

**The Use of Trunk-Mounted Accelerometers for Neuromuscular Testing in
Collegiate Women's Soccer**

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ABSTRACT

Team sports frequently use inertial measurement units (IMU) fixed at the scapulae for the quantification of athlete performance. Similar IMU are used in clinical settings for gait analysis and jump testing but are located at the center of mass (COM). For clinical methods of jump and gait analysis to be translated to sports related IMU, an investigation of the validity of measure from the scapulae should be assessed. The objective of the current study was to translate clinical methods of gait analysis and jump assessment to commercially available trunk-mounted accelerometers. The current study created a gait program to analyze and compile the gait data. Following completion of the gait program, the IMU (STATSports APEX) was investigated for validity against ankle accelerometers. Once the validity was determined, an application study evaluated the relevance of collecting gait data during a NCAA D1 Women's Soccer season. Similarly, the trunk-mounted accelerometer was validated against force plates to assess countermovement jump height. The final study assessed how both jump height and gait variables changed due to game-related decline in performance.

This study provides evidence that trunk-mounted accelerometers are a valid tool for assessing temporal gait variables ($ICC_{\text{Right}} = 0.95$ and $ICC_{\text{Left}} = 0.96$), CMJ height ($ICC_{\text{JH}} = 0.90$) and flight time ($ICC_{\text{FT}} = 0.88$). A longitudinal analysis of gait showed that StepL, StrideL, k_{leg} , and postural variables changed regularly in pre-post comparisons of performance. Postural variables had more changes towards the end of the season.

Root mean squares (RMS) of accelerations and angular velocities had the highest correlations to High Speed Running (HSR). Fractal step and stride length (StepL α and StrideL α) had the strongest correlation to Total Distance ($R_{\text{step}} = -0.29$ and $R_{\text{stride}} = -0.29$), or Tot Dist. When comparing gait and CMJ analyses to detect game-related changes in performance, CMJ was more descriptive of fatigue. In a proof-of-concept study, pre-post changes in CMJ immediately before and after a game had a moderate negative correlation ($R = -0.57$) to Tot Dist. When the protocol changed to assess the differences between the days before and after the game, the correlation weakened to $R = -0.27$. Spatiotemporal and spring mass variables did not change, whereas postural variables appeared to improve. The current study has provided evidence that running gait could be used as an athlete monitoring technique, however more data needs to be collected to understand how running gait variables change with team-sports related fatigue.

The use of Trunk-Mounted Accelerometers for Neuromuscular Testing in Collegiate Women's Soccer

Daniel J. Jaskowak

GENERAL AUDIENCE ABSTRACT

Trunk-mounted accelerometers have become widely popular in team sports such as soccer. Prior to their use in team sports, accelerometers were used in clinical settings to assess gait, and in some cases jump performance. Different from the trunk-mounted accelerometers, the clinical accelerometers were fixed on the lower back to approximate the position of the center of mass. Consequently, the methods to assess gait and jump performance using an accelerometer assume that the accelerometer is fixed on the lower back. For these methods to be translated to trunk-mounted accelerometers, the validity of the methods needs to be established. This paper investigated the validity of trunk-mounted accelerometers in evaluating gait and countermovement jump height. A season-long assessment of gait provided insight into the utility of monitoring gait in team sports athletes. Lastly, a comparison of gait to countermovement jump analyses helped to elucidate what the changes in gait indicate, and how team staff may effectively utilize that information.

The trunk-mounted accelerometer (STATSports APEX) was valid in estimating gait and jump variables. The seasonal analysis showed that gait variables changed frequently throughout the season. The main variables affected described the step and stride length of the individual, the stiffness of the leg, and variables representing the variability in trunk movements associated with running. The variability in trunk movements were more perturbed towards the end of the season when players may be

beginning to tire from continuous training and competition. In the final study, the jump analysis proved to be more representative of the player's state of fatigue than gait. The gait variables appeared to improve after exhaustive exercise. The apparent improvement in gait variables could indicate that the players recovered quickly from the exhaustive exercise, or that gait variables respond in a more complex fashion than jump variables. More data needs to be collected on how gait changes due to game-related fatigue in soccer players to better understand its effect on neuromuscular performance.

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CHAPTER 1: Introduction

1.1 Literature Review

Injury Risk and Training Load Monitoring

A consequence of fatigue from running based sports is a lack of integrity or stiffness to the joints of the leg.¹ The reduction in stiffness is exacerbated by running which utilizes prolonged stretch-shortening cycles (SSC).² Damage from SSC is more severe during eccentric contractions.² Stretch reflex activity is reduced following exercise induced muscle fatigue exposing athletes to injury risk through poor joint stiffness.¹ Anterior cruciate ligament (ACL) rupture is a common injury in women's soccer. The main antagonist to the ACL, the hamstrings muscle group, is compromised during periods of sustained running and explosive movements due to its eccentric function during running.³ During the swing phase of running gait, 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.³⁻⁵ The anatomy and biomechanics of the knee joint in women account for most of the difference in injury risk between the sexes.⁶ Smaller hamstrings,⁷ intercondylar notch, disadvantageous Q angles at the hip and knee, and poor neuromuscular training combine to increase the risk of ACL injury in women.⁶ Regular neuromuscular testing in women's soccer may help alert coaches and support staff of potential increases to injury risk.

For injury prevention monitoring, GPS and accelerometer derived loads have famously been used to construct acute-chronic workload ratios (ACWR). ACWR is a rolling average comparing a day to a week or a week to a month or even a day to a month. They have typically been used to monitor injury risk rather than fatigue. General consensus among the literature

agree with Gabbett's original proclamation: the magnitude of ACWR is associated with injury risk.⁸⁻¹¹ However, the reviews caution ACWR interpretation as an absolute truth due to inconsistencies in definitions, variables used, training modalities, and populations.⁸⁻¹⁰ Interestingly, ACWR is mostly assessed in terms of injury risk rather than fatigue and wellness. Considering that cumulative fatigue is a predecessor to injury, it would follow that investigations of ACWR as a wellness marker would be plentiful. However, few studies assess ACWR and creatine kinase (CK) levels, as well as other general wellness measures. Sampson and colleagues observed trivial associations of wellness (customized questionnaire) to the previous days exponentially weighted moving average ACWR.¹² In this case, training load was evaluated based on the PlayerLoad, or the summed squares of the three acceleration axes. Nobari and colleagues¹³ used a Hopper Index to evaluate wellness, and found moderate to large associations with acute load (1 week average). Acute loads were calculated using the session rating of perceived exertion multiplied by session duration (sRPE-TL). More research should work to determine the impact that ACWR has on wellness.

Separate from the evaluation of ACWR, variables derived from GPS and accelerometers have been assessed for their impact on muscle fatigue. CK was found to be altered through 72 hours postgame (G+72Hr), with varying associations to accelerometer and GPS derived load variables.¹⁴⁻¹⁷ The strongest relationship to CK was very high speed running (VHSR) at post game and G+24Hr.¹⁶ Limited evidence of a moderate correlation at G+48Hr was observed.¹⁶ High Speed Running (HSR) had strong evidence of a large correlation at post game and a moderate correlation with limited evidence at G+24Hr or G+48Hr.¹⁶ Total distance had small to moderate correlations at post and G+24Hr. Fatigue is a multifaceted phenomenon which is hardly translatable across individuals. While these studies provide an approximate time course

to recovery, they fail to capture the unique load and response that is experienced by each athlete separate from their physical performance.

Neuromuscular Testing

Neuromuscular testing provides an intimate assessment of recovery specific to the athlete. Mainstream methods of neuromuscular testing in team sports utilize assessment of countermovement jump (CMJ) performance, and evaluation of leg stiffness. Like monitoring training load, regular neuromuscular testing can help to avoid injury by adjusting training to avoid spikes in either volume or intensity. Methods of monitoring fatigue with CMJ have been effective.¹⁴⁻¹⁸ A systematic review of CMJ variables showed that height was sensitive to fatigue, with average height having a negative moderate effect size.¹⁸ CMJ height was substantially reduced at G+12Hr and G+24Hr, with varying degrees of recovery at G+48Hr and G+72Hr.¹⁵ Supercompensation was explained by eccentric mean power, peak power, height, peak force, peak velocity, and mean impulse in descending effect size order.¹⁸ Importantly, the review had wide ranging populations that were not exclusive to elite athletes. Two systematic reviews analyzed how CMJ peak power changed with fatigue.^{14,16} CMJ peak power has an inverse relationship with CK; that is, when CK levels increase CMJ peak power decreases.¹⁴ CMJ peak power and VHSR had strong evidence of a large negative correlation at G+24Hr, and with less clear evidence at G+48Hr.¹⁶ High accelerations (accelerations greater than or equal to + 3 m/s²) had a large negative correlation at G+24Hr.¹⁶ Though CMJ peak power was correlated to accelerometer and GPS derived variables, CK levels were more sensitive to changes. CMJ performance is therefore a useful method for assessing neuromuscular fatigue.

The forces experienced during running and jumping are relatively similar, so repetition causes similar decrements in force output.² Blickhan proposed the spring mass model (SMM),

which simplifies human motion to that of a spring.^{19,20} The SMM is applicable to both jumping and running. Since its conception, the SMM has been widely used to estimate vertical stiffness (the stiffness of the runner's body at stance, k_{vert}), leg stiffness (the stiffness of the leg at impact, k_{leg}), and center of mass (COM) displacement. Stiffness was estimated by Hooke's Law stating that the spring constant was equal to the ratio of maximum force at impact to the change in displacement of the COM. Until recently, stiffness measurements required a force plate for supplying measures of force. However, Morin and colleagues²¹ validated the sine-wave method in modeling the maximal force at stance touting a bias of less than 7% for all SMM variables.

SMM variables have been analyzed in sprinting, endurance, and ultra-endurance athletes with the aim in understanding how continuous exercise impacts them. In endurance type runs, changes in k_{vert} and k_{leg} are conflicting, with k_{vert} resulting in no change,²²⁻²⁵ and decreases^{26,27} during the run. Despite group significance not being reached, some mentioned that the majority of participants experienced a decrease in k_{vert} .^{22,23} Interestingly, the majority of the studies that saw no change in k_{vert} were performed on a treadmill,²²⁻²⁴ and those that had decreases in k_{vert} were performed on an indoor track.^{26,27} The difference in running mechanics on a treadmill could explain the reason for this phenomenon. However, measuring gait on a track requires a force plate which is only 5 meters in length such that continuous monitoring of stiffness variables was not able to take place. To observe the true nature of k_{vert} , researchers may consider continuous monitoring so as to not base conclusions on cyclic fluctuations of running gait. k_{leg} exhibited similar fluctuations in fatigue response with studies finding no change,^{22,26,27} and decreases.²³⁻²⁵ Comparison of length of exercise test did not yield a more cohesive understanding of how k_{vert} or k_{leg} act when fatigued. When considering the length of test, shorter runs at varied velocity resulted in a decrease in k_{vert} and no change in k_{leg} .^{26,27} Constant

pace runs to exhaustion (under 20 minutes) showed decreases in k_{leg} and no change in k_{vert} .^{23,25} Hour long constant pace runs had mixed results.^{22,24} Future research should work to clarify how k_{vert} and k_{leg} change over the course of endurance exercise.

Studying how the SMM changes with sprint fatigue is difficult due to speed confounding the results. However, fatigue causes an increase in temporal stride variables, and vertical displacement of the COM, and decreases in k_{vert} and stride frequency.²⁸⁻³² Consequently, without holding speed constant it is hard to delineate changes in spring mass behavior due to speed or sprint fatigue. A better method to determine the effect of sprint fatigue on spring mass behavior of the leg is through pre-post fatigue analysis. Morin and colleagues attempted to describe how sprint fatigue affects spring mass behavior by employing a simple repeated sprint protocol.³³ Despite decreases in sprint performance, the pre-post differences in spring mass behavior were not significant.

Anaerobic fatigue induced by CMJ would provide similar results to sprint fatigue due to similarity of muscular mechanisms and energetics. In fact, a fatiguing CMJ protocol changed the spring mass characteristics of its participants at different running speeds pre- and post-intervention.³⁴ For sprints at slower speeds, stride frequency increased, and displacement of the COM decreased. For sprints at self-selected speeds, flight times decreased, stride frequency increased, and stride length decreased. For sprints at faster speeds, pre-intervention speeds were not met post-intervention, flight times decreased, stride length decreased, and F_{max} (resultant impact peak) decreased. However, the inability to maintain speed confounds the results at higher speeds.

The only true pre-post evaluation of the SMM's interaction with fatigue have been in ultra-endurance athletes³⁵⁻³⁷ and after a 2000 meter time trial.³⁸ The aforementioned articles held

speed constant allowing for a true observation of how SMM variables change with fatigue. Across all studies with ultra-marathoners, k_{vert} and stride frequency increased, and change in COM displacement, and leg compression decreased.³⁵⁻³⁷ Interestingly, the pre-post fatigue results from the 2000 meter time trial had no significant changes.³⁸ The lack of effect of fatigue on the SMM could be the result of the test not truly fatiguing subjects, or that the differences between how the individuals fatigue are quite different considering the lengths of runs.

Specific measures of the SMM used to assess neuromuscular status after a regular training session in team sports is not well documented. Three studies have examined changes in the SMM in rugby³⁹ and soccer.^{40,41} After a sprint protocol, rugby players had a very likely trivial decrease in k_{leg} .³⁹ A simulated soccer match resulted in increases in F_{max} , decreases in COM displacement, and no difference in k_{vert} .⁴⁰ In another study, Buchheit and colleagues evaluated the use of the SMM to detect neuromuscular fatigue after different training modalities.⁴¹ Possible to very likely small increases in k_{vert} were found after all sessions, whereas F_{max} had unclear changes.⁴¹ More research should identify how training effects leg stiffness, and its impact on neuromuscular function in team sports athletes. Neuromuscular testing in team sports is primarily centered on jumping. However, jump testing can be burdensome for large scale implementation, and less specific of a skill to run-heavy sports.⁴² Therefore, the exploration of gait analyses is a necessity for the advancement of neuromuscular testing in team sports.

Validation of Accelerometers

Gait analysis has become a popular method of assessing fall risk in ageing.⁴³⁻⁴⁹ Gold standard methods of gait analysis such as instrumented walkways and motion capture systems are expensive and require specialized areas for data collection. Advancements in wearable

technologies have allowed for more convenient methods for gait analysis. Gait accelerometry is a cheaper method that can be utilized in and out of laboratory settings. The use of accelerometers situated on the lower back (L3-L5) for gait analysis has been validated by motion capture^{48,50} and force platforms.^{44-46,51-53} Measurements of speed, cadence, length, and time variables have been shown to be valid and reliable.^{44-46,51-53}

Assessing spatiotemporal gait variables from accelerometers requires data processing that is largely variant across research papers.^{44,48,54,55} McCamley and colleagues⁵⁴ proposed a method of gait event detection (initial and final contacts) based on a continuous wavelet transform (CWT). CWT was more valid than other proposed methods⁵⁵ for gait event detection, and had excellent validity in estimating time and length variables.^{44,54} However, discrepancies in gait characteristics were observed when comparing gait asymmetries and variability with gait measured using instrumented walkways.^{44,51} Del Din and colleagues⁵¹ postulated that due to the difference in functionality of the devices, differences in measured accelerometer based variables would persist. For instance, instrumented walkways detect the timing of gait events, whereas accelerometers mounted on the lower back are continuously recording acceleration signals. Consequently, accelerometers were shown to have excellent validity for estimating trunk accelerations with motion capture.⁵⁶ Therefore, the discrepancies encountered by Del Din and colleagues may be explained by the location in which acceleration variables are derived.⁵⁷ Kinematic variables decreased as distance from the ground increased, suggesting that higher placement of inertial sensors results in a dampening of accelerometer signal relevant to impacts.⁵⁷ Similarly, magnitudes of induced asymmetries were statistically different between an accelerometer on the ankle (bigger) than between the scapulae.⁵⁸ Despite the dampened

acceleration signal of a trunk-mounted accelerometer, the validity and reliability for detecting the timing of gait events was still excellent.^{44,51,54}

Accelerometers are not limited to clinical gait analysis. Team sports have been utilizing GPS embedded trunk-mounted accelerometers to estimate player load in soccer,⁵⁹ rugby,⁶⁰ and American football.⁶¹ Accelerometer based load variables do not incorporate physiologic responses to exercise, but rather quantify the amount of physical activity a player is experiencing. Quantifying load while useful for exercise prescription gives little insight into the physiological load experienced by the athlete. Sports scientists have addressed the lack of physiological consideration by including neuromuscular testing and wellness questionnaires as part of their athlete monitoring programs. The applicability of running to team sports is both functional and practical. Therefore, validation of gait accelerometry for running must be explored.

Thus far, most running experiments testing validity have been on recreational or elite level runners, locating the accelerometer near the COM. Gait accelerometry about the COM has been reasonably reliable and valid in estimating variables associated with running gait. Cadence had excellent reliability and validity across a range of speeds.⁶²⁻⁶⁴ Temporal variables had excellent reliability,⁶⁴ moderate reliability,⁶² moderate validity^{62,64} and excellent validity.⁶³ Additionally, vertical acceleration was valid when compared to timing gaits.⁶⁵ However, most accelerometers in team sports are placed between the scapulae. Since the location of the accelerometer is well superior to the point of contact, the acceleration signal experiences dampening when compared to gold standard measures.^{51,57,58} Therefore, validation of trunk-mounted accelerometers as measures of acceleration and running gait need to be examined.

Commercially-used accelerometers are not known to be clinically relevant in measuring ground reaction forces,⁶⁶ speed,⁶⁷ or even forward acceleration.⁶⁸ Interestingly, Wundersitz and colleagues⁶⁶ found excellent agreement between a Catapult accelerometer, and a motion capture system after applying a fast Fourier transform with a 10 Hz cutoff frequency. Proper signal processing is important to the validity of the accelerometer derived signal.^{66,69} Gait events derived from a trunk-mounted accelerometer had low agreement with force plates when filtered with a cutoff frequency of 100 Hz.⁶⁰ Conversely, a lower cutoff frequency of 10 Hz resulted in moderate agreement with an instrumented treadmill for ground contact times.⁷⁰ Given the variety of commercially available trunk-mounted GPS embedded accelerometers used for quantifying player loads, case by case validation is recommended.

Despite dampening, trunk-mounted accelerometers have acceptable validity in detecting gait events while running. However, it is important to note that clinical diagnoses from the trunk should be avoided until trunk-mounted accelerometers shown to be clinically relevant. For purposes of collecting gait data in a field setting, accelerometers are a valid tool. Validation of trunk-mounted accelerometers to measure accelerations and gait events should be explored to provide a more appropriate context to the data they provide.

Detrended Fluctuation Analysis

Detrended fluctuation analysis (DFA) is a fractal analysis of a stochastic process identifying the presence of long-range correlations within a time series. The analysis sums local fluctuations over a series of different window sizes. To eliminate the presence of nonstationarities, a local trend line is subtracted from the time series in each window such that the fluctuations are equal to the sum of the standard deviations of the residues from each local trend.⁴⁷ The analysis can be described by the following two equations:

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

where k is the number of data points, S_i is the i th step number and \bar{S} is the average step interval and:

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

2 Detrended Fluctuation Equation

where N is the number of data points in each window. The aforementioned process is typically performed from a window size of 4 observations to $(k-4)/4$ observations.⁷¹ As window size increases, typically so will fluctuations.⁴⁷ A linear relationship between window size and the summed fluctuations exists in a log-log plot. The slope of the resulting linear trend of the log-log plot is called α . The α exponent describes the presence or absence of long-range correlations in the time series. White noise or a completely random, uncorrelated time series corresponds to $\alpha = 0.5$. Long range correlations are present if $0.5 < \alpha \leq 1.0$. Values of $\alpha > 1.0$ indicate that the time series is nonstationary. Anticorrelations result if $\alpha < 0.5$. To maintain statistical power, Damouras and colleagues⁷² suggests that the number of observations should be over 600.

The introduction of fractal dynamics into human physiology began in detecting fractal properties of nucleotide sequencing,⁷³ and heart rate variability.⁷¹ Hausdorff and colleagues⁴⁷ applied the same technique to walking gait establishing that walking gait exhibits long term correlations.⁴⁷ Interestingly, they saw that forcing the participants to walk at a predetermined pace decreased the fractal scaling (lower α). They postulated that the forced pacing disrupted higher order neurons since introducing a supraspinal stimulus (metronome) decreased the presence of long range correlations.⁴⁷ Hausdorff suggests that the supraspinal component of

fractal scaling is indicative of a central pattern generator; a collection of motor programs located infraspinally which may allow the brain to delegate neural control.⁴⁷

The development of DFA as a tool to measure the fractality of gait has been studied in pathologic populations with supraspinal dysfunctions.⁷⁴⁻⁷⁶ Hausdorff saw that the severity of Parkinson's disease affected α , with the more severe cases of Parkinson's resulting in lower α values.⁷⁴ Similarly, Huntington's disease showed lower α levels when compared to healthy controls.⁷⁵ Disorders independent of the mainstream supraspinal dysfunctions, termed higher level gait disorders, had lower α values than controls.⁷⁶ Higher level gait disorders were characterized as having a shaky or cautious gait, and was generally experienced by older populations. Research into the effects of ageing on fractal scaling revealed that α tends to decrease with age, possibly due to a loss of dopamine content in the basal ganglia.⁷⁵ Conversely, when applying DFA to individuals with peripheral pathologies, α values were unaffected.⁷⁷

To further the scientific understanding on gait fractality, researchers began studying what perturbations of higher-level senses elicit changes in the fractality of walking gait. Auditory stimulation was documented to obstruct normal fractal properties, producing lower α values. Forced timing of gait using a metronome^{47,78} or partner walking,⁷⁸ decreased α values compared to normal controls. Walking on a treadmill also resulted in lower fractality.⁷⁹ Likewise, visual perturbations were found to have a similar effect. Varying the speed in which visual cues appeared while holding walking speed constant, changed the amount of long term correlations in gait.⁸⁰ Cuing speed matching preferred walking speed resulted in higher α values than when the cuing speed was slower or faster than preferred walking speed.⁸⁰ The same study also saw that when the participants were unable to see their feet and had no visual cuing, lower α values were recorded than visual cuing trials.⁸⁰

Outside of clinical methodologies and sensory perturbations, the effects of training and forced asymmetries have been monitored on gait fractality. Walking at a preferred walking speed had lower α values compared to both faster and slower walking speeds in healthy adults.⁸¹ The authors described the relationship of fractality between speeds, as having a U-shape with preferred walking speed being the vertex.⁸² Neuromuscular and cognitive training appear to affect the strength of long range correlations.⁴⁹ A study observing the impact of Tai Chi on older adults' gait health suggests that older adults who are experienced in Tai Chi, have higher α levels compared to older adults with no experience in Tai Chi.⁴⁹ The study also found that slight improvements (not significant) in α values were observed in older populations that began a Tai Chi intervention to improve gait and balance.

Thus far, the discussion surrounding gait fractality reflects the desire to characterize the functional capabilities of individuals with dysfunctional walking gait. As more research on gait fractality was available, researchers were left to wonder if fractal properties of running gait existed. The study establishing a U-shape relationship of α and walking speed,⁸² was translated to running.⁸³ Unsurprisingly, the same relationship was observed: as runners deviated from their preferred running speed, the movement become more ordered.⁸³ Another study introduced an auditory stimuli to try to disrupt the long range correlations present in running gait.⁸⁴ Running at a forced frequency decreased α ,⁸⁴ which is in agreement with findings in walking.^{47,78} The establishment of running gait fractality and the apparent similarities that exist between it and walking gait fractality, enabled the application of DFA to athletic populations. As DFA was originally applied to assess the gait health of clinical populations, application to athletic populations targeted compromised biomechanics due to cumulative fatigue, musculoskeletal injury, and exhaustive exercise.

Exploration of fractal dynamics of training status has yielded interesting results. Cumulative fatigue appears to have a negative impact on gait fractality.⁸⁵⁻⁸⁷ Periods of heavy training had a negative effect on 5k time trial, whereas periods of light training had no effect on gait fractality.^{85,86} Soccer match congestion (2 matches within 4 days) resulted in similar reductions in gait fractality.⁸⁷ The decreases in gait fractality were only seen in players who had the highest playing time. Additionally, both total distance ran and recovery scores had moderate correlations ($r = -0.833$ and $r = -0.650$) to gait fractality.⁸⁷ These results are in agreement with what was found by Jaskowak and colleagues.⁸⁸ During exhaustive exercise, gait fractality has been shown to decrease.⁸⁹ During a run to exhaustion (~5-6km), Meardon and colleagues⁸⁹ found that gait fractality decreased from the beginning of the run to the end of the run. Other factors that have been shown to affect gait fractality are previous injuries,⁸⁹ and running experience.^{84,90} Previously injured runners tended to have lower gait fractality than their noninjured counterparts.⁸⁹ Interestingly, more experienced runners had lower gait fractality than unexperienced runners.^{84,90} More evidence of how the fractal dynamics of gait change in different training states will help to determine the impact that gait fractality has on human performance.

Trunk Stability

With accelerometer placement generally on the trunk, researchers began to focus on how the position of the trunk varied in gait. Moe-Nilssen and Helbostad applied an autocorrelation function to the acceleration signal of a walk⁹¹. An autocorrelation compares the original acceleration signal to a lagged acceleration signal. Assume that the acceleration signal starts with at the onset of the first step. The autocorrelation at lag = 0 is $\rho = 1$; where ρ is the autocorrelation coefficient. The autocorrelation coefficient ρ is like the correlation coefficient R ,

such that $\rho = 1$ is a perfect correlation, and decreasing ρ decreases the correlation to the original signal. As the signal is lagged, ρ decreases and will continue to decrease until the first and the second step begin to overlap. Once the first step and the second step overlap, the autocorrelation function has its first dominant peak. The first dominant peak represents the similarity of the signal from the first and the second step. The first dominant peak is therefore called step regularity. The total lag between the onset of the autocorrelation and the first dominant peak is the time between steps. The signal is lagged further until it overlaps with the third step resulting in the second dominant peak of the autocorrelation function. The second dominant peak is the similarity between consecutive steps of the same foot and is termed stride regularity.

As a method of gait analysis, autocorrelation has been used in clinical populations,^{92,93} and has been validated as a tool to assess symmetry.⁹⁴ Autocorrelation has been included in the idea of dynamic stability, which attempts to quantify the movement variability of the trunk during gait. Dynamic stability includes the analyses of autocorrelation, root mean squares (RMS) of acceleration and angular velocities, and nonlinear time series analyses such as sample entropy and DFA. Regularity will typically decrease during exhaustive exercise,⁹⁵⁻⁹⁷ and RMS of accelerations will typically increase during exhaustive exercise.^{96,97} RMS of acceleration have been shown to be correlated with running economy, with lower RMS being associated with higher running economy.⁹⁸ More research needs to explore how RMS and regularity change from day-to-day variations associated with acute and chronic fatigue.

Summary

The necessity to monitor individual aspects of the athlete's neuromuscular performance are paramount to the investigation of fatigue and injury. VHSR, HSR, accelerations, and total distance are all correlated with changes in CK levels post exercise.^{14,16} It may be more

appropriate to monitor changes in running gait rather than jump ability due to the nature of VHSR, HSR and total distance being intimately linked to running. Hogarth and colleagues⁹⁹ showed that running performance decreased as a result of decreased neuromuscular performance from playing multiple tag football matches in a day. Integration of gait assessment with training load assessment offers both a biomechanical and neurophysiological perspective into the performance of athletes. Clinical methods of gait assessment have been used with accelerometers to observe gait insufficiencies in pathologic populations.^{47,92,100-102} McCamley and colleagues⁵⁴ applied a Gaussian CWT to acceleration signals to determine the time points of initial contact (IC) and final contact (FC). Access to these gait events allow for the observation of spatiotemporal variables during field use of accelerometers. Fortunately, most commercially available technologies for training load assessment are equipped with GPS embedded accelerometers (e.g., STATSports, Catapult Sports). Therefore, the purpose of this research was to explore the use of accelerometers to assess recovery status of athletes during real world training scenarios.

1.2 Objectives

Specific Aims

The objective of the current research was to utilize trunk-mounted accelerometers' capability to assess neuromuscular fitness in field-based tests for team sports athletes. Clinical methods of gait analysis were used to monitor gait during a NCAA D1 Women's Soccer season. Similarly, the trunk-mounted accelerometers were used to assess countermovement jump height, using methods previously established for other accelerometers. In attaining the research objective, the following specific aims guided the research process:

1. Develop a gait analysis program to process gait data and store it in a database for later analysis.
2. Assess the validity of gait measured at the trunk compared to gait measured at the ankle.
3. Evaluate the use of gait as a fatigue marker during a competitive soccer season.
 - a. Evaluate the testing method for data collection.
 - b. Establish a relationship between gait variables and training load variables.
 - c. Compare the changes in gait between the Starter and Reserve cohorts.
 - d. Determine which gait variables are most sensitive to game related fatigue.
4. Assess the validity of the accelerometer to determine jump height compared to a force platform.
5. Determine the best method for detecting Pre-Post differences in performance due to match-related fatigue.
 - a. Describe the associations of training load variables to gait and countermovement jump height.

Assumptions and Limitations

Several assumptions were made to use the analyses for gait monitoring. First, the leg length was approximated as being $0.53 \cdot h$, where h is height of the athlete. This was what was used in the literature.²¹ Furthermore, speed was assumed to be constant between steps which

was essential to the calculation of step length, and spring mass variables. The maximum force of impact was modeled by the equations developed by Morin and colleagues.²¹ The spring mass model (SMM) requires that the summation of the stiffness at each joint angle is generalized to the leg. This is an oversimplification since each joint works to stiffen the leg upon impact. Lastly, the accelerometer readings at the thorax are assumed to be like those at the center of mass (COM). Validation of accelerometers on the thorax were evaluated later. Due to the location of the accelerometer, measures of gait were likely difficult to detect transient changes in gait of clinical relevance. However, trunk accelerations related to gait fluctuate and change with fatigue.⁹⁶ The current study utilized collegiate women's soccer players. Generalizing results should be done cautiously to other populations. Weather was assumed to have negligible effect on gait variables. Pre-existing injuries, school related stress, diet, and hormonal status were not controlled for.

CHAPTER 2: The Gait Program

Abstract

Accelerometers have been used and validated for clinical methods of gait assessment. These same methods have relevance for sport science practitioners, and thus need to be translated to athletic populations. The current chapter first describes the gait analyses used in the gait program, and then the specific code used to compile the gait data is located in Appendix C. Once the gait data was compiled, the validity of the trunk-mounted accelerometers were assessed using ankle accelerometers. A comparison between the right and left stride times ($R_{StrideT}$, and $L_{StrideT}$) derived from the two methods was assessed for agreement with a Bland-Altman analysis, and intraclass correlation coefficients (ICC $3,k$). The trunk-mounted accelerometer had excellent agreement with the ankle accelerometers having low bias ($Bias_{left} = 1.48\%$, $Bias_{right} = 1.40\%$) and tight limits of agreement ($LOA_{left} = -0.93\% - 3.88\%$, $LOA_{right} = -0.71\% - 3.15\%$), as well as high ICC (Left = 0.96, Right = 0.95). The trunk-mounted accelerometer was found to be a valid method for assessing temporal gait data.

2.1 Methods of Gait Analysis

All data from a run was split and downloaded to .csv files. The .csv files were imported into RStudio where a custom R program transformed the acceleration data into gait related variables. Acceleration signals were converted from g to m/s^2 and a resultant signal calculated. The data was then corrected using the method established by Moe-Nilssen.¹⁰³ Due to the forward lean of human gait, true vertical acceleration is not experienced by the accelerometer; therefore a correction is necessary to obtain a true vertical signal. The gyroscopic data was converted from millivolts to deg/s (multiplying raw gyroscopic data by 0.07 derived from a calibration procedure). A 4th order Butterworth filter (40 Hz, 0.9 Hz) was applied to all

acceleration and gyroscopic signal components using the *filtfilt()* function from the signal package. Similarly, a 4th order Butterworth filter (3 Hz, 0.9 Hz) was applied to the mediolateral signal to detect left and right foot strikes.⁵⁵ Vertical acceleration was integrated to velocity (to aid in future data analysis) using the *cumtrapz()* function from the pracma package.

The data was transformed using a Gaussian continuous wavelet transform (CWT). The CWT integrates the vertical acceleration signal to velocity and then transforms the velocity into acceleration by fitting a uniform periodic wave to each period of the signal (Figure 1).⁵⁴

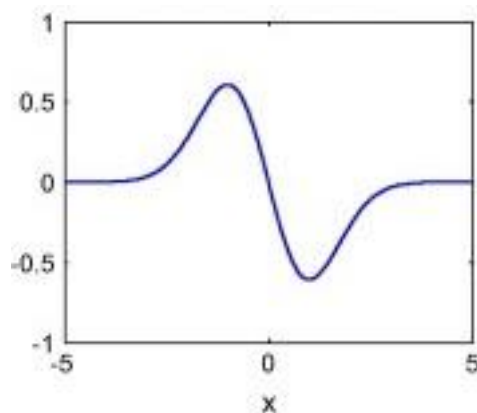


Figure 1 A first order Gaussian wavelet.

The local minima of the transformed acceleration signal represent the initial contact time points for each step. A second CWT of the transformed acceleration signal results in a transformed jerk signal. The local maxima of the transformed jerk represent the final foot contact time points for each step.⁵⁴ The current data processing technique used the *wavCWT()* function with scale of 10 from the wmtsa package. After the double transformation, the *findpeaks()* function from the pracma package located the local minima and maxima from the transformed acceleration and transformed jerk signals.

Delineation between left and right step was determined using the method described by Zijlstra and Hoff.⁵⁵ Positive deflections of the mediolateral signal correspond to right foot strikes (local minima), and negative deflections correspond to left foot strikes (local maxima).

Locating the time points of initial contact (IC) and final contact (FC) allowed for the computation of contact, step, and stride times using the following formulas:

$$CT = FC - IC \quad 3 \text{ Contact Time}$$

$$\text{StepT} = IC_{i+1} - IC_i \quad 4 \text{ Step Time}$$

$$\text{StrideT} = IC_{i+2} - IC_i \quad 5 \text{ Stride Time}$$

where CT is contact time, StepT is step time, and StrideT is stride time. Right and left component contact, step, and stride times (RCT, LCT, RLStep, LRStep, RStride, LStride) were calculated following the right component formulas:

$$RCT = RFC - RIC \quad 6 \text{ Right Contact Time}$$

$$\text{RLStep} = LIC - RIC \quad 7 \text{ Right to Left Step Time}$$

$$\text{RStride} = RIC_{i+1} - RIC_i \quad 8 \text{ Right Stride Time}$$

where RFC is the right final contact and RIC is the right initial contact. Flight times (FT) were calculated as follows:

$$\text{RFT} = \text{RLStep} - \text{RCT} \quad 9 \text{ Right Flight Time}$$

$$\text{FT} = \text{StepT} - \text{CT} \quad 10 \text{ Flight Time}$$

where RFT is right flight time. Symmetry indices (SI) were calculated for all variables using the following formula:

$$SI = 200 * \frac{X_R - X_L}{X_R + X_L} \quad 11 \text{ Symmetry Index}$$

Component step and stride lengths (RStepL, LStepL, RStrideL, and LStrideL) were calculated as follows:

$$\text{RStepL} = (\text{RIC.sp} + \text{LIC.sp})/2 * \text{LRStep} \quad 12 \text{ Right Step Length}$$

$$RStrideL = (RIC.sp_{i+1} + RIC.sp_i)/2 * RStride$$

13 Right Stride Length

where RIC.sp and LIC.sp are the speeds at RIC and LIC respectively. Composite StepL and StrideL vectors were composed alternating right and left components.

The spring mass model (SMM) posits that the vertical change in mass displacement (Δy) is proportional to the maximum force (F_{max}) exerted on the ground divided by the vertical spring constant of the leg (k_{vert}). SMM variables were calculated using the assumption that leg length (L) was approximately 0.53 of the total height.²¹ SMM variables were calculated based off of the equations described by Morin and colleagues.²¹ The following equations were used to calculate SMM variables:

$$F_{max} = 0.5\pi mg * \left(\frac{FT}{CT} + 1\right)$$

14 Maximum Force at Stance

$$\Delta y = \frac{F_{max}CT^2}{m\pi^2} + \frac{gCT^2}{8}$$

15 Vertical Displacement of the Center of Mass

$$k_{vert} = \frac{F_{max}}{\Delta y}$$

16 Vertical Stiffness

$$\Delta L = L - \sqrt{L^2 - \left(\frac{RLStep.sp * CT}{2}\right)^2} + \Delta y$$

17 Change in Leg Length

$$k_{leg} = \frac{F_{max}}{\Delta L}$$

18 Leg Stiffness

where m is the mass of the player, g is the acceleration due to gravity, k_{leg} is the spring constant of the leg while running, and $RLStep.sp$ is the speed between steps while running.

Root mean square (RMS) accelerations and angular velocities were calculated in all axes as well as the resultant. Peak accelerations and angular velocities were calculated for each step

in each axis and resultant using the *findpeaks()* function of the *pracma* package. SI were calculated for all variables.

A detrended fluctuation analysis (DFA) identifies the presence of long-range correlation through assessment of the fractal properties of a time series and was described previously. Briefly, the analysis systematically divides the time series into a series of window sizes. Window sizes typically range from 4 to $(k-4)/4$ observations. For each window, fluctuations from local trend lines are summed. The log of the summed fluctuations is plotted against the log of the window sizes. The slope of the log-log plot is called the alpha exponent (α) and represents the strength of long-range correlations for the time series. White noise is a completely random signal with $\alpha = 0.5$ and is generally associated with gait pathologies. $\alpha > 0.5$ indicates more structure to the time series, with $\alpha = 0.7$ being representative of healthy runners.⁸³

The recommended number of observations for DFA is between 500 and 600.^{72,104,105} However statistical power of the DFA can still be achieved with a lower number of strides after controlling for population size and trial number.¹⁰⁶ For both within and between subjects designs, increasing the number of strides decreased the number of trials necessary to achieve similar statistical power.¹⁰⁶ As strides were added for each trial, the number of subjects required for sufficient power drastically decreased. Therefore, it was determined that 400 observations would have sufficient power in assessing changes in DFA. This meant that unilateral variables, and SI, and RMS were not considered for DFA. DFA were analyzed with the *dfa()* function with a range in window size of 4 to $N/4$ (*nonlinearTseries* package).

Autocorrelations of acceleration and angular velocity signals were performed as described by Moe-Nilssen and Helbostad.⁹¹ Briefly, the signal was lagged such that consecutive step signals were overlaid. The lag between dominant peaks is equal to the time between

consecutive steps. The first dominant peak indicates the autocorrelation between the two consecutive steps. Autocorrelation coefficients are like correlation coefficients in that a perfect autocorrelation results in a coefficient of $\rho = 1$. Deviation from $\rho = 1$ results in less similarities between the signals. The second dominant peak is the autocorrelation between two consecutive steps with the same foot. The first dominant peak is referred to as step regularity, or the likeness between consecutive steps. Likewise, the second dominant peak is referred to as stride regularity, or the likeness between consecutive steps of the same foot. The *acf()* function from the stats package performed the autocorrelation for each signal. The first and second dominant peaks were found using the *findpeaks()* function from the pracma package.

Spatiotemporal data from each trial was stored in an athlete specific .csv file for further analysis. Average values for each run were compiled in a .csv file with all players and collected variables. For an abbreviated view of the Gait Program, reference Appendix C. The gait program resulted in 130 variables with abbreviations and descriptions shown in Table 2.1. For brevity, right (RX) and left (LX) variables were not included in the table.

Table of Variables and Their Abbreviations

	Abbreviation	Units
Spatiotemporal		
Flight Time	FT	ms
Contact Time	CT	ms
Step Time	StepT	ms
Stride Time	StrideT	ms
Step Length	StepL	m
Stride Length	StrideL	m
Spring Mass		
Max Force	F_{max}	N
Vertical Displacement of the Center of Mass	Δy	m
Vertical Stiffness	k_{vert}	Nm
Change in Leg length during Stance	Δl	m
Leg Stiffness	k_{leg}	Nm
Alpha and Difference Variables		
Fractal Exponent for Gait Variable	(α)	
Percent Difference for Gait Variable	$(.diff)$	%
Postural Variables		
Mediolateral Accelerometric Step Regularity	X.Step.Reg	
Mediolateral Accelerometric Stride Regularity	X.Stride.Reg	
Vertical Accelerometric Step Regularity	Y.Step.Reg	
Vertical Accelerometric Stride Regularity	Y.Stride.Reg	
Antero-posterior Accelerometric Step Regularity	Z.Step.Reg	
Antero-posterior Accelerometric Stride Regularity	Z.Stride.Reg	
Mediolateral Gyroscopic Step Regularity	X.Gyro.Step.Reg	
Mediolateral Gyroscopic Stride Regularity	X.Gyro.Stride.Reg	
Vertical Gyroscopic Step Regularity	Y.Gyro.Step.Reg	
Vertical Gyroscopic Stride Regularity	Y.Gyro.Stride.Reg	
Antero-posterior Gyroscopic Step Regularity	Z.Gyro.Step.Reg	
Antero-posterior Gyroscopic Stride Regularity	Z.Gyro.Stride.Reg	
Mediolateral Variability in Acceleration	X.Accel.RMS	
Vertical Variability in Acceleration	Y.Accel.RMS	
Antero-posterior Variability in Acceleration	Z.Accel.RMS	
Resultant Variability in Acceleration	R.Accel.RMS	
Mediolateral Variability in Angular Velocity	X.Gyro.RMS	
Vertical Variability in Angular Velocity	Y.Gyro.RMS	
Antero-posterior Variability in Angular Velocity	Z.Gyro.RMS	
Resultant Variability in Angular Velocity	R.Gyro.RMS	
Table 2.1 Abbreviations of variables derived from the Gait Program		

2.2 Validation of temporal gait characteristics derived from a trunk-mounted accelerometer.

Introduction

Team sports have become increasingly interested in physiological data derived from trunk-mounted accelerometers. Indeed the technology has permeated mainstream sports such as football,¹⁰⁷ rugby,³⁹ and soccer.^{40,41} Sports scientists therefore have the unique opportunity to translate accelerometer data into meaningful physiological data in the form of jump testing, and leg stiffness. Leg stiffness is derived from the spring mass model introduced by Blickhan in 1989.¹⁹ The model was used to calculate leg stiffness for both running and jumping, becoming a key measure of neuromuscular assessment for the lower legs. Few studies have assessed the changes in leg stiffness in team sports.³⁹⁻⁴¹ Sports scientists have thus far been interested in assessing stiffness of the legs to assess the neuromuscular toll athletes endure during regular training and competition,³⁹⁻⁴¹ much like what has been done with the countermovement jump.¹⁰⁸

Gait accelerometry has been used in clinical settings as an alternative to more expensive methods of gait analysis. Patient populations with osteoarthritis,⁹² Parkinson's,⁴⁷ peripheral neuropathy,⁷⁷ and others have utilized accelerometers to describe gait. In clinical settings, accelerometers were fixed about the center of mass (COM) rather than between the scapulae, the common location of accelerometers in team sports. Accelerometers have the capability to provide a lot of information about trunk location and movements which have not been readily explored in team sports athletes. Therefore, the need to validate gait assessment from the trunk is necessary before it can be used as a tool to assess changes in neuromuscular status. Trunk-mounted accelerometers have previously been validated for gait analysis to detect contact times while running on a treadmill.⁷⁰ Similarly, a case study showed excellent validity in measuring both leg stiffness and temporal gait characteristics with a trunk-mounted accelerometer

commonly used for monitoring training load in team sports.⁵⁹ However, the STATSports APEX has not been previously validated for use in assessing temporal stride variables. The purpose of the present study is to assess the difference in measurement of temporal stride characteristics between ankle accelerometers and a trunk-mounted accelerometer. It was hypothesized that there was no bias between the methods of measurement.

Methods

Participants

This study was part of a larger study that collects accelerometer and GPS data from the Virginia Tech Women's Soccer team. Four participants (age = 18.50 ± 1.00 , height = 170.18 ± 7.19 , 64.20 ± 4.39) were used to assess the difference in measurement between the ankle (IMeasureU, Blue Trident, 16g, 1125 HZ and 200g 1600 Hz accelerometers, 1125 Hz gyroscope and 112 Hz magnetometer) and trunk-mounted accelerometers (18 Hz GPS, 600 Hz accelerometer, 400 Hz gyroscope, and a 10 Hz magnetometer). All research and methods were approved by the Virginia Tech IRB (17-632).

Experimental Procedure

For each session participants were fitted with STATSports APEX units (SS) to log training load data. The units were placed in the manufacturer supplied vest between the scapulae. A random sample of the participants wore the IMeasureU (IMU) accelerometer for impact analysis. Two IMUs were placed on the anteromedial aspects of the left and right distal tibia, such that the Y-axis aligned with the craniocaudal axis. Following a standardized warm-up, the participants ran two linear, self-paced strides (SPS) the length of the practice field (~200m). The IMU has real-time data analysis capabilities, requiring researchers to tag drills as they happen. SPS were tagged, such that they could be identified later for data analysis. Upon completion of

the SPS, practice continued as scheduled. After each practice session, data was downloaded to the respective proprietary software. The IMU data was split to isolate the SPS from the whole session. The data from SS was downloaded and split to isolate the SPS from the whole session. The SPS data was imported into R for further analysis.

Data Processing

Once the SPS were isolated, the High G accelerometer data was imported into a custom R file. The data was first filtered using a 4th order Butterworth filter (Low pass 40 Hz, High pass 0.9 Hz), using the IRISSeismic and signal packages. Right and left stride times (RStrideT, LStrideT) were calculated as the difference between successive impact peaks for each leg. The *findpeaks()* function was used to isolate peaks from each participant corresponding with the impact of each step. Once the peaks were isolated, the difference in time between adjacent peaks was determined as the RStrideT or LStrideT.

SPS data from SS was imported into R and analyzed by the gait program described in Section 2.1 and Appendix C. Briefly, the accelerometer data was adjusted to account for the tilt of the trunk during running utilizing the method described by Moe-Nilsson 1998.¹⁰³ The vertical acceleration signal was filtered using a 4th order Butterworth filter (Low pass 40 Hz, High pass 0.9 Hz). A continuous wavelet transform (CWT) was applied to the vertical acceleration as described by McCamley et al. 2012.⁵⁴ This method detects initial contact and final contact of each foot according to the difference in peaks of the CWT transformed jerk and CWT transformed acceleration signal. Left and right foot strikes were determined by accounting for the sign of the mediolateral acceleration during each step.⁵⁵ Left foot strikes corresponded to negative deflections and right foot strikes corresponded to positive deflections. Stride times

were calculated as the difference in time between successive right (R-R) and left (L-L) foot strikes.

Statistical Analysis

A Bland-Altman analysis was used to assess biases and limits of agreement between ankle ($X_{\text{Stride}_{\text{ankle}}}$) and trunk-mounted accelerometers ($X_{\text{Stride}_{\text{trunk}}}$). The assumption of normality of residuals for the Bland-Altman analysis was checked using the *shapiro.test()* function from the stats package. A two-sample t-test was performed to assess the difference in means between the methods of measurements for both right and left components. To further assess the similarity of the measures, intraclass correlation coefficients (ICC $3,k$) were computed for both RStrideT and LStrideT.

Results

For LStrideT, the residuals were not normally distributed according to the Shapiro-Wilk normality test ($p = 0.0167$). However, due to the large sample size a quantile-quantile (QQ) plot was used to approximate normality (Figure 2).

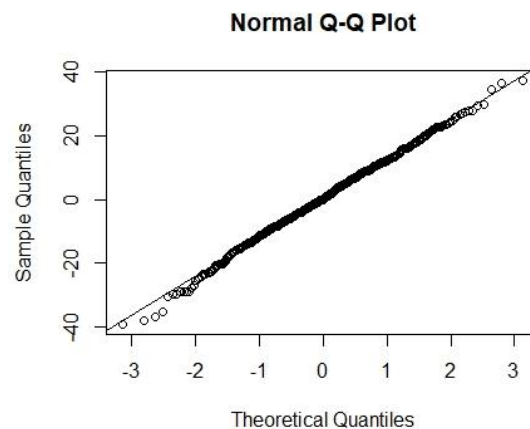


Figure 2 Normal quantile-quantile plot to test for normality for LStrideT. As the points mostly fall on the line, the residuals can be assumed to be normally distributed.

According to the QQ plot of the residuals, the data is normal. RStrideT had a normal distribution of residuals as noted by the Shapiro-Wilk normality test ($p = 0.5914$). Descriptive statistics are summarized in Table 2.2.

Descriptive Statistics				
Variable	Count	Mean (SD)	Lower 95% CI	Upper 95% CI
RStride _{trunk} (ms)	583	705.34 (30.89)	702.82	707.85
RStride _{ankle} (ms)	583	705.67 (30.34)	703.19	708.14
P value		0.85		
LStride _{trunk} (ms)	583	705.46 (31.24)	702.92	708.00
LStride _{ankle} (ms)	583	705.67 (30.30)	703.21	708.14
P value		0.90		

Table 2.2 Descriptive statistics of stride times in milliseconds (ms) for the different methods of measurement.

The Bland-Altman plots illustrated in Figure 3 show that most of the differences are between the confidence intervals.

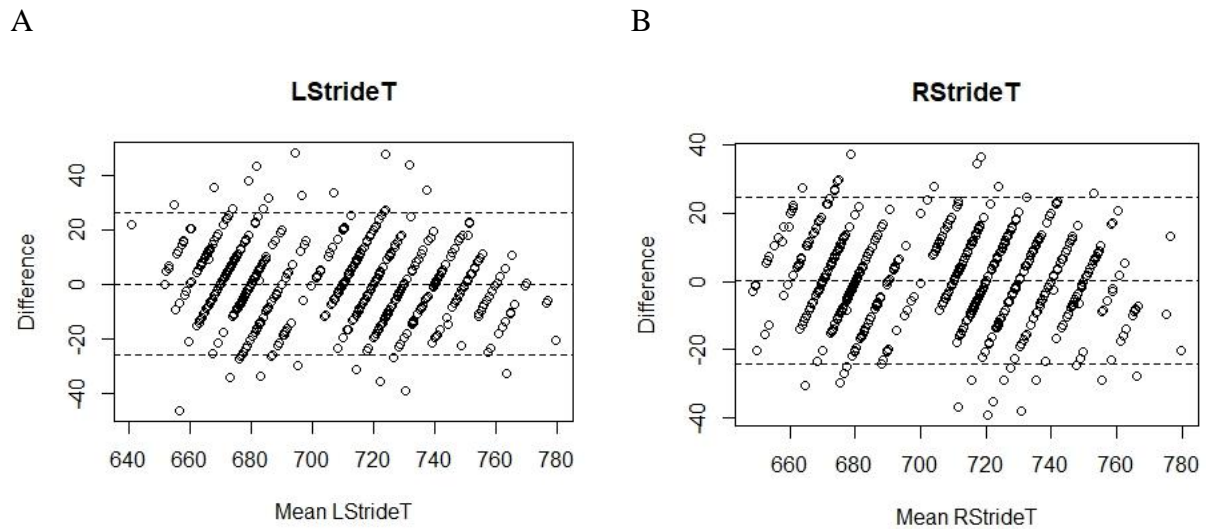


Figure 3. Bland-Altman plots of LStrideT (A) and RStrideT (B) in milliseconds.

The ICC (3,k) for LStrideT is 0.96 ($p > 0.001$) and RStrideT is 0.95 ($p > 0.001$). The mean bias for LStrideT and RStrideT were 1.48%, and 1.40%. The limits of agreement were -0.93% to 3.88% for LStrideT and -0.71% to 3.15% for RStrideT (Table 2.3).

Bias and Limits of Agreement				
LStrideT (ms)	Count	Mean (% Diff)	Lower 95% CI	Upper 95% CI
Bias (Difference)	583	0.22 (1.48%)	-0.88	1.31
Lower Limit of Agreement	583	-26.18 (-0.93%)	-28.07	-24.28
Upper Limit of Agreement	583	26.61 (3.88%)	24.71	28.51
RStrideT (ms)	Count	Mean (% Diff)	Lower 95% CI	Upper 95% CI
Bias (Difference)	583	0.33 (1.40%)	-0.69	1.34
Lower Limit of Agreement	583	-24.09 (-0.71%)	-25.84	-22.33
Upper Limit of Agreement	583	24.74 (3.15%)	22.99	26.50

Table 2.3 Results from the Bland-Altman analysis of agreement between measures of the stride times derived from a trunk-mounted vs an ankle mounted accelerometer.

Discussion

The mean bias is small, indicating a small amount of variability in bias across the comparisons. This is confirmed by the tight limits of agreement for both LStrideT and RStrideT. Bias appears to be consistent across means, indicating that the bias is not dependent on increases or decreases in StrideT. Therefore, the results of the current study validate the use of a trunk-mounted accelerometer to profile temporal gait characteristics.

In the athlete wellness paradigm, particular attention has been focused on assessing changes in neuromuscular status after competitive and noncompetitive sessions. Assessing changes in running gait offers an efficient method for large scale assessment of neuromuscular status. The assessment of leg stiffness has been used as a marker for neuromuscular function in several studies.³⁹⁻⁴¹ However, in two of these studies stiffness was derived through jump protocols.^{39,40} In the study calculating stiffness using the spring mass model,⁴¹ preliminary validation had been observed from the trunk-mounted accelerometers to measure leg stiffness and spatiotemporal variables in a case study.⁵⁹ More research needs to assess how gait can be used to evaluate neuromuscular health in team sports athletes. The validation of spatiotemporal variables at the trunk in the current study allows for valid calculation of leg stiffness through the

spring mass model. The results from the current study confirm the validity of accelerometers to assess spatiotemporal variables and leg stiffness.

It is important to reflect on the terms used to describe temporal gait characteristics in this study. As the accelerometer is trunk-mounted, the estimated stride time is more reflective of the complementary displacement of the trunk through the gait cycle. This may explain why the variability in bias is large. The trunk is merely responding to the displacement of the COM during the gait cycle, rather than mirroring it.¹⁰⁹ Importantly, a DFA of the trunk-mounted gait data should similarly reflect the fractal properties of running gait. Rather than assessing the variability in running gait, it assesses the variability in trunk movements in response to running gait. DFAs have been used to monitor fatigue through the use of running tests after intense periods of training and activity.^{86,87} Performing a DFA using gait data from a trunk-mounted accelerometer would be similarly valid in assessing the variability of gait characteristics.

Other possible explanations for the variation between devices is that the devices are different. The sampling frequency of IMU is much higher than SS. The higher sampling frequency increases the resolution of the signal, allowing for a more precise method of measuring gait variables. Similarly, two different methods were used to detect stride times. The peak detection method was used to assess the temporal variables at the ankle, whereas a CWT was used to assess temporal variables at the trunk. The difference in methods was primarily due to the differences in signal attained from the ankle accelerometers. The CWT was designed for assessment of gait data from the trunk such that both impact peaks would be present in the signal devoid of the swing phase. However, since the ankle accelerometers record only each ankle, the swing phase is recorded, and changes the signal properties substantially.

Conclusions

This study provides evidence that using trunk-mounted accelerometers commonly used to track training load are a valid instrument for temporal gait assessment. The mean bias indicates that the trunk-mounted accelerometer had approximately equal measurements of temporal gait variables to the ankle accelerometers. However, it is important to note that the methods had large absolute variability in measure, but low relative variability. Sports scientists should start to explore how to best incorporate running gait monitoring into their monitoring framework. Future studies should assess the behavior of gait variables during regular season play in team sports athletes.

CHAPTER 3: Analysis of gait during a NCAA Division 1 women's soccer season

Introduction

Neuromuscular testing in team sports has become common practice in the training monitoring paradigm. Sports science has evolved significantly since the conception of training load and the acute-chronic workload ratio. The microtechnology born out of the desire to quantify the stresses of training and competition are widely popular. Prior to their use in sport, microtechnologies were used in clinical settings for movement analysis of the trunk and lower limbs. Translation of clinical methods of movement analysis using microtechnology would provide sports scientists with mountains of data that characterize the movement patterns of their athletes. The fundamental need exists to exploit the popularity of microtechnology in team sports, such that gait or postural stability can be assessed to monitor changes in movement strategies due to fatigue, overtraining, and injury.

When using microtechnologies, the question of validity is a primary concern. Clinical methods of gait analysis with accelerometers have been validated at the center of mass (COM). The microtechnology used in team sports is generally situated between the scapulae, introducing the first problem to address: how can gait data be derived from between the scapulae? Running gait is complex pattern of motion that is coordinated between the trunk and lower limbs. The movements of the lower limbs are counterbalanced by the movement of the trunk. The movement of the trunk is similarly dependent on the movement of the lower legs through the gait cycle. Consequently, measuring gait from between the scapulae is less likely a reflection of gait at the lower limbs but rather that of the trunk. It has been demonstrated that measuring temporal gait variables at the trunk has been valid compared to temporal gait variables derived from ankle accelerometers (Section 2.2 and⁵⁹). Therefore, derivation of gait variables from other temporal gait variables will have similar validity.

Aside from more traditional spatiotemporal variables, trunk movements can be further assessed with postural stability, which describes the variation in movement of the trunk. Postural stability uses fractal methods of the detrended fluctuation analysis (DFA) and entropy, regularity derived from an autocorrelation function, and root mean square (RMS) quantification to describe the variability of movement of the trunk during gait. Postural stability has been studied primarily during exhaustive exercise rather than pre-post changes.⁹⁵⁻⁹⁷ In the fatigued state, athletes typically show decreases in regularity, and long range correlations (DFA and entropy).^{85,86,95-97} Gait fractality declined following a congested match schedule in a similar fashion.⁸⁷ RMS of accelerations increased after exhaustive exercise bouts.^{96,97} More data is necessary to understand how different levels of fatigue effect gait variables.

The use of standardized runs to assess neuromuscular status has been gaining traction in the sports science community.⁴² Standardized runs can be used to assess leg stiffness as described by the spring mass model. Stiffness has been measured in team sports via jump testing^{39,40} and standardized runs⁴¹ with varying results. Previously, measures of leg stiffness were reserved to laboratory assessment of the spring mass model. Most of the literature explores how the spring mass variables change during a run. Those that measured pre-post differences are hard to translate to teams sports as they were done in ultra-endurance events³⁵⁻³⁷ and a two kilometer time trial.³⁸ Runs to exhaustion that lasted at least an hour resulted in decreases in leg stiffness^{23,24}, and no significant change in leg stiffness.²² More research is needed to clarify how sports competition affect leg stiffness.

The purpose of the current study was to examine the use of standardized running to assess changes in gait, postural stability, and neuromuscular status in team sports athletes. This study was an exploratory assessment of the variability of gait variables over the course of a

Division 1 soccer season. Of particular interest was the variability of gait around games. Soccer involves intermittent sprinting bouts for 60 to 90 minutes depending on the level of play. It was hypothesized that the gait variables would change similarly to how they were affected by longer aerobic efforts. Gait regularity, α , and k_{leg} were expected to decrease from the pre-fatigued to the post-fatigued condition. RMS of acceleration and gyroscopic variables were expected to increase from the pre-fatigued to the post-fatigued condition. It was expected that changes in gait variables may increase in intensity as the season progresses due to the accumulation of fatigue.

Methods

Participants were 26 members of a NCAA D1 women's soccer team (age = 19.86 ± 1.46 , height = 168.55 ± 5.86 , weight = 59.63 ± 5.76). Each player was equipped with a GPS embedded trunk-mounted accelerometer (600 Hz accelerometer, 400 Hz gyroscope, 18 Hz GPS, APEX, STATSports, Newry, Northern Ireland). A coded heart rate monitor (Polar H10, Polar Electro, Kempele, Finland) was used to collect heart rate data. An institutional review board (IRB) protocol was submitted and approved by the IRB at Virginia Tech (17-632). The limitations of the IRB were such that interventions could not be imposed on the athletes that are not a part of their normal conditioning. It was necessary for the collection of gait data to coincide with normal practice activities, so a simple method of gait monitoring was employed. Gait data was collected during a ~400-meter run after a standardized warm-up during regular practice sessions. Pace was self-selected, and typically resulted in the athletes running in a pack. Upon completion of practice sessions, perceived effort (RPE), recovery (REC)¹¹⁰, and STATSports units were collected from each player. The data from the units was downloaded to

the STATSports software. The data pertaining to the gait run was split and downloaded to a .csv file for further processing.

Analysis of variables included athletes who participated in at least 30 gait runs. Exclusion criteria included season ending injuries (n=3), frequent injuries (n= 3), and time away from the team (n= 1). Other reasons for exclusion included erratic pacing (n= 1), playing through injuries (n = 1), returning from ACL protocol (n= 1), and goal keepers (n = 4). The remaining athletes were divided based on distance run per day into START (n=7), and RES (n= 7) groups (Table 3.1). Gait data was analyzed according to the procedure describe in Chapter 2.

Average Distance per Day During the Season			
START		RES	
Player ID	Distance	Player ID	Distance
03	6469	18	5017
04	6453	20	4938
09	6427	19	4780
11	6373	17	4745
05	6029	15	4515
01	5902	16	4476
10	5567	13	4450

Table 3.1 Formation of cohorts based on distance per day.

Statistical Analysis

A two-factor analysis of variance (ANOVA) with repeated measures was used to explain the variance across groups and time around games for both training load and gait variables. A Tukey post hoc test was used when the Greenhouse-Geisser epsilon was more than 0.5, and the Bonferroni post hoc test when the epsilon was lower than 0.5. ANOVA was run for both gait and training load variables. Where the normality assumption was violated, nonparametric analysis of aligned rank transformations was used to assess group differences. Following the aligned rank transform, an interaction contrasts post hoc test for pairwise comparisons was used to assess differences between days.

During the season, there were seven weeks where two games were played within the week. During weeks 3, 4, 5, 10, and 12, gait was measured the day before the first game (Pregame 1), and the day after the second game (Postgame 2). The weeks were analyzed on a case-by-case basis in the following section. As illustrated in Table 3.2, not all weeks constituted the same practice schedule. Week 3 was the only week in which gait data was collected for Pregame 1, Postgame 1, Pregame 2, and Postgame 2. Week 4 had two days with no data due to travel. During Week 5 most of START did not have gait data for Postgame 1 to adjust for a possible spike in training load after Game 1. Weeks 10 and 12 had built in off days to account for spikes in training load. Therefore, the weeks were analyzed separately. START and RES were reduced to n=5-7 due to unexpected off days or to avoiding spikes in training load.

Breakdown of Distances During Each Week						
Group	Pregame 1	Game 1	Postgame 1	Pregame 2	Game 2	Postgame 2
Week 3						
START	4076 (370)	10029 (3094) ^{a,b}	4277 (1516)	4276 (277)	11506 (1887) ^a	2876 (1342)
RES	4233 (171)	5031 (1675)	6127 (240)	3795 (370)	3752 (1873)	8470 (230) ^b
Week 4						
START	4698 (636) ^{b,c,e}	12723 (495) ^a	OFF	OFF	11962 (855) ^a	2800 (254) ^d
RES	3990 (519) ^{b,c,d}	4861 (1172) ^{b,e}			3062 (908) ^{c,d}	5681 (278) ^e
Week 5						
START	4400 (455)	10877 (2427) ^a	2126 (1673) ^b	3317 (394)	11214 (2318) ^a	3313 (1825)
RES	4066 (513)	4233 (1578)	5199 (219)	3399 (181)	5382 (3571)	6319 (1753)
Week 10						
START	4764 (238) ^c	15939 (908) ^a	926 (73) ^b	OFF	13744 (1337) ^a	2308 (177)
RES	4514 (396) ^c	5171 (1237) ^c	1582 (841) ^b		5868 (3592) ^c	3205 (202)
Week 12						
START	5064 (574) ^b	11711 (1017) ^a	1612 (738)	OFF	11325 (1157) ^a	1870 (239)
RES	5102 (270) ^b	2899 (1015)	2033 (1459)		2769 (2266)	4270 (2042) ^b

Table 3.2 Means and standard deviations of distances throughout the season. Post hoc comparisons were done for each week. Distance is measured in meters. Values with the same letter, or no letter, are not significantly different.

Training load was assessed as an average or sum of Pregame 1, Game 1, Postgame 1, Pregame 2, and Game 2 (5-TL). The purpose of looking at 5-TL was to assess the change in gait variables with the cumulative load experienced by the players. The gait run was performed at the beginning of practice on Postgame 2, such that the training load of Postgame 2 should not

affect changes in gait variables. Off days were included in the calculation of average 5-TL. The average 5-TL was compared between groups using a student's two tailed, pairwise, t-test. Total distance traveled in meters (Tot Dist), high speed running (HSR), dynamic stress load (DSL), RPE, REC, and speed intensity (Speed Int) were used to assess the training load at each time point. HSR was the distance covered while travelling over a relative zone 5 speed threshold. DSL is the weighted total impacts above 2g. Speed Int was the measure of total exertion based on the weightings for each individual speed, such that more time spent running at higher speeds results in a higher speed intensity. Associations were made using Pearson's correlation coefficients between the average 5-TL for each week (Pregame 1 to Game 2) and the change in gait variables from Pregame 1 to Postgame 2 (Postgame 2 – Pregame 1). Correlations were made with Tot Dist, and HSR to assess the correlation between a volume and intensity-based metric.

Results

For the definitions of gait variables, please refer to Table 2.1. A summary of the average Tot Dist during each training day observed in each week is shown in Table 3.2. A normal Tot Dist was between 3000-6000 meters, down days were generally under 2500 meters, and high days were over 8000 meters. The general trend for all weeks was that START had its highest Tot Dist on Game 1 and Game 2, and lowest Tot Dist in Postgame 1 and Postgame 2. RES only had one instance of a comparably high Tot Dist in Week 3 Postgame 2. Pregame 1 was always about the same between groups and across weeks.

Table 3.3 summarizes the weekly 5-TL. In all weeks START had a higher Tot Dist and Speed Int than RES. HSR and DSL was higher for START during Week 4. Average RPE was not different across weeks; however, REC was significantly higher for Week 10 and Week 12 for START compared to RES.

Average Five-Day Training Load From Pregame 1 to Game 2 (5-TL)						
	Tot Dist	Speed Int	HSR	DSL	RPE	REC
Week 3						
START	6833 (3686) ^a	322 (178) ^a	48 (57)	201 (177)	5.08 (1.87)	4.86 (1.56)
RES	4588 (1388)	215 (69)	44 (56)	133 (71)	4.32 (1.91)	4.44 (0.96)
Week 4						
START	5878 (3827) ^c	280 (185) ^c	71 (71) ^b	185 (161) ^c	2.58 (3.68)	1.80 (3.48)
RES	2383 (1123)	112 (54)	24 (31)	87 (56)	1.45 (2.39)	1.85 (2.23)
Week 5						
START	6387 (4243) ^a	304 (207) ^a	85 (115)	198 (161)	5.00 (2.05)	4.57 (1.81)
RES	4456 (1804)	208 (87)	47 (44)	142 (113)	4.57 (2.03)	4.30 (1.21)
Week 10						
START	7075 (6404) ^b	339 (311) ^b	106 (137)	257 (296) ^a	4.14 (2.81)	3.56 (2.26) ^a
RES	3427 (2454)	162 (113)	67 (144)	125 (110)	3.26 (2.02)	2.80 (1.56)
Week 12						
START	5943 (4443) ^c	284 (217) ^c	84 (119)	207 (218) ^b	4.43 (2.38)	3.07 (1.61) ^b
RES	2561 (1786)	121 (85)	50 (106)	84 (63)	2.38 (1.86)	2.80 (1.05)

Table 3.3 Descriptive statistics of average weekly five-day totals for all training load variables. Tot Dist is total distance, Speed Int is speed intensity, HSR is high speed running, DSL is dynamic stress load, RPE is rating of perceived exertion, and REC is perceived recovery score. a = p<0.5, b = p<0.01, c = p<0.001

Week 3

All ANOVA tables are in the Appendix D. All results from the ANOVAs are summarized in Table 3.4 and post hoc pairwise comparisons in Table 3.5. FT, StrideT, StepL, and StrideL had a significant effect of time. No spatiotemporal variables had a significant group effect. StepT and StrideT had significant interaction effects (group x session). There were no differences in spatiotemporal variables between groups. FT, StepL, and StrideL were the only variables that changed significantly, showing an increase in FT and decreases in StepL and StrideL as the week progresses.

Summary of ANOVAs from each Week of the Season

	Week 3			Week 4			Week 5			Week 10			Week 12		
	G	T	I	G	T	I	G	T	I	G	T	I	G	T	I
Speed	-	-	-	-	***	-	-	-	-	-	-	-	-	-	-
FT	-	***	-	-	-	-	-	-	-	-	-	-	-	**	*
StepT	-	-	*	-	**	-	-	-	-	*	-	-	-	-	*
StrideT	-	*	*	-	**	-	-	-	-	*	-	-	-	-	*
StepL	-	***	-	-	**	-	-	-	-	***	-	-	-	***	-
StrideL	-	***	-	-	**	-	-	-	-	***	-	-	-	***	-
F_{max}	-	*	-	-	-	-	-	-	-	-	-	-	-	-	-
k_{vert}	-	-	-	-	-	-	-	-	-	-	-	-	-	*	*
Δl	-	***	-	-	-	-	-	-	-	-	-	-	-	***	-
k_{leg}	-	***	-	-	-	-	-	-	-	***	-	-	-	***	-
X.Step.Reg	-	-	-	-	-	-	-	-	-	-	-	-	-	-	*
X.Stride.Reg	-	-	-	-	-	-	-	-	-	*	-	-	-	-	-
Z.Step.Reg	-	-	-	-	-	*	-	-	-	-	-	-	-	-	-
X.Gyro.Step.Reg	-	-	-	-	**	-	-	-	-	-	*	-	-	-	-
X.Gyro.Stride.Reg	-	-	-	-	*	-	-	-	-	***	-	-	-	-	-
Y.Gyro.Stride.Reg	-	-	-	-	-	-	-	*	-	*	-	-	-	-	-
Z.Gyro.Stride.Reg	-	-	-	-	-	-	-	-	-	**	-	-	-	-	-
X.Accel.RMS	-	-	-	-	-	-	-	-	-	*	-	-	-	***	*
Y.Accel.RMS	-	-	-	-	-	-	-	*	-	*	-	-	-	***	**
Z.Accel.RMS	-	-	-	-	-	-	-	-	-	*	-	-	-	***	*
R.Accel.RMS	-	-	-	-	-	-	-	*	-	*	-	-	-	***	**
X.Gyro.RMS	-	-	-	-	-	-	-	-	-	*	-	-	-	-	-
Y.Gyro.RMS	-	-	-	-	*	-	-	-	-	***	-	-	-	***	-
Z.Gyro.RMS	-	-	-	-	-	-	-	-	-	-	-	-	-	***	-
R.Gyro.RMS	-	-	-	-	-	-	-	-	-	***	-	-	-	***	-
StepL α	-	-	-	-	-	-	-	-	-	*	-	-	-	*	-
StrideL α	-	-	-	-	-	-	-	-	-	*	*	-	-	*	-

Table 3.4 Summary of ANOVA results from each week. G = Group effect, T = Time effect, I = interaction effect; * indicates $p < 0.05$, ** indicates $p < 0.01$, *** 0.001.

F_{max} , Δl , and k_{leg} had a significant effect of time. No spring mass variables had a significant group effect or interaction effect. Significant differences were observed in both Δl and k_{leg} for both groups. Δl decreased as the week went on, and k_{leg} increased. No significant effects of group, time or group by time interactions were detected for postural or

fractal (DFA) variables.

Summary of Changes in Means Through the Season

	Week 3			Week 4	Week 5	Week 10		Week 12	
	Post1	Pre2	Post2	Post2	Post2	Post1	Post2	Post1	Post2
Speed	-	-	-	↓ ^{S,d} ↓ ^{R,d}	-	-	-	-	-
FT	-	-	↑ ^{S,d,f} ↑ ^{R,g}	-	-	-	-	-	↓ ^{S,f}
StepT	-	-	-	↑ ^{R,d}	-	↓ ^{S,a,b}	-	-	-
StrideT	-	-	-	↑ ^{R,d}	-	↓ ^{S,a,b}	-	-	-
StepL	-	↓ ^{S,c,e} ↓ ^{R,c}	↓ ^{S,d,f} ↓ ^{R,g}	↓ ^{S,d}	-	↑ ^{S,b} ↑ ^{R,b}	↓ ^{R,f}	↓ ^{S,b} ↓ ^{R,b}	↑ ^{S,f} ↑ ^{R,f}
StrideL	-	↓ ^{S,c,e}	↓ ^{S,d,f} ↓ ^{R,d,f}	↓ ^{S,d}	-	↑ ^{S,b} ↑ ^{R,b}	↓ ^{R,f}	↓ ^{S,b} ↓ ^{R,b}	↑ ^{S,f} ↑ ^{R,f}
F_{max}	-	-	-	-	-	-	-	-	-
k_{vert}	-	-	-	-	-	-	-	-	↓ ^{S,f}
Δl	-	↓ ^{R,c}	↓ ^{S,d,f,g} ↓ ^{R,d}	-	-	-	-	↓ ^{R,b}	↑ ^{S,f}
k_{leg}	-	-	↑ ^{S,d,f} ↑ ^{R,d}	-	-	↓ ^{S,b}	-	-	↓ ^{S,f} ↓ ^{R,f}
X.Step.Reg	-	-	-	-	-	-	-	-	-
X.Stride.Reg	-	-	-	-	-	-	-	-	-
Z.Step.Reg	-	-	-	-	-	-	-	-	↑ ^{S,d}
X.Gyro.Step.Reg	-	-	-	↑ ^{S,d}	-	↑ ^{R,b}	-	-	-
X.Gyro.Strd.Reg	-	-	-	↑ ^{S,d}	-	-	-	-	-
Y.Gyro.Strd.Reg	-	-	-	-	↑ ^{S,d}	-	-	-	-
Z.Gyro.Strd.Reg	-	-	-	-	-	-	↑ ^{S,d}	-	-
X.Accel.RMS	-	-	-	-	-	-	-	-	-
Y.Accel.RMS	-	-	-	-	-	-	-	↓ ^{R,b}	↑ ^{R,f}
Z.Accel.RMS	-	-	-	-	-	-	-	-	-
R.Accel.RMS	-	-	-	-	-	-	-	↓ ^{S,a,b} ↓ ^{R,b}	↑ ^{R,f}
X.Gyro.RMS	-	-	-	-	-	-	-	-	-
Y.Gyro.RMS	-	-	-	↓ ^{S,d}	-	↑ ^{R,b}	↓ ^{R,f}	↓ ^{S,b} ↓ ^{R,b}	↑ ^{S,f}
Z.Gyro.RMS	-	-	-	-	-	↑ ^{S,b}	-	-	↑ ^{R,f}
R.Gyro.RMS	-	-	-	-	-	↑ ^{R,a,b}	↓ ^{R,f}	↓ ^{S,b} ↓ ^{R,b}	↑ ^{S,f}
StepL α	-	-	-	-	-	-	-	-	↑ ^{S,f}
StrideL α	-	-	-	-	-	-	-	-	↑ ^{S,f}

Table 3.5 Post Hoc changes in means for each week. Post1 = Postgame 1, Pre2 = Pregame 2, Post2 = Postgame 2; S – START cohort; R – RES cohort; a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Pregame 2; d – difference in Pregame 1 to Postgame 2; e – difference in Postgame 1 to Pregame 2; f – difference in Postgame 1 to Postgame 2; g – difference in Pregame 2 to Postgame 2. The arrow should be read as a change (indicated by the arrow direction) than the superscript. For example, ↓^{S,c,e} indicates a decrease for START from Pregame 1 to Pregame 2, and a decrease from Postgame 1 to Pregame 2. Group differences are not related to arrow directions.

Week 4

No group or interaction effects were observed in spatiotemporal variables. Session effects were observed for all spatiotemporal variables except FT and CT. Pairwise comparisons

of Pregame 1 and Postgame 2 saw a significant decrease in Speed, and significant decreases in StepL and StrideL for START. For RES, Speed decreased significantly, and StepT and StrideT increased significantly. No significant changes, effects or interactions were observed in spring mass variables.

X.Gyro.Step.Reg, X.Gyro.Stride.Reg, and Y.Gyro.RMS had significant session effects, and Z.Step.Reg had an interaction effect. For START, X.Gyro.Step.Reg, and X.Gyro.Stride.Reg increased, and Y.Gyro.RMS decreased from Pregame 1 to Postgame 2. No significant changes, effects or interactions were observed in fractal gait variables.

Week 5

No significant changes, effects or interactions were observed for spatiotemporal and spring mass variables. Session effects for postural variables were observed in Y.Accel.RMS, and R.Accel.RMS. Y.Gyro.Stride.Reg had a significant interaction effect. START had a significant increase in Y.Gyro.Stride.Reg from Pregame 1 to Postgame 2. No significant changes, effects or interactions were observed in fractal gait variables.

Week 10

StepT, StrideT, StepL, and StrideL had a significant effect of time. There were significant differences between groups in StepT and StrideT at Postgame 1. In the START cohort StepT and StrideT decreased, and StepL and StrideL increased significantly from Pregame 1 to Postgame 1. StepL and StrideL increased significantly for the RES cohort from Pregame 1 to Postgame 1.

k_{leg} had a significant effect of time, and decreased significantly after Pregame 1 in START. X.Stride.Reg, X.Gyro.Stride.Reg, Y.Gyro.Stride.Reg, Z.Gyro.Stride.Reg, X.Accel.RMS, Y.Accel.RMS, Z.Accel.RMS, R.Accel.RMS, X.Gyro.RMS, Y.Gyro.RMS and

R.Gyro.RMS had a significant effect of time. X.Gyro.Step.Reg, X.Gyro.RMS, and R.Gyro.RMS had significant interaction effects. START had a significant increase in Z.Gyro.Stride.Reg from Pregame 1 to Postgame 2, and Z.Gyro.RMS from Pregame 1 to Postgame 1. RES had a significant increase in X.Gyro.Stride.Reg, Y.Gyro.RMS, and R.Gyro.RMS from Pregame 1 to Postgame 1. Significant decreases in Y.Gyro.RMS and R.Gyro.RMS were observed from Postgame 1 to Postgame 2.

StrideL α had a significant group effect, and was significantly less in START compared to RES at Pregame 1. StepT α and StrideT α decreased significantly from Postgame 1 to Postgame 2 in the START cohort. No differences were observed in the RES cohort throughout the week.

Week 12

FT, StepL, and StrideL had a significant effect of time. START had a decrease in FT and an increase in StepL and StrideL from Postgame 1 to Postgame 2. StepL and StrideL decreased from Pregame 1 to Postgame 1. For RES, StepL and StrideL decreased from Pregame 1 to Postgame 1 and increased from Postgame 1 to Postgame 2.

k_{vert} , Δl , and k_{leg} had a significant effect of time. k_{vert} had a significant interaction effect. k_{vert} and k_{leg} decreased for START from Postgame 1 to Postgame 2, whereas Δl increased. RES had a decrease in Δl from Pregame 1 to Postgame 1, and a decrease in k_{leg} from Postgame 1 to Postgame 2.

X.Step.Reg, X.Accel.RMS, Y.Accel.RMS, Z.Accel.RMS, R.Accel.RMS, Y.Gyro.RMS, Z.Gyro.RMS, and R.Gyro.RMS had significant effects of time. X.Step.Reg, X.Accel.RMS, Y.Accel.RMS, Z.Accel.RMS, and R.Accel.RMS had significant interaction effects. START had a significant increase in Z.Step.Reg from Pregame 1 to Postgame 2. Y.Gyro.RMS and R.Gyro.RMS decreased significantly from Pregame 1 to Postgame 1 and increased significantly

from Postgame 1 to Postgame 2. R.Accel.RMS decreased significantly from Pregame 1 to Postgame 1. START had a significantly higher R.Accel.RMS at Postgame 1 than RES. RES had a significant decrease in Y.Accel.RMS, R.Accel.RMS, Y.Gyro.RMS, and R.Gyro.RMS from Pregame 1 to Postgame 1. A significant increase in Y.Accel.RMS, R.Accel.RMS, and Z.Gyro.RMS were observed from Postgame 1 to Postgame 2.

StepL α and StrideL α had a significant effect of time. StepL α and StrideL α increased significantly from Postgame 1 to Postgame 2 in START. No differences were observed in RES throughout the week.

Association to Training Load

Associations to changes in gait variables were made to the average 5-TL. As compared to the cumulative 5-TL, the average load per day had stronger correlations with changes in gait variables. START had weak associations with HSR and Tot Dist. HSR had weak negative correlations ($-0.2 > R > -0.39$) with Speed, Δl , X.Accel.RMS, Z.Accel.RMS, Y.Gyro.RMS, and R.Gyro.RMS. A negative moderate correlation ($-0.4 > R > -0.59$) was observed between HSR and Z.Gyro.RMS. HSR had a weak positive correlation ($0.20 < R < 0.39$) to k_{leg} . Tot Dist had a weak negative correlation to StepL α , StrideL α , Z.Accel.RMS, and X.Gyro.RMS. Tot Dist had a weak positive correlation with Z.Step.Reg.

RES had similarly weak associations with HSR, and Tot Dist. HSR had a weak negative correlation to StepT, StrideT, Δl , Y.Accel.RMS, R.Accel.RMS, and Y.Gyro.RMS. k_{leg} had a negative weak correlation to HSR. Tot Dist had positive weak correlations with Δl , X.Stride.Reg, Z.Step.Reg, Y.Gyro.Stride.Reg, and Z.Gyro.Stride.Reg. Tot Dist had negative weak correlations with FT, k_{leg} , R.Accel.RMS, and Y.Gyro.RMS. Tot Dist had a negative moderate correlation with Y.Accel.RMS in RES.

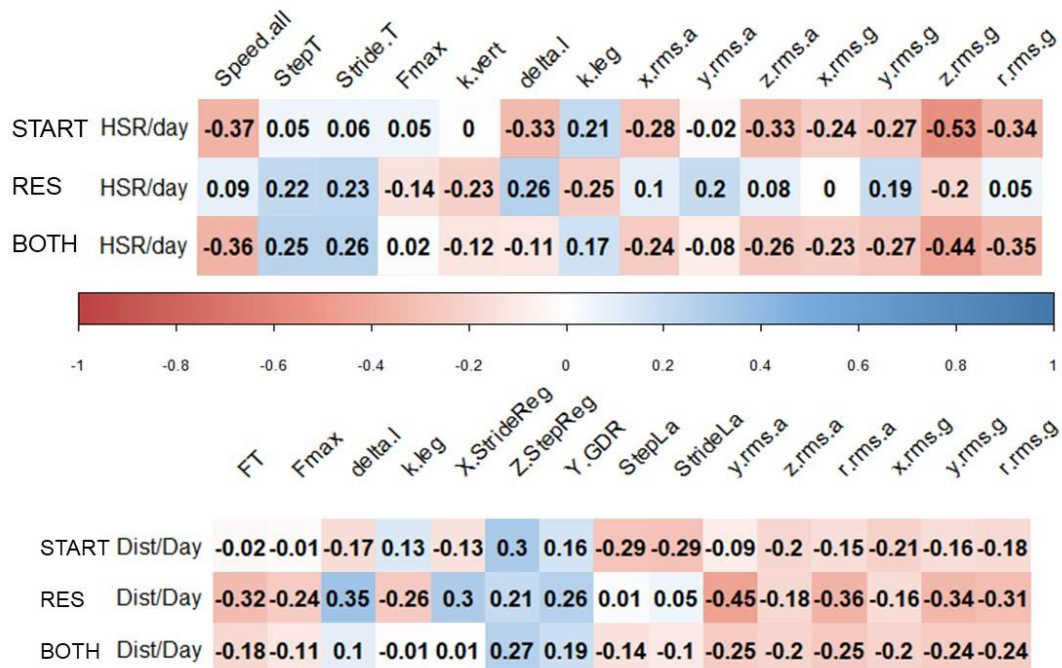


Figure 4 Correlation coefficients of top correlated gait variables ($R < -0.2$ or $R > 0.2$) to High Speed Running (HSR) and Distance. Average 5-TL was used rather than summed 5-TL. Y.Gyro.Stride.Reg is abbreviated as Y.GDR.

Discussion

Gait variables exhibited tremendous variability throughout the season. The general trend was a consistent change in StepL, StrideL, and k_{leg} . Similarly, as the season progressed, the postural variables become more important in describing the change in gait. Postural variables were most associated with average 5-TL of HSR and Tot Dist as compared to 5-TL correlated with spatiotemporal and spring mass variables.

Changes exhibited in StepL and StrideL need to be approached with caution. The correlation of speed to StepL and StrideL was strong, indicating that length variables are highly dependent on the variation in speed.¹¹¹ Therefore the comparison of spatiotemporal variables is only going to yield important results when all runs are at a constant speed. According to the ANOVAs, speed was not significantly different for most of the season. However, truly understanding the results may require that speed, time, and length be considered together rather

than one or the other. Since both cohorts ran together in a group, the pattern of between group differences in significance may be a more appropriate assessment of change. Using Week 3 as an example, the changes in FT noticed in the START cohort compared to the RES cohort may be evident of a change in running strategy. This is particularly evident in Pregame 2 and Postgame 2. START had an increase in FT from Pregame 1 and Postgame 2, and an increase in FT in Pregame 2 and Postgame 2. RES, however, had a significant difference only from Pregame 2 to Postgame 2. StepL for Pregame 1 and Postgame 1 are significantly different at both Pregame 2 and Postgame 2 for START but only Pregame 1 was significantly different at both Pregame 2 and Postgame 2. Therefore, a change to favor a smaller StepL or StrideL was observed in Week 3.

For START k_{leg} increased in the beginning of the season and decreased at the end of the season, suggesting that the time points have a different effect on k_{leg} . In the beginning of the season, the athletes are responding to training stimuli such that towards the end of the season they will be able to sustain a similar training volume. In Week 3, the gradual increase in k_{leg} may be an indication of the resilience of the athletes. In week 4, the lack of training due to travel (two off days) adjusted the training load curve such that a change in k_{leg} was unlikely. Week 5 could be the moment when the players start to transition from training to sustaining. Week 5 constituted a full week of training, however the majority of the START group began to counter the large training load of the games, with smaller practice volumes. The reduced training volume could explain the absence of change in k_{leg} . In the latter weeks of the season, the effects of higher volume sessions are more apparent. Therefore, the decreases in k_{leg} in Weeks 10 and 12 are largely impacted by the cumulative fatigue towards the end of the season.

Similarly, the increased activity of the postural variables in the later weeks of the season indicate a similar trend to k_{leg} . In week 4, there appears to be an increase in postural stability as explained by an increase in step and stride regularity for the X axis of the gyroscope. Similarly, the decrease in Y.Gyro.RMS indicates that postural stability was improved. Week 5 has similar results, showing an increase in stride regularity for the Y-axis of the gyroscope. In week 10 it is observed that the START cohort exhibits an increase in Z.Gyro.RMS, indicating a decrease in postural stability. Week 12 breaks the trend where the changes in postural stability are more variable than a steady decline. Z.Step.Reg increased from Pregame 1 to Postgame 2 in START. However, the change in both acceleration and angular velocity RMS were not significant. From Pregame 1 to Postgame 1 there was an improvement in postural stability with a decrease in R.Accel.RMS, Y.Gyro.RMS, and R.Gyro.RMS. However, the change from Postgame 1 and Postgame 2 returns to the previous trend where a decrease in postural stability was observed.

Typically, postural variables have not been considered for long exercise bouts (>30 minutes). However there have been studies assessing the changes after exhaustive exercise tests. These studies assessed acute fatigue in a pre-post workout design.⁹⁵⁻⁹⁷ Typically the RMS will increase,^{96,97} and the step and stride regularity will decrease⁹⁵⁻⁹⁷ after exhaustive exercise. The results in the literature clarify the changes that are observed in the current study. Specifically in Week 12, there is an improvement in postural variables at Postgame 1, and a decline in postural variables at Postgame 2. This may indicate that after Game 1 the athletes were able to sufficiently recover, but after Game 2 they could not. The decline in postural variables may be indicative of chronic fatigue, or a lingering state of fatigue from the whole week. The effects of game-related fatigue on postural variables needs further investigation.

Tot Dist and HSR had negative weak and moderate correlations to changes in postural variables. HSR was most correlated in START to Speed, Δl , Z.Accel.RMS, Z.Gyro.RMS, and R.Gyro.RMS. The weak negative correlation to speed could indicate that speed is sufficient to use for acute changes in spatiotemporal gait variables. Recall that F_{\max} is the product of Δl and k_{leg} . Notice that the correlations were negative for Δl and positive for k_{leg} . The associations suggest that F_{\max} remains relatively constant, with variations in the composition of F_{\max} . k_{leg} appears to increase with higher HSR. This may seem counterintuitive, however similar trends were observed after ultramarathons.^{35,36} Similarly, since the gait data are collected a day after the fatiguing activity, the athletes had some time to recover.

HSR had higher negative correlations to RMS variables. This means that higher levels of HSR led to a decrease in RMS. This trend is counter to what was observed in the pre-post differences from the ANOVAs and the available literature. Most significant differences resulted in an increase in RMS, rather than a decrease, and all literature references report increased RMS after fatiguing activity. The trend may be confounded by the nonsignificant changes in RMS from earlier weeks. Therefore, future studies should work to elucidate the relationship that HSR has with postural variables.

Gait fractality played a smaller role than anticipated. Previous research has shown that fractality changes due to overtraining, and match congestion.⁸⁵⁻⁸⁸ Training load adjustments are a possible explanation for the discrepancy in observation. Interestingly, StepL α and StrideL α both had weak negative correlations with Tot Dist, which are considerably lower than what was previously reported.⁸⁷

The method used for collecting gait data while convenient has some limitations worth noting. The group run resulted in the formation of groups rather than a singular group, such that

speed differences existed between these groups. Group running or walking may alter fractal dynamics.⁷⁸ Likewise, the pace of the group run was typically dictated by START, confounding the change seen in RES and possibly confounding the DFA results.⁷⁸ Future studies should avoid group running when assessing stride fractality. Sprints may be a better alternative in that sprints will be self-paced by the individual rather than governed by the team. Sprints may take away the ability to perform a DFA depending on the number of strides needed to complete the number of sprints. Future research should assess the change in gait variables in sprints to compare with what was found in the present study.

Conclusion

Monitoring running gait in athletic populations allows for insight into the effects of training load that athletes experience. Postural variables of dynamic stability, and leg stiffness derived from the spring mass model changed in concurrence to the later stages of training. Changes in postural and stiffness variables indicate that responses may be dependent on the presence of cumulative fatigue. Recovery of gait was consequently observed when spikes in training load were appropriately countered. Spatiotemporal gait variables are not a robust method for gait analysis in a group run format. A similar assessment of gait characteristics should be assessed with sprinting or striding. The current results should be generalizable to field-based sports comprised of intermittent sprinting and moderate intensity running for long durations.

CHAPTER 4: Comparison of Athlete Monitoring Techniques: Countermovement Jump Abstract

Thus far, accelerometers have been exploited for their ability to assess gait characteristics. However, accelerometers have also been used to assess changes in countermovement jump (CMJ) height. The following chapter assessed the validity of trunk-mounted accelerometers to assess changes in CMJ height as compared to the gold standard force plates. After validation, the changes in CMJ height were compared to changes in gait. The accelerometer had good agreement with the force plates for calculating jump height (ICC = 0.90) and flight time (ICC = 0.88). The Bland-Altman analysis revealed that the accelerometer underestimated jump height and flight time compared to the force plates. The accelerometer underestimated at lower values and overestimated at higher values. CMJ height had a moderate negative correlation ($R = -0.57$) with total distance (Tot Dist) when CMJ was assessed immediately after games and practice sessions. However, when evaluating Pregame to Postgame differences in CMJ height, the association weakened ($R = -0.27$). Postural variables appear to improve rather than decline after a game, which was inconsistent with what was found in the previous Chapter. The low correlation of CMJ height to Tot Dist combined with the apparent improvement of postural variables may indicate the players' resistance to game-related fatigue.

4.1 Validation of the countermovement jump height assessment from a trunk-mounted accelerometer

Introduction

The CMJ is a popular neuromuscular testing technique for the lower extremities. Force plates (FP) and motion capture are considered the gold standard method for collecting CMJ data. However, FP are expensive and hard to transport. Similarly, they require a sturdy, level surface which may not be accessible or convenient at a grass/turf field. With the high saturation of

accelerometers used in team sports, validation of the use of trunk-mounted accelerometers to measure CMJ height is needed. Various inertial measurement units have been validated to assess CMJ height.¹¹²⁻¹¹⁷ A key difference from the current study to previous validations is that the accelerometer was placed on the lower back closer to the center of mass (COM).

The purpose of the current study was to assess the validity of a trunk-mounted accelerometer at measuring CMJ height as compared to FP. The two methods of measure were not expected to be statistically different.

Methods

Participants

This study was part of a larger study that assessed the impact of training on CMJ performance in NCAA Football players. Five participants (height (cm) = 183.84 ± 4.32 , weight (kg) = 110.42 ± 10.29 , age = 21.00 ± 1.41) were used to determine the difference in measurement of the CMJ height by a trunk-mounted accelerometer (18 Hz GPS, 600 Hz accelerometer, 400 Hz gyroscope, and a 10 Hz magnetometer) compared to a dual force plate system (Force Decks FD4000, Vald Performance, Australia). All research and methods have been approved by the Virginia Tech IRB (20-071).

Experimental Procedure

Player activity was monitored for each practice session with the STATSports APEX (IMU) which was fixed between the scapulae. A random sample of participants were recruited to perform CMJ before and after selected practice sessions. CMJ variables were calculated from the Vald FP proprietary software. Each participant was asked to perform a standardized warm-up which included three practice CMJ. The participants were instructed to keep their hands on their waists through the duration of the jump. The participants were instructed to quickly

descend and then jump as high as possible being sure to stabilize upon landing, with one foot on either force plate. If participants failed to stabilize or removed their hands from their hips during the jump, the trial was repeated until completion of three successful trials.

Data Processing

Processed data from FP was downloaded to an excel spreadsheet and saved for further analysis. Data from IMU was split to create a csv file to include the accelerometer profile of each of the three jumps. The csv files were read into R for signal processing. The acceleration signal was converted from g to m/s^2 in each axis. A custom R function was created to filter the acceleration signal. First, the orientation of the accelerometer was corrected as described by Moe-Nilssen.¹⁰³ The vertical acceleration was filtered with a 4th order Butterworth filter (10 Hz, 0.9 Hz). The filtered acceleration signal was integrated using the trapezoidal rule to vertical velocity. The velocity was filtered with the same filter to remove drift. The acceleration and velocity vectors were up sampled to ~ 1000 Hz. Up-sampling provides higher resolution for determination of the timing of take-off and touch down. The jumps were divided into separate data frames for individual analyses. The *findpeaks()* function was used to find the maximum velocity which is the time point of take-off, and maximum negative velocity which is the time point of touch down. Flight time (FT) and jump height (JH) were recorded into an excel file for statistical analysis, and were calculated as follows:

$$FT = v_{MAX} - v_{MIN} \quad 19 \text{ Flight Time from Velocity Signal}$$

$$JH = \frac{g}{8} FT^2 \quad 20 \text{ Jump Height from Flight Time}$$

Statistical Analysis

Both FT and JH were assessed for agreement. A Bland-Altman analysis was used to assess the differences in measurement of FP and IMU. The analysis requires that the residuals

are normally distributed. A Shapiro-Wilk normality test was run to assess the normality assumption. Simple linear regression between measures was used to assess the trend of the Bland-Altman analysis. A two-sample t-test was performed to assess the difference in means between the two methods of measure. Intraclass correlation coefficients (ICC $3,k$) were computed for both FT and JH.

Results

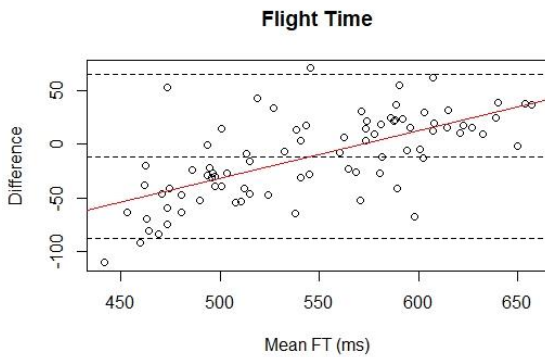
A Bland-Altman analysis assumes normality of the residuals for the two methods of measurement. The Shapiro-Wilk normality test yielded nonsignificant results for JH ($p=0.29$) and FT ($p=0.38$), and thus satisfies the normality assumption. Descriptive statistics of the different measurement devices are presented in Table 4.1. The IMU underestimated both FT ($FT_{IMU} = 540.16 \pm 71.67$ ms) and JH ($JH_{IMU} = 36.36 \pm 9.45$ cm) compared to FP ($FT_{FP} = 551.92 \pm 46.94$ ms and $JH_{FP} = 37.58 \pm 6.39$ cm). The mean measurement for FT and JH is not different.

Descriptive Statistics				
Variable	Count	Mean (SD)	Lower 95% CI	Upper 95% CI
FT_{IMU} (ms)	84	540.16 (71.67)	524.61	555.72
FT_{FP} (ms)	84	551.92 (46.94)	541.73	562.10
P value		0.21		
JH_{IMU} (cm)	84	36.36 (9.45)	34.31	38.42
JH_{FP} (cm)	84	37.58 (6.39)	36.19	38.97
P value		0.33		

Table 4.1 Descriptive statistics of flight time (FT) in milliseconds (ms) and jump heights (JH) in centimeters (cm) for the different methods of measurement.

Bland-Altman plots are shown in Figure 5. A positive linear trend is present in both measurements ($R_{FT} = 0.431$, and $R_{JH} = 0.404$). This indicates that the differences in measures have proportional error.

A



B

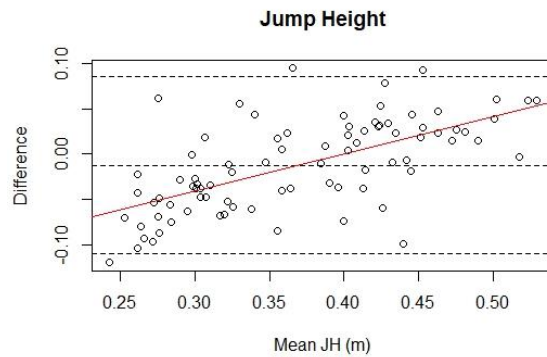


Figure 5 A) Bland-Altman plot of flight time (FT). The red line represents the positive trend between the Mean FT and Difference in measurement ($R = 0.431$, $R^2 = 0.424$); B) Bland-Altman plot of Jump Height (JH). The red line represents the positive trend between the Mean JH and Difference in measurement ($R = 0.404$, $R^2 = 0.397$).

The FT and JH showed good agreement between devices with an ICC of 0.88 and 0.90 respectively. The mean bias for FT was 6.63% with the limits of agreement at -4.17% and 17.44% (Table 4.2). The mean bias for JH was 12.81% with limits of agreement at -6.16% and 31.29%.

Bias and Limits of Agreement

Flight Time (ms)	Count	Mean (% Diff)	Lower 95% CI	Upper 95% CI
Bias (Difference)	84	-11.75 (6.63%)	-20.21	-3.30
Lower Limit of Agreement	84	-88.12 (-4.17%)	-102.75	-73.47
Upper Limit of Agreement	84	64.60 (17.44%)	49.96	79.25
Jump Height (cm)	Count	Mean (% Diff)	Lower 95% CI	Upper 95% CI
Bias (Difference)	84	-1.22 (12.81%)	-2.30	-0.14
Lower Limit of Agreement	84	-10.96 (-6.16%)	-12.83	-9.09
Upper Limit of Agreement	84	8.53 (31.79%)	6.66	10.40

Table 4.2 Results from the Bland-Altman analysis of agreement between measures of the stride times derived from a trunk-mounted vs an ankle mounted accelerometer.

Discussion

The ICCs for FT and JH indicated good agreement between measurement techniques, however the Bland-Altman analysis indicates that the difference between methods of

measurement may lead to more uncertainty in measure for the accelerometer. The wide LOA indicate a wide variation in measurement error. Similarly, the accelerometer produced proportional error, such that at lower values the accelerometer underestimates, and at higher values the accelerometer overestimates. The possible points of error include the location of the accelerometer, the difference in method of measurement of flight time between the instruments, and between person differences in jump technique.

The main difference between the current study and previous studies assessing the differences in measuring CMJ height from an accelerometer is the location at which the accelerometer is fixed. Most validations have occurred at the COM which has yielded promising results.¹¹²⁻¹¹⁷ However, the purpose of this study was to assess the appropriateness of a trunk-mounted accelerometer common to team sports to assess CMJ height. The different location of the accelerometer could introduce considerable error by increasing the noise in the acceleration signal. Similarly, the differences in technique between individuals exacerbates the noise that is introduced when placing the accelerometer between the scapulae. Regardless, CMJ analysis requires that trained personal assess the technique of each recorded jump. Group CMJ testing is best executed with multiple testers and small groups.

It is important to note the difference in methods of measurement between the instruments. The force plates calculate FT by an absence of force registered between take-off and landing. However, the method used in the current study utilizes the accelerometer waveform to pinpoint take-off and touchdown time points. Several researchers have observed that this method overestimates JH, because the maximum and minimum velocities happen before and after the jumping events.^{112,116} The vertical migration of the accelerometer to between the scapulae could increase the error observed by others. Furthermore, deriving JH from the accelerometer

waveform may be more work than necessary for the average youth soccer coach or organization. It may make more sense for both ease of use and certainty of data to utilize jump mats or other cheaper methods.

The data was collected before and after practice sessions. An error in the connection with the GPS signal prohibited recording of gyroscope data. When downloading data from the STATSports interface, accelerometer data can be accessed in two different files. One file includes only the accelerometer data, and the other includes the GPS, accelerometer, and gyroscope data. For over half of the trials, the interruption in GPS signal resulted in incomplete data recording or missing data. Therefore, for the current study, only accelerometer data was accessible. Typically, accelerometers measure accelerations from a set point of the accelerometer rather than in line with the real-world axes. In order to orient the accelerometer to the real world three dimensional space, the correction described by Moe-Nilssen was used.¹⁰³ Other methods have utilized a data fusion technique that uses gyroscopic data to enhance the correction.¹¹⁷ However that was not possible for the current data set.

Conclusions

The current study shows good agreement with proportional error between the force plates and the accelerometer in measuring FT and JH for the CMJ. It is important to be cognizant of the limitations inherent with measuring FT from the trunk-mounted accelerometer. The current study suggests that FT and JH derived from an accelerometer be part of a larger battery of neuromuscular testing to increase certainty of findings. Further, the assessment of CMJ for team sports still requires that athletes are monitored to ensure proper technique. The use of jump mats could be a cheaper alternative to force plates that provides less work for the practitioner as compared to the accelerometer.

4.2 Comparison between countermovement jump and gait analysis to detect changes in performance in a NCAA D1 women's soccer team

Introduction

The final experiment was a culmination of the current work. Chapter 2 established the Gait Program and validated temporal variables measured at the trunk. Chapter 3 trials the Gait Program in a population of interest. The results from Chapter 3 suggest that the gait run should incorporate sprints rather than a slow-paced group run. This is similarly seen as the preferred method of choice in another paper who assessed the use of sprints for monitoring neuromuscular performance.⁴¹ Chapter 4.1 validated the method for countermovement jump (CMJ) assessment. The last experiment was to examine the differences in gait and CMJ performance after a soccer match. CMJ has been documented to be perturbed up to 72 hours postgame.^{15,18} The CMJ height (JH) acted as the gold standard in detecting changes in performance. Similarly gait variables related to root mean square (RMS) accelerations ([axis].Accel.RMS) and angular velocities ([axis].Gyro.RMS), step (StepL) and stride lengths (StrideL), and leg stiffness (k_{leg}) were expected to be the most impacted. Changes in CMJ height were expected to be negatively correlated to distance.

Methods

Experimental Procedure

Participants were members ($n = 20$) of the Virginia Tech Women's Soccer team (age = 18.55 ± 0.76 , height (cm) = 169.71 ± 6.10 , weight (kg) = 61.86 ± 6.80). All methods and procedures were approved by the Virginia Tech IRB (17-632). Each player was fitted with a GPS embedded trunk-mounted accelerometer (STATSports APEX, 18 Hz GPS, 600 Hz accelerometer, 400 Hz gyroscope, and a 10 Hz magnetometer, Newry, Northern Ireland).

First, a proof-of-concept experiment emphasized the ability of CMJ data to detect fatigue-related declines in performance. A three-jump protocol was conducted after a warm-up consisting of dynamic stretching, jogging, and change of direction movements. Immediately after the warm-up, players were instructed to place their hands on their hips and execute a maximal CMJ. The depth of the countermovement was self-regulated. The jump was repeated three times with five to seven seconds between each jump. Players performed the three-jump protocol as a group, with each jump initiated by verbal command from the coaching staff. The total time required for the task was less than thirty seconds. The three-jump protocol was used before and after training sessions and matches.

The second experiment compares the efficacy of CMJ and gait in detecting fatigue-related declines in performance. Following the same warm-up as outlined above, the players were asked to complete two linear self-paced strides (SPS), then the three-jump protocol. Each SPS was about 200 meters in length. The CMJ were monitored for form, such that each player had three successful trials. The SPS and CMJ data were collected at Pregame and Postgame during two consecutive weeks of the season. The game for each week was the only game of the week for both weeks, so both games were considered together in the following analysis. Grouping the games together increased sample size, and statistical power. The players were not divided, because homogeneous groups based on training load data were impossible to create.

Data Processing

Both CMJ and gait data were derived from the STATSports accelerometer. After each practice session, the units were collected for download to the STATSports software. The data was then split to create a CMJ file and a SPS file for each player. Data was processed and analyzed for gait analysis as described in Section 2.1 and Appendix C. It is important to note

that the detrended fluctuation analysis (DFA) was not conducted. The observations needed to run the DFA are 500-600,^{72,104,106} where the SPS result in less than 200 observations. The gait data was compiled into an excel file with average values for each day. The CMJ data was analyzed according to the methods outlined in Section 4.1. For a list of gait variable definitions, consult Table 2.1. Two-sample paired t-tests and Wilcoxon signed rank tests were performed to assess significant differences between time points. Distance run (Tot Dist) was correlated to JH and gait variables using Pearson's correlation coefficients.

Results

Proof of Concept

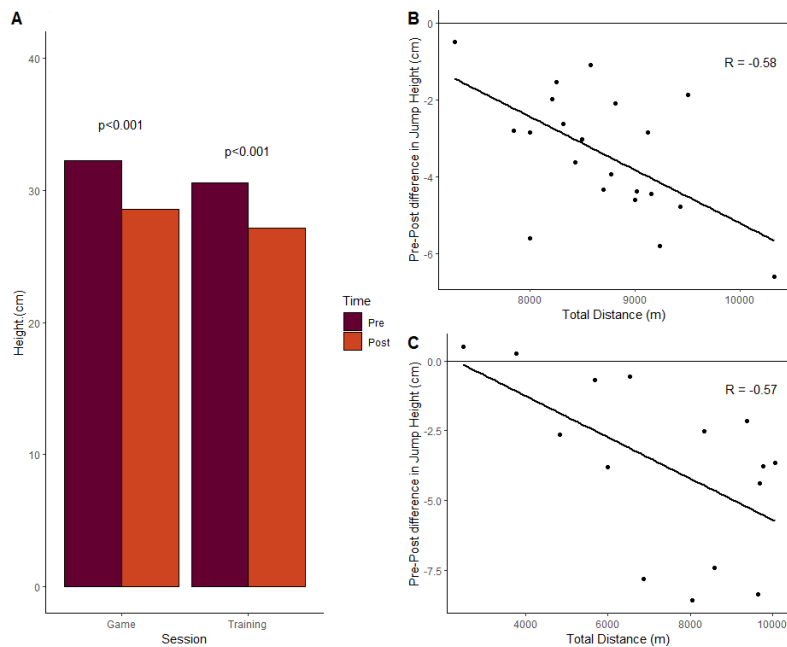


Figure 6 A) The Pre-Post differences in Jump Height (JH) in centimeters around a Game and Training Session. B) Correlation of the Pre-Post change in JH to Total Distance for Training Sessions. C). Correlation of the Pre-Post change in JH to Total Distance for Games.

JH decreased from the Pre ($JH = 32.27 \pm 6.12$ cm) to Post ($JH = 28.56 \pm 5.71$ cm) condition for both Training and Game sessions (Figure 6A). The change in JH had moderate correlations to Tot Dist for both Training ($R = -0.58$, Figure 6B) and Game ($R = -0.57$, Figure

6C). The data from the proof of concept demonstrates the sensitivity of CMJ to detect fatigue in soccer athletes.

Comparison of CMJ and Gait Data

No spatiotemporal or spring mass variables had significant changes from Pregame to Postgame. Step regularity (Step.Reg) decreased in the Y and Z axis for the acceleration and the Y axis for angular velocities. Stride regularity increased in the X, Y, and Z axis for acceleration and the Y and Z axis for angular velocities. All significance from RMS variables indicated an apparant improvement in variability. JH had a modest decrease from 31.67 ± 4.62 cm at Pregame to 30.36 ± 3.83 cm at Postgame (Table 4.3).

	Change in Variables from Pregame to Postgame			
	Pregame	Postgame	P value	Effect Size
X.Stride.Reg	0.63 (0.076)	0.67 (0.093)	0.003	0.47 ^s
Y.Step.Reg	0.74 (0.052)	0.77 (0.054)	0.002	0.57 ^m
Y.Stride.Reg	0.69 (0.086)	0.75 (0.066)	p<0.001	0.78 ^m
Z.Step.Reg	0.68 (0.13)	0.75 (0.074)	p<0.001	0.66 ^m
Z.Stride.Reg	0.69 (0.092)	0.74 (0.072)	0.003	0.61 ^m
Y.GyroStep.Reg	-0.73 (0.25)	-0.82 (0.089)	p<0.001	-0.48 ^s
Y.Gyro.Stride.Reg	0.82 (0.086)	0.85 (0.087)	0.003	0.35 ^s
Z.Gyro.Stride.Reg	0.88 (0.047)	0.90 (0.051)	0.015	0.41 ^s
Y.Accel.RMS	10.86 (1.13)	10.19 (0.91)	p<0.001	-0.65 ^m
R.Accel.RMS	13.65 (1.08)	12.98 (0.86)	0.002	-0.69 ^m
X.Gyro.RMS	85.21 (17.87)	65.34 (14.27)	p<0.001	-1.23 ^l
Y.Gyro.RMS	128.01 (17.90)	118.44 (16.39)	p<0.001	-0.56 ^m
R.Gryo.RMS	177.11 (21.46)	159.46 (17.14)	p<0.001	-0.91 ^l
Jump Height (cm)	31.67 (4.62)	30.36 (3.83)	0.020	-0.31 ^s

Table 4.3 Means \pm SD, P-value, and Cohen's d effect size for variables with significant changes from Pregame to Postgame. Cohen's d effect size designations: $d > 0.2^s$ = small effect, $d > 0.5^m$ = medium effect, $d > 0.8^l$ = large effect.

Weak to strong correlations to Tot Dist and JH are summarized in Table 4.4. Jump height was not well correlated with Tot Dist ($R = -0.27$). Tot Dist was most correlated to Y.Gyro.RMS ($R = -0.67$) and R.Gyro.RMS ($R = -0.56$). Speed, StepT, StrideT, StepL, and StrideL, had similar correlations with Tot Dist. Δy had the strongest correlation of the spring

mass variables ($R = 0.30$). Z.Gyro.Stride.Reg had the strongest correlation of the regularity variables ($R = -0.43$). JH had a weak positive correlation to Y.Gyro.Step.Reg ($R = 0.35$).

Otherwise, no gait variables had a strong correlation with JH.

Correlation Coefficients for Distance and Jump Height		
	Total Distance	Jump Height
Jump Height	-0.27	1.00
Speed	-0.38	0.15
StepT	0.38	-0.092
StrideT	0.39	-0.10
StepL	-0.31	0.041
StrideL	-0.31	0.041
Δy	0.30	-0.14
X.Stride.Reg	-0.32	-0.042
Y.Gyro.Step.Reg	-0.27	0.35
Z.Gyro.Stride.Reg	-0.43	-0.078
X.Accel.RMS	-0.37	0.026
X.Gyro.RMS	-0.36	-0.027
Y.Gyro.RMS	-0.67	-0.038
R.Gyro.RMS	-0.56	-0.013

Table 4.4 Correlation coefficients (R) of gait variables to Total Distance (Tot Dist) and Jump Height (JH).

Discussion

The results of the current study demonstrate the complexity of neuromuscular responses in team sports athletes. First, the protocol for the proof of concept suggests that the changes in JH are dependent on the same-day match load. When the recovery process was introduced (i.e., sleep), JH had a smaller percent change. Increased recovery time may explain the differences in correlation of JH to Tot Dist between protocols. The other important finding of this study was the gait variables appear to improve or did not change. The only variables that had significant differences were postural variables, indicating that the athletes changed their postural running strategy. The apparent improvement in running gait contradicts the hypothesis in the way the

variables changed. However, true to the hypothesis, the postural variables were the most affected variable group.

First, the CMJ analysis had similar results to previous research. Several reviews have found that CMJ was altered up to 72 hours postgame.¹⁵⁻¹⁷ Reductions in CMJ are likely strongest at 12 to 24 hours postgame with gradual recovery.¹⁵ In the current study, when pre-post differences were measured on the same day, JH was reduced by 11.23%. When pre-post differences in JH were assessed on the day before and the day after the game, JH was reduced by 4.22%. The results show less decline in performance with more recovery, which is consistent to what was seen previously.^{14,15} Since the change in JH was not very large, the effect of fatigue on running gait may be reduced.

Another important finding in the current study is that gait variables appear to improve rather than declined after the game. Similar studies also showed no real change in stiffness variables around games⁴⁰, and various submaximal practice modalities.⁴¹ Could it be that the athletes were not fatigued enough? The results of the CMJ analysis suggest that the athletes were fatigued, with moderate recovery at the Postgame practice. Compared to other investigations by this lab, the current study assessed the change after a single game rather than two (Chapter 3, ⁸⁷). The extra game will change the fatigue experienced, and the recovery time course. Similarly, the structure of the season was altered due to the novel coronavirus outbreak. The soccer season had a longer preseason period, and fewer games (2019 = 19 games, 2020 = 13 games), which may be more tolerable to the athletes.^{118,119} Therefore, the athletes could have been better prepared to manage the training load compared to a normal season impacting their neuromuscular response.

Another possibility is that gait is resilient in the presence of fatigue. Several studies have found that stiffness (k_{leg}) improves after ultramarathon events.^{35,36} This phenomenon may be explained by two prevailing properties of running coordination: 1) the repetitive nature of running has taught the body how to manage fatigue to maintain proper form; and 2) at preferred stride frequencies, the metabolic cost of running is less compared to other stride frequencies. Monjo and Forestier observed that fatigue management can be taught.¹²⁰ They trained their participants to generate the same kinematic output during a state of muscle fatigue. Since running is repetitive, it could be that the neural system responsible for the execution of the running program has been trained to replicate the nonfatigued running style during fatigued conditions. It is important to note that it has also been well documented that gait variables have decreased with fatigue.^{95,96,121} However, the neuromuscular impact of a soccer match may be less noticeable in running gait as gait is a complex coordination of movements in which systems of checks and balances are in place to maintain integrity.

Furthermore, preferred stride frequency has been shown to be more cost efficient than other stride frequencies.^{22,122,123} After an ultramarathon, CMJ performance had a 12.10 % decrease, but the metabolic cost of running was equivalent to non-fatigued controls at the preferred stride frequency.¹²² Similarly Hunter and Smith noticed that, during an hour run, VO_2 was lower at preferred stride frequency.²² In walking, Russel and Apatoczky found that EMG activity was lower in the major muscle groups in the thigh and lower leg when walking at preferred stride frequency.¹²³ The reduced EMG activity may contribute to the lower cost of running. Therefore, athletes may be able to replicate running form to model nonfatigued conditions. The apparent improvement of postural variables may ultimately be a result of the resiliency of the athletes' neuromuscular capability to produce proper running form in a fatigued

condition. It is important to note that this is contrary to what was found earlier. Chapter 3 had decrements in performance immediately following games. The changes however, were not always intuitive, but games generally resulted in a negative change in gait variables. Future research should continue to study how gait changes because of soccer and other team sports activities to elucidate the impact on athletes' neuromuscular health.

Conclusion

Running gait is a complex system of movement that is resilient to fatigue. The current study shows that gait variables appear to improve after an exhaustive exercise bout. Therefore, monitoring running gait may not be appropriate for day-to-day assessments of neuromuscular status. It could be that the level of fatigue necessary to register regular decrements in performance was not registered in this study. CMJ is a well studied alternative for neuromuscular assessments. Future research should continue to assess how running gait changes in response to team sports practices and competitions. Gait analysis may not be as translatable to neuromuscular fatigue as the CMJ test, but the data can be used to further inform the practitioner on the health of their athletes.

CONCLUSION

The current study provided evidence that gait variables measured at the ankle could be generalized at the trunk. Gait data changed during periods of high training loads, to favor a more fatigued state or a decline in performance. The trunk-mounted accelerometer was also validated to assess countermovement jump heights against force plates. The differences in measure were good ($ICC_{FT} = 0.89$ and $ICC_{JH} = 0.90$). However, the Bland-Altman analysis showed that the accelerometer had proportional error (i.e., it tended to underestimate at lower values, and overestimate at higher values). The proportional error indicates that caution should be used when relying solely on countermovement jump analysis for neuromuscular assessment. The final study describes the complexity of fatigue, and its apparent effect on running gait. The gait variables appeared to improve after fatiguing exercise, indicating that the athletes were not fatigued enough, or that they have the capability to produce “fresh” running gait profiles while in a fatigued state.

It may be worth the investment to purchase equipment specifically designed for countermovement jump height assessment. Though the trunk-mounted accelerometer had good validity, the process of calculating jump height from the acceleration signal may be more unnecessary work for the practitioner. Similarly, proper assessment of countermovement jump requires that athletes are monitored for form. It is better to monitor smaller groups of individuals, rather than jump the whole team at once. However, given enough staff are monitoring form, larger groups can be jumped simultaneously. Keep in mind that poor form will result in a noisier signal, and biased results.

For the biomechanics, I want to emphasize that the current study does not claim clinical relevance for the validation trials. The current study does not suggest that biomechanists can

start using sports accelerometers fixed between the scapulae and maintain the same sensitivity as clinical accelerometers. Rather, this study shows agreement of a trunk-mounted accelerometer assessing gait to an ankle accelerometer. The current study validates a trunk-mounted accelerometer to assess temporal gait in field-based collection methods. Investigating clinically relevant differences in impacts and temporal characteristics should be assessed with higher frequency accelerometers at the center of mass, or closer to the ground. The math on which the clinical methods of gait analysis were developed, depend on the accelerometer being at the center of mass. The obvious limitations of the current study all originate from the accelerometer being located between the scapulae. Commercial companies producing sports accelerometers should consider moving the accelerometer closer to the center of mass. Postural variables, however, are less affected by this limitation due to the method of calculation. Switching the position of the accelerometer would result in more valid gait data.

The current study was observational in that the researchers had little control over the protocols of practices, games, and the training cycle. Future research may work in collaboration with coaches and strength staff to impose more structured protocols to assess a dose-response relationship to changes in gait variables. It may be more appropriate to research sub-elite populations that have less financial risk associated with success. Alternatively, more structured study protocols could be more manageable in the offseason.

Gait analysis has ecological importance to the sports monitoring paradigm that was not addressed in this study. Future research should explore how gait analysis can be used more effectively to monitor individuals with high injury risk, and modeling return-to-play protocols. Our lab has been utilizing accelerometers to assess asymmetries and recovery from anterior

cruciate ligament (ACL) rupture. Gait accelerometry is a good screening tool to assess asymmetries prior to catastrophic injury.

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APPENDIX A IRB 17-632 Materials



**Division of Scholarly Integrity and
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MEMORANDUM

DATE July 17, 2020
TO Jay H Williams, David P Tegarden, Brian Orbrey Williams, Danny Tabitha Parks, Renee Selberg Eaton, Deborah Good, Marc Theron Lewis, Rizzuto, Michael Allen Lacina, et.
FROM: Virginia Tech Institutional Review Board (FWA00000572, expires October 2024)
PROTOCOL Quantifying the Physical Demands and Injury Risk of Training and Competing in College
IRB NUMBER: 17-632

The Virginia Tech Human Research Protection Program (HRPP), has reviewed your COVID-Resumption of HSR plan and determined that the plan is acceptable. You can now implement your plan and resume your in-person Human Subjects Research activities.

Please remember to provide all research participants with:

1. A copy of the COVID-19 Consent Addendum and obtain signatures. Please retain a copy for research records.
2. A lay language version of the COVID-19 Risk Mitigation

Any minor changes to your mitigation plan will NOT need to be submitted to the HRPP for review. If you need to make substantial changes that are inconsistent with recommendations or guidance released by the university, state, or other or other authorized entity please re-submit a new plan for review.

SPECIAL INSTRUCTIONS:

The in-person consent process adds unnecessary risk as compared to the other research activities. We encourage you to submit an amendment to move the consent process to a remote process (e.g., individual Zoom sessions to provide information and go over the consent form; players could then drop signed forms in a box at the next practice session).

Invent the Future

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
An equal opportunity, affirmative action institution

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.

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. 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 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.

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 participant, or need to report a research-related injury or event, you may contact the Virginia Tech Institutional Review Board at irb@vt.edu or (540) 231-3732.

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

APPENDIX B IRB 20-071 Materials



**Division of Scholarly Integrity and
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MEMORANDUM

DATE March 26, 2021
TO Jay H Williams, Marc Theron Lewis, Danny Jaskowak
FROM: Virginia Tech Institutional Review Board (FWA00000572, expires October 2024)
PROTOCOL Athlete Monitoring in American Football: Examining the Relationship between Training Load, Performance Metrics and Injury
IRB NUMBER: 20-071

Effective March 25, 2021, the Virginia Tech Institutional Review Board (IRB) approved the 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: <https://secure.research.vt.edu/external/irb/responsibilities.htm>

(Please review responsibilities before beginning) your research.

PROTOCOL

Approved **Expedited, under 45 CFR 46.110 category(ies) 4,5,6,7**
 Protocol Approval **February 9, 2021**
 Progress Review Date: **February 8, 2022**

ASSOCIATED

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

Invent the Future

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
An equal opportunity, affirmative action institution

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY
Consent to Take Part in a Research Study

Title of research study: Athlete Monitoring in American Football: Examining the Relationship between Training Load and Athletic Performance Metrics

Principal Investigator: Jay H. Williams, Ph.D. (Principal Investigator)

Email: jhwms@vt.edu

Phone: (540) 231- 8298

Other study contact(s): Marc T. Lewis, M.S. (Co-Investigator)

Email: marc7@vt.edu

Phone: (540) 231-2984

Key Information: The following is a short summary of this study to help you decide whether or not to be a part of this study. More detailed information is listed later on in this form.

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, every effort to maintain confidentiality will be taken.

Why am I being invited to take part in a research study?

You are being asked to be in a research study because you are a student-athlete participating in football at Virginia Tech. 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.”

What should I know about being in a research study?

- Someone will explain this research study to you
- Whether or not you take part is up to you
- You can choose not to take part
- You can agree to take part and later change your mind
- Your decision will not be held against you
- You can ask all the questions you want before you decide

Why is this research being done?

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.

How long will the research last and what will I need to do?

We are wanting to use data that is being currently being collected as part of our athlete monitoring program, which is led by Marc Lewis. If you decide to participate in this study, you will not have to engage in any other activity outside of what is normally expected of you during training and competition. We are simply asking for permission to use your data.

More detailed information about the study procedures can be found under, **“What happens if I say yes, I want to be in this research?”**

Is there any way being in this study could be bad for me?

There are no known risks associated with this study.

More detailed information about the risks of this study can be found under **“Is there any way being in this study could be bad for me? (Detailed Risks)”**.

Will being in this study help me in any way?

There are no benefits to you from your taking part in this research. We cannot promise any benefits to others from your taking part in this research. However, possible benefits to others include understanding the physical demands of American football and the relationship between athlete training and performance.

What happens if I do not want to be in this research?

Participation in research is completely up to you. You can decide to participate or not to participate.

If you are a student, the decision whether to participate or not participate will have no effect on your grades or relationship with Virginia Tech.

Detailed Information: The following is more detailed information about this study records in addition to the information listed above.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, talk to the research team: Jay H. Williams, Principle Investigator at jhwms@vt.edu or (540) 231-8298, or Marc T. Lewis, Co-Investigator at marc7@vt.edu.

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research
-

How many people will be studied?

We plan to include about 96 people in this research study.

What happens if I say, yes, I want to be in this research?

If you say yes, we will use your data to examine to the relationship between training load and athletic performance. You will not be required to engage in any activity outside of what is normally asked of you as part of our athlete monitoring program.

What happens if I say yes, but I change my mind later?

You can leave the research at any time, for any reason, and it will not be held against you. 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.

Is there any way being in this study could be bad for me? (Detailed risks)

While every effort will be made to ensure confidentiality, there is the risk of breach of confidentiality.

What happens to the information collected for the research?

We will make every effort to limit the use and disclosure of your personal information, including research study, only to people who have a need to review this information. We cannot promise complete confidentiality. Organizations that may inspect and copy your information include the IRB, Human Research Protection Program, and other authorized representatives of Virginia Tech.

If identifiers are removed from your private information or samples that are collected during this research, that information or those samples could be used for future research studies or distributed to another investigator for future research studies without your additional informed consent.

The results of this research study may be presented in summary form at conferences, in presentation, reports, academic papers, and as part of a thesis/dissertation.

Can I be removed from the research without my OK?

The person in charge of the research study or the sponsor can remove you from the research study without your approval. Possible reasons for removal include issues during data collection resulting in inaccurate data.

What else do I need to know?

As part of the athlete monitoring program, you are issued a vest (the one already assigned to you). If the vest is misplaced or damaged, we will replace the vest at no charge or penalty to you.

Signature Block for Capable Adult

Your signature documents your permission to take part in this research. We will provide you with a signed copy of this form for your records.

Signature of subject

Date

Printed name of subject

Signature of person obtaining consent

Date

Printed name of person obtaining consent

APPENDIX C The Gait Program

MARKDOWN FILE:

The gait program was composed of eight R script files embedded in an Rmarkdown file. The Rmarkdown file allowed for review of the analyzed data, bug detection, and database compilation. Rmarkdown has chunks, which are blocks of code that can be run upstream of the remaining code. The addition of chunks allows for checkpoints in the code to detect bugs. R chunks begin with the following notation: ````{r}` and end with `````. The first chunk was used to load the required libraries for the gait program.

```
```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = FALSE)
library(readxl)
library(openxlsx)
library(signal)
library(IRISseismic)
library(pracma)
library(wmtsa)
library(zoo)
library(ifultools)
library(nonlinearTseries)
library(permute)
library(ggplot2)
```

The second chunk is the first checkpoint. The accelerometer data is read into the program, participant data is defined, and the data is graphically illustrated. The illustration allows for the determination of where to snip the data to only analyze the segment of interest.

```
DATA PROCESSING
```{r}
data <- read.csv("Directory")
ggplot(data)+
  geom_line(mapping = aes(x = Elapsed.Time, y = Acc1.Y))

Name <- "Participant ID"
ID<-20 #Session ID
h<-1.67 # Height in m
m<-57.9 # Mass in kg

#data <- subset(data, data$Elapsed.Time > 51790)
#data <- subset(data, data$Elapsed.Time > 1185 & data$Elapsed.Time < 1335)
```

The third chunk contains all the embedded functions that were created to run the various gait analysis methodologies. First the acceleration vectors are converted to m/s^2 from g's, and the frequencies of the filter are defined. The individual R code files that house the functions are called via the *source()* function. The first function filters the data, and the second runs the CWT. After the CWT, the *findpeaks()* function was used to assign FC's (local maxima of second order CWT) and IC's (local minima of first order CWT). Once FC and IC are defined, the code is ready to calculate the spatiotemporal, spring mass, gyroscopic, and acceleration-related variables.

```

```{r}
accelx <- (data$Acc1.X- 1)*(9.8)
data$`Corrected Acc1 X` <- accelx
accely <- (data$Acc1.Y - 1)*(9.8)
data$`Corrected Acc1 Y` <- accely
accelz <- (data$Acc1.Z - 1)*(9.8)
data$`Corrected Acc1 Z` <- accelz

R.accel <- (accelx^2 + accely^2 + accelz^2)^0.5
data$Resultant <- R.accel

Filtering
fs <- 100 #frequency of the acceleration recording
fc0 <- 40 #Low pass cut off to remove noise
fc1 <- 3 #Low pass cut off for R/L detection (X-axis)
fc2 <- 0.9 #Highpass cut off to remove drift.

source("Directory/SIGNAL FILTERING.R")
filter <- my_filter(data, fs, fc0, fc1, fc2, accelx, accely, accelz, R.accel)
data <- cbind(data,filter)

Continuous Wavelet Transform
source("Directory/CWT Function.R")
cwt <- my_cwt(data)
data <- cbind(data,cwt)
Find Peaks

#PRACMA PACKAGE
IC.m <- findpeaks(data$ycwt1, minpeakdistance = 20)
IC.m <- as.data.frame(IC.m)
IC.m <- IC.m[order(IC.m$V2),]
IC <- IC.m$V2
FC.m <- findpeaks(data$ycwt.jerk, minpeakdistance = 20)
FC.m <- as.data.frame(FC.m)
FC.m <- FC.m[order(FC.m$V2),]
FC <- FC.m$V2

```

```

##Note that you are calculating the time of the peak rather than the
#amplitude.
FCpk<- data$Elapsed.Time[FC]
ICpk<- data$Elapsed.Time[IC]

if(IC[1] > FC[1]){
 FC <- FC[2:length(FC)]
 IC <- IC[1:length(IC)-1]
 FCpk<- FCpk[2:length(FCpk)]
 ICpk<- ICpk[1:length(IC)-1]
}

Time Calculations
source("Directory/Time_Vars_Function.R")
time.vars <- my_time(data, FC, FCpk, IC, ICpk)
time.mean<- time.vars$avg.times
bi.step.time <- time.vars$bi.step
uni.step.time <- time.vars$uni.step

Length Calculations
source("Directory/Length and Stiffness Function.R")
stiff.leg <- my_leg(h,m,uni.step.time,bi.step.time)

Acceleration Peaks
source("Directory/Accel_Peaks Function.R")
accel <- accel_peaks(data,time.vars)

DFA
source("Directory/DFA_Function.R")
alphas <- DFA_VARS(time.vars, stiff.leg, accel)

AUC
source("Directory/auc_function.R")
gait.reg <- gait_regularity(data)

#Database Creation
source("Directory/Database creation.R")
data_log <- data_log(time.vars, stiff.leg, accel)
uni.means <- colMeans(data_log$unilateral, na.rm = TRUE)
bi.means <- colMeans(data_log$bilateral, na.rm = TRUE)
mean_vars <- rbind(c(uni.means,bi.means,gait.reg, alphas, accel$RMS))
name <- colnames(mean_vars)
mean_vars <- unlist(mean_vars)
mean_vars <- as.numeric(mean_vars)
mean_vars <- as.data.frame(rbind(c(Name,ID,mean_vars)))
colnames(mean_vars) <- c("Name", "ID", name)
bi.step.time$CT

```

The last chunk was dedicated to appending the data from each file to the compiled files for later analysis. The first file is the master file compiling all mean values for gait variables. The second file was dedicated to the storage of vectors created by the program for each participant. Both unilateral (Right or Left) and bilateral variables had their own sheets in the Excel workbook.

```

```{r}
#Don't forget to change after the first one, to read in the data... or this
#function will just overwrite everything
wb <- loadworkbook("Directory/Master_file.xlsx")
old.2 <- read.xlsx("Directory/Master_file.xlsx")
colnames(old.2) <- colnames(mean_vars)
mean_vars <- rbind(old.2,mean_vars)
writeData(wb, sheet = "Sheet1", x = mean_vars) #add data to the sheet
saveworkbook(wb, "Directory/Master_file.xlsx", overwrite = T) #saves xlsx
#file

#same deal as above.
wb.2 <- loadworkbook("Directory/Participant_ID.xlsx")
old <- read.xlsx("Directory/Participant_ID.xlsx", sheet = "Sheet1")
unilateral <- data_log$unilateral
unilateral$ID <- ID
unilateral <- unilateral[c(1:(length(unilateral$ID)-5)),c(60,1:59)]
unilateral <- rbind(old,unilateral)
writeData(wb.2, sheet = "Sheet1", x = unilateral)
old.1 <- read.xlsx("Directory/Participant_ID.xlsx", sheet = "Sheet2")
bilateral <- data_log$bilateral
bilateral$ID <- ID
bilateral <- bilateral[c(1:(length(bilateral$ID)-5)),c(21,1:20)]
bilateral <- rbind(old.1,bilateral)
writeData(wb.2, sheet = "Sheet2", x = bilateral)
saveworkbook(wb.2, file = "Directory/Participant_ID.xlsx", overwrite = T)
```

```

*RCODE:*

### *SIGNAL FILTERING.R*

This function first applies the orientation correction described by Moe-Nilssen 1998.<sup>103</sup>

After the correction, the acceleration and angular velocity vectors were filtered. Vertical velocity and mediolateral rotation were derived by integrating the vertical acceleration and the mediolateral angular velocity, respectively.

```

FILTERING
library(signal)
library(IRISSeismic)

my_filter <- function(data, fs, fc0, fc1, fc2, accelx, accely, accelz,
R.accel){

 #### FILTERING ####
 # Moe-Nilssen 1998 # Adjusts tilt of axes due to tilt of trunk
 avg.x <- mean(accelx)
 avg.z <- mean(accelz)
 theta.ml <- asin(avg.x*pi/180)
 theta.ap <- asin(avg.z*pi/180)
 reoriented.ap <- accelz*cos(theta.ap) - accely*sin(theta.ap)
 temp.vt <- accelz*sin(theta.ap) + accely*cos(theta.ap)
 reoriented.ml <- accelx*cos(theta.ml) - temp.vt*sin(theta.ml)
 reoriented.vt <- accelx*sin(theta.ml) + temp.vt*cos(theta.ml) -1

 accelx <- reoriented.ml
 accely <- reoriented.vt
 accelz <- reoriented.ap

```

```

gyrox <- data$Gyro.X*0.07
gyroy <- data$Gyro.Y*0.07
gyroz <- data$Gyro.Z*0.07

wn0 <- fc0/(fs/2) # Divide the derived cutoff frequency by half the
wn1 <- fc1/(fs/2) # sampling frequency
wn2 <- fc2/(fs/2)

list0 <- butter(4, wn0, 'low') # \
list1 <- butter(4, wn1, 'low') # } filter coefficients in lists
list2 <- butter(4, wn2, 'high') # /

a0 <- as.vector(list0$a) # \
b0 <- as.vector(list0$b) # } unlisting the butter filter coefficients
a1 <- as.vector(list1$a) # |
b1 <- as.vector(list1$b) # /
a2 <- as.vector(list2$a) # \
b2 <- as.vector(list2$b) # /

x2 <- signal::filtfilt(b2, a2, accelx) #\
y2 <- signal::filtfilt(b2, a2, accely) # } Remove Drift
z2 <- signal::filtfilt(b2, a2, accelz) #/
r2 <- signal::filtfilt(b2, a2, R.accel)
x0 <- signal::filtfilt(b0, a0, x2) #\
y0 <- signal::filtfilt(b0, a0, y2) # } Remove Noise
z0 <- signal::filtfilt(b0, a0, z2) #/
r0 <- signal::filtfilt(b0, a0, r2)
x1 <- signal::filtfilt(b1, a1, x0) # -> Smooth for R/L Detection

y0.temp <- as.matrix(accely)
veloy <- cumtrapz(data$Elapsed.Time, y0.temp)
veloy <- signal::filtfilt(b2, a2, veloy)

x2 <- as.numeric(x2)
y2 <- as.numeric(y2)
z2 <- as.numeric(z2)
x0 <- as.numeric(x0)
y0 <- as.numeric(y0)
z0 <- as.numeric(z0)
x1 <- as.numeric(x1)
veloy <- as.numeric(veloy)

gx2 <- signal::filtfilt(b2, a2, gyrox) #\
gy2 <- signal::filtfilt(b2, a2, gyroy) # } Remove Drift
gz2 <- signal::filtfilt(b2, a2, gyroz) #/
gx0 <- signal::filtfilt(b0, a0, gx2) #\
gy0 <- signal::filtfilt(b0, a0, gy2) # } Remove Noise
gz0 <- signal::filtfilt(b0, a0, gz2) #/

x0.temp <- as.matrix(gyrox)
posix <- cumtrapz(data$Elapsed.Time, x0.temp)
posix <- signal::filtfilt(b2,a2,posix)

gx2 <- as.numeric(gx2)
gy2 <- as.numeric(gy2)
gz2 <- as.numeric(gz2)
gx0 <- as.numeric(gx0)
gy0 <- as.numeric(gy0)
gz0 <- as.numeric(gz0)

Create data frame to house desired data

```

```

filter <-
cbind(x2,y2,z2,r2,x0,y0,z0,r0,x1,veloy,gx2,gy2,gz2,gx0,gy0,gz0,posix)
Provide Column Names
colnames(filter) <- c("accel x no drift", "accel y no drift", "accel z no
drift", "accel r no drift",
 "filtered accel x", "filtered accel y", "filtered
accel z", "filtered accel r",
 "x.accel.RL", "veloy", "gyro x no drift", "gyro y no
drift", "gyro z no drift",
 "filtered gyro x", "filtered gyro y", "filtered gyro
z", "posix")
filter <- as.data.frame(filter)
return(filter)
}

```

### *CWT Function.R*

This function transformed the vertical velocity into acceleration using the *wavCWT()* function. This smoothed the resulting acceleration vector to be more sine-like while maintaining variation through each period. The second transform applies the CWT to the transformed acceleration.

```

CWT
library(wmmtsa)

my_cwt <- function(data){
N <- nrow(data)
veloy <- data$veloy #velocity vector obtained from Prior function
#First Transform to acceleration
ycwt.wavCWT <- wavCWT(veloy, scale.range = deltat(1/fs)*c(1, length(veloy)),
n.scale= 10, wavelet = "gaussian1", variance = 20)
ycwt.list <- as.list(ycwt.wavCWT)
ycwt.unlist <- unlist(ycwt.list, use.names = T)
#Vector of transformed accel values
ycwt1 <- ycwt.unlist[1:N]

#Second transform to jerk
ycwt.jerk.wavCWT <- wavCWT(ycwt1, scale.range = deltat(1/fs)*c(1,
length(veloy)), n.scale= 10, wavelet = "gaussian1", variance = 20)
ycwt.jerk.list <- as.list(ycwt.jerk.wavCWT)
ycwt.jerk.unlist <- unlist(ycwt.jerk.list, use.names = T)
ycwt.jerk <- ycwt.jerk.unlist[1:N]

cwt <- as.data.frame(cbind(ycwt1, ycwt.jerk))
return(cwt)
}

```

### *Time\_Vars\_Function.R*

Right and left steps were detected by using the *findpeaks()* function. When the 3 Hz filtered mediolateral (X) signal had local minima, the resulting foot taking the step was the right

foot. The code divides FC and IC into RIC, RFC, LIC, and LFC based on the pattern of the mediolateral signal. All time variables are subsequently derived by RIC, LIC, RFC, and LFC.

```
Time Variable Function
my_time <- function(data, FC, FCPks, IC, ICPks){
#Align IC and FC Vectors (IC < FC)

Make it so that Right Foot always starts.
#Assign R/L Footstrikes
data$x.accel.RL <- as.numeric(data$x.accel.RL)
x.accel.min.m <- findpeaks(-data$x.accel.RL, minpeakdistance = 50,
minpeakheight = -0.001)
x.accel.min.m <- as.data.frame(x.accel.min.m)
x.accel.min.m <- x.accel.min.m[order(x.accel.min.m$V2),]
x.accel.min <- x.accel.min.m$V2

x.accel.max.m <- findpeaks(data$x.accel.RL, minpeakdistance = 50)
x.accel.max.m <- as.data.frame(x.accel.max.m)
x.accel.max.m <- x.accel.max.m[order(x.accel.max.m$V2),]
x.accel.max <- x.accel.max.m$V2

#Splits FC and IC into Right and Left IC and FC
if(x.accel.max[1] > x.accel.min[1]){
 FCPks <- FCPks[2:length(FCPks)]
 ICPks <- ICPks[2:length(ICPks)]
 RIC <- ICPks[c(TRUE,FALSE)]
 RFC <- FCPks[c(TRUE,FALSE)]
 LIC <- ICPks[c(FALSE,TRUE)]
 LFC <- FCPks[c(FALSE,TRUE)]
}else{
 RIC <- ICPks[c(TRUE,FALSE)]
 RFC <- FCPks[c(TRUE,FALSE)]
 LIC <- ICPks[c(FALSE,TRUE)]
 LFC <- FCPks[c(FALSE,TRUE)]
}

#Calculate Contact Times
RCT <- RFC - RIC
LCT <- LFC - LIC
CT <- FCPks - ICPks
#Calculate Step Times and Flight Times

RLStep <- LIC - RIC[1:length(LIC)]
LRStep <- RIC[2:length(RIC)] - LIC[1:(length(LIC)-1)]
RFT <- RLStep-RCT[1:length(RLStep)]
LFT <- LRStep-LCT[1:length(LRStep)]

StepT <- c(RLStep, LRStep)[order(c(seq_along(RLStep)*2 - 1,
seq_along(LRStep)*2))]
FT <- c(RFT, LFT)[order(c(seq_along(RFT)*2 - 1, seq_along(LFT)*2))]
#Calculate Stride Times
i.vec <- 1:length(RIC)
LStride <- 1:length(RIC)
RStride <- 1:length(RIC)
for(i in i.vec){
 LStride[i] <- LIC[i+1] - LIC[i]
 RStride[i] <- RIC[i+1] - RIC[i]
}
LStride <- na.omit(LStride)
RStride <- na.omit(RStride)
```

```

Deconstruct into left and right components
StrideT <- c(RStride, LStride)[order(c(seq_along(RStride)*2 - 1,
seq_along(LStride)*2))]
FT <- c(RFT, LFT)[order(c(seq_along(RFT)*2 - 1, seq_along(LFT)*2))]
#Step Data Frame
RFT <- RFT*1000
LFT <- LFT*1000
FT <- FT*1000
RCT <- RCT*1000
LCT <- LCT*1000
CT <- CT*1000
RLStep <- RLStep*1000
LRStep <- LRStep*1000
StepT <- StepT*1000
LStride <- LStride*1000
RStride <- RStride*1000
StrideT <- StrideT*1000

Make all the vectors the same length
RFT <- RFT[1:length(LStride)]
RCT <- RCT[1:length(LStride)]
RLStep <- RLStep[1:length(LStride)]
RStride <- RStride[1:length(LStride)]
LFT <- LFT[1:length(RFT)]
LCT <- LCT[1:length(RCT)]
LRStep <- LRStep[1:length(RLStep)]

cutoff <- length(LStride)
IC<-IC[1:length(StrideT)]
FC<-FC[1:length(StrideT)]
RIC<-RIC[1:cutoff]
LIC<-LIC[1:cutoff]
RFC<-RFC[1:cutoff]
LFC<-LFC[1:cutoff]

FT.diff <- 200*(RFT-LFT)/(RFT+LFT)
CT.diff <- 200*(RCT-LCT)/(RCT+LCT)
StepT.diff <- 200*(RLStep-LRStep)/(RLStep+LRStep)
StrideT.diff <- 200*(RStride-LStride)/(RStride+LStride)

steps<-1:length(RCT)
uni.step.df <- as.data.frame(cbind(steps, RIC, RFC, LIC, LFC, RFT, LFT, RCT,
LCT, RLStep, LRStep, RStride, LStride, FT.diff, CT.diff,
StepT.diff, StrideT.diff))
colnames(uni.step.df) <- c("Steps", "RIC", "RFC", "LIC", "LFC", "RFT",
"LFT", "RCT", "LCT", "RLStep", "LRStep", "RStride", "LStride", "FT.diff",
"CT.diff", "StepT.diff", "StrideT.diff")
steps<-1:length(StrideT)
CT<-CT[1:length(StrideT)]
FT<-FT[1:length(StrideT)]
StepT<-StepT[1:length(StrideT)]

bi.step.df <- as.data.frame(cbind(steps, IC, FC, FT, CT, StepT, StrideT))
colnames(bi.step.df) <- c("Steps", "IC", "FC", "FT", "CT", "StepT", "StrideT")

time <- list(uni.step.df, bi.step.df)
names(time) <- c("uni.step", "bi.step")
return(time)
}

```

*Length and Stiffness Function.R*

Step and stride length were calculated by multiplying the average speed across the step by the corresponding step time. The first part of this function was to calculate the speeds of each step, as well as to align the vectors for ease of calculations. Once the lengths were calculated, the spring mass model variables were calculated.

```
Step Length and Leg Stiffness

my_leg <- function(h, m, uni.step.time,bi.step.time){
Step and Stride Lengths
IC <- bi.step.time$IC
FC <- bi.step.time$FC
RLStep <- uni.step.time$RLStep
LRStep <- uni.step.time$LRStep
#Redistribute index positions for IC/FC's
RIC <- IC[c(TRUE,FALSE)]
RFC <- FC[c(TRUE,FALSE)]
LIC <- IC[c(FALSE,TRUE)]
LFC <- FC[c(FALSE,TRUE)]
#Speed at IC/FC's
RIC.sp <- data$Speed..m.s.[RIC]
RFC.sp <- data$Speed..m.s.[RFC]
LIC.sp <- data$Speed..m.s.[LIC]
LFC.sp <- data$Speed..m.s.[LFC]
#Ensure Vector Length Congruency
if(length(LIC.sp) < length(RIC.sp)){
 RIC.sp <- RIC.sp[1:(length(RIC.sp)-1)]
}
RStepL.sp <- (RIC.sp+LIC.sp)/2
LStepL.sp <- (LIC.sp[1:length(LIC.sp)-1]+RIC.sp[2:length(RIC.sp)])/2
#Ensure Vector Length Congruency
if(length(RLStep) > length(RStepL.sp)){
 RLStep <- RLStep[1:length(RStepL.sp)]
}
#Ensure Vector Length Congruency
if(length(LRStep) > length(LStepL.sp)){
 LRStep <- LRStep[1:length(LStepL.sp)]
}
Step Legnth
RStepL <- LRStep*LStepL.sp/1000
LStepL <- RLStep*RStepL.sp/1000
if(length(LStepL)>length(RStepL)){
 LStepL <- LStepL[1:length(RStepL)]
}

Stride Length
Rstride <- uni.step.time$Rstride
Lstride <- uni.step.time$Lstride
RstrideL.sp <- (RIC.sp[1:length(RIC.sp)-1] +RIC.sp[2:length(RIC.sp)])/2
LstrideL.sp <- (LIC.sp[1:length(LIC.sp)-1] +LIC.sp[2:length(LIC.sp)])/2
if(length(Rstride)>length(RstrideL.sp)){
 Rstride <- Rstride[1:length(Rstride)-1]
}
if(length(Lstride)>length(LstrideL.sp)){
 Lstride <- Lstride[1:length(Lstride)-1]
}
RstrideL <- Rstride*RstrideL.sp/1000
LstrideL <- Lstride*LstrideL.sp/1000
```

```

Speed.Long <- c(RIC.sp, LIC.sp)[order(c(seq_along(RIC.sp)*2 - 1,
seq_along(LIC.sp)*2))]
StepL <- c(RStepL, LStepL)[order(c(seq_along(RStepL)*2 - 1,
seq_along(LStepL)*2))]
StrideL <- c(RStrideL, LStrideL)[order(c(seq_along(RStrideL)*2 - 1,
seq_along(LStrideL)*2))]

AvgRStepL <- mean(RStepL, na.rm = T)
AvgLStepL <- mean(LStepL, na.rm = T)
AvgRStrideL <- mean(RStrideL, na.rm = T)
AvgLStrideL <- mean(LStrideL, na.rm = T)
AvgStepL <- mean(StepL, na.rm = T)
AvgStrideL <- mean(StrideL, na.rm = T)
Speed <- mean(data$Speed..m.s.)
StepL.diff <- 200*(RStepL-LStepL)/(RStepL+LStepL)
StrideL.diff <- 200*(RStrideL-LStrideL)/(RStrideL+LStrideL)
Avg.StepL.diff <- mean(StepL.diff, na.rm = T)
Avg.StrideL.diff <- mean(StrideL.diff, na.rm = T)

mean.lengths <- as.data.frame(cbind(Speed, AvgRStepL, AvgLStepL, AvgStepL,
AvgRStrideL, AvgLStrideL, AvgStrideL, AvgStrideL.diff))
colnames(mean.lengths) <- c("Speed", "RStepL", "LStepL", "StepL",
"StrideL.diff", "RStrideL", "LStrideL", "StrideL", "StrideL.diff")

Stiffness
L <- 0.53*h #Morin et al. 2005

#RIGHT
RCT <- uni.step.time$RCT
RFT <- uni.step.time$RFT
if(length(RCT)>length(RFT)){
 RCT <- RCT[1:length(RFT)]
}
r.Fmax <- (m*9.8*pi/2*(RFT/RCT+1))/1000
r.delta.y <- r.Fmax*(RCT/1000)^2/m*pi^2 + 9.8*(RCT/1000)^2/8
r.k.vert <- r.Fmax/r.delta.y
r.delta.l <- L - sqrt(L^2-(RStepL.sp*RCT/2000)^2)+r.delta.y
r.k.leg <- r.Fmax/r.delta.l

#LEFT
LCT <- uni.step.time$LCT
LFT <- uni.step.time$LFT
if(length(LCT)>length(LFT)){
 LCT <- LCT[1:length(LFT)]
}
l.Fmax <- (m*9.8*pi/2*(LFT/LCT+1))/1000
l.delta.y <- l.Fmax*(LCT/1000)^2/m*pi^2 + 9.8*(LCT/1000)^2/8
l.k.vert <- l.Fmax/l.delta.y
if(length(LCT)>length(LStepL.sp)){
 LCT <- LCT[1:length(LStepL.sp)]
 l.delta.y <- l.delta.y[1:length(LStepL.sp)]
 l.Fmax <- l.Fmax[1:length(LStepL.sp)]
}
l.delta.l <- L - sqrt(L^2-(LStepL.sp*LCT/2000)^2)+l.delta.y

l.k.leg <- l.Fmax/l.delta.l

Fmax <- c(r.Fmax, l.Fmax)[order(c(seq_along(r.Fmax)*2 - 1,
seq_along(l.Fmax)*2))]
delta.y <- c(r.delta.y, l.delta.y)[order(c(seq_along(r.delta.y)*2 - 1,
seq_along(l.delta.y)*2))]
k.vert <- c(r.k.vert, l.k.vert)[order(c(seq_along(r.k.vert)*2 - 1,
seq_along(l.k.vert)*2))]

```

```

delta.l <- c(r.delta.l, l.delta.l)[order(c(seq_along(r.delta.l)*2 - 1,
seq_along(l.delta.l)*2))]
k.leg <- c(r.k.leg, l.k.leg)[order(c(seq_along(r.k.leg)*2 - 1,
seq_along(l.k.leg)*2))]

make vectors the same length
cut <- length(l.theta)
r.Fmax <- r.Fmax[1:cut]
r.delta.y <- r.delta.y[1:cut]
r.k.vert <- r.k.vert[1:cut]
r.delta.l <- r.delta.l[1:cut]
r.k.leg <- r.k.leg[1:cut]
l.k.vert <- l.k.vert[1:cut]
Fmax <- Fmax[1:length(StrideL)]
delta.y <- delta.y[1:length(StrideL)]
k.vert <- k.vert[1:length(StrideL)]
delta.l <- delta.l[1:length(StrideL)]
k.leg <- k.leg[1:length(StrideL)]

Fmax.diff <- 200*(r.Fmax-l.Fmax)/(r.Fmax+l.Fmax)
delta.y.diff <- 200*(r.delta.y-l.delta.y)/(r.delta.y+l.delta.y)
k.vert.diff <- 200*(r.k.vert-l.k.vert)/(r.k.vert+l.k.vert)
delta.l.diff <- 200*(r.delta.l-l.delta.l)/(r.delta.l+l.delta.l)
k.leg.diff <- 200*(r.k.leg-l.k.leg)/(r.k.leg+l.k.leg)

uni.leg <- as.data.frame(cbind(RStepL.sp, LStepL.sp, RStepL, LStepL,
StepL.diff, RStrideL, LStrideL, StrideL.diff, r.Fmax, l.Fmax, Fmax.diff,
r.delta.y, l.delta.y, delta.y.diff,
r.k.vert, l.k.vert, k.vert.diff, r.delta.l, l.delta.l,
delta.l.diff, r.k.leg, l.k.leg, k.leg.diff
))
colnames(uni.leg) <- c("Speed.R", "Speed.L", "RStepL", "LStepL",
"StepL.diff", "RStrideL", "LStrideL", "StrideL.diff", "r.Fmax", "l.Fmax",
"Fmax.diff", "r.delta.y",
"l.delta.y", "delta.y.diff", "r.k.vert", "l.k.vert",
"k.vert.diff", "r.delta.l", "l.delta.l", "delta.l.diff",
"r.k.leg", "l.k.leg", "k.leg.diff",
)
bi.leg <- as.data.frame(cbind(Speed.Long, StepL, StrideL, Fmax, delta.y,
k.vert, delta.l, k.leg))
colnames(bi.leg) <- c("Speed", "StepL", "StrideL", "Fmax", "delta.y",
"k.vert", "delta.l", "k.leg")

leg <- list(mean.lengths, uni.leg, bi.leg)
names(leg) <- c("mean.lengths", "uni.leg", "bi.leg")
return(leg)
}

```

### *Accel\_Peaks Function.R*

This function calculated the root mean square (RMS) of each acceleration and angular velocity vector as well as the resultant RMS. Peaks from acceleration vectors were found using the *findpeaks()* function.

```

ACCELERATION VARIABLES
accel_peaks <- function(data, time.vars){

#RMS Acceleration
x <- data$`filtered accel x`
y <- data$`filtered accel y`

```

```

z <- data$`filtered accel z`
IC <- time.vars$uni.step$IC
FC <- time.vars$uni.step$FC

rms.x <- seewave::rms(x)
rms.y <- seewave::rms(y)
rms.z <- seewave::rms(z)

rms.r <- sqrt(rms.x^2 +rms.y^2+rms.z^2)
#RMS Gyroscope

x <- data$`filtered gyro x`
y <- data$`filtered gyro y`
z <- data$`filtered gyro z`
IC <- time.vars$uni.step$IC
FC <- time.vars$uni.step$FC

g.rms.x <- seewave::rms(x)
g.rms.y <- seewave::rms(y)
g.rms.z <- seewave::rms(z)

g.rms.r <- sqrt(g.rms.x^2 +g.rms.y^2+g.rms.z^2)

[#Find the peaks of the accel vector
#R
data$`filtered accel r` <- as.numeric(data$`filtered accel r`)
R.peaks.m <- findpeaks(data$`filtered accel r`, minpeakdistance =25)
R.peaks.m <- as.data.frame(R.peaks.m)
R.peaks.m <- R.peaks.m[order(R.peaks.m$V2),]
R.peaks <- R.peaks.m$V2
R.peak.accel <- data$`filtered accel r`[R.peaks]
AvgRpeak <- mean(R.peak.accel, na.rm = T)

#First, determine which step is first in the vector (right or left) than
#deconstruct vector into left and right components.

RRpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]
R.peak.accel <- R.peak.accel[-1]
LRpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]

AvgRRpeak <- mean(RRpeak, na.rm = T)
AvgLRpeak <- mean(LRpeak, na.rm = T)

#X
data$`filtered accel x` <- as.numeric(data$`filtered accel x`)
X.peaks.m <- findpeaks(data$`filtered accel x`, minpeakdistance =25)
X.peaks.m <- as.data.frame(X.peaks.m)
X.peaks.m <- X.peaks.m[order(X.peaks.m$V2),]
X.peaks <- X.peaks.m$V2
X.peak.accel <- data$`filtered accel x`[X.peaks]
AvgXpeak <- mean(X.peak.accel, na.rm = T)

RXpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]
R.peak.accel <- R.peak.accel[-1]
LXpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]

AvgRXpeak <- mean(RXpeak, na.rm = T)
AvgLXpeak <- mean(LXpeak, na.rm = T)

#Y

```

```

data$`filtered accel y` <- as.numeric(data$`filtered accel y`)
Y.peaks.m <- findpeaks(data$`filtered accel y`, minpeakdistance = 25)
Y.peaks.m <- as.data.frame(Y.peaks.m)
Y.peaks.m <- Y.peaks.m[order(Y.peaks.m$V2),]
Y.peaks <- Y.peaks.m$V2
Y.peak.accel <- data$`filtered accel y`[Y.peaks]
AvgYpeak <- mean(Y.peak.accel, na.rm = T)

 RYpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]
 R.peak.accel <- R.peak.accel[-1]
 LYpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]

AvgRYpeak <- mean(RYpeak, na.rm = T)
AvgLYpeak <- mean(LYpeak, na.rm = T)

#Z
data$`filtered accel z` <- as.numeric(data$`filtered accel z`)
Z.peaks.m <- findpeaks(data$`filtered accel z`, minpeakdistance = 25)
Z.peaks.m <- as.data.frame(Z.peaks.m)
Z.peaks.m <- Z.peaks.m[order(Z.peaks.m$V2),]
Z.peaks <- Z.peaks.m$V2
Z.peak.accel <- data$`filtered accel z`[Z.peaks]
AvgZpeak <- mean(Z.peak.accel, na.rm = T)

 RZpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]
 R.peak.accel <- R.peak.accel[-1]
 LZpeak <- R.peak.accel[seq_along(R.peak.accel) %% 2 > 0]

RXpeak <- RXpeak[1:length(RZpeak)] #makes the vectors the same length
RYpeak <- RYpeak[1:length(RZpeak)]
RZpeak <- RZpeak[1:length(RZpeak)]
RRpeak <- RRpeak[1:length(RZpeak)]
LXpeak <- LXpeak[1:length(RZpeak)]
LYpeak <- LYpeak[1:length(RZpeak)]
LZpeak <- LZpeak[1:length(RZpeak)]
LRpeak <- LRpeak[1:length(RZpeak)]

X.peak.accel <- X.peak.accel[1:length(Z.peak.accel)] #same length
Y.peak.accel <- Y.peak.accel[1:length(Z.peak.accel)]
Z.peak.accel <- Z.peak.accel[1:length(Z.peak.accel)]
R.peak.accel <- R.peak.accel[1:length(Z.peak.accel)]

AvgRZpeak <- mean(RZpeak, na.rm = T)
AvgLZpeak <- mean(LZpeak, na.rm = T)

Rpeak.diff <- 200*(RRpeak - LRpeak)/(RRpeak+LRpeak)
Xpeak.diff <- 200*(RXpeak - LXpeak)/(RXpeak+LXpeak)
Ypeak.diff <- 200*(RYpeak - LYpeak)/(RYpeak+LYpeak)
Zpeak.diff <- 200*(RZpeak - LZpeak)/(RZpeak+LZpeak)

#Create data frame for bilateral variables
bi.accel <- as.data.frame(cbind(R.peak.accel, X.peak.accel, Y.peak.accel,
Z.peak.accel))
colnames(bi.accel) <- c("Rpeak", "Xpeak", "Ypeak", "Zpeak")
#Create data frame for unilateral variables
uni.accel <- as.data.frame(cbind(RRpeak, LRpeak, Rpeak.diff,
RXpeak, LXpeak, Xpeak.diff, RYpeak, LYpeak, Ypeak.diff, RZpeak, LZpeak,
Zpeak.diff))
#Edit column names
colnames(uni.accel) <- c("RRpeak", "LRpeak", "Rpeak.diff",
"RXpeak", "LXpeak", "Xpeak.diff", "RYpeak", "LYpeak", "Ypeak.diff", "RZpeak",
"LZpeak", "Zpeak.diff")
data.rms <- as.data.frame(cbind(rms.x, rms.y, rms.z, rms.r, g.rms.x, g.rms.y,
g.rms.z, g.rms.r))

```

```

names(data.rms) <- c("x.rms.a", "y.rms.a", "z.rms.a", "r.rms.a", "x.rms.g",
"y.rms.g", "z.rms.g", "r.rms.g")
accel <- list(bi.accel, uni.accel, data.rms)
names(accel) <- c("bi.accel", "uni.accel", "RMS")
return(accel)
}

```

#### *DFA\_Function.R*

The DFA function calculated the alpha variable by running a DFA and plotting the resulting log of the window sizes and log of the fluctuations. The slope of the best fit line of the log-log plot was used to extract the alpha variable.

```

DFA #### Sample of code (it's repetitive)
library(ifultools)
library(nonlinearTseries)
library(permute)
DFA_VARS <- function(time.vars, stiff.leg, accel){
Contact Times
CT <- time.vars$bi.step$CT
N4 <- length(CT)
scale <- logScale(scale.min = 4, scale.max = N4/4, scale.ratio = 2^(1/8))
nscale <-length(scale)
ct.dfa <- dfa(CT, window.size.range = c(4, N4/4), npoints=nscale, do.plot= F)
ct.logwin <- log10(windowSizes(ct.dfa)) # define log window sizes
ct.logfluc <- log10(fluctuationFunction(ct.dfa)) # define log fluctuations
ct.fit <- lm(ct.logfluc~ct.logwin) # create the log-log plot
CTa <- ct.fit$coefficients[2] # this gives you the alpha variable
...
return(dfa.alphas)
}

```

#### *auc\_function.R*

Regularity was calculated by an autocorrelation of the acceleration and angular velocity vectors. The *findpeaks()* function was used to find the first and second peak of the autocorrelation function.

```

GAIT REGULARITY
gait_regularity <- function(data){
#create lag function and auc variable
aucx <- ts(data = data$`filtered accel x`, start = 1, frequency = 1)
aucy <- ts(data = data$`filtered accel y`, start = 1, frequency = 1)
aucz <- ts(data = data$`filtered accel z`, start = 1, frequency = 1)

#ACF function
xacf <- acf(aucx, lag.max = (nrow(data)-1), plot = FALSE) #Runs ACF
yacf <- acf(aucy, lag.max = (nrow(data)-1), plot = FALSE)
zacf <- acf(aucz, lag.max = (nrow(data)-1), plot = FALSE)

data$x_acf <- as.vector(xacf$acf) # Gives ACF Coefficients
data$x_lag <- as.vector(xacf$lag)
data$y_acf <- as.vector(yacf$acf)
data$y_lag <- as.vector(yacf$lag)
data$z_acf <- as.vector(zacf$acf)
data$z_lag <- as.vector(zacf$lag)

```

```

#Find Peaks - Looking for first and second peak
xsr <- findpeaks(-data$x_acf, minpeakheight = 0.2, minpeakdistance = 30)
xsr <- as.data.frame(xsr)
xsr <- xsr[order(xsr$V2),]
x.step.reg <- xsr$V2 # First Valley is X.Step.Reg

xdr <- findpeaks(data$x_acf, minpeakheight = 0.4, minpeakdistance = 30)
xdr <- as.data.frame(xdr)
xdr <- xdr[order(xdr$V2),]
x.stride.reg <- xdr$V2 # First peak is X.Stride.Reg

yr <- findpeaks(data$y_acf, minpeakheight = 0.5, minpeakdistance = 30)
yr <- as.data.frame(yr)
yr <- yr[order(yr$V2),]
y.auc.peak <- yr$V2 # first and second peak are step and stride reg

zr <- findpeaks(data$z_acf, minpeakheight = 0.2, minpeakdistance = 30)
zr <- as.data.frame(zr)
zr <- zr[order(zr$V2),]
z.auc.peak <- zr$V2 # first and second peak are step and stride reg

Gyroscopic Autocorrelation
#create lag function and auc variable
auc.gyro.x <- ts(data = data$Gyro.X, start = 1, frequency = 1)
auc.gyro.y <- ts(data = data$Gyro.Y, start = 1, frequency = 1)
auc.gyro.z <- ts(data = data$Gyro.Z, start = 1, frequency = 1)

#ACF function
x.gyro.acf <- acf(auc.gyro.x, lag.max = (nrow(data)-1), plot = FALSE)
y.gyro.acf <- acf(auc.gyro.y, lag.max = (nrow(data)-1), plot = FALSE)
z.gyro.acf <- acf(auc.gyro.z, lag.max = (nrow(data)-1), plot = FALSE)

data$x_gyro_acf <- as.vector(x.gyro.acf$acf)
data$x_gyro_lag <- as.vector(x.gyro.acf$lag)
data$y_gyro_acf <- as.vector(y.gyro.acf$acf)
data$y_gyro_lag <- as.vector(y.gyro.acf$lag)
data$z_gyro_acf <- as.vector(z.gyro.acf$acf)
data$z_gyro_lag <- as.vector(z.gyro.acf$lag)

#Find Peaks
xgr <- findpeaks(data$x_gyro_acf, minpeakheight = 0.3, minpeakdistance = 30)
xgr <- as.data.frame(xgr)
xgr <- xgr[order(xgr$V2),]
x.auc.gyro.peak <- xgr$V2 # first and second peak are step and stride reg

ygpr <- findpeaks(-data$y_gyro_acf, minpeakheight = -0.5, minpeakdistance =
30)
ygpr <- as.data.frame(ygpr)
ygpr <- ygpr[order(ygpr$V2),]
y.gyro.step.reg <- ygpr$V2 # first peak is step reg

ygdr <- findpeaks(data$y_gyro_acf, minpeakheight = 0.5, minpeakdistance = 30)
ygdr <- as.data.frame(ygdr)
ygdr <- ygdr[order(ygdr$V2),]
y.gyro.stride.reg <- ygdr$V2 # first peak is stride reg

zgpr <- findpeaks(-data$z_gyro_acf, minpeakheight = -0.5, minpeakdistance =
30)
zgpr <- as.data.frame(zgpr)

```

```

zgpr <- zgpr[order(zgpr$V2),]
z.gyro.step.reg <- zgpr$V2 # first peak is step reg

zgdr <- findpeaks(data$z_gyro_acf, minpeakheight = 0.5, minpeakdistance = 30)
zgdr <- as.data.frame(zgdr)
zgdr <- zgdr[order(zgdr$V2),]
z.gyro.stride.reg <- zgdr$V2 # first peak is stride reg

#Make sure it all lines up - define index of desired value in vector
x.stp.reg.loc<-x.step.reg[1]
x.std.reg.loc<-x.stride.reg[1]
y.stp.reg.loc<-y.auc.peak[1]
y.std.reg.loc<-y.auc.peak[2]
z.stp.reg.loc<-z.auc.peak[1]
z.std.reg.loc<-z.auc.peak[2]

X.StepReg <- data$x_acf[x.stp.reg.loc] # define regularity values
X.StrideReg <- data$x_acf[x.std.reg.loc]
Y.StepReg <- data$y_acf[y.stp.reg.loc]
Y.StrideReg <- data$y_acf[y.std.reg.loc]
Z.StepReg <- data$z_acf[z.stp.reg.loc]
Z.StrideReg <-data$z_acf[z.std.reg.loc]

x.stp.pk <- x.auc.gyro.peak[1]
x.std.pk <- x.auc.gyro.peak[2]
y.stp.pk <- y.gyro.step.reg[1]
y.std.pk <- y.gyro.stride.reg[1]
z.stp.pk <- z.gyro.step.reg[1]
z.std.pk <- z.gyro.stride.reg[1]

X.GyroStepReg <- data$x_gyro_acf[x.stp.pk]
X.GyroStrideReg <- data$x_gyro_acf[x.std.pk]
Y.GyroStepReg <- data$y_gyro_acf[y.stp.pk]
Y.GyroStrideReg <- data$y_gyro_acf[y.std.pk]
Z.GyroStepReg <- data$z_gyro_acf[z.stp.pk]
Z.GyroStrideReg <-data$z_gyro_acf[z.std.pk]

#compile results
gait_regularity <- as.data.frame(cbind(X.StepReg, X.StrideReg, Y.StepReg,
Y.StrideReg, Z.StepReg, Z.StrideReg, X.GyroStepReg, X.GyroStrideReg,
Y.GyroStepReg, Y.GyroStrideReg,
Z.GyroStepReg, Z.GyroStrideReg))
colnames(gait_regularity) <- c("X.StepReg", "X.StrideReg", "Y.StepReg",
"Y.StrideReg", "Z.StepReg", "Z.StrideReg", "X.GyroStepReg",
"X.GyroStrideReg", "Y.GyroStepReg",
"Y.GyroStrideReg", "Z.GyroStepReg", "Z.GyroStrideReg")
return(gait_regularity)
}

```

### *Database creation.R*

This function synthesized a unilateral (Right and Left) and bilateral data frame with all variables included.

```

Database Creation #### (Sample)
data_log <- function(time.vars, stiff.leg, accel){
UNLIST - unilateral
RFT <- time.vars$uni.step$RFT
LFT <- time.vars$uni.step$LFT
unilateral <- as.data.frame(cbind(RFT,LFT))
#BILATERAL

```

```
FT <- time.vars$bi.step$FT
CT <- time.vars$bi.step$CT
bilateral<- as.data.frame(cbind(FT,CT))
bilateral <- bilateral[c(1:(length(FT)-3)),]
step.vars <- list(unilateral,bilateral)
names(step.vars) <- c("unilateral", "bilateral")
return(step.vars)
}
```

## APPENDIX D Data Tables from Chapter 3

### A. Week 3

#### 1. Spatiotemporal Variables

Week 3 ANOVA Results – Spatiotemporal

|         | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|---------|------------------------|--------------------------|------------------------------|
| Speed   | 0.757 (0.410)          | 0.408 (0.749)            | 0.155 (0.926)                |
| FT      | 0.240 (0.637)          | 12.989 (p<0.001)*        | 0.204 (0.893)                |
| CT      | 2.029 (0.192)          | 0.128 (0.943)            | 2.022 (0.138)                |
| StepT   | 1.031 (0.340)          | 2.911 (0.055)            | 3.009 (0.050)*               |
| StrideT | 1.027 (0.341)          | 3.107 (0.045)*           | 3.133 (0.044)*               |
| StepL   | 0.886 (0.374)          | 134.759 (p<0.001)*       | 1.251 (0.313)                |
| StrideL | 0.264 (0.622)          | 88.984 (p<0.001)*        | 0.899 (0.456)                |

Table D.1 F Statistics and P values for the ANOVA of spatiotemporal variables. Significance is indicated with a \*.

Week 3 Descriptive Statistics – Spatiotemporal

| Group, Response | Pregame 1                    | Postgame 1                   | Pregame 2                   | Postgame 2       |
|-----------------|------------------------------|------------------------------|-----------------------------|------------------|
| <b>START</b>    |                              |                              |                             |                  |
| Speed           | 2.632 (0.098)                | 2.564 (0.216)                | 2.573 (0.187)               | 2.559 (0.148)    |
| FT              | 91.055 (3.136) <sup>d</sup>  | 91.216 (3.258) <sup>f</sup>  | 93.634 (4.581)              | 95.425 (4.063)   |
| CT              | 247.657 (12.330)             | 247.458 (14.129)             | 250.376 (14.039)            | 247.491 (14.450) |
| StepT           | 338.712 (14.694)             | 338.674 (17.154)             | 344.010 (17.210)            | 342.916 (17.744) |
| StrideT         | 677.284 (29.382)             | 677.081 (34.334)             | 687.917 (34.348)            | 685.929 (35.527) |
| StepL           | 0.963 (0.048) <sup>c,d</sup> | 0.953 (0.045) <sup>e,f</sup> | 0.894 (0.047)               | 0.850 (0.054)    |
| StrideL         | 1.927 (0.096) <sup>c,d</sup> | 1.906 (0.091) <sup>e,f</sup> | 1.788 (0.095)               | 1.700 (0.107)    |
| <b>RES</b>      |                              |                              |                             |                  |
| Speed           | 2.673 (0.315)                | 2.549 (0.131)                | 2.653 (0.224)               | 2.652 (0.121)    |
| FT              | 90.126 (3.690)               | 90.318 (2.771)               | 91.682 (5.149) <sup>g</sup> | 94.430 (5.639)   |
| CT              | 259.969 (6.650)              | 259.07 (9.503)               | 256.032 (7.650)             | 258.318 (10.993) |
| StepT           | 350.096 (9.096)              | 349.345 (11.672)             | 347.714 (9.794)             | 352.748 (12.698) |
| StrideT         | 700.190 (18.148)             | 698.451 (23.151)             | 695.216 (19.437)            | 705.401 (25.661) |
| StepL           | 0.987 (0.013) <sup>c,d</sup> | 0.952 (0.024) <sup>f</sup>   | 0.910 (0.043) <sup>g</sup>  | 0.858 (0.006)    |
| StrideL         | 1.974 (0.026) <sup>d</sup>   | 1.902 (0.047) <sup>f</sup>   | 1.820 (0.086)               | 1.716 (0.012)    |

Table D.2 Means and standard deviations of spatiotemporal variables during Week 3. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Pregame 2; d – difference in Pregame 1 to Postgame 2; e – difference in Postgame 1 to Pregame 2; f – difference in Postgame 1 to Postgame 2; g – difference in Pregame 2 to Postgame 2

## 2. Spring Mass Variables

Week 3 ANOVA Results – Spring Mass

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| $F_{\max}$        | 0.009 (0.928)          | 6.440 (0.016)*           | 0.168 (0.799)                |
| $\Delta y$        | 1.956 (0.200)          | 0.039 (0.990)            | 1.922 (0.153)                |
| $k_{\text{vert}}$ | 1.645 (0.236)          | 1.028 (0.398)            | 1.380 (0.273)                |
| $\Delta l$        | 1.461 (0.261)          | 44.152 (p<0.001)*        | 1.162 (0.345)                |
| $k_{\text{leg}}$  | 0.756 (0.410)          | 37.464 (p<0.001)*        | 0.497 (0.688)                |

Table D.3 F Statistics and P value for the ANOVA of spring mass variables. Significance is indicated with a \*.

Week 3 Descriptive Statistics – Spring Mass

| Group, Response   | Pregame 1                    | Postgame 1                 | Pregame 2                  | Postgame 2     |
|-------------------|------------------------------|----------------------------|----------------------------|----------------|
| <b>START</b>      |                              |                            |                            |                |
| $F_{\max}$        | 1.274 (0.143)                | 1.275 (0.146)              | 1.282 (0.154)              | 1.289 (0.149)  |
| $\Delta y$        | 0.088 (0.009)                | 0.088 (0.010)              | 0.090 (0.010)              | 0.088 (0.010)  |
| $k_{\text{vert}}$ | 14.697 (1.367)               | 14.682 (1.396)             | 14.535 (1.825)             | 14.772 (1.328) |
| $\Delta l$        | 0.163 (0.014) <sup>d</sup>   | 0.161 (0.016) <sup>f</sup> | 0.154 (0.016) <sup>g</sup> | 0.145 (0.016)  |
| $k_{\text{leg}}$  | 8.013 (0.816) <sup>d</sup>   | 8.083 (0.942) <sup>f</sup> | 8.595 (1.145)              | 9.103 (1.073)  |
| <b>RES</b>        |                              |                            |                            |                |
| $F_{\max}$        | 1.279 (0.106)                | 1.281 (0.104)              | 1.291 (0.114)              | 1.299 (0.114)  |
| $\Delta y$        | 0.097 (0.005)                | 0.096 (0.007)              | 0.094 (0.006)              | 0.096 (0.009)  |
| $k_{\text{vert}}$ | 13.309 (0.800)               | 13.478 (1.042)             | 13.871 (1.370)             | 13.861 (1.339) |
| $\Delta l$        | 0.176 (0.006) <sup>c,d</sup> | 0.170 (0.011)              | 0.160 (0.013)              | 0.154 (0.010)  |
| $k_{\text{leg}}$  | 7.344 (0.648) <sup>d</sup>   | 7.672 (0.722)              | 8.184 (0.889)              | 8.654 (0.975)  |

Table D.4 Means and standard deviations of spring mass variables during Week 3. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Pregame 2; d – difference in Pregame 1 to Postgame 2; e – difference in Postgame 1 to Pregame 2; f – difference in Postgame 1 to Postgame 2; g – difference in Pregame 2 to Postgame 2

### 3. Postural

Week 3 ANOVA Results – Postural

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| X.Step.Reg        | 0.276 (0.614)          | 0.635 (0.600)            | 1.029 (0.397)                |
| X.Stride.Reg      | 0.024 (0.881)          | 0.899 (0.456)            | 0.751 (0.532)                |
| Y.Step.Reg        | 1.982 (0.197)          | 0.438 (0.728)            | 1.560 (0.225)                |
| Y.Stride.Reg      | 0.085 (0.778)          | 0.815 (0.498)            | 1.134 (0.355)                |
| Z.Step.Reg        | 1.318 (0.284)          | 0.349 (0.790)            | 0.059 (0.981)                |
| Z.Stride.Reg      | 0.403 (0.543)          | 0.977 (0.420)            | 1.158 (0.346)                |
| X.Gyro.Step.Reg   | 0.347 (0.572)          | 2.676 (0.070)            | 0.377 (0.771)                |
| X.Gyro.Stride.Reg | 0.163 (0.697)          | 1.791 (0.176)            | 0.883 (0.464)                |
| Y.Gyro.Step.Reg   | 0.543 (0.482)          | 1.363 (0.278)            | 0.745 (0.536)                |
| Y.Gyro.Stride.Reg | 0.009 (0.925)          | 1.427 (0.259)            | 0.255 (0.857)                |
| Z.Gyro.Step.Reg   | 0.371 (0.559)          | 1.935 (0.151)            | 1.801 (0.174)                |
| Z.Gyro.Stride.Reg | 0.002 (0.967)          | 2.448 (0.088)            | 0.570 (0.640)                |
| X.Accel.RMS       | 0.004 (0.948)          | 0.096 (0.962)            | 0.415 (0.744)                |
| Y.Accel.RMS       | 1.792 (0.218)          | 0.643 (0.595)            | 0.141 (0.934)                |
| R.Accel.RMS       | 0.004 (0.948)          | 0.096 (0.962)            | 0.415 (0.744)                |
| X.Gyro.RMS        | 0.025 (0.877)          | 0.548 (0.654)            | 1.009 (0.406)                |
| Y.Gyro.RMS        | 0.005 (0.943)          | 1.811 (0.172)            | 0.374 (0.772)                |
| Z.Gyro.RMS        | 1.741 (0.224)          | 1.822 (0.170)            | 0.932 (0.440)                |
| R.Gyro.RMS        | 0.132 (0.726)          | 1.054 (0.387)            | 0.831 (0.490)                |

Table D.5 F Statistics and P value for the ANOVA of postural variables. Significance is indicated with a \*.

Week 3 Descriptive Statistics – Postural

| Group, Response   | Pregame 1        | Postgame 1       | Pregame 2        | Postgame 2       |
|-------------------|------------------|------------------|------------------|------------------|
| <b>START</b>      |                  |                  |                  |                  |
| X.Step.Reg        | -0.467 (0.033)   | -0.378 (0.019)   | -0.438 (0.019)   | -0.398 (0.010)   |
| X.Stride.Reg      | 0.761 (0.004)    | 0.767 (0.001)    | 0.742 (0.002)    | 0.751 (0.001)    |
| Y.Step.Reg        | 0.817 (0.002)    | 0.822 (0.001)    | 0.800 (0.008)    | 0.826 (0.001)    |
| Y.Stride.Reg      | 0.839 (0.004)    | 0.841 (0.002)    | 0.829 (0.002)    | 0.839 (0.001)    |
| Z.Step.Reg        | 0.748 (0.010)    | 0.730 (0.018)    | 0.715 (0.010)    | 0.735 (0.006)    |
| Z.Stride.Reg      | 0.785 (0.010)    | 0.792 (0.012)    | 0.747 (0.010)    | 0.789 (0.002)    |
| X.Gyro.Step.Reg   | 0.728 (0.028)    | 0.703 (0.008)    | 0.652 (0.028)    | 0.590 (0.025)    |
| X.Gyro.Stride.Reg | 0.769 (0.044)    | 0.778 (0.017)    | 0.714 (0.0236)   | 0.704 (0.018)    |
| Y.Gyro.Step.Reg   | -0.925 (0.001)   | -0.910 (0.003)   | -0.842 (0.028)   | -0.900 (0.005)   |
| Y.Gyro.Stride.Reg | 0.940 (0.0002)   | 0.921 (0.003)    | 0.889 (0.009)    | 0.920 (0.001)    |
| Z.Gyro.Step.Reg   | -0.935 (0.000)   | -0.929 (0.0005)  | -0.926 (0.002)   | -0.927 (0.0004)  |
| Z.Gyro.Stride.Reg | 0.944 (0.0004)   | 0.938 (0.0004)   | 0.934 (0.0002)   | 0.930 (0.0002)   |
| X.Accel.RMS       | 4.471 (0.577)    | 4.552 (0.555)    | 4.448 (0.575)    | 4.166 (0.188)    |
| Y.Accel.RMS       | 9.283 (0.865)    | 9.350 (0.648)    | 9.236 (0.477)    | 9.146 (1.569)    |
| R.Accel.RMS       | 11.268 (0.994)   | 11.380 (0.969)   | 11.224 (0.247)   | 10.909 (1.125)   |
| X.Gyro.RMS        | 78.783 (14.320)  | 67.691 (18.863)  | 69.025 (11.759)  | 57.613 (17.645)  |
| Y.Gyro.RMS        | 117.354 (15.375) | 113.010 (13.494) | 116.061 (15.001) | 103.183 (13.574) |
| Z.Gyro.RMS        | 76.458 (5.814)   | 73.273 (5.424)   | 74.907 (5.547)   | 67.454 (3.544)   |
| R.Gyro.RMS        | 161.010 (11.061) | 151.971 (10.062) | 154.635 (17.646) | 137.461 (5.823)  |
| <b>RES</b>        |                  |                  |                  |                  |
| X.Step.Reg        | -0.461 (0.034)   | -0.526 (0.028)   | -0.469 (0.051)   | -0.408 (0.028)   |
| X.Stride.Reg      | 0.747 (0.011)    | 0.765 (0.001)    | 0.765 (0.003)    | 0.722 (0.005)    |
| Y.Step.Reg        | 0.847 (0.003)    | 0.869 (0.002)    | 0.869 (0.001)    | 0.836 (0.003)    |
| Y.Stride.Reg      | 0.841 (0.005)    | 0.863 (0.003)    | 0.857 (0.001)    | 0.825 (0.004)    |
| Z.Step.Reg        | 0.734 (0.014)    | 0.716 (0.022)    | 0.693 (0.036)    | 0.650 (0.030)    |
| Z.Stride.Reg      | 0.796 (0.007)    | 0.764 (0.022)    | 0.752 (0.023)    | 0.664 (0.025)    |
| X.Gyro.Step.Reg   | 0.803 (0.001)    | 0.674 (0.028)    | 0.721 (0.029)    | 0.629 (0.029)    |
| X.Gyro.Stride.Reg | 0.846 (0.001)    | 0.739 (0.036)    | 0.798 (0.007)    | 0.701 (0.018)    |
| Y.Gyro.Step.Reg   | -0.935 (0.001)   | -0.927 (0.001)   | -0.689 (0.296)   | -0.645 (0.352)   |
| Y.Gyro.Stride.Reg | 0.953 (0.0001)   | 0.938 (0.001)    | 0.879 (0.024)    | 0.887 (0.015)    |
| Z.Gyro.Step.Reg   | -0.906 (0.010)   | -0.916 (0.006)   | -0.915 (0.006)   | -0.885 (0.010)   |
| Z.Gyro.Stride.Reg | 0.954 (0.000)    | 0.949 (0.0001)   | 0.928 (0.002)    | 0.918 (0.003)    |
| X.Accel.RMS       | 4.360 (0.167)    | 4.326 (0.194)    | 4.388 (0.954)    | 4.468 (1.176)    |
| Y.Accel.RMS       | 10.292 (0.385)   | 10.241 (1.330)   | 10.015 (1.489)   | 9.849 (3.118)    |
| R.Accel.RMS       | 12.013 (0.269)   | 11.957 (0.894)   | 11.808 (2.621)   | 11.747 (4.144)   |
| X.Gyro.RMS        | 65.329 (5.779)   | 60.767 (8.165)   | 71.055 (33.487)  | 70.028 (37.047)  |
| Y.Gyro.RMS        | 111.666 (12.071) | 110.921 (13.854) | 116.632 (27.261) | 107.744 (20.867) |
| Z.Gyro.RMS        | 68.118 (10.972)  | 69.611 (14.317)  | 66.028 (4.356)   | 65.850 (10.760)  |
| R.Gyro.RMS        | 146.693 (11.061) | 145.173 (13.106) | 153.286 (35.734) | 146.782 (32.462) |

Table D.6 Means and standard deviations of postural variables during Week 3. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Pregame 2; d – difference in Pregame 1 to Postgame 2; e – difference in Postgame 1 to Pregame 2; f – difference in Postgame 1 to Postgame 2; g – difference in Pregame 2 to Postgame 2

#### 4. Alpha Variables

Week 3 ANOVA Results – DFA

|                  | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------------|------------------------|--------------------------|------------------------------|
| StepT $\alpha$   | 0.001 (0.973)          | 1.063 (0.369)            | 1.517 (0.249)                |
| StrideT $\alpha$ | 0.563 (0.474)          | 1.927 (0.178)            | 1.070 (0.366)                |
| StepL $\alpha$   | 4.581 (0.065)          | 3.671 (0.049)*           | 0.201 (0.820)                |
| StrideL $\alpha$ | 5.399 (0.049)*         | 5.880 (0.012)*           | 0.076 (0.928)                |

Table D.7 F Statistics and P value for the ANOVA of fractal variables. Significance is indicated with a \*.

Week 3 Descriptive Statistics – DFA

| Group, Response  | Pregame 1       | Postgame 1      | Pregame 2       | Postgame 2      |
|------------------|-----------------|-----------------|-----------------|-----------------|
| <b>START</b>     |                 |                 |                 |                 |
| StepT $\alpha$   | 0.545 (0.00567) | 0.506 (0.0178)  | 0.519 (0.0251)  | 0.573 (0.00186) |
| StrideT $\alpha$ | 0.744 (0.0145)  | 0.716 (0.0239)  | 0.750 (0.0215)  | 0.760 (0.00640) |
| StepL $\alpha$   | 0.954 (0.00558) | 0.916 (0.00613) | 0.886 (0.00705) | 0.977 (0.00203) |
| StrideL $\alpha$ | 1.04 (0.00566)  | 1.01 (0.00821)  | 1.00 (0.00660)  | 1.04 (0.00145)  |
| <b>RES</b>       |                 |                 |                 |                 |
| StepT $\alpha$   | 0.694 (0.0145)  | 0.574 (0.0248)  | 0.621 (0.0373)  | 0.655 (0.0173)  |
| StrideT $\alpha$ | 0.886 (0.0216)  | 0.765 (0.0267)  | 0.817 (0.0387)  | 0.821 (0.00653) |
| StepL $\alpha$   | 0.907 (0.0129)  | 1.01 (0.00136)  | 0.961 (0.0247)  | 1.09 (0.00643)  |
| StrideL $\alpha$ | 0.966 (0.0182)  | 1.12 (0.00129)  | 1.06 (0.0164)   | 1.13 (0.00269)  |

Table D.8 Means and standard deviations of fractal variables during Week 3. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Pregame 2; d – difference in Pregame 1 to Postgame 2; e – difference in Postgame 1 to Pregame 2; f – difference in Postgame 1 to Postgame 2; g – difference in Pregame 2 to Postgame 2

#### B. Week 4

##### 1. Spatiotemporal Variables

Week 4 ANOVA Results – Spatiotemporal

|         | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|---------|------------------------|--------------------------|------------------------------|
| Speed   | 0.083 (0.779)          | 31.761 (p<0.001)*        | 0.712 (0.419)                |
| FT      | 0.005 (0.947)          | 1.957 (0.192)            | 0.000162 (0.990)             |
| CT      | 0.564 (0.470)          | 2.907 (0.119)            | 0.105 (0.753)                |
| StepT   | 0.516 (0.489)          | 15.239 (0.003)*          | 0.239 (0.635)                |
| StrideT | 0.502 (0.495)          | 15.946 (0.003)*          | 0.328 (0.580)                |
| StepL   | 0.560 (0.472)          | 18.016 (0.002)*          | 1.025 (0.335)                |
| StrideL | 0.548 (0.476)          | 17.176 (0.002)*          | 1.068 (0.326)                |

Table D.9 F Statistics and P value for the ANOVA of spatiotemporal variables. Significance is indicated with a \*.

Week 4 Descriptive Statistics – Spatiotemporal

| Group, Response | Pregame 1                     | Postgame 2       |
|-----------------|-------------------------------|------------------|
| <b>START</b>    |                               |                  |
| Speed (m/s)     | 2.533 (0.054) <sup>b</sup>    | 2.397 (0.092)    |
| FT (ms)         | 95.631 (5.386)                | 96.829 (6.852)   |
| CT (ms)         | 254.996 (9.841)               | 256.758 (8.096)  |
| StepT (ms)      | 350.627 (10.356)              | 353.587 (7.100)  |
| StrideT (ms)    | 700.967 (20.766)              | 706.920 (14.184) |
| StepL (m)       | 0.887 (0.023) <sup>b</sup>    | 0.847 (0.027)    |
| StrideL (m)     | 1.774 (0.045) <sup>b</sup>    | 1.694 (0.054)    |
| <b>RES</b>      |                               |                  |
| Speed (m/s)     | 2.506 (0.071) <sup>b</sup>    | 2.405 (0.054)    |
| FT (ms)         | 95.392 (4.659)                | 96.611 (6.615)   |
| CT (ms)         | 251.003 (8.507)               | 253.591 (7.568)  |
| StepT (ms)      | 346.395 (10.567) <sup>b</sup> | 350.202 (8.764)  |
| StrideT (ms)    | 692.464 (21.086) <sup>b</sup> | 700.410 (17.488) |
| StepL (m)       | 0.868 (0.037)                 | 0.843 (0.033)    |
| StrideL (m)     | 1.735 (0.074)                 | 1.687 (0.067)    |

Table D.10 Means and standard deviations of spatiotemporal variables during Week 3. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

2. Spring Mass Variables

Week 4 ANOVA Results – Spring Mass

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| $F_{\max}$        | 0.540 (0.479)          | 0.116 (0.741)            | 0.011 (0.917)                |
| $\Delta y$        | 0.574 (0.466)          | 2.894 (0.120)            | 0.154 (0.703)                |
| $k_{\text{vert}}$ | 1.528 (0.245)          | 1.484 (0.251)            | 0.001 (0.974)                |
| $\Delta l$        | 0.817 (0.387)          | 2.800 (0.125)            | 0.699 (0.423)                |
| $k_{\text{leg}}$  | 1.557 (0.241)          | 1.270 (0.286)            | 0.063 (0.808)                |

Table D.11 F Statistics and P value for the ANOVA of spring mass variables. Significance is indicated with a \*.

Week 4 Descriptive Statistics – Spring Mass

| Group, Response   | Pregame 1      | Postgame 2     |
|-------------------|----------------|----------------|
| <b>START</b>      |                |                |
| $F_{\max}$        | 1.291 (0.126)  | 1.292 (0.126)  |
| $\Delta y$        | 0.094 (0.007)  | 0.095 (0.006)  |
| $k_{\text{vert}}$ | 14.056 (1.160) | 13.800 (1.142) |
| $\Delta l$        | 0.156 (0.009)  | 0.151 (0.009)  |
| $k_{\text{leg}}$  | 8.485 (0.774)  | 8.702 (0.870)  |
| <b>RES</b>        |                |                |
| $F_{\max}$        | 1.345 (0.127)  | 1.348 (0.139)  |
| $\Delta y$        | 0.091 (0.006)  | 0.093 (0.005)  |
| $k_{\text{vert}}$ | 15.119 (1.649) | 14.877 (2.030) |
| $\Delta l$        | 0.150 (0.012)  | 0.148 (0.008)  |
| $k_{\text{leg}}$  | 9.227 (1.131)  | 9.365 (1.209)  |

Table D.12 Means and standard deviations of spring mass variables during Week 4. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

3. Postural Variables

Week 4 ANOVA Results – Postural

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| X.Step.Reg        | 0.001 (0.975)          | 6.377 (0.030)*           | 2.487 (0.146)                |
| X.Stride.Reg      | 1.704 (0.221)          | 3.359 (0.097)            | 1.080 (0.323)                |
| Y.Step.Reg        | 0.231 (0.641)          | 2.779 (0.126)            | 1.880 (0.200)                |
| Y.Stride.Reg      | 0.278 (0.609)          | 2.778 (0.127)            | 0.906 (0.364)                |
| Z.Step.Reg        | 1.128 (0.313)          | 0.524 (0.486)            | 7.229 (0.023)*               |
| Z.Stride.Reg      | 0.084 (0.778)          | 1.315 (0.278)            | 3.630 (0.086)                |
| X.Gyro.Step.Reg   | 1.446 (0.257)          | 13.264 (0.005)*          | 2.634 (0.136)                |
| X.Gyro.Stride.Reg | 0.531 (0.483)          | 8.358 (0.016)*           | 4.868 (0.052)                |
| Y.Gyro.Step.Reg   | 0.733 (0.412)          | 0.279 (0.609)            | 3.327 (0.098)                |
| Y.Gyro.Stride.Reg | 0.544 (0.478)          | 0.740 (0.410)            | 5.904 (0.035)*               |
| Z.Gyro.Step.Reg   | 1.564 (0.240)          | 0.198 (0.666)            | 0.689 (0.426)                |
| Z.Gyro.Stride.Reg | 1.077 (0.324)          | 0.750 (0.407)            | 0.535 (0.481)                |
| X.Accel.RMS       | 0.324 (0.582)          | 4.220 (0.067)            | 2.797 (0.125)                |
| Y.Accel.RMS       | 0.888 (0.368)          | 5.576 (0.040)*           | 1.358 (0.271)                |
| Z.Accel.RMS       | 0.005 (0.947)          | 0.815 (0.388)            | 2.965 (0.116)                |
| R.Accel.RMS       | 0.577 (0.465)          | 4.567 (0.058)            | 2.743 (0.129)                |
| X.Gyro.RMS        | 1.254 (0.289)          | 0.086 (0.775)            | 1.200 (0.299)                |
| Y.Gyro.RMS        | 0.016 (0.902)          | 8.724 (0.014)*           | 1.408 (0.263)                |
| Z.Gyro.RMS        | 2.301 (0.160)          | 0.301 (0.595)            | 0.307 (0.592)                |
| R.Gyro.RMS        | 0.090 (0.770)          | 3.073 (0.110)            | 1.235 (0.292)                |

Table D.13 F Statistics and P value for the ANOVA of postural variables. Significance is indicated with a \*.

Week 4 Descriptive Statistics – Postural

| Group, Response   | Pregame 1                    | Postgame 2       |
|-------------------|------------------------------|------------------|
| <b>START</b>      |                              |                  |
| X.Step.Reg        | -0.416 (0.234)               | -0.539 (0.158)   |
| X.Stride.Reg      | 0.744 (0.059)                | 0.782 (0.048)    |
| Y.Step.Reg        | 0.787 (0.109)                | 0.836 (0.062)    |
| Y.Stride.Reg      | 0.820 (0.057)                | 0.855 (0.045)    |
| Z.Step.Reg        | 0.661 (0.132)                | 0.748 (0.145)    |
| Z.Stride.Reg      | 0.677 (0.116)                | 0.767 (0.176)    |
| X.Gyro.Step.Reg   | 0.500 (0.140) <sup>b</sup>   | 0.624 (0.166)    |
| X.Gyro.Stride.Reg | 0.590 (0.160) <sup>b</sup>   | 0.737 (0.150)    |
| Y.Gyro.Step.Reg   | -0.838 (0.140)               | -0.924 (0.036)   |
| Y.Gyro.Stride.Reg | 0.884 (0.074)                | 0.936 (0.021)    |
| Z.Gyro.Step.Reg   | -0.918 (0.025)               | -0.924 (0.034)   |
| Z.Gyro.Stride.Reg | 0.928 (0.020)                | 0.941 (0.021)    |
| X.Accel.RMS       | 4.579 (0.556)                | 4.012 (0.686)    |
| Y.Accel.RMS       | 9.413 (0.958) <sup>b</sup>   | 8.956 (1.074)    |
| R.Accel.RMS       | 11.450 (0.917)               | 10.632 (1.154)   |
| X.Gyro.RMS        | 74.402 (15.474)              | 55.777 (16.633)  |
| Y.Gyro.RMS        | 119.902 (9.419) <sup>b</sup> | 106.945 (12.747) |
| Z.Gyro.RMS        | 73.781 (6.604)               | 70.495 (8.490)   |
| R.Gyro.RMS        | 154.864 (13.368)             | 140.815 (11.751) |
| <b>RES</b>        |                              |                  |
| X.Step.Reg        | -0.460 (0.177)               | -0.488 (0.166)   |
| X.Stride.Reg      | 0.724 (0.048)                | 0.735 (0.046)    |
| Y.Step.Reg        | 0.829 (0.057)                | 0.833 (0.059)    |
| Y.Stride.Reg      | 0.814 (0.082)                | 0.824 (0.071)    |
| Z.Step.Reg        | 0.635 (0.166)                | 0.585 (0.190)    |
| Z.Stride.Reg      | 0.711 (0.119)                | 0.689 (0.133)    |
| X.Gyro.Step.Reg   | 0.638 (0.160)                | 0.685 (0.129)    |
| X.Gyro.Stride.Reg | 0.709 (0.130)                | 0.729 (0.115)    |
| Y.Gyro.Step.Reg   | -0.835 (0.194)               | -0.679 (0.494)   |
| Y.Gyro.Stride.Reg | 0.884 (0.126)                | 0.859 (0.122)    |
| Z.Gyro.Step.Reg   | -0.876 (0.188)               | -0.856 (0.104)   |
| Z.Gyro.Stride.Reg | 0.909 (0.071)                | 0.910 (0.046)    |
| X.Accel.RMS       | 4.592 (1.048)                | 4.534 (1.026)    |
| Y.Accel.RMS       | 9.943 (1.684)                | 9.788 (1.247)    |
| R.Accel.RMS       | 11.763 (2.199)               | 11.659 (1.693)   |
| X.Gyro.RMS        | 74.402 (38.930)              | 78.727 (33.133)  |
| Y.Gyro.RMS        | 114.758 (28.073)             | 109.228 (24.825) |
| Z.Gyro.RMS        | 65.500 (11.348)              | 65.515 (9.557)   |
| R.Gyro.RMS        | 154.099 (39.130)             | 150.951 (36.973) |

Table D.14 Means and standard deviations of postural variables during Week 4. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES, b – difference in Pregame 1 to Postgame 2

#### 4. DFA Variables

Week 4 ANOVA Results – DFA

|                  | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------------|------------------------|--------------------------|------------------------------|
| StepT $\alpha$   | 0.024 (0.881)          | 0.031 (0.863)            | 1.976 (0.190)                |
| StrideT $\alpha$ | 0.216 (0.652)          | 0.000269 (0.987)         | 0.862 (0.375)                |
| StepL $\alpha$   | 0.049 (0.829)          | 2.710 (0.131)            | 0.420 (0.532)                |
| StrideL $\alpha$ | 0.019 (0.893)          | 2.075 (0.180)            | 1.316 (0.278)                |

Table D.15 F Statistics and P value for the ANOVA of fractal variables. Significance is indicated with a \*.

Week 4 Descriptive Statistics – DFA

| Group, Response  | Pregame 1     | Postgame 2    |
|------------------|---------------|---------------|
| <b>START</b>     |               |               |
| StepT $\alpha$   | 0.556 (0.209) | 0.628 (0.071) |
| StrideT $\alpha$ | 0.797 (0.162) | 0.843 (0.055) |
| StepL $\alpha$   | 0.927 (0.181) | 0.968 (0.094) |
| StrideL $\alpha$ | 1.035 (0.145) | 1.047 (0.058) |
| <b>RES</b>       |               |               |
| StepT $\alpha$   | 0.625 (0.161) | 0.533 (0.299) |
| StrideT $\alpha$ | 0.814 (0.154) | 0.769 (0.149) |
| StepL $\alpha$   | 0.915 (0.148) | 1.009 (0.070) |
| StrideL $\alpha$ | 0.994 (0.115) | 1.099 (0.046) |

Table D.16 Means and standard deviations of fractal variables during Week 4. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

### C. Week 5

#### 1. Spatiotemporal Variables

Week 5 ANOVA Results – Spatiotemporal

|         | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|---------|------------------------|--------------------------|------------------------------|
| Speed   | 0.286 (0.605)          | 1.167 (0.305)            | 0.861 (0.375)                |
| FT      | 1.529 (0.245)          | 2.843 (0.123)            | 2.671 (0.133)                |
| CT      | 2.186 (0.170)          | 0.000853 (0.977)         | 0.413 (0.535)                |
| StepT   | 0.867 (0.374)          | 0.813 (0.388)            | 0.039 (0.848)                |
| StrideT | 0.865 (0.374)          | 0.841 (0.381)            | 0.055 (0.820)                |
| StepL   | 0.144 (0.712)          | 3.322 (0.098)            | 0.990 (0.343)                |
| StrideL | 0.146 (0.711)          | 3.486 (0.091)            | 0.991 (0.343)                |

Table D.17 F Statistics and P value for the ANOVA of spatiotemporal variables. Significance is indicated with a \*.

Week 5 Descriptive Statistics – Spatiotemporal

| Group, Response | Pregame 1        | Postgame 2       |
|-----------------|------------------|------------------|
| <b>START</b>    |                  |                  |
| Speed (m/s)     | 2.533 (0.054)    | 2.397 (0.092)    |
| FT (ms)         | 95.631 (5.386)   | 96.829 (6.852)   |
| CT (ms)         | 254.996 (9.841)  | 256.758 (8.096)  |
| StepT (ms)      | 350.627 (10.356) | 353.587 (7.100)  |
| StrideT (ms)    | 700.967 (20.766) | 706.920 (4.184)  |
| StepL (m)       | 0.887 (0.023)    | 0.847 (0.027)    |
| StrideL (m)     | 1.774 (0.045)    | 1.694 (0.054)    |
| <b>RES</b>      |                  |                  |
| Speed (m/s)     | 2.506 (0.071)    | 2.405 (0.054)    |
| FT (ms)         | 95.392 (4.659)   | 96.611 (6.615)   |
| CT (ms)         | 251.003 (8.507)  | 253.591 (7.568)  |
| StepT (ms)      | 346.395 (10.567) | 350.202 (8.764)  |
| StrideT (ms)    | 692.464 (21.086) | 700.410 (17.488) |
| StepL (m)       | 0.868 (0.037)    | 0.843 (0.033)    |
| StrideL (m)     | 1.735 (0.074)    | 1.687 (0.067)    |

Table D.18 Means and standard deviations of spatiotemporal variables during Week 5. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

2. Spring Mass Variables

Week 5 ANOVA Results – Spring Mass

|            | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------|------------------------|--------------------------|------------------------------|
| $F_{max}$  | 1.978 (0.190)          | 1.507 (0.248)            | 2.059 (0.182)                |
| $\Delta y$ | 2.098 (0.178)          | 0.012 (0.916)            | 0.408 (0.537)                |
| $k_{vert}$ | 0.278 (0.6090)         | 0.098 (0.761)            | 0.648 (0.440)                |
| $\Delta l$ | 0.982 (0.345)          | 0.712 (0.419)            | 2.049 (0.183)                |
| $k_{leg}$  | 0.034 (0.857)          | 0.091 (0.769)            | 2.069 (0.1810)               |

Table D.19 F Statistics and P value for the ANOVA of spring mass variables. Significance is indicated with a \*.

Week 5 Descriptive Statistics – Spring Mass

| Group, Response   | Pregame 1      | Postgame 2     |
|-------------------|----------------|----------------|
| <b>START</b>      |                |                |
| $F_{\max}$        | 1.291 (0.126)  | 1.292 (0.126)  |
| $\Delta y$        | 0.094 (0.007)  | 0.095 (0.006)  |
| $k_{\text{vert}}$ | 14.056 (1.160) | 13.800 (1.142) |
| $\Delta l$        | 0.156 (0.009)  | 0.151 (0.009)  |
| $k_{\text{leg}}$  | 8.485 (0.774)  | 8.702 (0.870)  |
| <b>RES</b>        |                |                |
| $F_{\max}$        | 1.345 (0.127)  | 1.348 (0.139)  |
| $\Delta y$        | 0.091 (0.006)  | 0.093 (0.006)  |
| $k_{\text{vert}}$ | 15.119 (1.649) | 14.877 (2.030) |
| $\Delta l$        | 0.150 (0.012)  | 0.148 (0.008)  |
| $k_{\text{leg}}$  | 9.227 (1.131)  | 9.365 (1.209)  |

Table D.20 Means and standard deviations of spring mass variables during Week 5. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

3. Postural Variables

Week 5 ANOVA Results – Postural

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| X.Step.Reg        | 0.013 (0.910)          | 3.353 (0.097)            | 0.327 (0.580)                |
| X.Stride.Reg      | 0.149 (0.708)          | 0.020 (0.890)            | 0.528 (0.484)                |
| Y.Step.Reg        | 0.102 (0.756)          | 0.600 (0.457)            | 0.395 (0.544)                |
| Y.Stride.Reg      | 0.004 (0.952)          | 0.028 (0.870)            | 0.201 (0.664)                |
| Z.Step.Reg        | 0.998 (0.341)          | 0.176 (0.684)            | 2.569 (0.140)                |
| Z.Stride.Reg      | 0.042 (0.841)          | 3.678 (0.084)            | 0.088 (0.772)                |
| X.Gyro.Step.Reg   | 0.297 (0.598)          | 2.638 (0.135)            | 1.454 (0.256)                |
| X.Gyro.Stride.Reg | 0.030 (0.865)          | 4.599 (0.058)            | 0.364 (0.560)                |
| Y.Gyro.Step.Reg   | 0.030 (0.867)          | 2.365 (0.155)            | 2.403 (0.152)                |
| Y.Gyro.Stride.Reg | 0.032 (0.863)          | 1.760 (0.214)            | 5.420 (0.042)*               |
| Z.Gyro.Step.Reg   | 0.470 (0.509)          | 1.158 (0.307)            | 1.383 (0.267)                |
| Z.Gyro.Stride.Reg | 0.000154 (0.990)       | 0.179 (0.682)            | 2.490 (0.146)                |
| X.Accel.RMS       | 0.811 (0.389)          | 3.724 (0.082)            | 0.123 (0.734)                |
| Y.Accel.RMS       | 0.197 (0.666)          | 5.033 (0.049)*           | 0.841 (0.381)                |
| R.Accel.RMS       | 0.018 (0.896)          | 5.405 (0.042)*           | 0.105 (0.752)                |
| X.Gyro.RMS        | 0.819 (0.387)          | 3.177 (0.105)            | 1.630 (0.231)                |
| Y.Gyro.RMS        | 0.660 (0.435)          | 1.765 (0.214)            | 0.492 (0.499)                |
| Z.Gyro.RMS        | 0.748 (0.407)          | 1.122 (0.314)            | 0.463 (0.512)                |
| R.Gyro.RMS        | 1.325 (0.276)          | 4.539 (0.059)            | 1.013 (0.338)                |

Table D.21 F Statistics and P value for the ANOVA of postural variables. Significance is indicated with a \*.

Week 5 Descriptive Statistics – Postural

| Group, Response   | Pregame 1        | Postgame 2                 |
|-------------------|------------------|----------------------------|
| <b>START</b>      |                  |                            |
| X.Step.Reg        | -0.441 (0.136)   | -0.525 (0.165)             |
| X.Stride.Reg      | 0.752 (0.053)    | 0.722 (0.155)              |
| Y.Step.Reg        | 0.844 (0.030)    | 0.846 (0.059)              |
| Y.Stride.Reg      | 0.852 (0.036)    | 0.847 (0.065)              |
| Z.Step.Reg        | 0.661 (0.133)    | 0.755 (0.062)              |
| Z.Stride.Reg      | 0.719 (0.117)    | 0.796 (0.084)              |
| X.Gyro.Step.Reg   | 0.608 (0.182)    | 0.627 (0.190)              |
| X.Gyro.Stride.Reg | 0.687 (0.139)    | 0.741 (0.203)              |
| Y.Gyro.Step.Reg   | -0.884 (0.45)    | -0.933 (0.028)             |
| Y.Gyro.Stride.Reg | 0.900 (0.042)    | 0.940 (0.022) <sup>b</sup> |
| Z.Gyro.Step.Reg   | -0.910 (0.033)   | -0.936 (0.016)             |
| Z.Gyro.Stride.Reg | 0.926 (0.030)    | 0.945 (0.019)              |
| X.Accel.RMS       | 4.636 (0.956)    | 4.250 (0.696)              |
| Y.Accel.RMS       | 9.836 (0.553)    | 9.178 (0.495)              |
| R.Accel.RMS       | 11.867 (0.905)   | 10.996 (0.746)             |
| X.Gyro.RMS        | 74.956 (21.168)  | 60.989 (10.460)            |
| Y.Gyro.RMS        | 114.256 (18.545) | 108.927 (9.943)            |
| Z.Gyro.RMS        | 73.173 (7.296)   | 72.448 (7.180)             |
| R.Gyro.RMS        | 155.912 (22.530) | 144.662 (12.145)           |
| <b>RES</b>        |                  |                            |
| X.Step.Reg        | -0.411 (0.193)   | -0.572 (0.185)             |
| X.Stride.Reg      | 0.747 (0.079)    | 0.767 (0.111)              |
| Y.Step.Reg        | 0.842 (0.068)    | 0.863 (0.037)              |
| Y.Stride.Reg      | 0.843 (0.063)    | 0.853 (0.059)              |
| Z.Step.Reg        | 0.664 (0.170)    | 0.610 (0.189)              |
| Z.Stride.Reg      | 0.718 (0.161)    | 0.774 (0.090)              |
| X.Gyro.Step.Reg   | 0.602 (0.202)    | 0.731 (0.103)              |
| X.Gyro.Stride.Reg | 0.681 (0.172)    | 0.777 (0.139)              |
| Y.Gyro.Step.Reg   | -0.904 (0.048)   | -0.904 (0.069)             |
| Y.Gyro.Stride.Reg | 0.930 (0.030)    | 0.919 (0.066)              |
| Z.Gyro.Step.Reg   | -0.904 (0.077)   | -0.903 (0.064)             |
| Z.Gyro.Stride.Reg | 0.941 (0.015)    | 0.930 (0.046)              |
| X.Accel.RMS       | 4.401 (0.797)    | 3.844 (0.450)              |
| Y.Accel.RMS       | 9.857 (0.880)    | 9.581 (1.387)              |
| R.Accel.RMS       | 11.695 (0.986)   | 11.038 (1.318)             |
| X.Gyro.RMS        | 63.495 (10.163)  | 61.186 (7.349)             |
| Y.Gyro.RMS        | 106.856 (9.391)  | 105.210 (10.636)           |
| Z.Gyro.RMS        | 69.323 (13.107)  | 65.997 (13.886)            |
| R.Gyro.RMS        | 143.070 (10.353) | 139.039 (12.808)           |

Table D.22 Means and standard deviations of postural variables during Week 5. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

#### 4. Alpha Variables

Week 5 ANOVA Results – DFA

|                  | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------------|------------------------|--------------------------|------------------------------|
| StepT $\alpha$   | 0.242 (0.633)          | 3.216 (0.103)            | 0.045 (0.837)                |
| StrideT $\alpha$ | 0.232 (0.6400)         | 3.529 (0.090)            | 0.890 (0.368)                |
| StepL $\alpha$   | 0.073 (0.793)          | 1.804 (0.209)            | 1.549 (0.242)                |
| StrideL $\alpha$ | 0.352 (0.566)          | 0.077 (0.787)            | 0.716 (0.417)                |

Table D.23 F Statistics and P value for the ANOVA of alpha variables. Significance is indicated with a \*.

Week 5 Descriptive Statistics – DFA

| Group, Response  | Pregame 1     | Postgame 2    |
|------------------|---------------|---------------|
| <b>START</b>     |               |               |
| StepT $\alpha$   | 0.556 (0.209) | 0.628 (0.071) |
| StrideT $\alpha$ | 0.797 (0.162) | 0.843 (0.055) |
| StepL $\alpha$   | 0.927 (0.181) | 0.968 (0.094) |
| StrideL $\alpha$ | 1.035 (0.145) | 1.047 (0.058) |
| <b>RES</b>       |               |               |
| StepT $\alpha$   | 0.625 (0.161) | 0.533 (0.229) |
| StrideT $\alpha$ | 0.814 (0.154) | 0.769 (0.149) |
| StepL $\alpha$   | 0.915 (0.148) | 1.009 (0.070) |
| StrideL $\alpha$ | 0.994 (0.115) | 1.099 (0.046) |

Table D.24 Means and standard deviations of alpha variables during Week 5. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 2

#### D. Week 10

##### 1. Spatiotemporal Variables

Week 10 ANOVA Results – Spatiotemporal

|         | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|---------|------------------------|--------------------------|------------------------------|
| Speed   | 0.218 (0.653)          | 0.214 (0.810)            | 0.767 (0.481)                |
| FT      | 0.083 (0.780)          | 0.770 (0.479)            | 0.972 (0.400)                |
| CT      | 0.277 (0.613)          | 1.012 (0.385)            | 0.621 (0.550)                |
| StepT   | 0.458 (0.518)          | 4.182 (0.035)*           | 1.136 (0.346)                |
| StrideT | 0.449 (0.522)          | 4.094 (0.037)*           | 1.074 (0.365)                |
| StepL   | 0.011 (0.920)          | 32.675 (p<0.001)*        | 0.627 (0.547)                |
| StrideL | 0.010 (0.923)          | 32.747 (p<0.001)*        | 0.606 (0.557)                |

Table D.25 F Statistics and P value for the ANOVA of spatiotemporal variables. Significance is indicated with a \*.

Week 10 Descriptive Statistics – Spatiotemporal

| Group, Response | Pregame 1                     | Postgame 1                    | Postgame 2       |
|-----------------|-------------------------------|-------------------------------|------------------|
| <b>START</b>    |                               |                               |                  |
| Speed           | 2.583 (0.138)                 | 2.547 (0.219)                 | 2.569 (0.247)    |
| FT              | 92.834 (4.383)                | 88.655 (4.844)                | 92.099 (4.112)   |
| CT              | 250.221 (14.469)              | 246.812 (12.866)              | 249.545 (15.860) |
| StepT           | 343.054 (15.990) <sup>b</sup> | 335.467 (11.145) <sup>a</sup> | 341.644 (7.842)  |
| StrideT         | 686.186 (33.881) <sup>b</sup> | 671.041 (32.272) <sup>a</sup> | 683.240 (32.762) |
| StepL           | 0.838 (0.054) <sup>b</sup>    | 0.923 (0.061)                 | 0.873 (0.041)    |
| StrideL         | 1.676 (0.108) <sup>b</sup>    | 1.847 (0.122)                 | 1.745 (0.082)    |
| <b>RES</b>      |                               |                               |                  |
| Speed           | 2.547 (0.133)                 | 2.645 (0.089)                 | 2.624 (0.111)    |
| FT              | 89.885 (16.608)               | 92.291 (5.707)                | 95.130 (6.719)   |
| CT              | 259.614 (29.147)              | 252.133 (7.552)               | 248.924 (8.394)  |
| StepT           | 349.499 (16.699)              | 344.424 (16.182)              | 344.054 (16.411) |
| StrideT         | 699.035 (32.208)              | 688.743 (22.219)              | 688.028 (15.595) |
| StepL           | 0.841 (0.024) <sup>b</sup>    | 0.938 (0.038) <sup>d</sup>    | 0.862 (0.031)    |
| StrideL         | 1.681 (0.048) <sup>b</sup>    | 1.877 (0.077) <sup>d</sup>    | 1.724 (0.063)    |

Table D.26 Means and standard deviations of spatiotemporal variables during Week 10. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

## 2. Spring Mass Variables

Week 10 ANOVA Results – Spring Mass

|            | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------|------------------------|--------------------------|------------------------------|
| $F_{\max}$ | 0.220 (0.651)          | 1.561 (0.240)            | 0.228 (0.799)                |
| $\Delta y$ | 0.487 (0.505)          | 1.093 (0.359)            | 0.713 (0.505)                |
| $k_{vert}$ | 0.077 (0.789)          | 0.359 (0.704)            | 0.965 (0.402)                |
| $\Delta l$ | 0.272 (0.616)          | 1.677 (0.218)            | 1.084 (0.362)                |
| $k_{leg}$  | 0.104 (0.755)          | 10.434 (0.001)*          | 1.045 (0.374)                |

Table D.27 F Statistics and P value for the ANOVA of spring mass variables. Significance is indicated with a \*.

Week 10 Descriptive Statistics – Spring Mass

| Group, Response | Pregame 1                  | Postgame 1     | Postgame 2     |
|-----------------|----------------------------|----------------|----------------|
| <b>START</b>    |                            |                |                |
| $F_{max}$       | 1.297 (0.142)              | 1.285 (0.145)  | 1.295 (0.138)  |
| $\Delta y$      | 0.090 (0.010)              | 0.088 (0.009)  | 0.090 (0.011)  |
| $k_{vert}$      | 14.680 (1.481)             | 14.871 (1.326) | 14.710 (1.753) |
| $\Delta l$      | 0.146 (0.016) <sup>b</sup> | 0.157 (0.017)  | 0.150 (0.017)  |
| $k_{leg}$       | 9.136 (1.060) <sup>b</sup> | 8.385 (1.137)  | 8.819 (1.098)  |
| <b>RES</b>      |                            |                |                |
| $F_{max}$       | 1.337 (0.165)              | 1.327 (0.142)  | 1.345 (0.155)  |
| $\Delta y$      | 0.103 (0.034)              | 0.091 (0.005)  | 0.089 (0.006)  |
| $k_{vert}$      | 15.110 (2.922)             | 14.750 (1.659) | 15.413 (2.397) |
| $\Delta l$      | 0.161 (0.040)              | 0.163 (0.011)  | 0.148 (0.011)  |
| $k_{leg}$       | 9.387 (1.856)              | 8.351 (1.041)  | 9.389 (1.609)  |

Table D.28 Means and standard deviations of spring mass variables during Week 10. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1, c – difference in Pregame 1 to Postgame 2, d – difference in Postgame 1 to Postgame 2

### 3. Postural Variables

Week 10 ANOVA Results – Postural

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| X.Step.Reg        | 0.503 (0.498)          | 0.157 (0.856)            | 1.010 (0.386)                |
| X.Stride.Reg      | 2.553 (0.149)          | 4.488 (0.028)*           | 1.569 (0.239)                |
| Y.Step.Reg        | 1.420 (0.268)          | 0.566 (0.579)            | 0.892 (0.429)                |
| Y.Stride.Reg      | 1.793 (0.2170)         | 1.950 (0.175)            | 0.551 (0.587)                |
| Z.Step.Reg        | 0.589 (0.465)          | 0.877 (0.435)            | 1.383 (0.2790)               |
| Z.Stride.Reg      | 0.183 (0.680)          | 2.051 (0.161)            | 1.151 (0.341)                |
| X.Gyro.Step.Reg   | 0.117 (0.741)          | 1.373 (0.282)            | 3.865 (0.043)*               |
| X.Gyro.Stride.Reg | 0.076 (0.790)          | 10.385 (0.001)*          | 1.862 (0.187)                |
| Y.Gyro.Step.Reg   | 0.196 (0.669)          | 1.049 (0.3730)           | 0.103 (0.902)                |
| Y.Gyro.Stride.Reg | 0.201 (0.666)          | 5.546 (0.015)*           | 0.252 (0.780)                |
| Z.Gyro.Step.Reg   | 0.085 (0.778)          | 2.884 (0.085)            | 0.107 (0.899)                |
| Z.Gyro.Stride.Reg | 0.048 (0.832)          | 11.701 (0.007)*          | 0.522 (0.603)                |
| X.Accel.RMS       | 0.231 (0.644)          | 3.896 (0.042)*           | 0.451 (0.645)                |
| Y.Accel.RMS       | 1.405 (0.270)          | 4.631 (0.026)*           | 0.572 (0.575)                |
| Z.accel.RMS       | 0.026 (0.875)          | 3.854 (0.043)*           | 0.452 (0.644)                |
| R.Accel.RMS       | 0.996 (0.348)          | 4.959 (0.021)*           | 0.344 (0.714)                |
| X.Gyro.RMS        | 2.648 (0.142)          | 4.406 (0.030)*           | 5.030 (0.020)*               |
| Y.Gyro.RMS        | 0.002 (0.969)          | 13.134 (p<0.001)*        | 2.333 (0.129)                |
| Z.Gyro.RMS        | 0.00041 (0.984)        | 0.888 (0.431)            | 0.975 (0.398)                |
| R.Gyro.RMS        | 0.172 (0.689)          | 16.622 (p<0.001)*        | 4.840 (0.023)*               |

Table D.29 F Statistics and P value for the ANOVA of postural variables. Significance is indicated with a \*.

Week 10 Descriptive Statistics – Postural

| Group, Response   | Pregame 1                     | Postgame 1                    | Postgame 2       |
|-------------------|-------------------------------|-------------------------------|------------------|
| <b>START</b>      |                               |                               |                  |
| X.Step.Reg        | -0.493 (0.199)                | -0.461 (0.199)                | -0.498 (0.077)   |
| X.Stride.Reg      | 0.754 (0.040)                 | 0.800 (0.043)                 | 0.795 (0.055)    |
| Y.Step.Reg        | 0.854 (0.031)                 | 0.851 (0.061)                 | 0.851 (0.049)    |
| Y.Stride.Reg      | 0.840 (0.044)                 | 0.846 (0.037)                 | 0.852 (0.052)    |
| Z.Step.Reg        | 0.671 (0.153)                 | 0.770 (0.086)                 | 0.744 (0.119)    |
| Z.Stride.Reg      | 0.720 (0.124)                 | 0.796 (0.094)                 | 0.791 (0.117)    |
| X.Gyro.Step.Reg   | 0.645 (0.132)                 | 0.602 (0.131)                 | 0.614 (0.232)    |
| X.Gyro.Stride.Reg | 0.645 (0.178)                 | 0.734 (0.108)                 | 0.659 (0.234)    |
| Y.Gyro.Step.Reg   | -0.896 (0.057)                | -0.910 (0.077)                | -0.907 (0.052)   |
| Y.Gyro.Stride.Reg | 0.907 (0.046)                 | 0.938 (0.031)                 | 0.932 (0.031)    |
| Z.Gyro.Step.Reg   | -0.908 (0.036)                | -0.939 (0.022)                | -0.923 (0.044)   |
| Z.Gyro.Stride.Reg | 0.915 (0.026) <sup>c</sup>    | 0.944 (0.013)                 | 0.942 (0.016)    |
| X.Accel.RMS       | 4.087 (0.431)                 | 4.365 (0.290)                 | 4.400 (0.642)    |
| Y.Accel.RMS       | 8.981 (1.016)                 | 9.323 (0.988)                 | 8.971 (1.089)    |
| Z.accel.RMS       | 4.087 (0.431)                 | 4.364 (0.290)                 | 4.400 (0.0642)   |
| R.Accel.RMS       | 10.687 (1.111)                | 11.190 (0.944)                | 10.931 (1.290)   |
| X.Gyro.RMS        | 48.813 (10.476)               | 49.703 (13.437)               | 57.796 (13.194)  |
| Y.Gyro.RMS        | 105.219 (17.726)              | 111.443 (21.385)              | 109.996 (14.993) |
| Z.Gyro.RMS        | 67.206 (4.011) <sup>b</sup>   | 72.166 (5.585)                | 72.587 (5.731)   |
| R.Gyro.RMS        | 134.968 (11.510)              | 142.956 (15.676) <sup>a</sup> | 144.694 (12.123) |
| <b>RES</b>        |                               |                               |                  |
| X.Step.Reg        | -0.421 (0.109)                | -0.469 (0.178)                | -0.385 (0.121)   |
| X.Stride.Reg      | 0.733 (0.050)                 | 0.742 (0.035)                 | 0.735 (0.058)    |
| Y.Step.Reg        | 0.803 (0.061)                 | 0.824 (0.043)                 | 0.812 (0.068)    |
| Y.Stride.Reg      | 0.794 (0.064)                 | 0.818 (0.038)                 | 0.812 (0.046)    |
| Z.Step.Reg        | 0.677 (0.129)                 | 0.673 (0.173)                 | 0.646 (0.187)    |
| Z.Stride.Reg      | 0.738 (0.066)                 | 0.764 (0.103)                 | 0.733 (0.087)    |
| X.Gyro.Step.Reg   | 0.560 (0.081)                 | 0.731 (0.124)                 | 0.654 (0.143)    |
| X.Gyro.Stride.Reg | 0.595 (0.067) <sup>b</sup>    | 0.801 (0.083)                 | 0.708 (0.088)    |
| Y.Gyro.Step.Reg   | -0.876 (0.034)                | -0.903 (0.038)                | -0.895 (0.043)   |
| Y.Gyro.Stride.Reg | 0.905 (0.025)                 | 0.929 (0.034)                 | 0.918 (0.031)    |
| Z.Gyro.Step.Reg   | -0.909 (0.034)                | -0.933 (0.022)                | -0.913 (0.036)   |
| Z.Gyro.Stride.Reg | 0.921 (0.030)                 | 0.950 (0.016)                 | 0.937 (0.011)    |
| X.Accel.RMS       | 4.342 (0.628)                 | 4.551 (0.716)                 | 4.473 (0.712)    |
| Y.Accel.RMS       | 9.349 (0.659)                 | 10.094 (0.596)                | 9.572 (0.571)    |
| Z.accel.RMS       | 4.075 (0.598)                 | 4.405 (0.529)                 | 4.232 (0.419)    |
| R.Accel.RMS       | 11.098 (0.889)                | 11.936 (0.755)                | 11.409 (0.496)   |
| X.Gyro.RMS        | 56.286 (11.339)               | 74.426 (14.453)               | 2.668 (17.163)   |
| Y.Gyro.RMS        | 101.197 (18.138) <sup>b</sup> | 115.984 (13.236) <sup>d</sup> | 108.228 (12.792) |
| Z.Gyro.RMS        | 70.732 (10.857)               | 71.962 (10.225)               | 69.516 (7.993)   |
| R.Gyro.RMS        | 136.130 (20.642) <sup>b</sup> | 155.797 (18.981) <sup>d</sup> | 143.462 (19.665) |

Table D.30 Means and standard deviations of postural variables during Week 10. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

#### 4. Alpha Variables

Week 10 ANOVA Results – DFA

|                  | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------------|------------------------|--------------------------|------------------------------|
| StepT $\alpha$   | 0.001 (0.973)          | 1.063 (0.369)            | 1.517 (0.249)                |
| StrideT $\alpha$ | 0.563 (0.474)          | 1.927 (0.178)            | 1.070 (0.366)                |
| StepL $\alpha$   | 4.581 (0.065)          | 3.671 (0.049)*           | 0.201 (0.820)                |
| StrideL $\alpha$ | 5.399 (0.049)*         | 5.880 (0.012)*           | 0.076 (0.928)                |

Table D.31 F Statistics and P value for the ANOVA of fractal variables. Significance is indicated with a \*.

Week 10 Descriptive Statistics – DFA

| Group, Response  | Pregame 1                  | Postgame 1    | Postgame 2    |
|------------------|----------------------------|---------------|---------------|
| <b>START</b>     |                            |               |               |
| StepT $\alpha$   | 0.653 (0.188)              | 0.744 (0.108) | 0.616 (0.094) |
| StrideT $\alpha$ | 0.803 (0.148)              | 0.888 (0.115) | 0.778 (0.099) |
| StepL $\alpha$   | 1.060 (0.077)              | 1.049 (0.059) | 0.956 (0.082) |
| StrideL $\alpha$ | 1.143 (0.065) <sup>a</sup> | 1.116 (0.058) | 1.028 (0.069) |
| <b>RES</b>       |                            |               |               |
| StepT $\alpha$   | 0.631 (0.187)              | 0.670 (0.196) | 0.702 (0.205) |
| StrideT $\alpha$ | 0.827 (0.141)              | 0.897 (0.108) | 0.897 (0.153) |
| StepL $\alpha$   | 1.145 (0.066)              | 1.095 (0.074) | 1.046 (0.145) |
| StrideL $\alpha$ | 1.229 (0.060)              | 1.176 (0.063) | 1.106 (0.143) |

Table D.32 Means and standard deviations of fractal variables during Week 10. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

#### E. Week 12

##### 1. Spatiotemporal Variables

Week 12 ANOVA Results – Spatiotemporal

|         | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|---------|------------------------|--------------------------|------------------------------|
| Speed   | 0.042 (0.843)          | 0.003 (0.997)            | 0.920 (0.419)                |
| FT      | 0.045 (0.837)          | 5.906 (0.012)*           | 4.322 (0.032)*               |
| CT      | 0.361 (0.564)          | 1.778 (0.201)            | 1.384 (0.279)                |
| StepT   | 0.165 (0.695)          | 0.299 (0.746)            | 3.945 (0.040)*               |
| StrideT | 0.167 (0.693)          | 0.292 (0.752)            | 3.974 (0.040)*               |
| StepL   | 0.505 (0.497)          | 37.517 (p<0.001)*        | 0.704 (0.509)                |
| StrideL | 0.515 (0.493)          | 38.027 (p<0.001)*        | 0.717 (0.503)                |

Table D.33 F Statistics and P value for the ANOVA of spatiotemporal variables. Significance is indicated with a \*.

Week 12 Descriptive Statistics – Spatiotemporal

| Group, Response | Pregame 1                  | Postgame 1                 | Postgame 2       |
|-----------------|----------------------------|----------------------------|------------------|
| <b>START</b>    |                            |                            |                  |
| Speed           | 2.549 (0.193)              | 2.573 (0.194)              | 2.661 (0.252)    |
| FT              | 94.377 (6.446)             | 99.077 (7.192)             | 91.847 (5.549)   |
| CT              | 246.237 (15.116)           | 245.695 (12.979)           | 245.942 (13.776) |
| StepT           | 340.614 (19.226)           | 344.771 (17.255)           | 337.789 (18.349) |
| StrideT         | 681.080 (38.237)           | 689.417 (34.501)           | 675.496 (36.660) |
| StepL           | 0.879 (0.042) <sup>b</sup> | 0.781 (0.038) <sup>d</sup> | 0.902 (0.060)    |
| StrideL         | 1.758 (0.083) <sup>b</sup> | 1.562 (0.077) <sup>d</sup> | 1.803 (0.120)    |
| <b>RES</b>      |                            |                            |                  |
| Speed           | 2.626 (0.184)              | 2.612 (0.140)              | 2.510 (0.139)    |
| FT              | 94.285 (5.239)             | 94.550 (8.312)             | 93.965 (6.037)   |
| CT              | 252.604 (10.434)           | 245.770 (7.912)            | 252.049 (7.732)  |
| StepT           | 346.890 (5.789)            | 340.320 (9.303)            | 346.014 (3.681)  |
| StrideT         | 693.703 (11.639)           | 680.469 (18.640)           | 692.001 (7.573)  |
| StepL           | 0.915 (0.041) <sup>b</sup> | 0.779 (0.016) <sup>d</sup> | 0.912 (0.054)    |
| StrideL         | 1.830 (0.081) <sup>b</sup> | 1.557 (0.033) <sup>d</sup> | 1.824 (0.107)    |

Table D.34 Means and standard deviations of spatiotemporal variables during Week 12. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

2. Spring Mass Variables

Week 12 ANOVA Results – Spring Mass

|            | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------|------------------------|--------------------------|------------------------------|
| $F_{max}$  | 1.528 (0.251)          | 0.067 (0.935)            | 1.482 (0.257)                |
| $\Delta y$ | 0.311 (0.592)          | 1.698 (0.214)            | 1.455 (0.263)                |
| $k_{vert}$ | 0.045 (0.837)          | 5.906 (0.012)*           | 4.322 (0.032)*               |
| $\Delta l$ | 0.263 (0.622)          | 19.645 (p<0.001)*        | 0.610 (0.555)                |
| $k_{leg}$  | 0.319 (0.587)          | 23.107 (p<0.001)*        | 0.323 (0.729)                |

Table D.35 F Statistics and P value for the ANOVA of spring mass variables. Significance is indicated with a \*.

Week 12 Descriptive Statistics – Spring Mass

| Group, Response | Pregame 1                  | Postgame 1                  | Postgame 2     |
|-----------------|----------------------------|-----------------------------|----------------|
| <b>START</b>    |                            |                             |                |
| $F_{max}$       | 1.528 (0.251)              | 0.067 (0.935)               | 1.482 (0.257)  |
| $\Delta y$      | 0.311 (0.592)              | 1.698 (0.214)               | 1.455 (0.263)  |
| $k_{vert}$      | 14.943 (1.530)             | 15.140 (1.634) <sup>d</sup> | 14.843 (1.141) |
| $\Delta l$      | 0.148 (0.016)              | 0.133 (0.013) <sup>d</sup>  | 0.154 (0.015)  |
| $k_{leg}$       | 8.897 (1.071)              | 9.959 (1.284) <sup>d</sup>  | 8.613 (1.144)  |
| <b>RES</b>      |                            |                             |                |
| $F_{max}$       | 1.280 (0.149)              | 1.299 (0.164)               | 1.271 (0.151)  |
| $\Delta y$      | 0.088 (0.011)              | 0.087 (0.009)               | 0.087 (0.010)  |
| $k_{vert}$      | 15.507 (2.095)             | 15.889 (2.164)              | 15.545 (1.709) |
| $\Delta l$      | 0.157 (0.014) <sup>b</sup> | 0.133 (0.007)               | 0.157 (0.016)  |
| $k_{leg}$       | 9.159 (1.356)              | 10.405 (1.431) <sup>d</sup> | 9.206 (1.299)  |

Table D.36 Means and standard deviations of spring mass variables during Week 12. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

### 3. Postural Variables

Week 12 ANOVA Results – Postural

|                   | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|-------------------|------------------------|--------------------------|------------------------------|
| X.Step.Reg        | 0.545 (0.481)          | 0.540 (0.593)            | 4.127 (0.036)*               |
| X.Stride.Reg      | 0.783 (0.402)          | 2.585 (0.106)            | 0.645 (0.538)                |
| Y.Step.Reg        | 0.057 (0.817)          | 1.074 (0.365)            | 0.569 (0.577)                |
| Y.Stride.Reg      | 0.044 (0.838)          | 1.599 (0.233)            | 0.056 (0.945)                |
| Z.Step.Reg        | 0.005 (0.944)          | 0.171 (0.845)            | 0.758 (0.485)                |
| Z.Stride.Reg      | 0.145 (0.713)          | 0.631 (0.545)            | 0.334 (0.721)                |
| X.Gyro.Step.Reg   | 0.170 (0.691)          | 0.284 (0.756)            | 0.625 (0.548)                |
| X.Gyro.Stride.Reg | 0.607 (0.458)          | 1.510 (0.251)            | 0.318 (0.732)                |
| Y.Gyro.Step.Reg   | 0.414 (0.538)          | 1.476 (0.258)            | 0.904 (0.424)                |
| Y.Gyro.Stride.Reg | 1.189 (0.3070)         | 1.610 (0.231)            | 0.904 (0.425)                |
| Z.Gyro.Step.Reg   | 0.141 (0.717)          | 0.048 (0.953)            | 0.344 (0.714)                |
| Z.Gyro.Stride.Reg | 1.585 (0.244)          | 0.810 (0.462)            | 3.330 (0.062)                |
| X.Accel.RMS       | 0.011 (0.921)          | 13.758 (p<0.001)*        | 5.200 (0.018)*               |
| Y.Accel.RMS       | 0.004 (0.952)          | 32.021 (p<0.001)*        | 7.258 (0.006)*               |
| Z.accel.RMS       | 0.538 (0.484)          | 14.509 (p<0.001)*        | 4.169 (0.035)*               |
| R.Accel.RMS       | 0.028 (0.871)          | 33.296 (p<0.001)*        | 7.375 (0.005)*               |
| X.Gyro.RMS        | 0.0000593 (0.994)      | 2.599 (0.105)            | 0.504 (0.613)                |
| Y.Gyro.RMS        | 0.007 (0.937)          | 15.004 (p<0.001)*        | 1.893 (0.183)                |
| Z.Gyro.RMS        | 0.901 (0.371)          | 17.967 (p<0.001)*        | 0.535 (0.596)                |
| R.Gyro.RMS        | 0.129 (0.729)          | 20.495 (p<0.001)*        | 1.924 (0.178)                |

Table D.37 F Statistics and P value for the ANOVA of postural variables. Significance is indicated with a \*.

Week 12 Descriptive Statistics – Postural

| Group, Response   | Pregame 1                     | Postgame 1                    | Postgame 2       |
|-------------------|-------------------------------|-------------------------------|------------------|
| <b>START</b>      |                               |                               |                  |
| X.Step.Reg        | -0.367 (0.110)                | -0.419 (0.188)                | -0.430 (0.202)   |
| X.Stride.Reg      | 0.730 (0.074)                 | 0.759 (0.056)                 | 0.749 (0.051)    |
| Y.Step.Reg        | 0.805 (0.092)                 | 0.0845 (0.053)                | 0.816 (0.081)    |
| Y.Stride.Reg      | 0.811 (0.080)                 | 0.858 (0.035)                 | 0.824 (0.044)    |
| Z.Step.Reg        | 0.643 (0.156) <sup>c</sup>    | 0.653 (0.150)                 | 0.703 (0.126)    |
| Z.Stride.Reg      | 0.700 (0.116)                 | 0.713 (0.114)                 | 0.724 (0.115)    |
| X.Gyro.Step.Reg   | 0.575 (0.143)                 | 0.549 (0.153)                 | 0.572 (0.154)    |
| X.Gyro.Stride.Reg | 0.640 (0.140)                 | 0.633 (0.180)                 | 0.557 (0.313)    |
| Y.Gyro.Step.Reg   | -0.851 (0.152)                | -0.883 (0.082)                | -0.864 (0.130)   |
| Y.Gyro.Stride.Reg | 0.875 (0.118)                 | 0.905 (0.057)                 | 0.898 (0.069)    |
| Z.Gyro.Step.Reg   | -0.921 (0.017)                | -0.915 (0.023)                | -0.925 (0.024)   |
| Z.Gyro.Stride.Reg | 0.927 (0.019)                 | 0.923 (0.026)                 | 0.932 (0.011)    |
| X.Accel.RMS       | 4.857 (0.755)                 | 4.123 (0.641)                 | 4.595 (0.625)    |
| Y.Accel.RMS       | 9.860 (1.051)                 | 9.191 (0.835)                 | 9.813 (1.194)    |
| R.Accel.RMS       | 12.033 (1.322) <sup>b</sup>   | 10.917 (0.808) <sup>a</sup>   | 11.784 (1.339)   |
| X.Gyro.RMS        | 62.856 (15.663)               | 51.057 (6.638)                | 59.813 (19.577)  |
| Y.Gyro.RMS        | 118.007 (11.641) <sup>b</sup> | 105.228 (12.870) <sup>d</sup> | 119.130 (15.537) |
| Z.Gyro.RMS        | 77.291 (7.679)                | 67.407 (6.356)                | 81.257 (11.894)  |
| R.Gyro.RMS        | 155.219 (11.680) <sup>b</sup> | 135.150 (14.050) <sup>d</sup> | 157.457 (15.507) |
| <b>RES</b>        |                               |                               |                  |
| X.Step.Reg        | -0.536 (0.130)                | -0.478 (0.160)                | -0.412 (0.156)   |
| X.Stride.Reg      | 0.741 (0.084)                 | 0.818 (0.051)                 | 0.763 (0.070)    |
| Y.Step.Reg        | 0.835 (0.056)                 | 0.838 (0.070)                 | 0.821 (0.072)    |
| Y.Stride.Reg      | 0.827 (0.061)                 | 0.861 (0.033)                 | 0.825 (0.115)    |
| Z.Step.Reg        | 0.660 (0.077)                 | 0.677 (0.207)                 | 0.644 (0.133)    |
| Z.Stride.Reg      | 0.714 (0.049)                 | 0.761 (0.113)                 | 0.729 (0.106)    |
| X.Gyro.Step.Reg   | 0.590 (0.216)                 | 0.660 (0.192)                 | 0.537 (0.136)    |
| X.Gyro.Stride.Reg | 0.668 (0.185)                 | 0.764 (0.056)                 | 0.603 (0.151)    |
| Y.Gyro.Step.Reg   | -0.912 (0.038)                | -0.923 (0.036)                | -0.870 (0.075)   |
| Y.Gyro.Stride.Reg | 0.931 (0.036)                 | 0.955 (0.015)                 | 0.912 (0.047)    |
| Z.Gyro.Step.Reg   | -0.906 (0.057)                | -0.915 (0.093)                | -0.908 (0.045)   |
| Z.Gyro.Stride.Reg | 0.936 (0.020)                 | 0.955 (0.014)                 | 0.931 (0.030)    |
| X.Accel.RMS       | 4.448 (0.415)                 | 4.071 (0.612)                 | 5.163 (0.599)    |
| Y.Accel.RMS       | 9.833 (0.888) <sup>b</sup>    | 8.518 (1.126) <sup>d</sup>    | 10.397 (1.085)   |
| R.Accel.RMS       | 11.624 (0.573) <sup>b</sup>   | 10.208 (0.819) <sup>d</sup>   | 12.592 (1.167)   |
| X.Gyro.RMS        | 58.888 (17.646)               | 46.994 (9.743)                | 67.712 (18.999)  |
| Y.Gyro.RMS        | 112.700 (8.221) <sup>b</sup>  | 101.108 (10.056)              | 126.605 (22.432) |
| Z.Gyro.RMS        | 70.134 (10.824)               | 63.102 (9.393) <sup>d</sup>   | 79.285 (3.715)   |
| R.Gyro.RMS        | 146.120 (12.922) <sup>b</sup> | 128.488 (12.824)              | 165.325 (18.367) |

Table D.38 Means and standard deviations of postural variables during Week 12. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

#### 4. Alpha Variables

Week 12 ANOVA Results – DFA

|                  | Group Effect (p value) | Session Effect (p value) | Interaction Effect (p value) |
|------------------|------------------------|--------------------------|------------------------------|
| StepT $\alpha$   | 0.026 (0.875)          | 0.814 (0.461)            | 0.877 (0.435)                |
| StrideT $\alpha$ | 0.039 (0.848)          | 0.100 (0.906)            | 0.689 (0.516)                |
| StepL $\alpha$   | 0.348 (0.572)          | 3.698 (0.048)*           | 0.148 (0.863)                |
| StrideL $\alpha$ | 0.736 (0.416)          | 5.554 (0.015)*           | 0.547 (0.589)                |

Table D.39 F Statistics and P value for the ANOVA of fractal variables. Significance is indicated with a \*.

Week 12 Descriptive Statistics – DFA

| Group, Response  | Pregame 1     | Postgame 1                 | Postgame 2    |
|------------------|---------------|----------------------------|---------------|
| <b>START</b>     |               |                            |               |
| StepT $\alpha$   | 0.587 (0.066) | 0.601 (0.087)              | 0.604 (0.197) |
| StrideT $\alpha$ | 0.789 (0.037) | 0.783 (0.065)              | 0.819 (0.181) |
| StepL $\alpha$   | 0.982 (0.104) | 0.949 (0.060) <sup>d</sup> | 1.043 (0.058) |
| StrideL $\alpha$ | 1.073 (0.106) | 1.006 (0.039) <sup>d</sup> | 1.137 (0.067) |
| <b>RES</b>       |               |                            |               |
| StepT $\alpha$   | 0.609 (0.165) | 0.672 (0.122)              | 0.549 (0.198) |
| StrideT $\alpha$ | 0.807 (0.150) | 0.848 (0.089)              | 0.774 (0.190) |
| StepL $\alpha$   | 0.957 (0.091) | 0.943 (0.062)              | 1.006 (0.098) |
| StrideL $\alpha$ | 1.023 (0.083) | 1.013 (0.056)              | 1.087 (0.107) |

Table D.40 Means and standard deviations of fractal variables during Week 12. Post hoc assessment of differences in means are indicated with the following superscripts: a – difference between START and RES; b – difference in Pregame 1 to Postgame 1; c – difference in Pregame 1 to Postgame 2; d – difference in Postgame 1 to Postgame 2

#### 5. Correlations to Training Load Variables

Association of Training Load to the Change in Gait

|                  | Distance | REC    | RPE    | HSR    | Speed Intensity | Dynamic Stress Load |
|------------------|----------|--------|--------|--------|-----------------|---------------------|
| Speed.all        | 0.159    | -0.001 | 0.212  | 0.175  | 0.165           | 0.254               |
| FT               | -0.121   | -0.272 | -0.242 | -0.108 | -0.127          | 0.001               |
| CT               | 0.040    | -0.017 | 0.025  | 0.079  | 0.038           | 0.102               |
| StepT            | -0.013   | -0.122 | -0.074 | 0.026  | -0.017          | 0.089               |
| Stride.T         | -0.013   | -0.122 | -0.074 | 0.024  | -0.017          | 0.089               |
| StepL            | 0.136    | -0.069 | 0.149  | 0.168  | 0.140           | 0.279               |
| StrideL          | 0.136    | -0.069 | 0.147  | 0.166  | 0.139           | 0.279               |
| Fmax             | -0.038   | -0.192 | -0.086 | 0.069  | -0.042          | 0.093               |
| delta.y          | 0.030    | -0.028 | 0.016  | 0.074  | 0.028           | 0.093               |
| k.vert           | -0.093   | -0.195 | -0.124 | -0.012 | -0.096          | -0.021              |
| delta.l          | 0.126    | -0.018 | 0.146  | 0.150  | 0.128           | 0.213               |
| k.leg            | -0.148   | -0.186 | -0.190 | -0.068 | -0.153          | -0.104              |
| X.StepReg        | 0.109    | 0.147  | 0.067  | 0.166  | 0.108           | 0.190               |
| X.StrideReg      | -0.003   | -0.132 | -0.028 | -0.139 | -0.009          | -0.023              |
| Y.StepReg        | 0.160    | 0.196  | 0.106  | 0.026  | 0.161           | 0.016               |
| Y.StrideReg      | 0.102    | 0.076  | 0.050  | 0.054  | 0.100           | 0.091               |
| Z.StepReg        | 0.321    | 0.241  | 0.209  | 0.287  | 0.323           | 0.290               |
| Z.StrideReg      | 0.351    | 0.257  | 0.165  | 0.291  | 0.351           | 0.288               |
| X.GyroStepReg    | 0.257    | 0.243  | 0.121  | 0.172  | 0.255           | 0.169               |
| X.GyroStrideReg  | 0.216    | 0.210  | 0.064  | 0.144  | 0.214           | 0.170               |
| Y.GyroStepReg    | -0.203   | -0.082 | -0.146 | -0.085 | -0.200          | -0.113              |
| Y.GyroStrideReg  | 0.280    | 0.180  | 0.213  | 0.125  | 0.277           | 0.179               |
| Z.GyroStepReg    | -0.010   | 0.027  | 0.002  | 0.024  | -0.008          | -0.038              |
| Z.GyroStrideReg  | 0.267    | 0.092  | 0.167  | 0.151  | 0.262           | 0.245               |
| StepT $\alpha$   | 0.074    | 0.080  | 0.157  | 0.130  | 0.077           | -0.001              |
| StrideT $\alpha$ | 0.140    | 0.097  | 0.248  | 0.224  | 0.144           | 0.111               |
| StepL $\alpha$   | -0.045   | -0.032 | -0.123 | -0.111 | -0.049          | -0.210              |
| StrideL $\alpha$ | -0.044   | 0.011  | -0.112 | -0.032 | -0.045          | -0.197              |
| X.Accel.RMS      | -0.218   | -0.251 | -0.139 | -0.131 | -0.215          | -0.037              |
| Y.Accel.RMS      | -0.087   | -0.131 | -0.104 | -0.166 | -0.085          | -0.154              |
| Z.Accel.RMS      | -0.225   | -0.292 | -0.181 | -0.146 | -0.219          | -0.044              |
| R.Accel.RMS      | -0.187   | -0.244 | -0.168 | -0.210 | -0.184          | -0.150              |
| X.Gyro.RMS       | -0.094   | -0.185 | -0.256 | -0.028 | -0.092          | 0.077               |
| Y.Gyro.RMS       | -0.238   | -0.305 | -0.035 | -0.179 | -0.231          | -0.031              |
| Z.Gyro.RMS       | -0.079   | -0.246 | -0.167 | -0.027 | -0.077          | 0.069               |
| R.Gyro.RMS       | -0.219   | -0.342 | -0.181 | -0.138 | -0.213          | 0.029               |

Table D.41 The correlation coefficients describing the relationship between the weekly training load and the change in gait variable (Postgame 2- Pregame 1). RPE is rating of perceived exertion. REC is perceived recovery.

## APPENDIX E Data Tables from Chapter 4.2

### Association of Training Load to the Change in Gait

|                 | Distance | Jump.Height |
|-----------------|----------|-------------|
| Distance        | 1.000    | 0.275       |
| Jump.Height     | 0.275    | 1.000       |
| Speed.all       | 0.383    | 0.044       |
| FT              | -0.146   | 0.071       |
| CT              | -0.296   | -0.136      |
| StepT           | -0.381   | -0.092      |
| Stride.T        | -0.395   | -0.100      |
| StepL           | 0.313    | 0.041       |
| StrideL         | 0.314    | 0.041       |
| Fmax            | 0.044    | 0.136       |
| delta.y         | -0.304   | -0.144      |
| k.vert          | 0.238    | 0.123       |
| delta.l         | 0.204    | -0.015      |
| k.leg           | -0.209   | 0.016       |
| X.StepReg       | -0.191   | 0.049       |
| X.StrideReg     | 0.322    | -0.042      |
| Y.StepReg       | 0.070    | -0.067      |
| Y.StrideReg     | 0.004    | -0.028      |
| Z.StepReg       | -0.053   | -0.013      |
| Z.StrideReg     | 0.073    | -0.075      |
| X.GyroStepReg   | 0.276    | 0.093       |
| X.GyroStrideReg | 0.238    | -0.033      |
| Y.GyroStepReg   | 0.275    | 0.352       |
| Y.GyroStrideReg | -0.076   | -0.132      |
| Z.GyroStepReg   | -0.161   | 0.005       |
| Z.GyroStrideReg | 0.428    | -0.078      |
| X.Accel.RMS     | 0.373    | 0.026       |
| Y.Accel.RMS     | 0.252    | -0.061      |
| Z.Accel.RMS     | 0.090    | -0.074      |
| R.Accel.RMS     | 0.268    | -0.073      |
| X.Gyro.RMS      | 0.360    | -0.027      |
| Y.Gyro.RMS      | 0.671    | 0.038       |
| Z.Gyro.RMS      | 0.262    | -0.077      |
| R.Gyro.RMS      | 0.556    | -0.014      |

Table E.1 Correlation coefficients relating the change in gait (Postgame – Pregame) to game distance or change in jump height.

Change in Variables from Pregame to Postgame

|                  | Pregame          | Postgame         | P value | Effect Size        |
|------------------|------------------|------------------|---------|--------------------|
| Speed.all        | 3.540 (0.230)    | 3.541 (0.285)    | 0.985   | -0.004             |
| FT               | 80.292 (5.665)   | 79.565 (0.744)   | 0.326   | 0.111              |
| CT               | 257.019 (15.159) | 259.077 (14.047) | 0.101   | -0.141             |
| StepT            | 337.312 (17.761) | 338.642 (18.675) | 0.293   | -0.073             |
| Stride.T         | 674.839 (35.488) | 677.497 (37.458) | 0.291   | -0.073             |
| StepL            | 1.192 (0.094)    | 1.193 (0.081)    | 0.919   | -0.011             |
| StrideL          | 2.383 (0.187)    | 2.386 (0.162)    | 0.930   | -0.017             |
| Fmax             | 1.250 (0.139)    | 1.246 (0.143)    | 0.217   | 0.028              |
| delta.y          | 0.095 (0.011)    | 0.096 (0.010)    | 0.097   | -0.140             |
| k.vert           | 13.558 (1.620)   | 13.330 (1.364)   | 0.160   | 0.153              |
| delta.l          | 0.223 (0.030)    | 0.227 (0.026)    | 0.465   | -0.145             |
| k.leg            | 5.924 (0.817)    | 5.844 (0.816)    | 0.537   | 0.098              |
| X.StepReg        | -0.419 (0.119)   | -0.438 (0.136)   | 0.337   | 0.149              |
| X.StrideReg      | 0.63 (0.076)     | 0.67 (0.093)     | 0.003   | 0.47 <sup>s</sup>  |
| Y.StepReg        | 0.74 (0.052)     | 0.77 (0.054)     | 0.002   | 0.57 <sup>m</sup>  |
| Y.StrideReg      | 0.69 (0.086)     | 0.75 (0.066)     | p<0.001 | 0.78 <sup>m</sup>  |
| Z.StepReg        | 0.68 (0.13)      | 0.75 (0.074)     | p<0.001 | 0.66 <sup>m</sup>  |
| Z.StrideReg      | 0.69 (0.092)     | 0.74 (0.072)     | 0.003   | 0.61 <sup>m</sup>  |
| X.GyroStepReg    | 0.544 (0.134)    | 0.562 (0.138)    | 0.422   | -0.132             |
| X.GyroStrideReg  | 0.595 (0.135)    | 0.592 (0.145)    | 0.892   | 0.021              |
| Y.GyroStepReg    | -0.73 (0.25)     | -0.82 (0.089)    | p<0.001 | -0.48 <sup>s</sup> |
| Y.GyroStrideReg  | 0.82 (0.086)     | 0.85 (0.087)     | 0.003   | 0.35 <sup>s</sup>  |
| Z.GyroStepReg    | -0.868 (0.066)   | -0.864 (0.049)   | 0.171   | -0.069             |
| Z.GyroStrideReg  | 0.88 (0.047)     | 0.90 (0.051)     | 0.015   | 0.41 <sup>s</sup>  |
| X.Accel.RMS      | 4.913 (0.702)    | 5.102 (0.684)    | 0.144   | -0.273             |
| Y.Accel.RMS      | 10.86 (1.13)     | 10.19 (0.91)     | p<0.001 | -0.65 <sup>m</sup> |
| Z.Accel.RMS      | 6.222 (1.098)    | 6.378 (1.019)    | 0.493   | -0.147             |
| R.Accel.RMS      | 13.65 (1.08)     | 12.98 (0.86)     | 0.002   | -0.69 <sup>m</sup> |
| X.Gyro.RMS       | 85.21 (17.87)    | 65.34 (14.27)    | p<0.001 | -1.23 <sup>l</sup> |
| Y.Gyro.RMS       | 128.01 (17.90)   | 118.44 (16.39)   | p<0.001 | -0.56 <sup>m</sup> |
| Z.Gyro.RMS       | 81.769 (11.671)  | 84.616 (13.676)  | 0.137   | -0.225             |
| R.Gyro.RMS       | 177.11 (21.46)   | 159.46 (17.14)   | p<0.001 | -0.91 <sup>l</sup> |
| Jump Height (cm) | 31.67 (4.62)     | 30.36 (3.83)     | 0.020   | -0.31 <sup>s</sup> |

Table E.2 Means ± SD, P-value, and Cohen's d effect size for variables with significant changes from Pregame to Postgame. Cohen's d effect size designations: d>0.2<sup>s</sup> = small effect, d>0.5<sup>m</sup> = medium effect, d> 0.8<sup>l</sup> = large effect.