

**Detecting Transient Changes in Gait Using Fractal Scaling of Gait Variability in Conjunction with
Gaussian Continuous Wavelet Transform**

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Abstract

Accelerometer data can be analyzed using a variety of methods which are effective in the clinical setting. Time-series analysis is used to analyze spatiotemporal variables in various populations. More recently, investigators have focused on gait complexity and the structure of spatiotemporal variations during walking and running.

This study evaluated the use of time-series analyses to determine gait parameters during running. Subjects were college-age female soccer players. Accelerometer data were collected using GPS-embedded trunk-mounted accelerometers. Customized Matlab[®] programs were developed that included Gaussian continuous wavelet transform (CWT) to determine spatiotemporal characteristics, detrended fluctuation analysis (DFA) to examine gait complexity and autocorrelation analyses (ACF) to assess gait regularity. Reliability was examined using repeated running efforts and intraclass correlation. Proof of concept was determined by examining differences in each variable between various running speeds. Applicability was established by examining gait before and after fatiguing activity.

The results showed most variables had excellent reliability. Test-retest R^2 values for these variables ranged from 0.8 to 1.0. Low reliability was seen in bilateral comparisons of gait symmetry. Increases in running speed resulted in expected changes in spatiotemporal and acceleration variables. Fatiguing exercise had minimal effects on spatiotemporal variables but resulted in noticeable declines in complexity.

This investigation shows that GPS-embedded trunk-mounted accelerometers can be effectively used to assess running gait. CWT and DFA yield reliable measures of spatiotemporal characteristics of gait and gait complexity. The effects of running speed and fatigue on these variables provides proof of concepts and applicability for this analytical approach.

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General Audience Abstract

Fitness trackers have become widely accessible and easy to use. So much so that athletic teams have been using them to track activity throughout the season. Researchers are able to manipulate data generated from the fitness monitors to assess many different variables including gait. Monitoring gait may generate important information about the condition of the individual. As a person fatigues, running form is theorized to breakdown, which increases injury risk. Therefore the ability to monitor gait may be advantageous in preventing injury. The purpose of this study is to show that the methods in this study are reproducible, respond reasonably to changes in speed, and to observe the changes of gait in the presence of fatigue or on tired legs. Three analyses are used in this study. The first method called autocorrelation, overlays acceleration signals of consecutive foot strikes, and determines the similarity between them. The second method utilizes a wave transformation technique that is able to determine foot contact times. The final method attempts to determine any pattern in the running stride. This method looks for changes in the structure of the pattern. Less structure would indicate a stride that is fatigued. The results showed that the methods of gait analysis used in this study were reproducible and responded appropriately with changes in speed. Small changes in gait were observed due to the presence of fatigue. Further investigation into the use of these methods to determine changes in gait due to the presence of fatigue are warranted.

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Abbreviations

CWT:	Continuous wavelet transform
DFA:	Detrended fluctuation analysis
ACF:	Autocorrelation function
FS:	Foot Strike
IC:	Initial Contact (corresponds to FS)
TO:	Toe off, the time the foot leaves the ground
FC:	Final contact (corresponds to TO)
CT:	Contact time, the time the foot is in contact with the ground
FT:	Flight time, the amount of time spent when both feet are not in contact with the ground
ML:	Mediolateral or x-axis
AP:	Anteroposterior or y-axis
V:	Vertical or z-axis
R:	Resultant vector of the three axes
Step:	Consecutive right to left foot strikes
Stride:	Consecutive right to right or left to left foot strikes
ACL:	Anterior cruciate ligament, anchors femur to the tibia and prevents the tibia from sliding too far forward.
RMS:	Root Mean Square
Jerk:	Rate of change in acceleration

Chapter 1

Introduction

1.1 Introduction

Laboratory methods of simulating team sports-based situations have struggled to provide ecologically valid data. Creating a simulated environment in order to estimate observable physiologic variables does not adequately describe the stresses that athletes are subject to during regular practice and competition. Recent developments in technology have provided new methods of fitness tracking that act as promising replacements for lab simulated experiments. Wearable fitness trackers have begun to become reliable methods of physiological monitoring in team-based sports. Accelerometers and GPS devices are now small enough to wear on a person in the form of a watch, band, or a trunk mounted monitor. The ease in which these devices can be worn combined with their ability to simultaneously collect large amounts of data, makes fitness trackers a valuable tool in measuring physiologic changes during team sports activities.

A key hindrance to athletic performance is fatigue and injury. Therefore, it would be advantageous to have the ability to conveniently monitor fatigue and assess injury risk. Physiological monitor-derived measures of training load have been used to monitor training habits through competitive seasons in team sports. However, the interpretation of training load data is not sensitive to the day or even the workout. Ratings of perceived exertion (RPE) are another measure of fatigue that have some validity, however in team sports they tend to become less valid as the team adopts a group RPE (rather than a true RPE) in order to maintain status (i.e. are in as good of shape as others). Therefore, having a marker of fatigue that would be sensitive enough to detect changes from workout to workout, while also observing individual athletes independent of bias, would be advantageous. Accelerometric gait analysis could provide

an opportunity to achieve this objective. In clinical populations, accelerometric gait analysis has been shown to be able to distinguish changes in gait due to different pathologies. It has not been extensively studied in athletic populations or while running.

1.2 Specific Aims

The overall aim of this investigation is develop a method of gait analysis using continuous wavelet transform (CWT), peak acceleration detection and autocorrelation procedures. Specifically, this study sought to:

1. Develop a system to generate variable describing spatiotemporal, accelerometric and structural variability parameters of the running gait. Specifically to employ:
 - a. Gaussian CWT to generate spatiotemporal variables.
 - b. Peak analysis to generate accelerometric variables.
 - c. Autocorrelation analysis to determine step and stride regularity.
 - d. Detrended fluctuation analysis (DFA) to generate fractal scaling indices describing the structural variability of the spatiotemporal variables.
2. Determine the within and between day reliability of these variables generated by these methods.
3. Establish proof of concept for these methods by perturbing gait using varied running speeds.
4. Establish applicability by applying the analysis to gait before and after fatiguing exercise.

1.3 Limitations and Delimitations

1.3.1 Limitations

Data collection was done during the fall season which consists of competitive games and practices. The consistency of weather was hard to maintain. Likewise, instances of altitude, surface, time, and athlete training status may change trial to trial. Injuries occurring in season, pre-existing injuries, diet, well-being, and school or social stress cannot be controlled.

1.3.2 Assumptions

Weather conditions had negligible effect on change in gait variables. All players were physically healthy and not suffering from acute or chronic injury.

1.3.3 Delimitations

Subjects were delimited to female collegiate soccer players (members of a Division I NCAA team). Speed and acceleration data were generated the GPSports SPI HPU GPS and accelerometric receivers that come with wearable vests and proprietary software package. The location of the accelerometer was between the scapulae.

Chapter 2

Literature Review

2.1 Introduction

For years, researchers have studied the spatial and temporal patterns of the human gait. More recently, interest in the variability and complexity of the gait pattern has increased. Tools used to quantify gait are now being employed to analyze gait of various populations and under various conditions. In short, changes in gait complexity seem to be associated with abnormal gait that is often present in conditions of neuromuscular disease, injury and fatigue. The purpose of this literature review is to summarize the current state of gait analysis and its application to the understanding and identification of normal and pathological gait. The second goal of this chapter is to lay the foundation for further characterizing gait in athletic populations.

2.2 Gait

2.2.1 Effects of Fatigue

A common side effect of training is muscle fatigue. While regular muscle fatigue is necessary in creating advantageous muscle adaptations, fatigue alters the physiological properties of the muscles in order to continue carrying out the exercise. This alteration in physiological properties may make individuals more susceptible to injury. Fatigue decreases muscle force and increases reflex loop times (More et al. 1993, Nelson and Hutton 1985, Behrens et al. 2015, Yavuz et al. 2014) as well as reducing stretch reflex activity (Avela and Komi 1998, Nicol et al. 1996). Avela and Komi (1998) found that exercise induced muscle fatigue leads to a decrease in the excitability of the Ia afferent pathway. A consequence of this afferent impairment, decreases muscle stiffness (Avela and Komi 1998). Furthermore Avela and

Komi (1998) showed a reduction in stretch reflex sensitivity and muscle stiffness after prolonged stretch shortening cycles of exercise. Assessment of fatigue on coactivation of the quadriceps was assessed by Nyland et al. (1997). They found that quadriceps femoris fatigue lead to “earlier gastrocnemius activation and delayed vastus medialis, rectus femoris, and vastus lateralis activation” (Nyland et al.1997). Quadriceps femoris fatigue showed earlier activation of the gastrocnemius during the stance phase of running (Nyland et al. 1997). Delayed activation due to fatigue is not unique to the muscles in the thigh. Sinkjaer et al. (1996) saw that the calf muscles had low reflex stiffness which was attributed to the cocontraction of the dorsiflexors and plantar flexors at the ankle joint. Clearly, when fatigue is introduced the muscular function deteriorates. The deterioration of proper muscle function may lead to asymmetries in gait and could even lead to injury.

2.2.2 Hamstring Injuries

A common location for injury during running related activities is the hamstring muscle group. The hamstring muscle group coordinates the movements between the sacroiliac joint and the patellofemoral joint. This group of muscles is composed of the biceps femoris, the semitendinosus, and the semimembranosus. Two common hamstring related injuries are hamstring strain and anterior cruciate ligament (ACL) tear.

Hamstring strains arise from explosive overloading of the hamstring muscle. The majority of the activation of the hamstrings during gait is during late swing and initial stance (Chumanov et al 2012, Daly et al. 2016, Duysens et al. 1998, Kuitunen et al. 2002, Kyrolainen et al. 1999, Schache et al. 2009). The hamstrings are substantially loaded during both swing and stance phases of running (Chumanov et al. 2011). Injuries normally arise during swing phase because of the substantial loading pattern combined with an eccentric contraction (Chumanov et

al. 2011). During the swing phase the hamstrings are working to eccentrically extend the knee. The eccentric contraction works to decrease the acceleration of the tibia as it extends forward. At the patellofemoral joint the hamstrings work to both flex and rotate the knee. The hamstrings work to eccentrically slow the acceleration of knee extension during the late swing phase in order to initiate knee flexion (Schache et al. 2009, Chumanov et al. 2012, Daly et al. 2016). At the sacroiliac joint, the hamstrings work to extend the hip during terminal swing (Schache et al. 2009). Furthermore EMG analysis during running has shown that the biceps femoris become more active during periods of exercise engaging higher %VO₂max (Camic et al. 2015). Increasing activation at higher intensity puts the hamstrings at increased strain due to the load they are trying to accommodate.

ACL tears are a common injury in team sports athletes which can be caused by hamstring muscle deficiency. Though non-contact ACL injury is a multifactorial problem (Shultz et al. 2015), a risk factor is unbalanced hamstring to quadriceps strength ratios. Specifically, weak hamstring muscles in comparison to quadriceps lead to increased risk of ACL injury. A comparison of male and female thigh muscle characteristics done by Hannah et al. (2015) showed that males had larger maximum and explosive voluntary force production of the hamstring muscles when weight was normalized. The authors postulate that the hamstring muscles of females may just be smaller than in males, and therefore risk of ACL injury is increased in females. Biomechanical differences at the hip and knee (differences in joint angles) as well as improper proprioceptive training increase risk of ACL injury in women (Shultz et al. 2015).

Furthermore Daly et al. (2016) found that previous injuries to the biceps femoris led to the following running asymmetries in gait: increased anterior pelvic tilt, increased hip flexion,

and increased medial knee rotation. It has been shown that injury to the biceps femoris caused an increase in activation of the ipsilateral erector spinae, gluteus maximus and external obliques, and the contralateral rectus femoris (Daly et al. 2016). Monitoring gait in individuals susceptible to hamstring related injuries may help in injury prevention.

2.2.3 Laterality

Assessment of foot dominance showed that there is a tendency for one foot to take on movements involved with more neuromuscular control, while the other acts to stabilize the body (Sadeghi et al. 2000). Sadeghi et al. (2000) assert that the dominant foot's primary role is forward progression whereas the nondominant foot acts to stabilize gait. This idea is seen in how older individuals' gait adapts over time. Nagano et al. (2011) found that older individuals tend to have a higher step with their nondominant foot. This action is seen as a defensive strategy against falling, allowing the dominant foot to help recover from the fall. If the dominant foot does indeed have higher neuromuscular control, it would be advantageous to try to catch oneself with the dominant leg during a fall. Interestingly, Echeverria et al. (2010) found that limb dominance switches between steps. They conclude that foot dominance is not static, rather dynamic during running. In addition to the fluid limb dominance seen during running, fatigue appears to have no significant interaction between the dominant and non-dominant leg with respect to joint kinetics (Brown et al. 2014). Therefore, while it appears that the dominant foot plays a bigger role in movements utilizing neuromuscular specialization, foot dominance was seen to switch during running (from step to step) and to not show significant differences in knee, hip, or ankle kinetics and kinematics during running.

2.3 Accelerometry and Gait Analysis

2.3.1 Accelerometers

Accelerometers are a noninvasive technology useful in estimating gait metrics.

Accelerometers are inertial sensor units that estimate accelerations. Tri-axial accelerometers estimate accelerations in three axes: vertical, anteroposterior, and mediolateral. Advances in technology have made accelerometers cheap and convenient for field work due to their being small and easily attachable to the body without causing physiological hindrances. Popular locations for accelerometers are on the L3 spinous process of the back, and between the scapulae. They are placed on the body by a range of methods including adhesives, pouches, and specialized vests. Placing the accelerometer on the trunk while convenient leads to dampened acceleration signals. However, despite the dampening effect of trunk-mounted accelerometers, their validity has been shown to be good (Del Din et al. 2016). Researchers have found that accelerometers show good to excellent agreement in measuring gait variables when compared to motion capture systems (Byun et al. 2016, Hartmann et al. 2009, Cole et al. 2014).

Of interest to trainers is the pattern of an athlete's stride or gait. When players are injured and/or fatigued, gait characteristics can change. For example, an injured player who may "limp" on one leg will show gait differences between the right and left limb – gait imbalance or asymmetry. Also, fatigue may cause change in the timing of the gait such as prolonged ground contact time with one or both feet as well as alterations in stride length.

To analyze gait, raw signals are obtained from the accelerometer such as the GPSports SPI HPU units. This device yields accelerations along three axes as well as a

resultant. In addition, jerk or the rate of change in acceleration can be computed (jerk is often used as a measure of “body load”).

Superoinferior Axis	z -axis or vertical (V)	
Mediolateral Axis	x -axis or mediolateral (ML)	
Anteroposterior Axis	y -axis or anteroposterior (AP)	
Resultant	$R = \sqrt{x^2 + y^2 + z^2}$	(1)

Jerk	$J = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2}$	(2)
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2.3.2 Measuring Gait

The applicability of accelerometer measurements to characterize gait is diverse. Methods have been developed to measure leg and surface stiffness (Butler et al. 2003, Gaudino et al. 2013, Girard et al. 2010, Girard et al. 2011, Morin et al. 2005), ground reaction forces (Gaudino et al. 2013, Girard et al. 2010), gait symmetry, and contact times (Ammann et al. 2015). For the purposes of this paper, gait symmetry, foot contact, step and stride times are going to be the primary focus. Stride length, cadence and step frequency will also be included, and derived from the autocorrelation data. Information on leg stiffness and ground reaction forces will be included in section 2.4.

2.3.4 Spatiotemporal Analysis

McCamley et al. (2012) offered a unique way to quantify spatiotemporal gait characteristics using accelerometry data. Gaussian Continuous Wavelet Transform (CWT) works as a unique filter for acceleration data that enables the detection of specific gait events. Gait is cyclic and variable in nature.

Therefore, the estimation of the acceleration data using a stoic

function would not capture the variability inherent in gait. The genius of the CWT, allows for

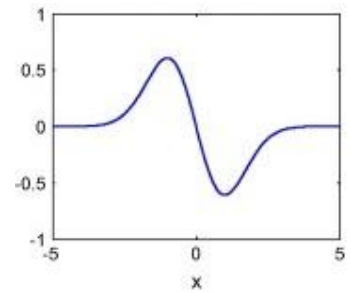


Figure 1. A first order Gaussian wavelet.

each individual step to be fitted to a wavelet (Figure 1), which allows for the variability in gait metrics. This wavelet consists of a single, alternating positive and negative deflections. This is similar to the tri-axial acceleration patterns seen during running as well as vertical acceleration.

The first step in the transform, is to integrate the raw acceleration data to velocity, and then differentiate it using the CWT to get a smoothed acceleration signal. The minima of the new signal represent initial contact (IC) times (McCamley et al. 2012, Godfrey et al. 2015, Del Din et al. 2016.). Further differentiation using the CWT gives the jerk function. The maxima of the jerk function are representative of the final contact (FC) times or toe off (McCamley et al. 2012, Godfrey et al. 2015, Del Din et al. 2016). It is important to note that this process has been demonstrated using the raw accelerations from the vertical axis and not the other axes (mediolateral, anteroposterior).

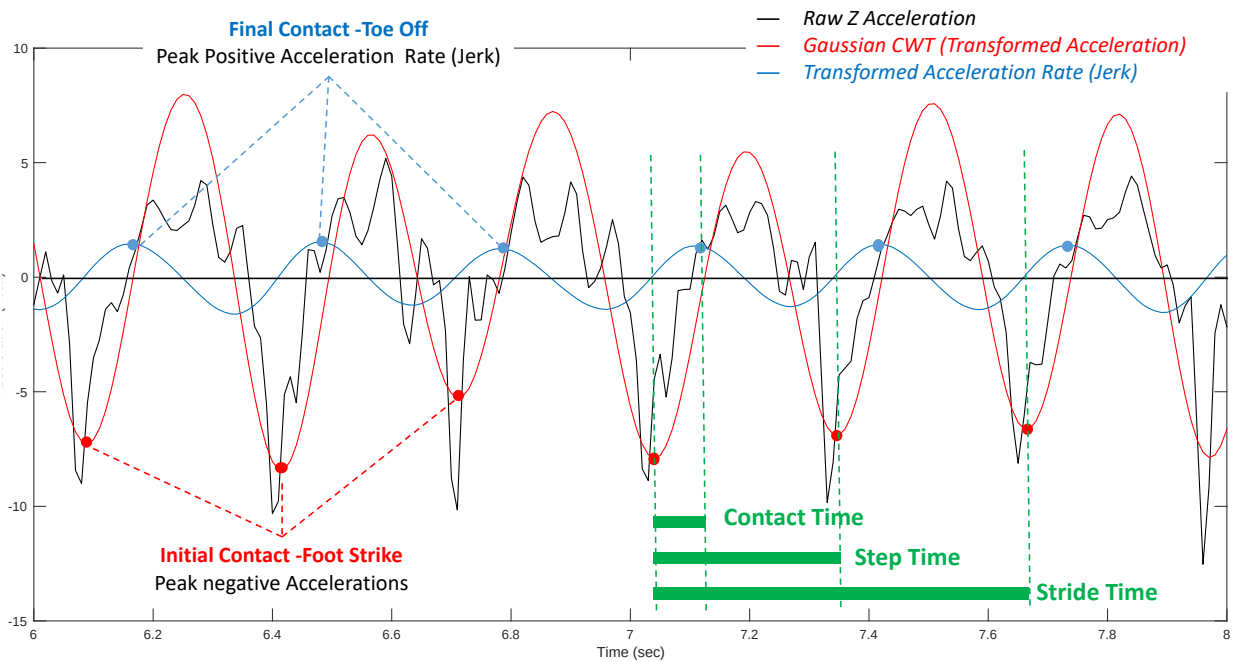


Figure 2. Example of how CWT can be used to calculate contact times. The black line represents the raw vertical acceleration data. The red line represents the first differentiation using the CWT, and the blue line is the second differentiation of the CWT. The minima of the dashed line represents the initial contact period, and the maxima of the dotted line represent the final contact period. The time between the minima of the dashed line and the maxima of the dotted line is the contact time.

The difference between adjacent IC and FC times represent the contact time (CT). The difference between adjacent initial contacts represent step time StpT while the difference between “every other” IC is the stride time (StrT) (see Figure 2).

$$\text{Contact Time (s)} \quad CT = FC_i - IC_i \quad (3)$$

$$\text{Step Time (s)} \quad StpT = IC_{i+1} - IC_i \quad (4)$$

$$\text{Stride Time (s)} \quad StrT = IC_{i+2} - IC_i \quad (5)$$

Zijlstra and Hof (2003) demonstrated a convenient way to delineate the left from right foot contacts. During stance, the center of mass accelerates to the left when stepping with the right leg, and vice versa. Therefore, in reference to the mediolateral accelerations, positive accelerations correspond to right foot step, and negative accelerations correspond to left foot step (Zijlstra and Hof, 2003) (see Figure 3). Once right and left steps are identified, right and left foot contact times can be identified. In addition, $R \rightarrow L$ and $L \rightarrow R$ step times as well as $R \rightarrow R$ and $L \rightarrow L$ stride times can be determined. By identifying right and left limb values, difference values can be calculated. For example, CT difference is calculated as:

$$\text{Difference (\%)} = 200 \cdot \frac{CT_R - CT_L}{(CT_R + CT_L)} \quad (6)$$

Traditionally, step and stride length (StpL, StrL) have been calculated using vertical displacement (double integration of the z-axis acceleration signal) (Figure 4) and an inverted pendulum model (Zijlstra & Hoff, 2003). The following equation is then applied to determine step length (StpL),

$$\text{Step Length (m)} \quad StpL = 2 \sqrt{(2lh - h^2)} \quad (7)$$

where l = height of the unit and h = vertical displacement of the unit. As before, mediolateral accelerations can be used to determine right and left step lengths.

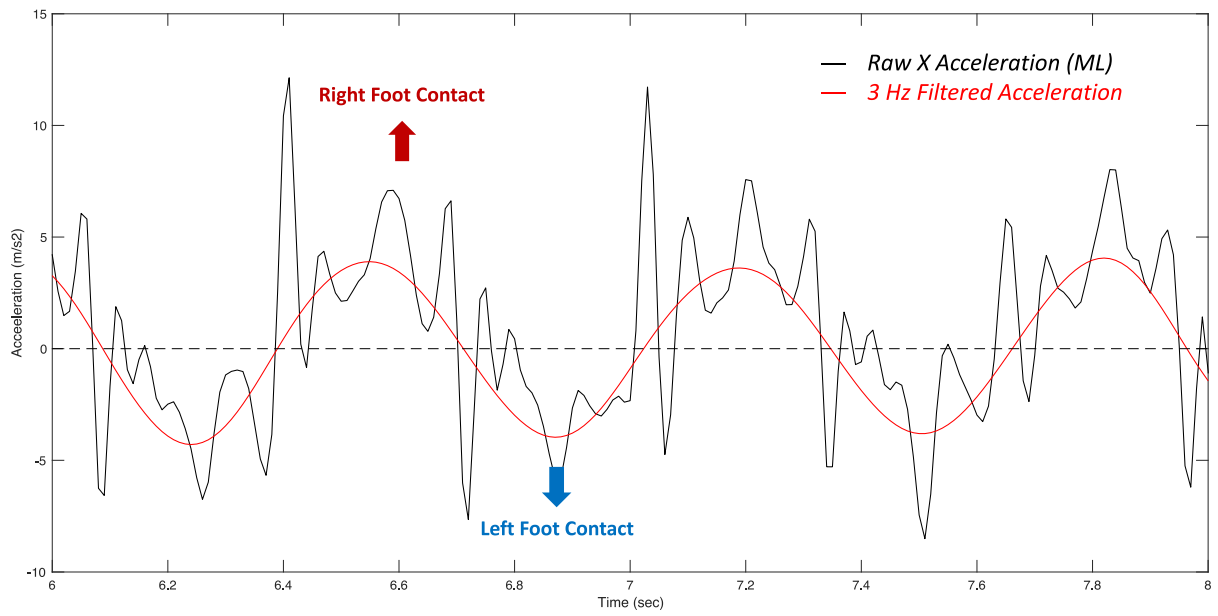


Figure 3. Determination of right and left foot strikes using ML axis acceleration. The black line represents the raw ML acceleration and the red line represents the filtered signal. Filtering the raw signal improves right and left event determination.

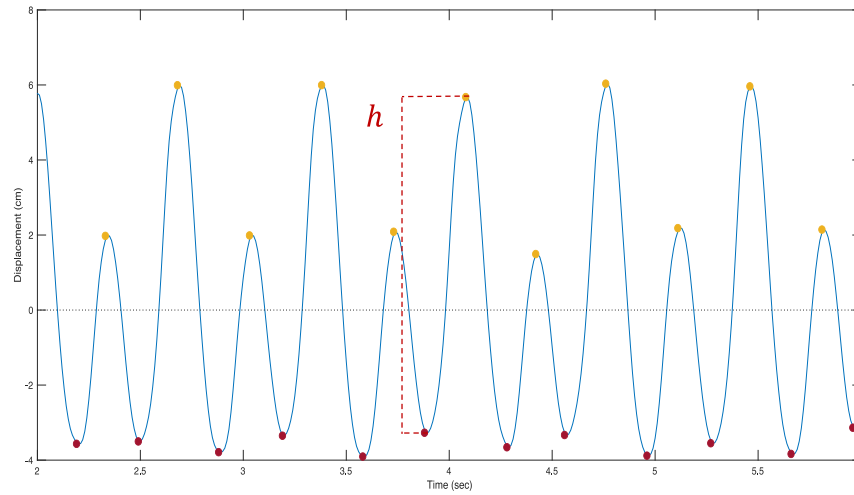


Figure 4. Determination of vertical displacement (h) for use in the calculation of step length. Data from a player 10 months post ACL reconstruction surgery.

Double integration of the acceleration signal can be affected by signal noise and drift as well as movement artifact. This requires bandpass filtering of the raw and integrated signals. As a result, vertical displacement values can be less reliable than anticipated. Alternatively, using the GPS derived velocity signals obtained from the units coupled with StpT and StrT, StpL and StrL can be computed as:

$$\text{Step Length (m)} \quad \text{StpL} = \text{StpT} \cdot \bar{v}_{stp} \quad (8)$$

$$\text{Stride Length (m)} \quad \text{StrL} = \text{StrT} \cdot \bar{v}_{str} \quad (9)$$

where $\bar{v}_{stp}$ and $\bar{v}_{str}$ are the average velocities during the corresponding step and stride, respectively.

2.3.3 Autocorrelation and Gait Regularity

Auto and cross correlation as a statistical comparison method has become more popular within the exercise physiology field. Its effectiveness has been demonstrated in both evaluating gait and cardiorespiratory kinetics (Gouwanda et al. 2011, Nelson-Wong et al. 2009, Koschate et al. 2016, Hoffmann et al. 2013, Drescher et al. 2016). Autocorrelation takes periodic data sets, shifts adjacent periods back to match the time of the first period in order to correlate consecutive periods to the first period. For example, a common autocorrelation is taking accelerometry data and comparing foot strike accelerations. The first foot strike is compared to the second, third, fourth, etc. Each comparison corresponds with a lag that is equal to the amount of time between each shift. The comparison at each time shift produces an autocorrelation coefficient. The coefficients are used in order to create a new autocorrelation function (ACF) (Figure 5). To compute the ACF, the following equation is used,

$$ACF = \frac{1}{N-|m|} \sum_{i=1}^{N-|m|} x_i x_{i+m} \quad (10)$$

where N is the number of samples in the series to be analyzed and m is the lag parameter (Moe-Nilsson and Helbostad 2004).

At a lag of zero, $r = 1.0$ (i.e. the signal perfectly correlates with itself). As the signal is lagged, the ACF declines then increases to a second peak (A_{d1} in Figure 5). This second peak reflects the point at which adjacent foot strikes (right and left) overlay each other. The magnitude of the ACF at this peak is the step regularity (StpReg). It quantifies the similarity or regularity between right and left foot strikes. The greater the ACF, the more similar or regular the adjacent (right and left) steps.

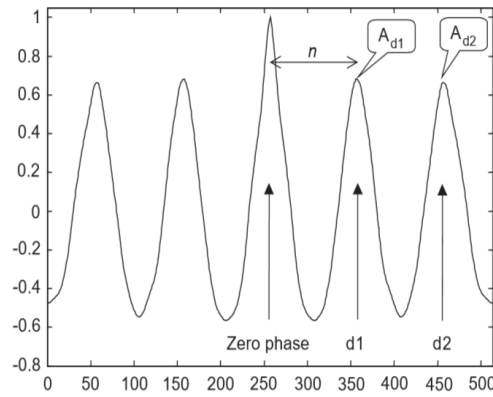


Figure 5. ACF of gait accelerations. A_{d1} is denoted as step regularity. A_{d2} is denoted as stride regularity. (Moe-Nilsson and Helbostad 2004).

Lower ACF values indicate decreasing regularity and some dissimilarity between right and left steps. A second peak occurs that represents the overlay of foot strike on the same side (A_{d2}). The second peak of the ACF is termed stride regularity (StrReg) and represents the similarity or regularity of right foot strikes and of left foot strikes. This approach can be used for acceleration signals of all three axes as well as the resultant (Schutte et al. 2015, Moe-Nilsson and Helbostad 2004). Gait symmetry for each axis is evaluated as a ratio between step regularity and stride regularity:

$$\text{x-axis Symmetry (\%)} \quad XSymm = 200 \cdot \frac{|StpReg - StrReg|}{StepReg + StrReg} \quad (11)$$

where StpReg and StrReg represent the ACF coefficients in the same period (Kobsar et al. 2015). The closer the number to zero, the better the gait symmetry (Kobsar et al. 2015). Stride length (l) and cadence (c) were derived from the autocorrelation data using equations developed by Moe-Nilsson and Helbostad (2004).

$$\text{Stride Cadence (strides per min)} \quad c = 60 \cdot \frac{f}{n} \quad (12)$$

$$\text{Stride Length (m)} \quad l = \frac{v}{f} \quad (13)$$

where f is the sampling frequency (Hz), n is the number of samples per dominant period (dominant period is the periodicity of the ACF also known as lag), and v is the running velocity in m/s (Moe-Nilsson and Helbostad 2004).

2.3.5 Detrended Fluctuation Analysis

While early work focused on the extent or amount of variability one displays during walking and running, more recent efforts emphasize the importance of addressing the structure of variability (Harbourne & Stergiou, 2009; Decker et al., 2010). For example, in healthy individuals, the variability in step or stride interval during a walking or running task is not random but contains underlying structure, incorporating long-range correlations. Several analytical tools are available to assess the non-linear dynamics of gait (Decker et al., 2010). Detrended fluctuation analysis (DFA) evaluates long-term correlations within a time series and has been applied to the study of gait complexity (Peng et al., 1995; Hausdorff et al., 1995; 1996). DFA is an adapted root mean square analysis of a “random walk” that generates a self-similarity

parameter, the fractal scaling index, also referred to as FSI (Hausdorff et al., 1995; 1996). It attempts to quantify the amount of randomness between data points of a cyclic action (e.g. heart rate, stride pattern, etc.).

To execute DFA, the time series is first integrated by subtracting the mean from every data point through the following equation (i.e. detrending):

$$y(k) = \sum_{i=1}^k [S_i - \bar{S}] \quad (14)$$

Where k is the number of data points, S_i is the i th step number and $\bar{S}$ is the average step interval (Figure 6a). The integrated time series $y(k)$ is then divided into “windows” consisting of an equal number of data points. Linear regression then fits a trend line to the data contained within each window (Figure 6b). Fluctuations are computed as well as the RMS error for the points in the window:

$$F(N) = \sqrt{\frac{1}{N} \sum_{k=1}^N [y(k) - y_N(k)]^2} \quad (15)$$

where N is the number of data points in the window (Hausdorff et al. 1995, 1996).

This process is repeated across increasing window sizes which typically range in length from 4 data points to one-quarter of the series length ($\frac{k}{4}$). The log RMS of the detrended fluctuations ($F(N)$) for each window length is then plotted against the log N . Least squares regression is used to calculate the slope of the line (Figure 6c). This slope corresponds to the fractal scaling index (FSI or α) value

FSI values of 0.5 represent random variability whereas values between 0.5 and 1.0 indicate the presence of persistent long-range correlations. Thus, FSI values above 0.5 indicate gait variability that is structured rather than random over time (Decker et al., 2010; Hausdorff et al., 1995). This procedure is often verified by randomly shuffling the time series data then recalculating α . Shuffling the data will retain the mean values and underlying variability (i.e. standard deviation). However, any long-term correlations or structural pattern is destroyed. Using this approach, α -values will approach 0.5.

FSI values increase during maturation (Hausdorff et al., 1999) and decline with aging (Hausdorff et al., 2001) and with certain neurodegenerative diseases (Hausdorff et al., 2009). In addition, low back pain (Newell & van der Laan, 2010), fatigue (Meardon et al., 2011), injury (Meardon et al., 2011) and overtraining (Fuller et al., 2017) are associated with reduced FSI. However, physical training increases gait structure (Nakayama et al., 2010; Gow et al., 2017). Based on these results, Decker et al., (2010) suggest that a decline in the FSI value towards 0.5 represents a decrease in gait complexity and structure. This in turn, reflects a decline in motor control and progression towards an “unhealthy” gait (Decker et al., 2010).

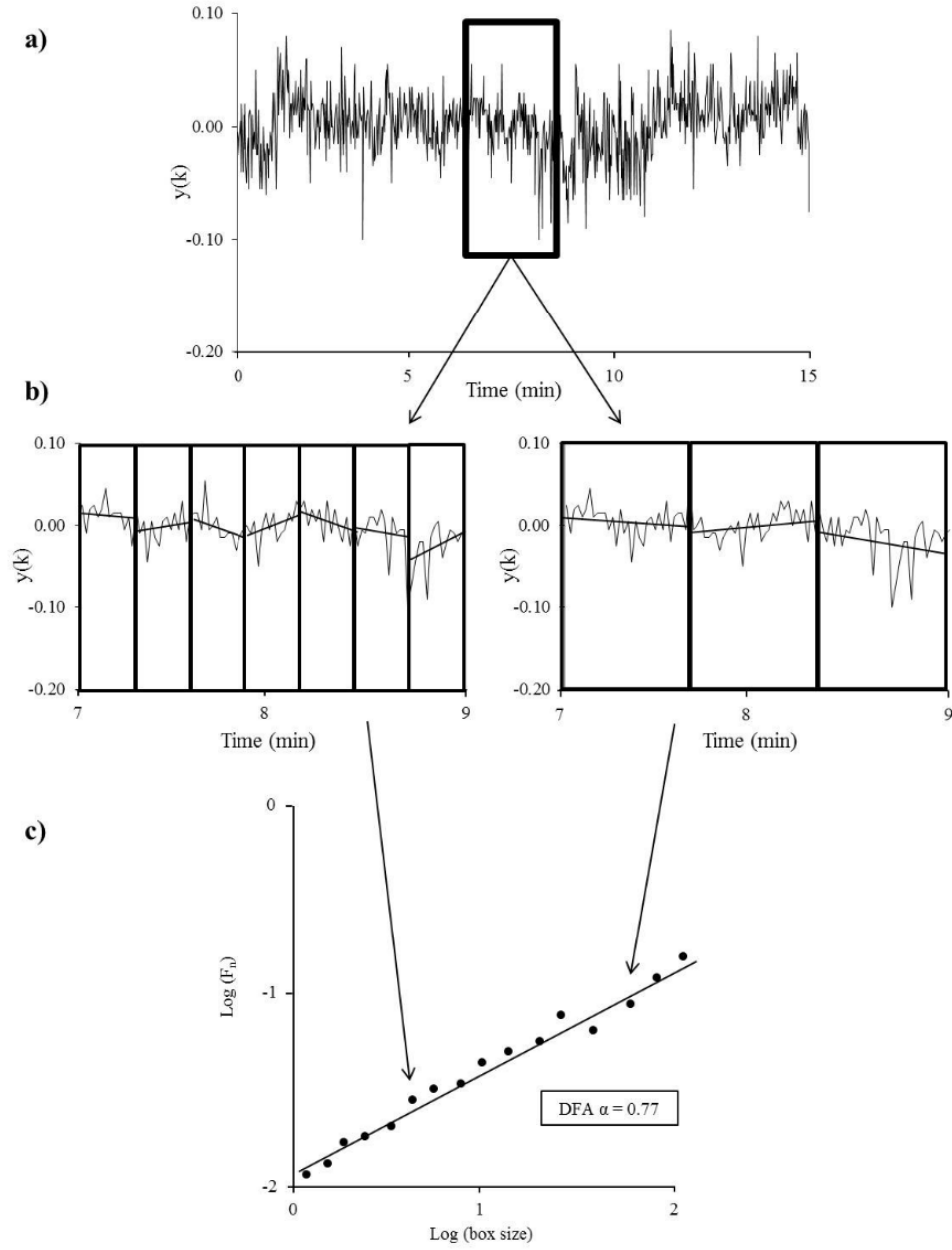


Figure 6. Detrended fluctuation analysis (taken from Rhea and Kiefer, 2014). Panel a) shows the raw, detrended time series data. Panel b) shows the time series partitioned into two different window sizes. Also, a line if fit through the data within the window. The distance of each points from the line represents the “fluctuation”. Panel c) shows the log-log plot of the average RMS error within each window versus the window size. The slope of this relationship represents the FSI or α .

2.3.6 Ground Reaction Forces

GPSports fitness monitors have been used in many team sports to estimate innumerable physiologic variables during performance (Buchheit et al. 2015, Gaudino et al. 2013, Higham et al. 2016, Wellman et al. 2016, Scott et al. 2015). As such the reliability and validity of these fitness devices have been under intense scrutiny, yielding promising results (Buchheit et al. 2015, Scott et al. 2015, Gaudino et al. 2013, Waldron et al. 2011). Gaudino et al. (2013) were able to demonstrate high validity and reliability in the GPSports software to serve as an estimate of ground reaction forces. They used flight time and contact time of the foot to estimate the maximum force experienced by the foot or the max ground reaction force (Gaudino et al. 2013). Their primary purpose was to account for the characteristics of the surface and how that would affect the ground reaction forces experienced by the athletes. In doing so they were able to relate the maximum ground reaction forces to leg stiffness and the vertical change of the center of mass (Eq 5-8). The calculations for leg stiffness were developed by Morin et al. (2005), but adapted by Gaudino et al. (2013). Morin et al. (2005) derived the following equations in an effort to find an alternative to measuring ground reaction forces with a force plate:

$$\text{Total Spring Constant} \quad K_{\text{tot}} = F_{\text{peak}} / \Delta y_{\text{tot}} \quad (16)$$

$$\text{Peak force (N)} \quad F_{\text{peak}} = mg \frac{\pi}{2} * \left(\frac{FT}{CT} + 1 \right) \quad (17)$$

$$\text{Vertical Displacement (m)} \quad \Delta y_{\text{tot}} = F_{\text{peak}} * CT^2 / (m * \pi^2) + g * CT^2 / 8 \quad (18)$$

Gaudino et al. (2013) observed the legs and the running surface as springs in series which results in the following relationship:

$$\text{Total Spring Constant} \quad k_{\text{tot}} = (k_{\text{leg}}^{-1} + k_{\text{surf}}^{-1})^{-1} \quad (19)$$

Gaudino et al. (2013) was looking at the difference in running surface and how that would affect the ground reaction forces experience by the foot during foot strike. Cormack et al.

(2013) used a similar approach to measure leg fatigue during a jumping test by measuring the ratio of flight time to contact time in Australian football players. It would not make sense to apply this ratio to a running test, however using the same group of equations, the GPSports technology should be able to detect a decrease in leg stiffness represented by the value k_{leg} in the equation 19.

2.4 Alterations in Gait

2.4.1 Gait Analysis in Clinical Populations

The majority of gait analysis has been done with clinical purpose. Gait analysis has been assessed of patients with osteoarthritis (Barden et al. 2016, Barrois et al. 2016, Hodt-Billington et al. 2012, Staab et al. 2014), amputees (Iosa et al. 2014, Tura et al. 2010), joint arthroplasty (Rapp et al. 2015, Calliess et al. 2014), hemiparesis (Saremi et al. 2006), ageing (Auvinet et al. 2002, Valenti et al. 2015), Parkinson's disease (Demonceau et al. 2015, Yogev et al. 2007), stroke (Sanchez et al. 2015), and previous lower leg injuries (Setuain et al. 2017, Zifchock et al. 2008, Zifchock et al. 2006),

Tura et al. (2010) examined the usefulness of inertial sensors in maintaining proper use of prostheses in transfemoral amputees. The accelerometer was placed on the thorax, and autocorrelation analysis was used to determine step and stride regularity. Tura et al. determined that the accelerometers could detect differences in step and stride symmetry in a rectilinear path with 15 and 20 steps respectively.

Barden et al. (2016) examined gait variables in older adults with bilateral knee osteoarthritis. Using autocorrelation, the authors were able to detect a significant difference in

step regularity in the vertical and anteroposterior directions, whereas the same was not found with stride regularity.

Yang et al. (2011) analyzed gait in a population with complex regional pain syndrome (CRPS). The accelerometer was placed on the lower back and autocorrelation analysis was used to assess step and stride symmetry. Participants went through a short physical performance battery (SPPB) which is used to measure lower limb function. The authors found that in the vertical direction, accelerations had the same magnitude as the controls, which is contrary to the decreased magnitudes in accelerations in the mediolateral and anteroposterior axes for the CRPS group. The accelerometer was sufficient in detecting differences in the control and the CRPS group.

Trojaniello et al. (2015) observed the gait of hemiparetic, elderly, Huntington's, and Parkinson's patients using accelerometers mounted on the lower back. In doing so they were attempting to validate the ability of the accelerations to detect different gait events using specified methods against a motion capture system. The first method was smoothing the acceleration data in order to detect gait events using both calculus and physics properties of the acceleration curve. The second method is a filtered integration of the acceleration data and the third method used Gaussian continuous wavelet transform which was referenced earlier. The results showed that the accelerometer could accurately detect gait events in the healthy elderly population. However, using the methods of gait event detection described above, the researchers noted that the presence of a pathological gait hinders the reliability and accuracy of the methods.

Hausdorff et al. (1997; 1999) found that the FSI, α , was greater in young adults compared to the elderly. Hausdorff and colleagues (for review see Hausdorff, 2007) have also studied the fractal scaling index in healthy individuals and those with neuromuscular disorders. They found

that patients with Huntington's and Parkinson's diseases showed lower α values than healthy individuals (Hausdorff et al. 1997; 1998; 2001; 2003). Healthy individuals showed $\alpha \sim 0.7$ whereas the patient's values were closer to 0.5, indicating greater randomness in their gait variability. This has been attributed to possible degeneration of the central motor system, altering the control of rhythmic movement (Ducharme & van Emmerik, 2018). Several groups have also shown that declines in α in the elderly and patients with neurodegenerative disorders are associated with a "cautious gait" and increased risk of falling (Herman et al., 2005; Hausdorff et al., 2001).

Interestingly, peripheral neuropathies do not impact α to nearly the same extent as do diseases of the central nervous system. Gates et al., (2007) and Richardson et al. (2004) found that patients with diabetic neuropathy as well as other general neuropathies maintained α near 0.85, values that compared closely to healthy controls. Despite changes in proprioception and increased stride to stride variability, these patients maintained gait complexity. This has lead these researchers to conclude that control of gait complexity and long-range correlations in stride to stride variability reside within the supra-spinal control regions of the nervous system.

A further test of this central control of the fractal-like structure of gait was performed by Hausdorff et al., (1996). Researchers had subjects freely walk at their self-selected pace. They were also asked to walk at that pace while coordinating gait to a metronome. This later trial resulted in the breakdown of the long-range correlations and reduced α . Thus when the control of the central nervous system is perturbed, individuals take on a more randomly structured gait.

2.4.2 Gait Analysis in Walking

The usefulness of accelerometric analysis of gait has been studied in walkers. Byun et al. (2016) set out to test the test-retest reliability and validity of an accelerometer to measure

spatiotemporal gait parameters. The test was done in older healthy adults. Contact times were measured using the raw acceleration data, interpolating it and then resampling it at 100 Hz (was originally 32 Hz). The contact time was then observed as the time between the two troughs of the interpolated resampled acceleration data. Test-retest reliability was assessed by computing intraclass correlation coefficients between the second and third walking trials. Four steps were required to obtain most gait measurements with great reliability. Step time needed 26 steps to obtain great reliability. Further, the most reliable results came from gait parameters derived from the vertical axis. The validity of the accelerometer findings were compared with the data computed by a GAITRite system. In terms of validity, the accelerometer had great levels of agreement in the vertical and anteroposterior axes. The mediolateral axis showed poor agreement with the GAITRite data.

Helbostad et al. (2007) observed the effects of fatigue on gait parameters in elderly subjects. A fatiguing protocol was performed and then a walking test to observe gait. The accelerometer was placed on the lumbar vertebrae and autocorrelation was used for gait analysis. The fatigue group had increases in variability in the anteroposterior and the vertical directions and decreased variability in the mediolateral direction.

Wundersitz et al. (2015) observed recreationally active individuals walking, running, and jogging on an instrumented treadmill to determine the validity of using an accelerometer. The researchers were interested in measuring peak acceleration. They found that while walking, the accelerometers provided the most agreeable data to the instrumented treadmill. As speed increased, agreement and validity decreased. It was postulated by the researchers that the increase in speed creates a more unstable environment for the accelerometer unit, thereby increasing the noise experienced by the unit.

Auvinet et al. (2002) set out to learn about the progression of gait through the human lifespan. They found that vertical acceleration was greater in men at heel contact, mid-stance, and at initial push-off. The only metrics that declined with age was impulse, speed and stride length. Stride length was longer in men, even when height was accounted for.

Another study by McGrath et al. looked into determining the reliability of the accelerometer to detect heel strike and toe off using different methods they found in the literature. Walking tests showed excellent agreement in stride time, whereas running yielded moderate agreement. Stride time was the most reliable metric across all variables and methods of calculation.

Jordan et al., (2007, 2008) showed that fractal scaling of the walking gait is altered by speed. They found that a preferred or self-selected pace, α -values were minimized. Increasing or decreasing speed increased the FSI values. Interestingly, this does not seem to be the case with running (Nakayama et al., 2010). Jordan et al. (2007, 2008) suggested that at a preferred speed, any given stride is less constrained by those that preceded it and more readily adaptable that when subjects are forced to walk at sub-optimal speeds.

2.4.3 Gait Analysis in Running

Running gait has also been assessed, however not as extensively. Analysis has been used extensively in clinical settings, but not in field settings. Ammann et al. (2015) observed the change in ground contact times (CT) during a 5 km time trial in elite runners. CT differed between the right and the left foot, with the left foot having a significantly longer CT. Interestingly, CT did not change appreciably during the 5 km time trial. The time trial was performed on a 400 meter track surface and 200 meter segments were observed for analysis. Another study by Gilman-Ammann et al. (2017) measured gait symmetry in terms of ground CT

in previously injured vs. uninjured runners. They found that shorter running distances led to quicker CT and greater asymmetries. CT did not change appreciably throughout the intervals. For the uninjured group, no difference in CT between the dominant and non-dominant leg were observed. In the previously injured group the CT were significantly longer on the injured side.

Furthermore, CT were seen to decrease after a fatiguing hopping protocol (Mudie et al. 2016) and after a long-distance race (Willems et al. 2012). However, Garcia-Perez (2013) found that CT were not changed due to fatigue. What they did find that was interesting was that fatigue decreased stride frequency and increased stride length. Furthermore, it was seen that CT were greater on a treadmill than during overground running (Garcia-Perez et al. 2013).

Schutte et al. (2015) observed the different effects that running surface had on accelerometry signals. Their experiment tested three surfaces: asphalt, a synthetic track, and wood chips. No significant differences in acceleration signals were found between the asphalt and synthetic track however, the wood chip trials had surprising results. Wood chip running led to a decrease in step frequency, step regularity in the anteroposterior and mediolateral axes, the RMS ratio in the vertical axis, and the anteroposterior step entropy. Schutte et al. (2016 Surface) later released a paper performing the exact experiment a second time, this time with slightly different outcome measures. They found that between the synthetic track and the concrete, synthetic track had higher vertical stride regularity. Again woodchip running showed significant differences in gait metrics. Woodchip running led to lower step frequency, lower vertical RMS, higher anteroposterior RMS, and lower step and stride regularity in the mediolateral direction. Furthermore woodchip running decreased the impact force of landing and decreased anteroposterior braking accelerations which the authors hypothesize could lead to differences in performance and injury risk between surfaces.

Patterson et al. (2011) did a case study on a recreational distance runner testing the effects of fatigue on gait dynamics. An accelerometer paired with a motion capture system were used to measure gait kinematics and kinetics. The fatiguing protocol on a treadmill began with a 10 minute warmup at an easy pace, and then ran 5 minutes at faster than 10k pace, and then did 5x45 second pickups with a minute rest between intervals and then a cooldown. The researchers found that as early as his second rep (of the five) the runner's gait mechanics were starting to breakdown. The author's did not comment on the validity of the accelerometer data in comparison to the motion capture system, but rather combined the data together to pinpoint accelerometric gait events with different stages of running.

Girard et al. (2010) attempted to measure ground reaction forces, vertical stiffness, and leg stiffness using a similar method to that proposed above by Gaudino et al. (2013) but was originally derived by Butler et al. (2003) (the difference between the two methods, is that Gaudino et al. (2013) observe the leg during stance as a spring in series with the ground, whereas Butler et al. (2003) and Girard et al. (2010) observed the leg during stance as a single spring acting against the ground). Girard et al. (2010) showed that leg stiffness remained constant during a fatiguing exercise protocol. The researchers also concluded that contact time was inversely related to aerobic capacity. This data is consistent with conclusions drawn from other studies testing the effect of fatigue on leg stiffness (De Ste Croix et al. 201x, Hunter and Smith 2007, Oliver et al. 2014).

On the other hand, there have been studies showing contrary data to the above point (Girard et al. 2011, Lehnert et al. 2017, Fourchet et al. 2015). The above study by Girard et al. (2010) was done during a 5k run on a 200 meter indoor track. In 2011, Girard et al. released a paper assessing fatigue on leg stiffness using a sprinting protocol. What they found was that as

speed increased, k_{leg} decreased, which lead to shorter contact times, longer stride lengths and smaller stride frequencies (Girard et al. 2011). Furthermore, population bias may be present in the data. Multiple studies were done in adolescents (De Ste Croix et al. 201x, Fourchet et al. 2015, Lehnert et al. 2017, Oliver et al. 2014) while others were less in mature populations (Girard et al. 2010, Girard et al. 2011, Hunter and Smith 2007). Clearly there is some uncertainty in the role of fatigue on effecting the k_{leg} during exercise.

Running exercise can lead to the development of fatigue. Fatigue is a complex process that is dependent on the volume and intensity of activity as well as the fitness status of the individual. It also involves alterations in both the central and peripheral nervous systems as well as within the muscle fiber. There are few studies using DFA to understand the fatigue process. Meardon et al., (2011) found that during a prolonged run, α -values decreased. This was the case in healthy, non-injured runners as well as those with previous injury. Bellenger et al. (2018) and Fuller et al. (2017) showed that a period of overtraining in trained runners resulted in reduced fractal scaling of running gait. Further, subjective measures of fatigue, exhaustion and lethargy were correlated to the degree of change in α . While the effects of fatigue on gait complexity is poorly understood, the perceptual data presented in the latter two studies suggest a role for the central nervous system. It is possible that muscular pain or discomfort, increased perception of effort or staleness associated with short- and/or long-term fatigue may alter gait structure. Accordingly, Newell and van der Laan (2010) showed that the gait variability of patients with chronic low back pain was less than their healthy counterparts (i.e. lower α). A preliminary report (Roberts 2004) suggests that this can be resolved by using analgesia treatments. However, further work is clearly warranted before such ideas can be confirmed.

2.5 Conclusions

Fatigue decreases the integrity of musculature and reflexes which makes the muscle more susceptible to injury. If the muscles of the legs are losing integrity, then it would stand to reason that fatigue would alter gait mechanics (Patterson et al. 2008). Further, the central nervous system plays an important role in the development of fatigue (Maclaren et al., 1989; Carroll et al., 2016). Monitoring gait metrics during fatiguing exercise bouts may have a protective effect on athletes. Observing gait variables may be able to alert researchers, coaches, and players to susceptibility to injury due to fatigue.

Autocorrelation has been used extensively in clinical populations to evaluate walking gait. Little research has been done using autocorrelation analysis in healthy, athletic populations in the field, particularly while running. The ease in which accelerometers can be worn on masses of athletes is incredibly useful for data collection. Accelerometers make it possible for data recording during athletic competition and practices. In fact, a lot of collected accelerometric data is paired with GPS technology to determine training loads in rugby, soccer, and Australian Rules Football athletes. As stated before, the presence of fatigue may deteriorate normal running gait (Patterson et al. 2008). Another method of measuring gait deterioration is assessing changes in contact times (Ammann et al. 2015). As the muscles fatigue, muscle stiffness decreases (Avel and Komi 1998). If the spring constant of the leg is decreasing, then there would be less elastic energy for the leg to use to continue the cyclic motion of running. As a result contact times are expected to decrease.

The intent of collecting and manipulating this data is so that players and coaches have an extra tool that can help strategize training to more effectively condition athletes. Overworking a tired athlete will result in injury, over training, and poor performance. Our goal is to take some

of the guess work out of producing training plans in order to more efficiently cater to the needs of athletes.

Chapter 3

Methods

3.1 GPSports SPI HPU Units

Player movements (accelerations, running distances, speeds, etc) and heart rates were recorded non-invasively using a GPSports SPI HPU unit and Polar heart rate monitor (or strap). Each unit was assigned a number and the numbers were assigned to each players randomly generated identification number. The units contain a 15 Hz GPS receiver and a 100Hz, 16g accelerometer. They record positional data at 5 Hz which is then supplemented or augmented by accelerometer data to record interpolated position at 15 Hz. The triaxial accelerometer orientation is determined by a 50 Hz magnetometer (used to orient the axes of the accelerometer). Each unit measures 74mm x 42mm x 16mm and weighs 56g. The units also communicate with a Polar T31 coded heart rate monitor/transmitter (15Hz determination of heart rate).

During training sessions, subjects were asked to wear the units and heart rate straps. The units were secured on the back, between the scapulae, using a custom designed vest (similar to a women's sports bra). Heart rate monitors were also secured to the vests and situated on the front of the thorax, just below the sternum. Signals from the units are transmitted in real time to a receiver located adjacent to the playing field using two-way wireless encryption and manufacturer's software (GPSport RealTime). Following each session, data stored on the units were downloaded onto a laptop computer, stored on a secured hard-drive and analyzed off-line.

Data were initially analyzed off-line using manufacturer's software (GPSports, TeamAMS). Each subject's data (heart rate, accelerometer and GPS) will be split into segments corresponding to various drills and activities.

3.2 Analytic Procedures

3.2.1 Signal Preprocessing

For the spatiotemporal measurements, the method of McCamley et al. (2012) and Godfrey et al. (2015) was used. All analyses were performed using the Matlab Signal Processing Toolbox (v 7.5). Data from the SPI HPU units are initially downloaded and pre-processed and split into desired segments using the manufacturer's proprietary software (Team AMS). Accelerometer and velocity data (from GPS signals) were then exported to an Excel spreadsheet. A custom program was developed using Matlab to import data from Excel and perform all of the analyses.

Accelerometer signals (*x*-, *y*-, *z*-axes and *R*) were low-pass filtered at 40 Hz (4th order Butterworth) to remove noise and high-pass filtered 0.9 Hz to remove baseline drift (e.g. 0.9-40 Hz bandpass filter) (using *<butter>* and *<filtfilt>* MatLab functions). In addition, the mediolateral signal was low-pass filtered at 3 Hz for the detection of right and left steps.

After filtering, correction for offset and alignment (i.e. tilt) of the tri-axial data was performed as described by Moe-Nilsson (1998) and Millegamps et al. (2004). In short, this procedure estimates the gravitational acceleration components in the anteroposterior and mediolateral directions and transforms the data to a horizontal-vertical coordinate system.

3.2.2 Spatiotemporal Variables

For the spatiotemporal measurements, the method of McCamley et al. (2012), Godfrey et al. (2015) and Del Din et al. (2016) were followed with minor changes. The preprocessed

vertical acceleration signal was integrated to obtain vertical velocity (<cumtrapz>) then differentiated by a Gaussian CWT using a scale of 10 (<cwt>). The differentiated signal further differentiated to obtain a jerk signal. Initial contact (IC) times were identified as the minima of the CWT acceleration signal and final contact times (FC) were identified as the maxima of the jerk signal (<findpeaks>). The sign of the mediolateral acceleration signal (positive or negative) at the IC and FC points was used to identify left and right foot contact values. Subsequent analyses were arbitrarily chosen to begin with the first right foot IC.

Difference between subsequent ICs and FCs was identified as the CT. The difference between subsequent right and left IC's was determined as StpT ($R \rightarrow L$ and $L \rightarrow R$ StpT) and the differences between subsequent right and subsequent left ICs was the StrTs ($R \rightarrow R$ and $L \rightarrow L$ StrT).

The speed variable, determined from the GPS and accelerometer data, was used to calculate step and stride lengths (StpL, StrL). This was done for two reasons. First, the inverted pendulum approach (Zijstra & Hoff, 2003) is not applicable for running as the running gait is characterized by periods of non-support. Thus, the accelerometer movement during a single step does not simulate that of an inverted pendulum. In this case, the pendulum axis translates during the period of non-support (defines running). Second, we have shown that the SPI HPU units used here are very accurate and reliable for distance measurements during rapid movements (Tessaro & Williams, 2018). Thus, it is reasonable to use distance traveled between IC times for computing StpL and StrL. For StpL, average speed between subsequent IC times of alternating limbs were integrated to give distance. This value was divided by the corresponding StpT to yield

StpL. StrL was computed the same way except that average speed between subsequent IC values from the same limb were used (see Equations 8 and 9).

3.2.3 Peak Acceleration and Area Acceleration

A resultant vector (R) was calculated using the x-, y- and z-axis accelerations. Using the IC and FC time points, the peak acceleration (Peak) of the resultant vector was determined for each step. In addition, the area under the acceleration curve (Area) was calculated using trapezoid approximation for each step (IC to FC).

3.2.4 Step and Stride Regularity

Step and stride regularity are determined using the approach of Moe-Nilssen and Helbostad (2004). Filtered R_a signals are processed using the autocorrelation (<xcov>) function. This function removes any offset (mean value) from the signal then performs an autocorrelation (<xcorr>) function. By definition, the values of the ACF function at zero lag is 1.0 as the signal perfectly correlates to itself. Step regularity is determined as the first local maxima of the ACF function while stride regularity is determined as the second maxima. The location of these values (lags) also represent StpT and StrT. The ratio of step and stride regularity is defined as step symmetry (see Equation 11).

3.2.5 Graphical Output

For visual inspection, graphical outputs are generated by the MatLab program (<plot>). Graphical outputs for two players are shown below and specific variables are shown in Figure 7. This figure represents a player who is returning from ACL reconstruction surgery (10 months post-operation) who is expected to have right-left gait asymmetries. As can be seen, several of the variables (e.g. CT, StpL and Peak) show bilateral differences.

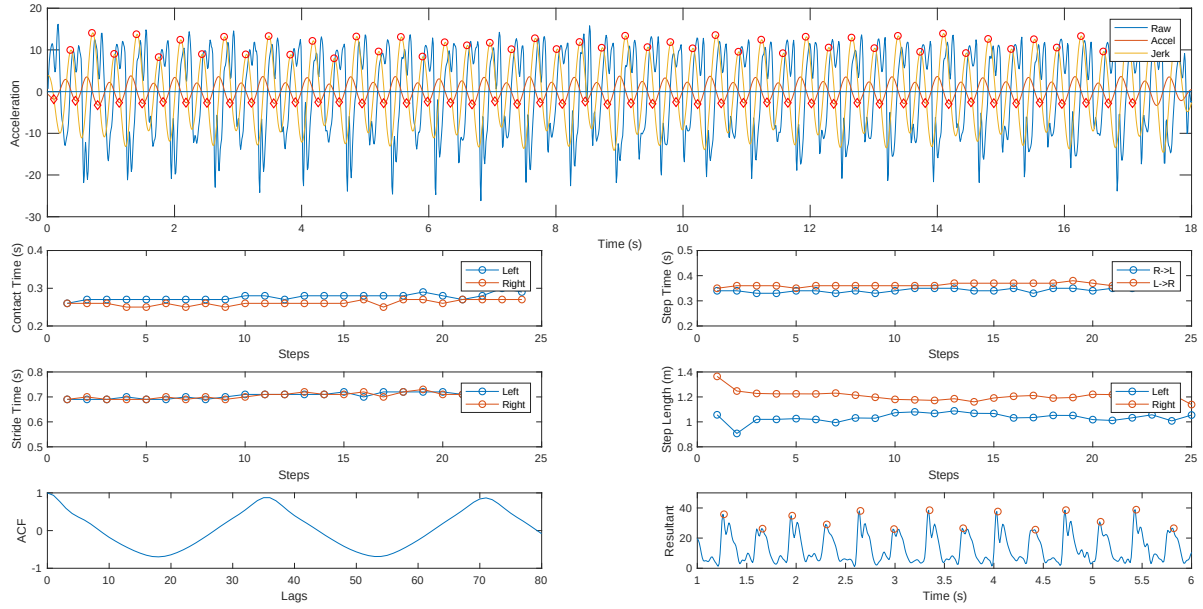


Figure 7. Matlab graphical output. The data are from a player 10 months post ACL reconstruction surgery with expected bilateral gait differences.

3.3. Specific experiments

3.3.1 Subjects

For this study, all subject were 20 members of the Virginia Tech Women’s soccer team (168.2 ± 1.5 cm, 65.1 ± 8.0 kg). Subjects ranged in age from 18 to 22 years and were cleared for participation by the Virginia Tech Sports Medicine staff. Prior to data collection, all procedures were approved by the Virginia Tech Institutional Review Board and the Virginia Tech Athletic Department and informed consent was obtained for each subject (see Appendix for approval letters, signed forms, subject recruiting script and consent form). All data were collected during regular training sessions.

3.3.2 Within and Between Day Reliability

A key aim of the study was to establish the reliability of the CWT, DFA, ACF and acceleration analysis methods. To do this, reliability was examined by subjects performing performing repeated efforts on the same day and on three different days. For the within-day day reliability study, players performed three 90 m runs at a moderate to high pace (~15 km/hr). In this instance, players received verbal feedback regarding pace (i.e. 5 sec intervals “called out”). However, each player did set her own pace.

For the between-day reliability study, the above protocol was repeated with at least two weeks between trials.

Data from each trial were collected and analyzed as described above. Mean values and standard deviations for each parameters were determined. Intraclass correlations (ICC) were used to determine the reliability of each variable generated by the spatiotemporal, DFA, autocorrelation and peak acceleration analyses. For the within-day trial, the three individual efforts were compared. For the between-day trials, the three efforts on the same day were averaged and compared across days.

3.3.3 Proof of Concept

It is well established that the spatiotemporal and vertical acceleration characteristics of gait change with variations in running speed. This concept was used to establish proof of concept. If the approach used here is valid, speed-induced changes in gait should be reflected in expected alterations in the CWT and acceleration derived variables. For example, CT, StpT and StrT were expected to decrease with faster running speed while StpL, StrL, Peak and Area values were expected to increase. Players performed 70 m runs at a jog and at slow, moderate and high-speed running approximating 8, 12, 15 and 20 km/hr. A one-way repeated measures ANOVA with a Tukey’s post-hoc exam was used to determine differences between running speeds.

3.3.4 Application

The final experiment was evaluating gait alterations in the presence of acute fatigue. Fatigue alters neuromuscular coordination that could increase injury risk in the presence of over exertion. For this study, players performed a series of 40, 90m sprints of increasing then decreasing speed. Each sprint was separated by a 90m jog. The trial was structured so that the 90m sprint and subsequent jog was performed within 60 sec. Thus, as sprint speed increased, the recovery (jogging) speed decreased. Data were collected throughout the trial. To examine the effects of fatigue, the first and final sprints were compared (these were performed at the same speed). The volume and intensity of the session was quantified using measures of running speed and distance obtained from GPS signals. To determine differences in pre-and post-fatigued conditions, pair t-tests were utilized.

Table 1. Description of the variables used in this study

Variable Name (units)	Abbreviation
<u>Exercise Bout</u>	
Average Speed (km/hr)	VelocAvg
Number of steps analyzed	Steps
<u>Spatiotemporal Variables (CWT)</u>	
Right foot CT (msec)	RCT
Left foot CT (msec)	LCT
Average CT (msec)	CTAvg
R-L CT Difference (%)	CTDiff
Right - Left Step time (msec)	RLStpT
Left - Right Step time (msec)	LRStpT
Average Step time (msec)	StpTAvg
Step Time Difference (%)	StpTDiff
Right foot Stride time (msec)	RStrT
Left foot Stride Time (msec)	LStrT
Average Stride Time (msec)	StrTAvg
Stride Time Difference (%)	StrTDiff
R-L Step Length (m)	RStpL
L-R Step Length (m)	LStpL
Average Step Length (m)	StpLAv
Step Length Difference (%)	StpLDiff
Right Foot Stride Length (m)	RStrL
Left Foot Stride Length (m)	LStrL
Average Stride Length (m)	StrLAv
Stride Length Difference (%)	StrLDiff
<u>Acceleration Variables</u>	
Right Foot Acceleration Area (m/s)	RArea
Left Foot Acceleration Area (m/s)	LArea
Average Acceleration Area (m/s)	AreaAvg
Acceleration Area Difference (%)	AreaDiff
Right Foot Peak Acceleration (m/s ²)	RPeak
Left Foot Peak Acceleration (m/s ²)	LPeak
Average Acceleration Peak (m/s ²)	PeakAvg
Peak Acceleration Difference (%)	PeakDiff
<u>Gait Regularity Variables (ACF)</u>	
X-axis Step Regularity	XStpReg
Y-axis Step Regularity	YStpReg
Z-axis Step Regularity	ZStpReg
Resultant Step Regularity	RStpReg
X-axis Stride Regularity	XStrReg
Y-axis Stride Regularity	YStrReg

Z-axis Stride Regularity	ZStrReg
Resultant Stride Regularity	RStrReg
X-axis ACF Symmetry	XSymm
Y-axis ACF Symmetry	YSymm
Z-axis ACF Symmetry	ZSymm
Resultant ACF Symmetry	RSymm

Gait Complexity Variables (DFA)

Contact Time DFA alpha	CTa
Step Time DFA alpha	StpTa
Stride Time DFA alpha	StrTa
Step Length DFA alpha	StpLa
Stride Length DFA alpha	StrLa
Acceleration Area alpha	Areaa
Acceleration Peak alpha	Peaka

Chapter 4

Results

4.1 Raw Data

Figure 8 shows raw accelerometer tracings recorded during a typical trial. In all cases, accelerometer signals were clear and easily analyzed using CWT.

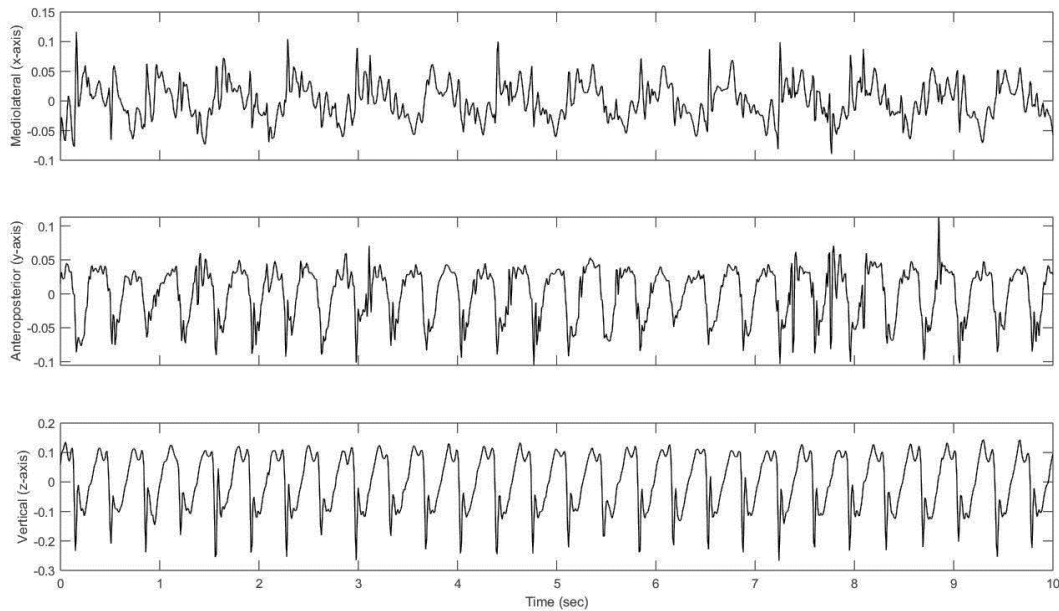


Figure 8. Typical raw accelerometer data obtained from a single trial.

4.1.1 Detection of Spatiotemporal Variables

Figure 9 shows a portion of those data analyzed by CWT. In this example, the raw signal as well as the transformed acceleration (green) and jerk (red) signals are shown. Also, the detected times of initial and final foot contacts are shown (green and red symbols, respectively). The mediolateral acceleration signal was used to identify right and left foot values (not shown). In no case was the CWT analysis unable to analyze acceleration data.

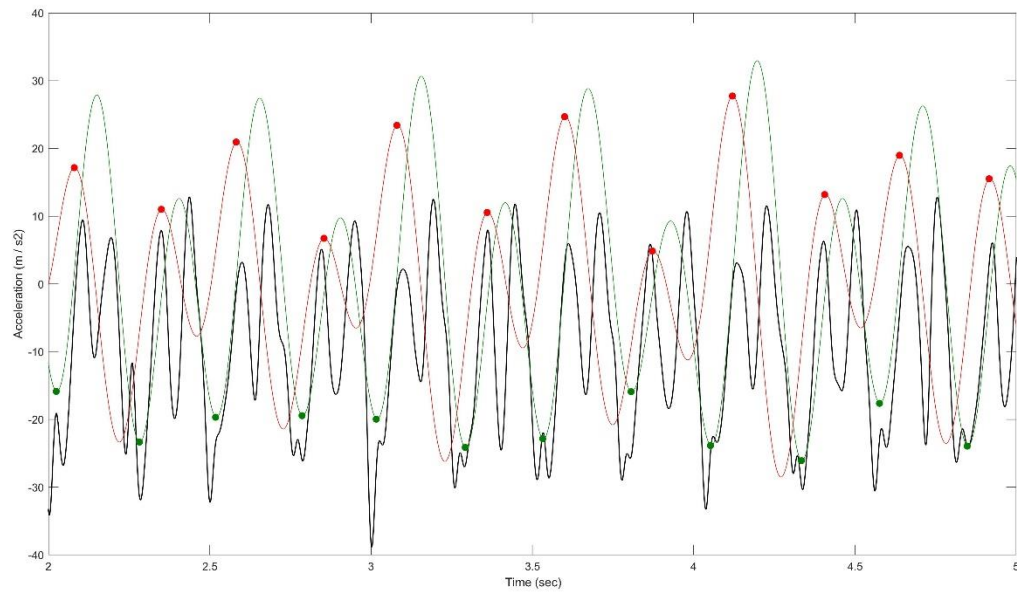


Figure 9. Partial CWT analysis obtained from a single trial. The black line represents the raw vertical axis acceleration. The green and red lines represent the continuous wavelet transformed acceleration and jerk signals. The solid dots represent initial (green) and final (red) foot contact times.

Figure 10 shows the resultant acceleration from a portion of a single trial. This figure also shows peak acceleration (symbols) as well as the area under the acceleration curve during foot contact for each step (shaded area).

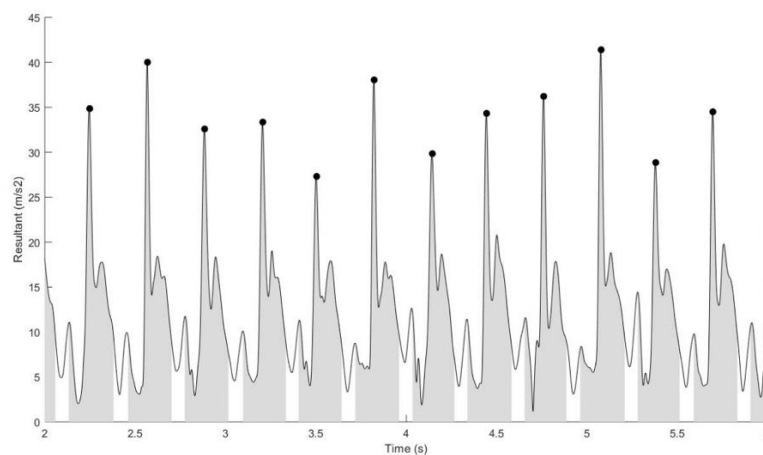


Figure 10. Calculation of peak acceleration and the acceleration area variable within a single trial. The black dots represent peak values. The shaded region is the area between initial and final foot contact.

The approaches shown in Figures 9 and 10 were used to compute the spatiotemporal and acceleration variables displayed in Figure 11. In this figure, bilateral CT, StpT, StrT, StpL, StrL, Peak and Area values are shown. As can be seen, there is considerable variability across the series of steps.

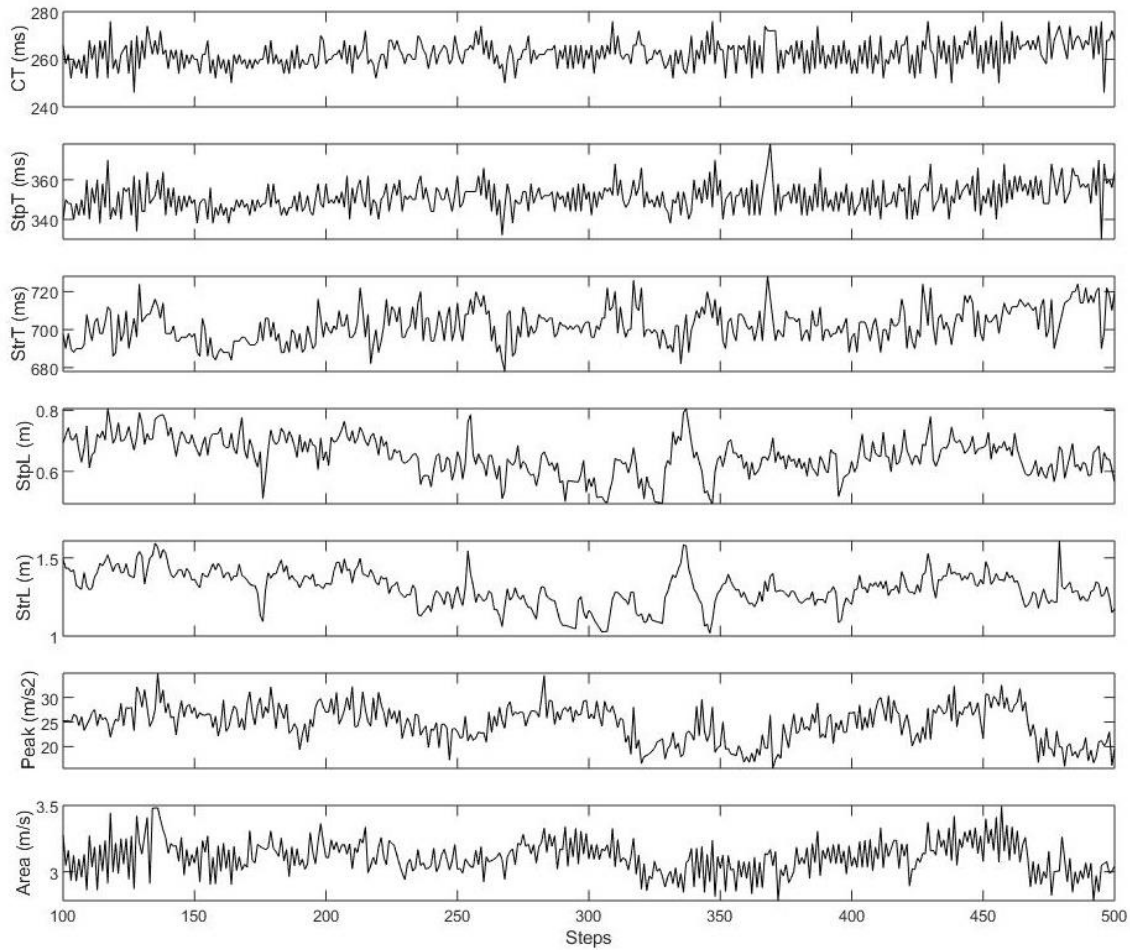


Figure 11. Spatiotemporal variables recorded during a running trial at constant, self-selected speed.

4.1.2 Determination of Gait Complexity with DFA

The effect of the DFA on the spatiotemporal variables is shown in Figure 12. The values above each figure represent the α -values for each variables. As can be seen, the relationships

between $\log F(N)$ and $\log N$ are linear. It was found that detrending the data using 2nd order polynomial (quadratic) did not improve the relationship between these two variables.

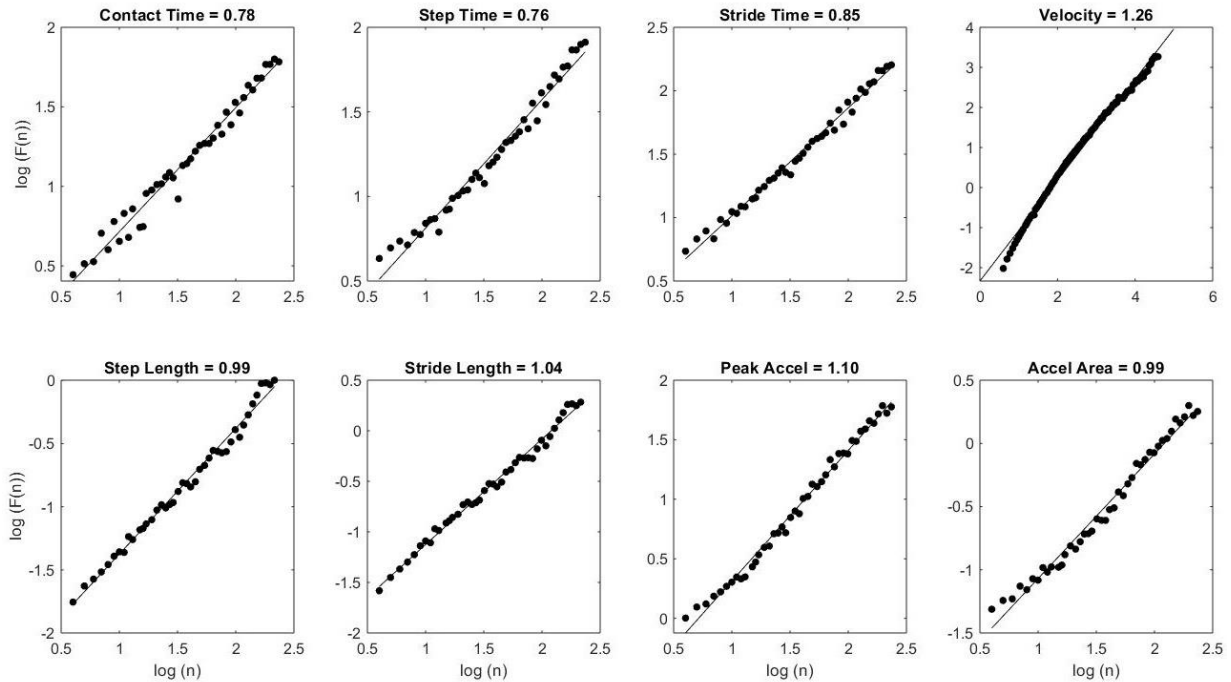


Figure 12. Results of the DFA analysis. Shown are the relationships between the $\log(F(n))$ vs the $\log(n)$. Shown are typical examples of all five spatiotemporal variables along with running velocity.

To confirm the use of DFA as a measure of structured variability, individual parameter values for each subject were randomly shuffled 5 times and FSI recomputed. Random shuffling retains the mean and standard deviation of the original data but destroys any long-range correlations and structured variability. Typical results of this procedure are also shown in Figure 13. The α -value for the shuffled data is less than the original data (i.e. flatter slope) and very close to 0.5. The mean FSI for 81 sets of shuffled data (within and between day reliability data) was 0.499 ± 0.003 ($p > .05$ vs 0.500, effect size = 0.04).

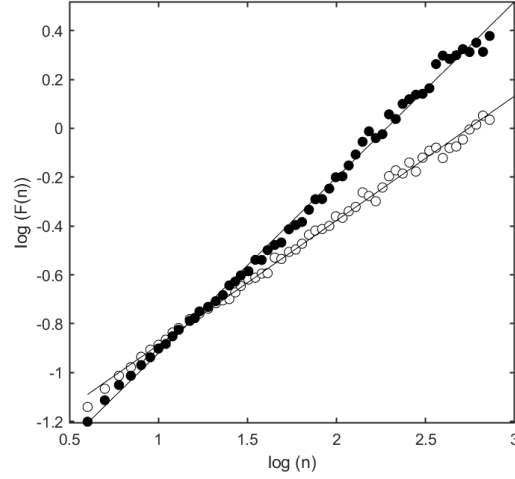


Figure 13. Effect of random shuffling of StpL data on the DFA. In this figure, α values were 0.923 for the raw data (●) and 0.498 for the shuffled data (○).

4.1.3 Determination of Gait Regularity Using Autocorrelation

An example of the autocorrelation analyses of the accelerometry signal is shown in Figure 14. Local peaks of the ACFs are identified by the symbols. The magnitude of the first peak to the right of zero lag represents StpReg while the magnitude of the adjacent local peak represents StrReg. The location of the peaks (lags) are proportional to and represent StpT and StrT, respectively. For the mediolateral axis, the first local peak is negative, indicating the alternating positive and negative accelerations of right and left foot contact.

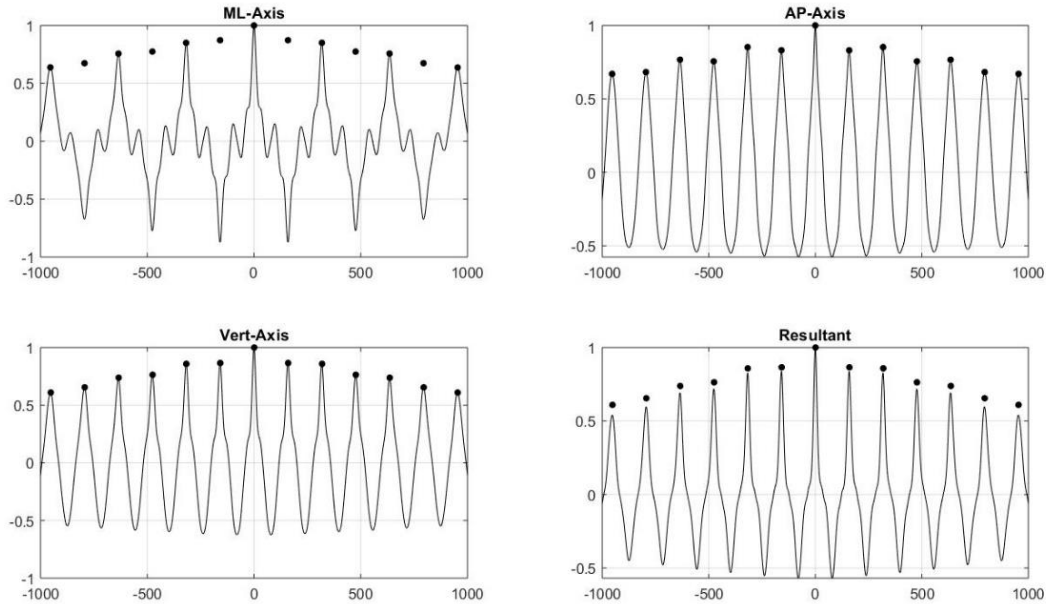


Figure 14. Results of the autocorrelation analyses from each axis as well as the calculated resultant. In these figures, the horizontal axis represents the lag (in points) and the vertical axis is the correlation coefficient. The first two symbols to the right of 0 lag represent step and stride similarity, respectively.

4.2 Test Retest Analyses

Test-retest reliability was assessed two ways. First, reliability between three trials performed within a single day were evaluated (within-day). Second, reliability between individual trials performed on three different days (between-day).

4.2.1 Within-Day Reliability

Within-day intraclass correlation coefficient (ICC) values for all variables are shown in Table 2 along with mean values ($\pm$ SD). For the spatiotemporal variables, there was excellent agreement across all variables except those indicating bilateral difference. ICC values ranged between 0.86 and 0.97. For the difference variables, poor ICC values were found (<0.35).

Calculations of the resultant acceleration showed excellent agreement except for the difference variables with ICC values ranging from 0.93 to 0.98. For AreaDiff and PeakDiff, ICC values were fair to poor (0.34 and 0.65, respectively).

Gait regularity generally showed good to excellent agreement with all ICC's being above 0.70. In general, StrReg variables showed better agreement than the StpReg variables. The X component had excellent agreement, the Y and Z components had good agreement, and the resultant symmetry had fair agreement. For the symmetry variables, agreement ranged from fair to good ($R^2 = 0.53 - 0.86$).

All of the DFA variables showed good to excellent agreement for all variables observed. ICC values ranged from 0.79 to 0.92.

4.2.2 Between-Day Reliability

Between-day ICC values are shown in Table 3 along with mean values. Mean values for the between-day conditions were not compared to the within-day due to differences in the speed of the exercise bout. In general, between-day reliability measures were similar to those of the within-day study. Agreement was very good for the spatiotemporal and acceleration variables except for the difference variables. Also, most of the gait regularity and complexity variables showed good to excellent ICC. The only exception was YStpReg. Overall, ICC values for the between-day study tended to be greater than for the within-day study. This may be due to more consistent running speed between the sets of trials (ICC = 0.80 vs 0.65).

Table 2. Within-Day Reliability. Intraclass correlation, mean and SD values for each of the variables recorded during three trials conducted on the same day (n=48, 16 subjects x 3 trials).

Variable Name (units)	Variable	ICC	Mean	SD
Average Speed (km/hr)	VelocAvg	0.6450	13.71	0.30
Steps analyzed	Steps	0.7416	61.92	2.65
<u>Spatiotemporal Variables</u>				
Right foot CT (msec)	RCT	0.9215	253.66	2.85
Left foot CT (msec)	LCT	0.9343	253.80	2.86
Average CT (msec)	CTAvg	0.9724	253.73	1.73
R-L CT Difference (%)	CTDiff	0.3224	-0.03	1.61
Right - Left Step time (msec)	RLStpT	0.9126	339.14	4.04
Left - Right Step time (msec)	LRStpT	0.9451	338.34	3.71
Average Step time (msec)	StpTAvg	0.9727	338.74	2.47
Step Time Difference (%)	StpTDiff	0.2088	-0.17	2.29
Right foot Stride time (msec)	RStrT	0.9739	677.91	4.78
Left foot Stride Time (msec)	LStrT	0.9722	678.04	4.85
Average Stride Time (msec)	StrTAvg	0.9732	677.98	4.81
Stride Time Difference (%)	StrTDiff	0.1041	0.19	0.71
R-L Step Length (m)	RStpL	0.8191	1.30	0.04
L-R Step Length (m)	LStpL	0.8701	1.31	0.03
Average Step Length (m)	StpLAvG	0.8763	1.31	0.03
Step Length Difference (%)	StpLDiff	0.2083	-0.17	2.28
Right Foot Stride Length (m)	RStrL	0.8616	2.61	0.06
Left Foot Stride Length (m)	LStrL	0.8835	2.62	0.06
Average Stride Length (m)	StrLAvG	0.8761	2.61	0.20
Stride Length Difference (%)	StrLDiff	0.0968	0.19	0.70
<u>Acceleration Variables</u>				
Right Foot Acceleration Area (m/s)	RArea	0.9356	3.61	0.07
Left Foot Acceleration Area (m/s)	LArea	0.9377	3.62	0.07
Average Acceleration Area (m/s)	AreaAvg	0.9781	3.62	0.04
Acceleration Area Difference (%)	AreaDiff	0.3415	-0.42	2.86
Right Foot Peak Acceleration (m/s ²)	RPeak	0.9430	35.75	1.35
Left Foot Peak Acceleration (m/s ²)	LPeak	0.9312	36.19	1.14
Average Acceleration Peak (m/s ²)	PeakAvg	0.9663	35.97	0.90
Peak Acceleration Difference (%)	PeakDiff	0.6543	-1.71	4.19
<u>Gait Regularity Variables</u>				
X-axis Step Regularity	XStpReg	0.9180	-0.72	0.02
Y-axis Step Regularity	YStpReg	0.8955	0.81	0.02
Z-axis Step Regularity	ZStpReg	0.9298	0.88	0.01
Resultant Step Regularity	RStpReg	0.8820	0.86	0.02
X-axis Stride Regularity	XStrReg	0.7567	0.78	0.02
Y-axis Stride Regularity	YStrReg	0.8197	0.81	0.02
Z-axis Stride Regularity	ZStrReg	0.7567	0.78	0.02
Resultant Stride Regularity	RStrReg	0.7089	0.82	0.03

X-axis ACF Symmetry	XSymm	0.8581	-0.93	0.03
Y-axis ACF Symmetry	YSymm	0.6285	1.01	0.02
Z-axis ACF Symmetry	ZSymm	0.6363	1.04	0.02
Resultant ACF Symmetry	RSymm	0.5289	1.05	0.02
<u>Gait Complexity Variables</u>				
Contact Time DFA alpha	CTa	0.8854	0.49	0.02
Step Time DFA alpha	StpTa	0.8506	0.50	0.03
Stride Time DFA alpha	StrTa	0.7937	0.86	0.03
Step Length DFA alpha	StpLa	0.9039	0.90	0.02
Stride Length DFA alpha	StrLa	0.8608	1.13	0.02
Acceleration Area alpha	Areaa	0.8665	0.50	0.02
Acceleration Peak alpha	Peaka	0.9214	0.63	0.02

ICC values in red are considered “excellent” while values in green are considered “good”.

Table 3. Between-Day Reliability. Intraclass correlation, mean and SD values for each of the variables recorded during three trials conducted on different days (n=33, 11 subjects X 3 days).

Variable Name	Variable	ICC	Mean	SD
Average Speed (km/hr)	VelocAvg	0.8028	10.14	0.27
Steps analyzed	Steps	0.8770	350.09	16.49
<u>Spatiotemporal Variables</u>				
Right foot CT (msec)	RCT	0.9518	261.12	12.66
Left foot CT (msec)	LCT	0.9580	260.36	12.51
Average CT (msec)	CTAvg	0.9677	260.74	12.44
R-L CT Difference (%)	CTDiff	0.3786	0.29	1.49
Right - Left Step time (msec)	RLStpT	0.9563	347.55	16.52
Left - Right Step time (msec)	LRStpT	0.9653	347.14	17.06
Average Step time (msec)	StpTAvg	0.9665	347.35	16.57
Step Time Difference (%)	StpTDiff	0.2371	0.20	2.00
Right foot Stride time (msec)	RStrT	0.9669	694.71	33.14
Left foot Stride Time (msec)	LStrT	0.9670	694.71	33.14
Average Stride Time (msec)	StrTAvg	0.9670	694.71	33.14
Stride Time Difference (%)	StrTDiff	0.5820	0.25	0.57
R-L Step Length (m)	RStpL	0.9678	0.98	0.05
L-R Step Length (m)	LStpL	0.8886	0.98	0.05
Average Step Length (m)	StpLAvg	0.9524	0.98	0.05
Step Length Difference (%)	StpLDiff	0.2453	0.21	2.03
Right Foot Stride Length (m)	RStrL	0.9301	1.96	0.10
Left Foot Stride Length (m)	LStrL	0.9468	1.96	0.10
Average Stride Length (m)	StrLAvg	0.9389	1.96	0.10
Stride Length Difference (%)	StrLDiff	0.5554	0.24	0.57
<u>Acceleration Variables</u>				
Right Foot Acceleration Area (m/s)	RArea	0.9267	3.54	0.24
Left Foot Acceleration Area (m/s)	LArea	0.9170	3.55	0.24
Average Acceleration Area (m/s)	AreaAvg	0.9684	3.54	0.23
Acceleration Area Difference (%)	AreaDiff	0.3661	-0.24	4.17
Right Foot Peak Acceleration (m/s ²)	RPeak	0.9204	30.27	5.16
Left Foot Peak Acceleration (m/s ²)	LPeak	0.9391	30.94	4.24
Average Acceleration Peak (m/s ²)	PeakAvg	0.9404	30.60	4.54
Peak Acceleration Difference (%)	PeakDiff	0.7424	-2.54	8.54
<u>Gait Regularity Variables</u>				
X-axis Step Regularity	XStpReg	0.8760	-0.74	0.06
Y-axis Step Regularity	YStpReg	0.4936	0.85	0.04
Z-axis Step Regularity	ZStpReg	0.9025	0.90	0.04
Resultant Step Regularity	RStpReg	0.8828	0.89	0.04
X-axis Stride Regularity	XStrReg	0.8691	0.81	0.06
Y-axis Stride Regularity	YStrReg	0.8402	0.86	0.04
Z-axis Stride Regularity	ZStrReg	0.9291	0.81	0.06
Resultant Stride Regularity	RStrReg	0.8509	0.87	0.04

X-axis ACF Symmetry	XSymm	0.8236	-0.92	0.06
Y-axis ACF Symmetry	YSymm	0.8972	0.99	0.03
Z-axis ACF Symmetry	ZSymm	0.8924	1.02	0.04
Resultant ACF Symmetry	RSymm	0.7742	1.03	0.05
<u>Gait Complexity Variables</u>				
Contact Time DFA alpha	CTa	0.9258	0.72	0.07
Step Time DFA alpha	StpTa	0.8508	0.75	0.04
Stride Time DFA alpha	StrTa	0.9100	0.90	0.13
Step Length DFA alpha	StpLa	0.8505	1.02	0.01
Stride Length DFA alpha	StrLa	0.8975	1.09	0.10
Acceleration Area alpha	Areaa	0.8775	0.66	0.04
Acceleration Peak alpha	Peaka	0.8827	0.69	0.06

ICC values in red are considered “excellent” while values in green are considered “good”.

4.3 Varied speed

Data for the varied speed trials are presented in Table 4. For this analysis, bilateral data were not included. This was due to the poor reliability of these measures. Thus, only average data are shown. Shown in Table 4 are mean values ($\pm$ SEM) for each speed along with the ANOVA p-value. For significance ANOVA's Tukey post-hoc exam results are shown. Lastly the correlation coefficient for speed versus each variable is shown.

Spatiotemporal and accelerations variables showed significant differences between speeds whereas the difference variables were not significant. Post-hoc exams showed some differences with speed. Also, temporal variables increased with running speed while spatial variables decreased. In short, increased running speed was associated with decreased contact, stride and step times and increased acceleration.

Gait regularity also changed with running speed as indicated by the significant ANOVA p-values. As speed increased, regularity tended to decrease.

Varied speed data did not yield significant differences in gait complexity between speeds for the DFA. The α -values were not significantly different between speeds. Also, the strengths of the relationships between α and speed were small or trivial. This suggests that the structure of gait variability remains consistent as speed varies.

In summary, increasing running speed decreased the temporal variables associated with gait and increased the spatial variables. In addition, peak acceleration increased while the area of the acceleration curve associated with foot strike decreased. Similarly gait and stride regularity decreased with increasing speed. On the other hand, measures of gait complexity were not affected by running speed.

Table 4. Effects of Varied Speed on Gait Variables. Mean comparison of each variable recoded during different running speeds (n=18 subjects for each speed).

Variable	Jog		Low		Medium		High		ANOVA	Tukey Post-Hoc				Correl vs Speed
	Mean	SEM	Mean	SEM	Mean	SEM	Mean	SEM	p-Value	Jog	Low	Med	High	
AvgVeloc	8.36	0.04	12.09	0.06	15.16	0.08	20.41	0.13	0.0001	A	A	A	A	
<u>Spatiotemporal Variables</u>														
CTAvg	260.80	2.37	252.15	2.91	244.27	2.44	235.12	3.11	0.0475	A	AB	AB	B	-0.7584
CTDiff	0.33	0.59	-0.24	0.50	0.03	0.62	2.34	1.12	0.0945					0.2281
StpTAvg	347.55	3.23	335.61	3.95	325.31	3.35	292.29	3.37	0.0001	A	B	C	D	-0.8051
StpTDiff	0.21	0.49	-0.37	0.57	-0.44	0.73	-0.33	1.27	0.9453					-0.0543
StrTAvg	695.31	6.44	672.60	7.85	652.02	6.74	589.93	6.81	0.0001	A	B	C	D	-0.7931
StrTDiff	0.19	0.20	0.29	0.20	-0.18	0.30	0.38	0.20	0.3517					0.0382
StpLAvg	0.81	0.01	1.15	0.01	1.40	0.02	1.72	0.02	0.0001	A	B	C	D	0.9790
StpLDiff	0.22	0.48	-0.37	0.58	-0.44	0.73	-0.27	1.25	0.9435					-0.0501
StrLAvg	1.62	0.02	2.29	0.03	2.80	0.04	3.44	0.04	0.0001	A	B	C	D	0.9787
StrLDiff	0.19	0.20	0.29	0.20	-0.17	0.30	0.43	0.20	0.3117					0.0538
<u>Acceleration Variables</u>														
AreaAvg	4.35	0.42	3.54	0.06	3.56	0.05	3.66	0.19	0.0398	A	A	A	A	-0.1978
AreaDiff	0.49	1.10	-0.74	1.38	-0.06	1.36	1.04	1.55	0.8394					0.0541
PeakAvg	29.88	1.77	34.89	1.44	36.75	1.32	44.09	1.31	0.0001	A	B	B	C	0.6337
PeakDiff	-0.87	1.74	-0.54	2.35	2.53	2.94	2.64	1.89	0.5456					0.1679
<u>Gait Complexity Variables</u>														
CTa	0.65	0.02	0.69	0.05	0.68	0.06	0.82	0.17	0.0641					0.1608
StTa	0.64	0.02	0.73	0.07	0.62	0.07	0.67	0.08	0.6522					0.0093
StrTa	0.84	0.03	1.12	0.07	1.01	0.08	1.01	0.09	0.0606					0.1463
StpLa	0.96	0.05	0.82	0.09	0.88	0.09	1.05	0.10	0.2860					0.1250
StrLa	1.10	0.04	1.12	0.08	1.23	0.09	1.29	0.14	0.3612					0.1935
Areaa	0.51	0.04	0.64	0.04	0.58	0.08	0.79	0.17	0.2960					0.2089
Peaka	0.57	0.04	0.73	0.05	0.72	0.06	0.71	0.10	0.2899					0.1781
<u>Gait Regularity Variables</u>														
XStpReg	-0.75	0.02	-0.65	0.02	-0.67	0.02	-0.51	0.03	0.0001	A	B	B	C	0.6190

YStpReg	0.84	0.02	0.70	0.03	0.72	0.03	0.50	0.03	0.0001	A	B	B	C	-0.6363
ZStpReg	0.92	0.01	0.84	0.01	0.85	0.01	0.58	0.02	0.0001	A	B	B	C	-0.8499
RStpReg	0.86	0.04	0.81	0.02	0.82	0.01	0.52	0.02	0.0001	A	A	A	B	-0.6994
XStrReg	0.84	0.01	0.67	0.03	0.66	0.02	0.46	0.02	0.0001	A	B	B	C	-0.8368
YStrReg	0.85	0.01	0.68	0.04	0.69	0.03	0.38	0.03	0.0001	A	B	B	C	-0.7812
ZStrReg	0.84	0.01	0.67	0.03	0.66	0.02	0.46	0.02	0.0001	A	B	B	C	-0.8368
RStrReg	0.87	0.02	0.73	0.03	0.74	0.01	0.34	0.03	0.0001	A	B	B	C	-0.8391
XSymm	-0.90	0.03	-0.99	0.03	-1.01	0.02	-1.12	0.03	0.0001	A	AB	B	C	-0.5651
YSymm	0.98	0.01	1.06	0.05	1.04	0.02	1.41	0.11	0.0001	A	B	B	B	0.5047
ZSymm	1.02	0.01	1.12	0.03	1.11	0.01	1.63	0.08	0.0001	A	B	B	B	0.7070
RSymm	0.98	0.04	1.14	0.03	1.11	0.01	1.66	0.08	0.0001	A	B	B	B	0.7318

p-values in red are statistically significant ($p < .05$). ES values in red are “small”, those in green are “medium” and those in blue are “large”.

4.4 Acute Exercise Data

The acute exercise bout for a single player is shown in Figure 15. In this figure, both running speed and acceleration are shown. For determining the effects of fatigue on gait characteristics, the first and last sprint trial were used. Figure 16 shows that raw GPS data overlaid on the practice field. These data show the path characteristics of the bout.

The work load during the acute exercise session are shown in Table 5. Players covered nearly 7500m and exercise at an average HR of 166 bpm (approximately 82% of maximal). Peak HR values indicated that players did not reach their measured maximal HR of 202.47 bpm. Energy expenditure during the session was approximately 516 kcal.

Significance was detected ($p < 0.05$) for CTAvg, StTAvg, StrTAvg, AreaAvg, and Areaa (Table 6). Despite this, effect sizes for several variables, between the two conditions were small and medium. For gait complexity, effect sizes in StpLa, StrLa, Areaa between pre-and post-exercise were medium. Step regularity in the Y, Z and resultant had small effect sizes. Stride regularity had small effect sizes in all fields except for Z and the resultant. Symmetry in the x- and y-axis direction had small effect sizes.

In order to more clearly visualize pre-post changes in each variable, differences are plotted as percent differences (Figure 17).

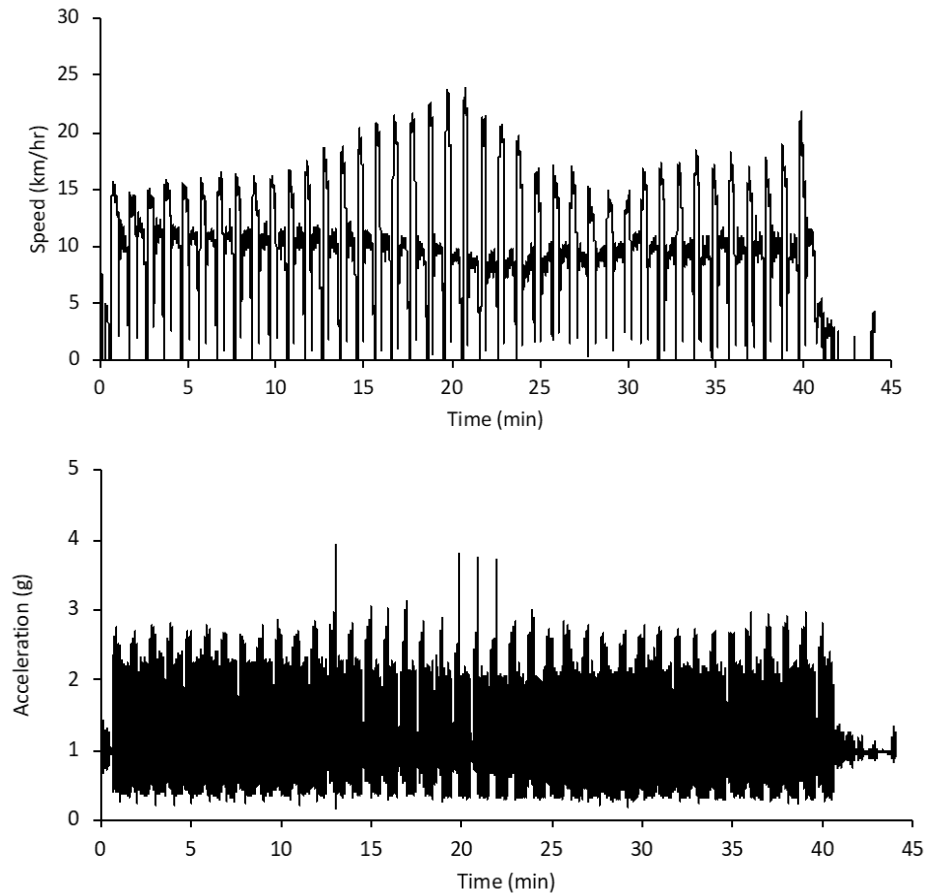


Figure 15. Examples of running speed (top) and resultant vector acceleration (bottom) during the acute exercise bout.

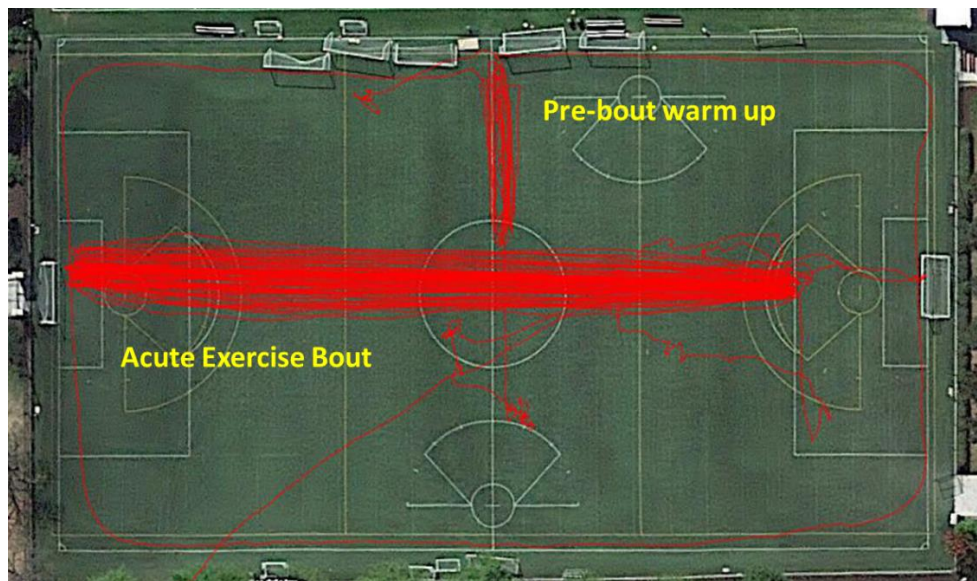


Figure 16. GPS data showing the acute exercise bout overlaid on the practice field.

Table 5. Work load during the acute exercise bout. Values describing the workload experienced during the training session (n=10 players).

Variable	Mean	S/D
Total Distance (m)	7404.25	173.89
Maximal Speed (km/hr)	22.57	2.52
Average Speed (km/hr)	9.90	0.46
Peak Heart Rate (bpm)	190.92	16.17
Average Heart Rate (bpm)	166.08	24.02
Body Load (au)	86.68	40.96
Energy Expended (kJ/kg)	34.40	1.96

Table 6. Effects of Exercise on Gait Variables. Mean comparisons between pre- and post-training session.

Variable	Pre		Post		t-test	Effect
	Mean	SEM	Mean	SEM	p-value	Size
Speed	13.88	0.52	13.83	0.59	0.8564	0.0265
Steps	63.23	2.11	62.98	2.01	0.7231	0.0923
<u>Spatiotemporal Variables</u>						
CT	251.06	4.12	255.51	4.19	0.0454	0.2861
StepT	328.25	5.55	332.68	5.73	0.1055	0.2099
StrideT	656.88	11.16	665.64	11.40	0.1212	0.2075
StepL	1.27	0.04	1.29	0.05	0.5145	0.1090
StrideL	2.54	0.07	2.57	0.10	0.5172	0.1085
<u>Acceleration Variables</u>						
Area	3.54	0.07	3.63	0.08	0.0290	0.3311
Peak	36.17	1.93	35.68	1.83	0.5205	0.0697
<u>Gait Complexity Variables</u>						
Cta	0.7799	0.0603	0.6081	0.0382	0.0279	0.9098
StrTa	0.7045	0.0521	0.5546	0.0374	0.0149	0.8840
StpTa	0.9304	0.0477	0.7539	0.0385	0.0015	1.0882
StpLa	0.9669	0.0625	0.8055	0.0606	0.0067	0.7007
StrLa	1.2685	0.0589	1.0976	0.0486	0.0096	0.8466
Aaaa	0.9567	0.7632	0.7580	0.0718	0.0349	0.7161
Peaka	1.2222	0.0778	1.1126	0.0567	0.1176	0.4300
<u>Gait Regularity Variables</u>						
XStepReg	0.6424	0.0374	0.6414	0.0332	0.9742	0.0073
XStrideReg	0.7385	0.0301	0.7452	0.0308	0.7843	0.0586
XSymm,	0.8736	0.0420	0.8624	0.0318	0.7382	0.0807
YStepReg	0.7522	0.0102	0.7462	0.0238	0.7785	0.0875
YStrideReg	0.7215	0.0177	0.7211	0.0341	0.9898	0.0041
YSymm,	1.0481	0.0204	1.0493	0.0280	0.9627	0.0130
ZStepReg	0.8593	0.0140	0.8458	0.0169	0.3624	0.2322
ZStrideReg	0.8039	0.0245	0.7862	0.0262	0.3287	0.1865
ZSymm	1.0767	0.0219	1.0861	0.0272	0.4963	0.1016
RStepReg	0.8387	0.0151	0.8161	0.0194	0.2050	0.3481
RStrideReg	0.7759	0.0249	0.7484	0.0267	0.1986	0.2849
RSymm	1.0892	0.0222	1.1015	0.0288	0.4703	0.1277

p-values in red are statistically significant ($p < .05$). ES values in red are “small”, those in green are “medium” and values in blue are “large”.

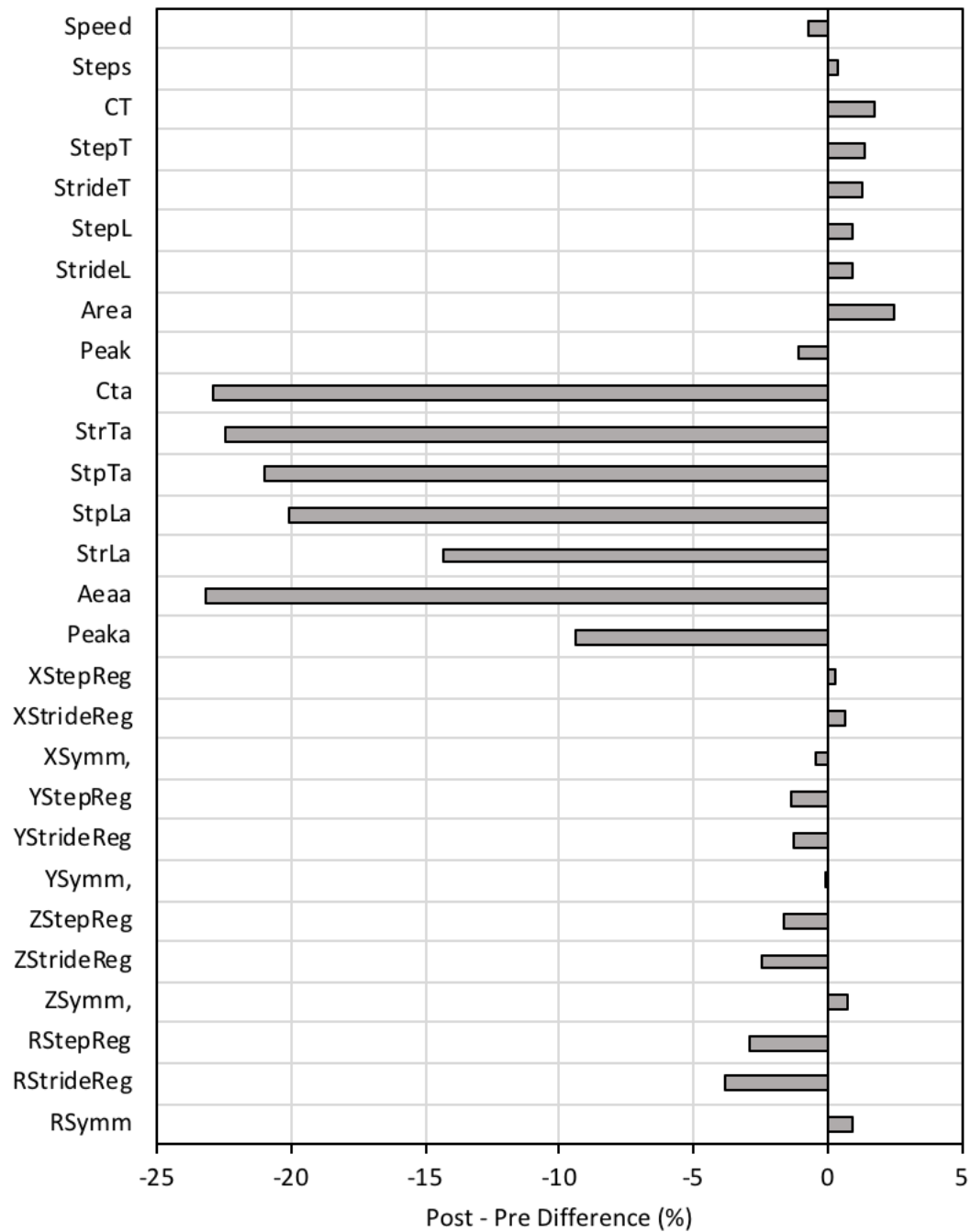


Figure 17. Effects acute fatigue on gait characteristics. Shown are the percent changes from the initial bout to the final.

Chapter 5

Discussion

Overall, the results of this study show that many of the derived spatiotemporal, regularity and complexity measures of gait are very reliable with the majority of metrics having large ICC values. The only major exceptions were variables of bilateral differences. For these variables, ICC values were poor. The results also provide proof of concept for the spatiotemporal measures. As running speed increased, expected changes in spatiotemporal variables were found. That is contact, step and stride times decreased while step and stride lengths increased, while gait regularity variables were decreased with increasing speed. On the other hand, gait complexity variables were not affected by changes in running speed. Lastly, in terms of application, fatiguing exercise had minimal effects on spatiotemporal and regularity gait parameters. However, Gait complexity was noticeably affected FSI values were decreased. Overall, the results of this study show that gait spatiotemporal, complexity and regularity variables derived using CWT, DFA and ACF applied to trunk-mounted accelerometry during running are both reliable and valid as are measures of gait regularity. Further, this approach appears to be both valid and applicable to the study of running gait.

5.1 Reliability

The tests for reliability showed consistency with the majority of the variables having excellent ICC's. The only exceptions were the bilateral comparison variables. Across these parameters, the percent difference between left and right events yielded poor reliability. Given that the other gait variables have excellent reliability, it would be expected that the difference in left and right gait components would also have excellent reliability. However, our data show the opposite effect, suggesting that between stride differences are a commonality in gait resulting

from the complexity of human locomotion. Also, it is possible that the bilateral comparisons are not robust enough to detect true differences in running symmetry. Measures of gait regularity using autocorrelation produced repeatable step and stride regularities. In this approach, the autocorrelation function is “shifted” until right and left foot strikes “overlap”. In short, this is a direct comparison of the accelerometer signal from alternating right and left events, using the entire signal. Such an approach may be more sensitive to bilateral differences. Thus, autocorrelation using mediolateral, anteroposterior, vertical and/or the resultant accelerations may be a better measure of bilateral symmetry than the comparison of right and left spatiotemporal events.

Across all variables, measures of gait complexity using DFA showed excellent reliability. This is the first study to demonstrate with- and between-day reliability of these measures. The validity of DFA for measuring complexity during running is indicated by the use of “shuffled” data (Figure 5.6). As noted earlier, randomly shuffling the spatiotemporal data destroys any embedded complexity as well as long-term correlations. It does not alter the total variance with the sample. When the DFA was performed on the shuffled data, α values approached 0.5. A value of 0.5 indicated true random variation while values above 0.5 indicate structured variation including long-term correlations. In short, $\alpha > 0.5$ indicates a gait pattern whereby successive steps are dependent on previous event with that dependency decaying over time. Thus, the present data suggest that the present DFA measures obtained during running are both reliable and valid.

5.2 Effects of Running Speed

The variables from the present study respond appropriately to changes in speed; peak acceleration and stride length increased, and contact times decreased in response to increasing

speeds. As early as 1952 physiologists have noticed that certain spatiotemporal characteristics increased with speed. Hogberg (1952) found that stride length increased with increases in speed and contact times decreased with increases in speed. Likewise in 1989 Nilsson and Thorstensson found that contact times were decreasing with increases in speed. Weyand et al. (2000) described their findings in the following manner: “Speed increases were made primarily through increasing stride lengths and decreasing contact times” (Weyand et al. 2000). Mercer et al. (2002) saw that stride length increased with speed, and peak accelerations increased with increases in speed. Thus, the CWT analysis used here was able to confirm expected changes in spatiotemporal variables as running speed increased.

The present study indicates that DFA measures of gait complexity are not altered by running speed, within the range of speed used here. This is in contrast to others (Jordan et al. 2006; 2007). These groups showed a U-relationship between α and preferred walking and running speed. As subjects increased or decreased walking speed, α increased. This was the case for several spatiotemporal gait variables. The authors suggested that “biological stress” may increase the gait complexity. They further suggest that a source of biological stress may be the available range of stride length and stride time combinations that allow the individual to maintain the appropriate running speed. Differences between the present results and those of Jordan et al. (2006; 2007), may reside in the subjects included in the studies. Here, trained athletes were used as subjects. In fact, Nakayama et al. (2010) showed that trained runners exhibit higher α values across a range of speeds than non-runners. A second source of difference may lie in the speeds selected for study. In the aforementioned studies, subjects selected a preferred speed and that speed was increased and decreased. In the present study, subjects ran as

a group at the same speed (instructed to jog or run at high, medium and low speeds). Thus, preferred speed was not measured.

That running speed did not affect the DFA variables suggesting that this measure could be used to assess gait complexity independent of running speed. For example, using α to monitor long-term changes in gait (such as might occur with injury or overtraining), small day-to-day fluctuations in running speed would not have a major impact on observed changes.

5.3 Effects of Fatiguing Exercise

One of the few articles found to compare running gait symmetry in pre-fatigue and post-fatigue conditions, had a more lab based approach (Schutte et al. 2015). Step and stride regularity values were computed using a motion capture system, a treadmill, and accelerometers mounted on the participant's lower back. The participants then ran until termination criteria were reached signaling exhaustion. Despite signal dampening experienced by the accelerometers used in the present study, Schutte et al. (2015) had similar step and stride regularity values in the vertical axis for both conditions. The only significant change in regularity was a decrease in step regularity in the AP axis from pre-fatigue to the fatigued state.

A more field-based approach was executed by Le Bris et al. (2006). An accelerometer placed on the lower back continuously measured accelerations during a 3200 meter time trial to exhaustion. A significant decrease in regularity was observed over the course of the run. The present data showed small effect sizes for increases in regularity in the fatigued state.

Contact times reported in this paper are similar to those reported elsewhere (Gilman-Amman et al. 2017 and Amman et al. 2015). Likewise, α values for stride interval (StrTa) in the present study are similar to those found by others (Jordan et al. 2009, Meardon et al. 2011). Meardon et al. examined long range correlations of stride interval variability in distance

runners. They found that as participants fatigued, StrTa decreased. This finding is consistent with the findings in the current study. Further, chronic exercise leading to overtraining can negatively impact the structure of gait variability and the FSI (Bellenger et al., 2018; Fuller et al., 2017).

At present, it is not clear how fatiguing activity might alter gait complexity. If earlier work suggesting that the FSI is dependent on the CNS rather than peripheral factors (see Hausdorff, 2007), then some aspect of central fatigue would lead to reductions in α . In this regard, pain, muscle soreness and discomfort during and after exercise may be responsible. The work of Newell and van der Laan (2010) and Roberts et al. (2004) suggest that pain may play a role. However, it should be pointed out that the mechanisms by Hausdorff (2007) were based on walking data in healthy adults and diseased patients. In the present study, highly trained, young adult athletes were examined. It is possible that the mechanisms responsible for gait complexity and structured variability are different in the present subjects and those described by Hausdorff (2007).

5.4 Application and Limitations

As with any study, the results lend themselves to practical applications. The convenience of using accelerometers in collecting mass amounts of field data makes them a more attractive option for sports scientists with budgetary limitations to monitor gait and activity patterns. As these devices are used by numerous sports teams (Aughey, 2011, Cummins et al, 2013), one could evaluate gait in a large number of subjects simultaneously. Such evaluations could lend themselves to monitoring injury or overtraining (Buchheit et al., 2015; Ehrmann et al., 2016). Further, given that the spatiotemporal variables are affected by running speed, inclusion

of a GPS system with the accelerometer allows for simultaneous measurement of speed. Thus, researchers and clinicians would be able to adjust for speed in the evaluation of gait.

On the other hand, there are several issues that limit the applicability of the results. First, an important limitation to this study is the inability to precisely control running speed. Ideally the current subjects would be running at a constant speed regulated by a treadmill. However, as indicated in Tables 2 and 3, the reliability of the subjects to reproduce a consistent running speed was quite good.

Second, along that same line of thinking, this study did not impose a verified method to fatigue its participants. Instead a more realistic (in terms of in-season training plan) approach to a fatiguing protocol was used. In addition, fatigue was not evaluated by a pre-post session evaluation. Thus, the condition of the subjects after the training session should not be described as “fatigued” but simply post-exercise.

Third, the majority of papers using CWT, DFA, and ACF’s are using accelerometers mounted on the lower back. Dampening of the accelerometer signal will likely impact the data obtained from our results. However, Del Din et al. (2016) has shown that trunk-mounted accelerometry has produced similar results to accelerometers placed near the center of mass.

Lastly, it should also be noted, that the participants in this experiment were elite women’s soccer players participating in the National Collegiate Athletics Association (NCAA) at the Division 1 level. Thus, the results obtained may not be applicable for other populations, particularly clinical populations. The data generated from this experiment is in an effort to generate methods of injury prevention based upon quantifiably activity variables.

Chapter 6

Conclusions

The reliability and reproducibility of the results of this paper are excellent, validating the use of our methods to offer consistent data. Furthermore, the analyses responded predictably with increases in speed thereby validating their ability to appropriately address changes in speed. This paper has provided evidence in support of using changes in contact, step, and stride times as markers for fatigue in exercising individuals. Future research should be dedicated to exploring DFA and stride variability as they appeared to have the largest change in the fatigued state. Further, entropy is a method that has been used to try and measure the complexity of gait. It may serve as a superior assessment of the variation of the between stride differences in gait components. Changes in sample entropy may also be more sensitive in detecting fatigue than examining gait symmetry (Schutte et al. 2018), and therefore should be included in future studies of gait characteristics.

Validation of a fatigue protocol that coaches could implement in season with little impact on player training load would allow for more accurate descriptions of gait data experienced by soccer players during regular season training. Also exploration of fatigue responses in track and field and cross country student athletes would offer a unique perspective on gait deterioration with fatigue. As track athletes are trained to maintain form through the influence of fatigue, a similar experiment on this population should yield interesting results.

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Appendix

The appendix.

Approval Letter and forms are shown for the 2017-2018 period. Renewal of the application was approved for data collection during 2018-2019

MEMORANDUM

DATE: July 14, 2017 

TO: Jay H Williams, David P Iegarden, Sarah Marie Vitalis Hoffman, Brian Orbrey Williams

FROM: Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)

PROTOCOL TITLE: Quantifying the Physical Demands and Injury Risk of Training and Competing in College Athletics

IRB NUMBER: 17-632

Effective July 14, 2017, the Virginia Tech Institutional Review Board (IRB) Chair, David M Moore, approved the New Application request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at: <http://www.irb.vt.edu/pages/responsibilities.htm>

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As: Expedited, under 45 CFR 46.110 category(ies) 4,7
Protocol Approval Date: July 14, 2017
Protocol Expiration Date: July 13, 2018
Continuing Review Due Date*: June 29, 2018

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

Virginia Tech Athletics Department
Coach's Permission
to Allow Research to be Conducted
Using Student-Athletes
Involved in a Team Sport

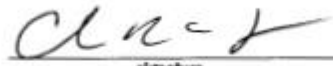
I, Charles Adjar, as Coach for the following sports team – Virginia Tech Women's Soccer
☒ **Do** or ☐ **Do Not** give permission for my student-athletes to participate in research to be conducted by Jay H. Williams, with research activities described in IRB Protocol # 17-632.

I recognize that while approval for the research may have been granted by the Virginia Tech Institutional Review Board for Protection of Human Subjects Involved in Research (the IRB), and separately granted by the VT Athletics Department Research Subcommittee, I, as Coach, have the authority to refuse to allow research to be conducted on student-athletes on the team which I coach, or ancillary student personnel that I supervise.

I further recognize and understand –

- that student-athletes cannot be compelled to participate in a research project based on their role as a team sport member
- that the team and all its members cannot be required to participate as a whole
- that individuals who choose to participate in the research activity must do so willingly, and that they are not coerced into participation
- that individuals who choose not to participate in the research activity are not to be punished, sanctioned, or inappropriately treated
- that individuals who desire to withdraw from the research activity are allowed to do so without punishment or sanction, as federal law allows them the right to withdraw at any time

I ☒ **Have** or ☐ **Have Not** been provided with a copy of the Consent document that will be provided to the student-athletes on my team.


signature

7/10/17
date

Should you have question about the conduct of the study, you may contact the Principle Investigator, Jay H. Williams at jhwms@vt.edu or (540) 231-8298

Should you have any questions or concerns about the study's conduct or participants' rights as a research subject, or need to report a research-related injury or event, you may contact the VT IRB Chair, Dr. David M. Moore at moored@vt.edu or (540) 231-4991.

Copy of the signed Virginia Tech Athletics Department Coach's Approval form

Virginia Tech Athletics Research Application Form

Principal Investigator: Jay H. Williams Date: July 14, 2017
Contact Information: Phone: 540-231-8298 Email: jhwms@vt.edu
Research Topic: Monitoring training loads in collegiate athletes
Title of Proposed Research: Quantifying the Physical Demands and Injury Risk of Training and Competing in College Athletics (IRB #17-632)

Description of Project:

Unfortunately, injuries to both competitive and recreational athletes are far too common. While injuries affect physical performance, the personal and financial costs are tremendous. For example, surgical repair and rehabilitation costs of a ruptured anterior cruciate ligament are near \$10,000. It is estimated that in the US alone, around \$2 billion annually is spent on these procedures. These estimates do not include indirect or personal costs such as work time lost, pain, discomfort, etc. as well as the diminished player and team performance. Thus, there is considerable interest in finding methods to minimize injury risk.

One factor thought to play a role in sports-related injury is the physical demands of training and competing or what is called "training load". Many feel that "overtraining" is a key component determining one's risk of injury. Unfortunately, the exact relationship between the acute and chronic demands of the sport, overtraining and injury risk are not fully understood. Thus, the purpose of this investigation is to quantify the physical demands of training and competing in intercollegiate athletics. Using non-invasive, global positioning, acceleration, heart rate and perceptual monitoring, we hope to determine relationships between the physical demands and injury risk. As such, we hope to identify metrics and develop models that will allow coaching and medical staffs to design training programs and will maximize competitive performance and limit the risk of injury.

Briefly describe your interest in using student-athletes as your research participants:

This study focuses on intercollegiate athletes. This population is unique in that they undergo regular exercise training and competition in a tightly controlled environment. Thus, they are well suited for monitoring of their physical demands. They are also at unique risk for injury based on their participation in competitive sports. As such, detailed records of training sessions and injury occurrences are maintained by the VT Sports Medicine and coaching staffs. Given this, intercollegiate athletes are an excellent model for studying how competitive sport elicits physical demands and how those demands influence injury risk.

Other pertinent information to be shared with Athletics Department

A player's contribution to a team is a function of their performance and availability. Injured athletes are generally unable to contribute. This work uses state-of-the-art equipment and monitoring techniques to assess and monitor training load. Thus, this project has tremendous potential to improve athlete performance and reduce injury risk (maximize their availability).

Copy of the Virginia Tech Athletics approved Research Application Form, page 1

Virginia Tech Athletics Research Application Form, cont.

Please attach the following:

IRB Letter of Approval (including approval date and approval expiration date)

Copy of the Informed Consent Form

Any known conflict of interests

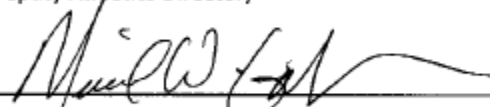
Expected commitment and inconveniences for student-athlete participants

(For Athletic Department Use only)

- ☒ The Athletic Department approves this research to be conducted on its student-athletes.
- ☐ The Virginia Tech Athletic Department DOES NOT approve this research to be conducted on its student-athletes for the following reasons:

n/a

(Deputy Athletics Director)



(Date)

7/28/17

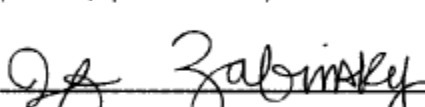
(Associate Athletics Director, Sports Medicine)



(Date)

7/28/17

(Director, Sports Medicine)



(Date)

7/28/17

(Assistant Athletics Director, Sports Nutrition)

see coach's permission form

(Date)

(Sport(s) Representative, Coaching Staff)

Copy of the Virginia Tech Athletics approved Research Application Form, page 2

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
Informed Consent for Participants
In Research Projects Involving Human Subjects

Title: Quantifying the Physical Demands and Injury Risk of Training and Competing in College Athletics

Investigators: Jay H. Williams, Ph.D. (Principal Investigator)
David Tegarden, Ph.D.
Sarah Hoffman
Brian Williams

You are being asked to be in a research study. It is entirely your choice. In order to decide whether you want to be a part of this study, it is important that you read and understand this form. It is also important that you ask any questions that you may have and that you understand all the information in this form. This process is called "informed consent."

I. Purpose of this Research Project

This research is being conducted by faculty and graduate students of the Department of Human Nutrition, Foods and Exercise at Virginia Tech. The purpose of this study is to determine the relationship between physical demands of participating in varsity collegiate athletics and the risk of injury. Our goal is to establish guidelines for developing training programs that will improve competitive performance while minimizing the risk of injury. This study will provide the groundwork for those goals. You are being asked to participate because you are a member of a Virginia Tech intercollegiate varsity sports team. You have also been cleared for participation in intercollegiate athletics by medical personnel. We plan to enroll student-athletes over the course of three years. It is also important for you to know that the results from this study may be used for research publications. However, your anonymity and confidentiality is insured.

II. Procedures

You must be 18 years of age or older to participate in this study. This study will require your participation for pre-season, in-season and off-season training. During all practices and competitions, you will be asked to wear a small device that records your movements and heart rates through global positioning, acceleration and heart rate monitoring (GPSports units). The data from this device will then be downloaded and analyzed by the investigators. Prior to practice and competition, you will be asked to provide your level of physical recovery from the prior day's session. After each session, you will be asked to rate your level of perceived exertion for the session.

The Virginia Tech Athletic Department Sports Medicine staff will also provide the researchers with information regarding any injuries that you might suffer during practice or competitions. This information will be limited to the type of injury, body location of the injury, and cause of injury (if known). The Sports Medicine staff will also notify the researcher you are required to limit or miss practice or competition due to the injury.

During the course of the study, you will not be asked to perform or participate in any physical activities outside of normal practice and competition. If you are diagnosed with an injury or illness that requires you to sit out or miss a session, you will not be asked to participate until you are medical cleared. Thus, your participation will be limited as allowed and required by the coaching and medical staff. In addition, the injury information collected will be limited to that which is routinely exchanged between the coaching and Sports Medicine staffs.

The data collected will be used for research purposes and included in scientific publications and

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presentations. It is important to consider that the data will also be provided to the Virginia Tech coaching and medical staffs to be used for performance, injury prevention and injury rehabilitation monitoring purposes.

Should you agree to participate, you will be expected to:

- Participate in all practices and competitive events as allowed by the sports medicine staff and required by the coaching staff.
- Wear the GPSports HPU SPI units and heart rate monitor during all practices and competitions.
- Provide your body weight before and after practices and competitions.
- Provide perceptual evaluations before and after practices and competitions.
- Notify the Sports Medicine staff of all injuries.

Consider these procedures and expectations before you agree to participate in this study

III. Risks

You may experience discomfort and fatigue during practices and competition due to physical exertion. In some cases, extreme physical exertion can result in injury and health problems including death. As such, Virginia Tech Sports Medicine staff will be present at all practice session and competitive events. However, it is important to emphasize you will not be asked to perform any physical activities other than those normally required of a varsity student-athlete and directed by the coaching staff. Thus, the added risks of participating in this study are minimal.

Neither the researchers nor the University has money set aside to pay for medical treatment that would be necessary if injured because of your participation in this study. Any expenses that you incur including emergencies and long-term expenses would be your own responsibility. In addition, you will not be compensated for damages to personal valuables (shoes, clothing, etc). You should consider this limitation before you agree to participate in this study.

IV. Benefits

The benefits of this research is an understanding of the physical demands of participating in intercollegiate athletics and their association to performance and injury risk. Our goal is to use this information to help the coaching and medical staffs to better train athletes in a manner that maximizes performance but minimizes injury risk.

No promise or guarantee of benefits has been made to encourage you to participate.

V. Extent of Anonymity and Confidentiality

The results of this research project may be published but your name or identity will not be revealed. Your name will not appear on any of the results. No individual responses will be reported. Only group findings will be reported to publications. Information obtained during the course of the study will remain confidential, to the extent allowed by the law. Confidentiality will be maintained by assigning each participant an identification number and recording all data by those identification numbers. The only record with the participant's name and identification number will be kept on a password secured hard drive stored in a locked office. At no time will the researchers break confidentiality or release identifiable results of the study to anyone other than individuals working on the project without your written consent.

The Virginia Tech (VT) Institutional Review Board (IRB) may view the study's data for auditing purposes. The IRB is responsible for the oversight of the protection of human subjects involved in research.

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VI. Compensation

You will receive no compensation for participating in this study.

VII. Freedom to Withdraw

It is important for you to know that you are free to withdraw from this study at any time without penalty. You are free not to answer any questions that you choose or to respond to what is being asked of you without penalty. If you no longer wish to participate in the study, simply notify one of the investigators.

Please note that there may be circumstances under which the investigator may determine that a subject should not continue as a subject. These include long-term injury or illness, failure to comply with the study requirements or withdrawal from the team.

VIII. Questions or Concerns

Should you have any questions about this study, you may contact Jay H. Williams, Principle Investigator at jhwms@vt.edu or (540) 231-8298. You may also contact one of the other investigators listed at the top of this document.

Should you have any questions or concerns about the study's conduct or your rights as a research subject, or need to report a research-related injury or event, you may contact the VT IRB Chair, Dr. David M. Moore at moored@vt.edu or (540) 231-4991.

IX. Subject's Consent

I have read this Consent Form and conditions of this project. I certify that I am 18 years of age or older. I have had all my questions answered. I agree to abide by the rules of the project to the best of my ability. I understand that I may withdraw from the study at any time without penalty. I hereby acknowledge the above and give my voluntary consent.

Subject Signature

Date

Subject Printed Name

Investigator / Witness

Date

Investigator / Witness Printed Name

Virginia Tech Institutional Review Board Project No. 17-832
Approved July 14, 2017 to July 13, 2018

IRB Protocol

TITLE: Estimating Training Load in Collegiate Athletes: Implications for Injury Prevention
PI: Jay H. Williams, Department of Human Nutrition, Foods and Exercise

Subject Recruiting Script

The following text will be used to recruit potential subjects during a face-to-face meeting with each team.

My name is Jay Williams and I am a faculty member in the HNFE Department here at Virginia Tech. I teach exercise science classes such as kinesiology and exercise physiology.

As a member of a Virginia Tech varsity sports team, you are well aware of the relationship between sports participation and injury risk. We are asking you to participate in a research project entitled "Estimating Training Load in Collegiate Athletes: Implications for Injury Prevention". The goal of this project is to determine the relationship between the physical demands of participating in your sport and the risk of injury. With this research, we hope to establish guidelines for developing training programs that will improve competitive performance while minimizing the risk of injury. This study will provide the groundwork for those goals. In addition, we will use the data collected for scientific publications and grant applications.

If you decide to participate, we ask that you sign the Informed Consent document that is in front of you. Please read this carefully and if you have any questions, please don't hesitate to ask. You will need to be cleared for intercollegiate athletics participation by the VT Sports Medicine staff.

In order to participate, you must be over the age of 18. We will ask that you verify this by showing us a driver's license or other form of identification. We also ask that you attest to this by signing Informed Consent document. We will then ask you to have your body weight measured.

Each day, we will ask you to wear a small, non-invasive GPS tracking device and heart rate monitor during training and competitions. These will allow us to calculate the physical demands of the session by calculating your movements and heart rate responses. We will also ask you rate your readiness for each day's session and provide a rating to your perceived effort during that session. Lastly, we ask that you allow the VT Sports Medicine staff to communicate to us any injuries that you may suffer and notify us if an injury limits or excludes you from participating. Note that there is no additional time commitment from you and you will not be asked to perform any activities outside of those normally required and expected from the coaching and sports medicine staffs.

We assure that your individual results will be held in confidence and only group results will be reported. However, please know that the data collected will be shared with the coaching and sports medicine staffs for performance improvement and injury prevention and rehabilitation purposes.

Please realize that your participation is voluntary and is not required as a member of your sports team. In addition, you may withdraw from the project at any time. If you decide not to participate or wish to withdraw from the study, neither your grades nor standing with the team will be impacted.

< Show potential subjects the GPSports device and demonstrate how it is used. Explain the types of data to be collected. >

< Ask coaching and sports medicine staffs to emphasize that participation is not required and that players will not be penalized if they choose not to participate in the study. >

< Discuss the informed consent document >

< Address questions >

Thank you for considering participating in this project. If you have any questions about the project, the informed consent document or any other aspect of your participation, please let me know. I am happy to speak with you privately and can be reached by email at jhwms@vt.edu or by phone at 540-231-8298.

Jay H. Williams, Ph.D.
Professor, Department of Human Nutrition, Foods and Exercise

IRB approved subject recruitment script



Graphic used to demonstrate use of the GPSports device.