some training characteristics predict running-related injuries in recreational runners: a prospective cohort study. *Journal of Physiotherapy*, *59*(4), 263–269. https://doi.org/10.1016/S1836-9553(13)70203-0

Hobara, H., Hashizume, S., & Kobayashi, Y. (2017). Effects of prophylactic ankle and knee braces on leg stiffness during hopping. *Open Access Journal of Sports Medicine*, *8*, 107–112. https://doi.org/10.2147/OAJSM.S132275

Hulin, B. T., Gabbett, T. J., Blanch, P., Chapman, P., Bailey, D., & Orchard, J. W. (2014). Spikes in acute workload are associated with increased injury risk in elite cricket fast bowlers. *Br J Sports Med*, *48*(8), 708–712. https://doi.org/10.1136/bjsports-2013-092524

Humeau-Heurtier, A. (2015). The Multiscale Entropy Algorithm and Its Variants: A Review. *Entropy*, *17*(5), 3110–3123. https://doi.org/10.3390/e17053110

Knowles, S. B., Marshall, S. W., Miller, T., Spicer, R., Bowling, J. M., Loomis, D., … Mueller, F. O. (2007). Cost of injuries from a prospective cohort study of North Carolina high school athletes. *Injury Prevention: Journal of the International Society for Child and Adolescent Injury Prevention*, *13*(6), 416–421. https://doi.org/10.1136/ip.2006.014720

Kreher, J. B., & Schwartz, J. B. (2012). Overtraining syndrome: a practical guide. *Sports Health*, *4*(2), 128–138. https://doi.org/10.1177/1941738111434406

Lake, D. E., Richman, J. S., Griffin, M. P., & Moorman, J. R. (2002). Sample entropy analysis of neonatal heart rate variability. *American Journal of Physiology. Regulatory, Integrative and Comparative Physiology*, *283*(3), R789-797. https://doi.org/10.1152/ajpregu.00069.2002

Leverick, G., Szturm, T., & Wu, C. Q. (2014). Using Entropy Measures to Characterize Human Locomotion. *Journal of Biomechanical Engineering*, *136*(12), 121002. https://doi.org/10.1115/1.4028410

Lindsay, T. R., Noakes, T. D., & McGregor, S. J. (2014). Effect of Treadmill versus Overground Running on the Structure of Variability of Stride Timing. *Perceptual and Motor Skills*, *118*(2), 331–346. https://doi.org/10.2466/30.26.PMS.118k18w8

Lipsitz, L. A. (2002). Dynamics of StabilityThe Physiologic Basis of Functional Health and Frailty. *The Journals of Gerontology: Series A*, *57*(3), B115–B125. https://doi.org/10.1093/gerona/57.3.B115

Martínez-Silván, D., Díaz-Ocejo, J., & Murray, A. (2017). Predictive Indicators of Overuse Injuries in Adolescent Endurance Athletes. *International Journal of Sports Physiology and Performance*, *12*(Suppl 2), S2153–S2156. https://doi.org/10.1123/ijspp.2016-0316

McClay, I., & Manal, K. (1999). Three-dimensional kinetic analysis of running: significance of secondary planes of motion. *Medicine and Science in Sports and Exercise*, *31*(11), 1629–1637.

McGregor, S. J., & Bollt, E. (2012). Control entropy: What is it and what does it tell us? *Clinical Kinesiology*, *66*(1), 7–12.

McGregor, S. J., Busa, M. A., Skufca, J., Yaggie, J. A., & Bollt, E. M. (2009). Control entropy identifies differential changes in complexity of walking and running gait patterns with increasing speed in highly trained runners. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *19*(2), 26109. https://doi.org/10.1063/1.3147423

McMahon, T. A., & Cheng, G. C. (1990). The mechanics of running: how does stiffness couple with speed? *Journal of Biomechanics*, *23 Suppl 1*, 65–78.

Meardon, S. A., Hamill, J., & Derrick, T. R. (2011). Running injury and stride time variability over a prolonged run. *Gait and Posture*, *33*(1), 36–40. https://doi.org/10.1016/j.gaitpost.2010.09.020

Meeusen, R., Duclos, M., Foster, C., Fry, A., Gleeson, M., Nieman, D., … American College of Sports Medicine. (2013). Prevention, diagnosis, and treatment of the overtraining syndrome: joint consensus statement of the European College of Sport Science and the American College of Sports Medicine. *Medicine and Science in Sports and Exercise*, *45*(1), 186–205. https://doi.org/10.1249/MSS.0b013e318279a10a

Miller, R. H., Chang, R., Baird, J. L., Van Emmerik, R. E. A., & Hamill, J. (2010). Variability in kinematic coupling assessed by vector coding and continuous relative phase. *Journal of Biomechanics*, *43*(13), 2554–2560. https://doi.org/10.1016/j.jbiomech.2010.05.014

Morin, J. B., Jeannin, T., Chevallier, B., & Belli, A. (2005). Spring-Mass Model Characteristics During Sprint Running: Correlation with Performance and Fatigue-Indcued Changes. *International Journal of Sports Medicine*, *27*(2), 158–165.

Nielsen, R. O., Buist, I., Parner, E. T., Nohr, E. A., Sørensen, H., Lind, M., & Rasmussen, S. (2014). Foot pronation is not associated with increased injury risk in novice runners wearing a neutral shoe: a 1-year prospective cohort study. *British Journal of Sports Medicine*, *48*(6), 440–447. https://doi.org/10.1136/bjsports-2013-092202

Niemuth, P. E., Johnson, R. J., Myers, M. J., & Thieman, T. J. (2005). Hip muscle weakness and overuse injuries in recreational runners. *Clinical Journal of Sport Medicine: Official Journal of the Canadian Academy of Sport Medicine*, *15*(1), 14–21.

Nigg, B. M. (2001). The role of impact forces and foot pronation: a new paradigm. *Clinical Journal of Sport Medicine: Official Journal of the Canadian Academy of Sport Medicine*, *11*(1), 2–9.

Novacheck, null. (1998). The biomechanics of running. *Gait & Posture*, *7*(1), 77–95.

Parshad, R. D., McGregor, S. J., Busa, M. A., Skufca, J. D., & Bollt, E. (2012). A statistical approach to the use of control entropy identifies differences in constraints of gait in highly trained versus untrained runners. *Mathematical Biosciences and Engineering: MBE*, *9*(1), 123–145.

Pathria, R. K., & Beale, P. D. (2011). *Statistical Mechanics, Third Edition* (3 edition). Amsterdam ; Boston: Academic Press.

Qu, X., & Yeo, J. C. (2011). Effects of load carriage and fatigue on gait characteristics. *Journal of Biomechanics*, *44*(7), 1259–1263. https://doi.org/10.1016/j.jbiomech.2011.02.016

Requa, R. K., DeAvilla, L. N., & Garrick, J. G. (1993). Injuries in recreational adult fitness activities. *The American Journal of Sports Medicine*, *21*(3), 461–467. https://doi.org/10.1177/036354659302100323

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate and sample entropy. *American Journal of Physiology - Heart and Circulatory Physiology*, *278*(6 47-6), H2039–H2049.

Roger Enoka. (2015). *Neuromechanics of Human Movement* (5th ed.). Human Kinetics.

Schubert, A. G., Kempf, J., & Heiderscheit, B. C. (2014). Influence of stride frequency and length on running mechanics: a systematic review. *Sports Health*, *6*(3), 210–217. https://doi.org/10.1177/1941738113508544

Schütte, K. H., Maas, E. A., Exadaktylos, V., Berckmans, D., Venter, R. E., & Vanwanseele, B. (2015). Wireless Tri-Axial Trunk Accelerometry Detects Deviations in Dynamic Center of Mass Motion Due to Running-Induced Fatigue. *PLoS ONE*, *10*(10). https://doi.org/10.1371/journal.pone.0141957

Seyfarth, A., Geyer, H., Günther, M., & Blickhan, R. (2002). A movement criterion for running. *Journal of Biomechanics*, *35*(5), 649–655. https://doi.org/10.1016/S0021-9290(01)00245-7

Silva, L. E. V., Cabella, B. C. T., Neves, U. P. da C., & Murta Junior, L. O. (2015). Multiscale entropy-based methods for heart rate variability complexity analysis. *Physica A: Statistical Mechanics and Its Applications*, *422*, 143–152. https://doi.org/10.1016/j.physa.2014.12.011

Strogatz, S. H. (2014). *Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering* (2 edition). Boulder, CO: Westview Press.

Valencia, J. F., Porta, A., Vallverdu, M., Claria, F., Baranowski, R., Orlowska-Baranowska, E., & Caminal, P. (2009). Refined Multiscale Entropy: Application to 24-h Holter Recordings

of Heart Period Variability in Healthy and Aortic Stenosis Subjects. *IEEE Transactions on Biomedical Engineering*, *56*(9), 2202–2213. https://doi.org/10.1109/TBME.2009.2021986

Videbæk, S., Bueno, A. M., Nielsen, R. O., & Rasmussen, S. (2015). Incidence of Running-Related Injuries Per 1000 h of running in Different Types of Runners: A Systematic Review and Meta-Analysis. *Sports Medicine (Auckland, N.Z.)*, *45*(7), 1017–1026. https://doi.org/10.1007/s40279-015-0333-8

Wackerbauer, R., Witt, A., Atmanspacher, H., Kurths, J., & Scheingraber, H. (1994). A comparative classification of complexity measures. *Chaos, Solitons & Fractals*, *4*(1), 133–173. https://doi.org/10.1016/0960-0779(94)90023-X

Warden, S. J., Davis, I. S., & Fredericson, M. (2014). Management and prevention of bone stress injuries in long-distance runners. *The Journal of Orthopaedic and Sports Physical Therapy*, *44*(10), 749–765. https://doi.org/10.2519/jospt.2014.5334

Winter, D. A., Sidwall, H. G., & Hobson, D. A. (1974). Measurement and reduction of noise in kinematics of locomotion. *Journal of Biomechanics*, *7*(2), 157–159. https://doi.org/10.1016/0021-9290(74)90056-6

Wu, S.-D., Wu, C.-W., Lee, K.-Y., & Lin, S.-G. (2013). Modified multiscale entropy for short-term time series analysis. *Physica A: Statistical Mechanics and Its Applications*, *392*(23), 5865–5873. https://doi.org/10.1016/j.physa.2013.07.075

Zifchock, R. A., Davis, I., Higginson, J., McCaw, S., & Royer, T. (2008). Side-to-side differences in overuse running injury susceptibility: a retrospective study. *Human Movement Science*, *27*(6), 888–902. https://doi.org/10.1016/j.humov.2008.03.007