The Development and Application of a Novel Method of Analysing Within-step Accelerations Collected During Australian Rules Football Games

Alec Thomas Buttfield

Institute of Sport, Exercise and Active Living

College of Sport and Exercise Science, Victoria University

Thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

June 2016

Abstract

Resolving intra-stride accelerations from training and game data routinely collected by athlete tracking devices is rarely attempted, even though these data can provide important insights into the physical condition of athletes. This thesis proposes a new method of extracting stride accelerations from athlete tracking data via a novel analysis tool, describes methods of analysing the results generated by the analysis tool and reports and the influence of instances of missed or modified training and game activity on those results. Accelerometer and GPS Data from twenty-two professional Australian Rules Footballers were examined from competitive games during an Australian Football League season. These data were processed with a novel analysis tool developed specifically for the purpose of identifying instances of high speed running in a straight line during games, extracting step waveforms in three axes from those sections and determining the variability of those waveforms via a within-section and between-section co-efficient of multiple determination (CMD) over the course of the game. The steps taken in the development of the analysis tool are described in the thesis. Numerous approaches to identifying matched sections of high speed running in a straight line were investigated, with the method resulting in the highest number of waveforms while still being mindful of theoretical considerations adopted. Similarly, numerous statistical approaches to identifying step waveform variability were investigated and the methods demonstrating the highest repeatability within the context of the number of waveforms available for analysis were adopted, and methods with a high possibility of providing limited value in an applied setting eliminated. Results exported from the analysis tool were analysed in a number of contexts. Season averages from raw CMD scores were calculated on steps taken on the left and right foot, and the magnitude of the difference between those scores within each subject was estimated through determining the 99% confidence interval for the mean raw CMD on each side and identifying where those confidence intervals for the left and right foot did not overlap. There was one subject whose 99% confidence intervals did not overlap in any analysis condition (within-section and between-section CMD across x, y and z axes), one subject where the 99% confidence intervals did not overlap in four of the six analysis conditions, ten subjects where there was an overlap in between one and three of the analysis conditions, and ten subjects where there were no analysis conditions in which there was an overlap. Raw co-efficient of multiple correlation scores were converted to z-scores within side and axis for each subject, and confidence intervals for z-scores collated by axis (combining steps from all subjects on right and left side) were determined via an empirical bootstrapping procedure. When combined with data on

instances of missed or modified training in the week preceding or following a game, some significant results were identified. Instances of missed or modified training were divided into five categories; “load”, “groin”, “leg soft tissue”, “leg structural” and “other”. A lower within-section z-score (indicating more step waveform variability) was found when a training was modified due to “load” ($p=0.02$) and higher between-section z-scores (which indicates less step waveform variability) were found in the week preceding a training modification due to “leg structural” injuries encompassing injuries to a leg not encompassed by soft tissue injuries, such as an ankle ligament sprain ($p=0.02$). Subjects with no difference between sides in average within-section z-axis raw CMD scores or average between-section x-axis raw CMD scores were unlikely to require training modifications due to “load” (correctly predicted in 82% of cases) and “groin” (correctly predicted in 92% of cases) respectively. These procedures and results can immediately be integrated into athlete monitoring systems, though investigations into combining these procedures with more established parameters may enhance their ability to predict adverse events. In addition, results supported previous research into the association between movement variability and pathology, and further research into the mechanism behind the changes in step waveform variability utilising the procedures outlined in this study will aid in the development and testing of our theoretical hypothesis.

Student Declaration

I, Alec Buttfield, declare that the PhD thesis entitled "The development and application of a novel method of analysing within-step accelerations collected during Australian Rules Football games" is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature [redacted] Date 7/6/2016

Acknowledgements

I would like to acknowledge the guidance and support provided by my supervisors, Dr Kevin Ball and Dr Clare MacMahon, particularly for the balance of academic freedom and constraint you have provided over the course of this journey.

I would also like to acknowledge the support provided by the administration staff within the College of Sport and Exercise Science at Victoria University who made the difficult process of completing a PhD part-time as an external student a bit easier. In particular, I would like to acknowledge the assistance provided by Grace Schirripa during her time at Victoria University.

Thank you to the players and staff of the Port Adelaide Football Club, in particular Darren Burgess, Stuart Graham and Kris Veugelers for the hard work in collecting the data in the first place.

I would also like to say a huge thank you to all of my colleagues in Sport Science who have provided direction and advice over my career. A special mention for three individuals in particular; Pitre Bourdon, who had the faith to give me a start in the industry and has always been available for anything that I have asked of him over the years (including proof reading this thesis), as well as Darren Burgess and Kevin Ball, whose professional support and personal friendship has kept me going along the path I have chosen when it would have been much easier to quit.

To my mum and dad, thank you for the incredible opportunity in life you have afforded me, and for instilling a life-long enthusiasm for both learning and sport, which have culminated in this thesis. A special thanks also to my sisters (and their families) and to my wife's family, who have played a larger role in this document than they could possibly imagine.

Finally, this and anything I do would not be possible without the amazing love and support of my wonderful wife, Jayne, and our two boys. The unwavering belief and encouragement I have received from them is the foundation of this thesis, and there are no words to describe the thanks I have for everything they give to me.

Table of Contents

List of Figures

List of Tables

1 Introduction

Athlete monitoring tools incorporating GPS and inertial sensors have dramatically expanded the range of metrics available to scientists, trainers and coaches that are available be used to describe training load and training effect in applied environments. Early studies into these devices focussed on validating basic variables such as velocity during different types of game style movements (Duffield, Reid, Baker, & Spratford, 2010; D. Jennings, S. Cormack, A. J. Coutts, L. Boyd, & R. J. Aughey, 2010a; D. Jennings, S. Cormack, A. J. Coutts, L. J. Boyd, & R. J. Aughey, 2010b) and how those variables can be used to describe training and gameplay, especially with athletes of different ability (Brewer, Dawson, Heasman, Stewart, & Cormack, 2010; Burgess, Naughton, & Norton, 2012; Gabbett, 2012; Hiscock, Dawson, Heasman, & Peeling, 2012). As practitioners have become more experienced and familiar with these devices, some more innovative practitioners have played a role in devising and examining new methods of analysis, some relying on inertial sensors to describe the physiological stress placed on the body, commonly referred to as load (Boyd, Ball, & Aughey, 2013), others finding alternative methods of analysing basic variables (Coutts et al., 2015; Osgnach, Poser, Bernardini, Rinaldo, & Di Prampero, 2010; Polglaze, Dawson, & Peeling, 2015).

The inertial sensors integrated into athlete monitoring devices offer great possibilities for developing new metrics and analysis techniques. They have been used to identify game specific movements (Chambers, Gabbett, Cole, & Beard, 2015) which can be integrated with other metrics to increase the complexity and resolution of descriptions of external and internal physical load. Recently, the possibilities of analysing intra-stride accelerometer data to assess neuromuscular fatigue (a decrease in the body's ability to maintain power output or achieve an optimal task performance) have been assessed by Buchheit, Gray, and Morin (2015) This study demonstrated the ability of athlete monitoring devices that incorporate inertial sensors to not only identify strides within a continuous time series of accelerometer data collected via a single tri-axial accelerometer mounted on the upper torso but also use these data to evaluate neuromuscular fatigue via stride characteristics such as stance time.

The full accelerometer waveform (or curve representing the accelerometer output) of a cyclic movement such as gait offers many possibilities for analysis. In addition to the temporal stride characteristic variables such as step time identified by Buchheit et al. (2015), the shape of the entire waveform can be assessed for measures such as the repeatability of the waveform (Dadashi, Millet, & Aminian, 2015). The ability to analyse the consistency of a gait waveform is an exciting prospect, given the recent focus on the relationship between variability (in particular the variability of waveforms generated during gait) and pathology (Bartlett, Wheat, & Robins, 2007; Stergiou & Decker, 2011; Stergiou, Harbourne, & Cavanaugh, 2006).

The possibilities of combining gait detection algorithms such as were used in Buchheit et al. (2015) with techniques for assessing waveform repeatability (Kavanagh, Morrison, James, & Barrett, 2006) and the implications of changes in the variability of movement over time (Stergiou & Decker, 2011; Stergiou et al., 2006) are very appealing. Currently, applied scientists within professional sporting clubs rely predominantly on measures describing the quantity of an activity to assess the potential physiological strain placed on an athlete. By combining gait detection algorithms with measures of stride waveform variability, there is the potential to establish metrics which describe the quality of movement, thereby adding to an applied practitioners' understanding of the current physical state of an athlete in their care. Furthermore, identifying methods where this process (in particular the detection of gait waveforms and subsequent assessment of variability) can be automated, the potential usefulness within the applied environment will be maximised.

The aim of this research was to investigate these possibilities by developing algorithms and an analysis tool for identifying stride waveforms within training and gameplay data, describe possible methods for applying that analysis tool to real data collected during competitive games, and to determine the usefulness of the analysis tool in the applied environment by examining results from longitudinal analyses of data in conjunction with instances where normal training activity was modified due to injury.

The development of the analysis tool will be outlined in Chapter 3, where methods used to identify and extract stride waveforms from similar periods of running (in this case, straight line running at high speed) as well as the statistical methods used to analyse these waveforms are described. Chapter 4 details the application of the analysis tool to data collected from professional Australian Rules footballers competing in Australian Football League games. Finally, the potential importance of this tool in applied situations such as a professional football club will be presented in Chapter 5 through cross-referencing results from the analysis tool to instances of missed or modified training during an Australian Football League season.

2 Review of literature

2.1 Athlete monitoring in sport

There is a long history of quantifying movement within team sport activities, in particular in soccer, through observation of gameplay, obtaining physiological measures during matches and simulated matches, and through determining the physiological capacity of elite players (Bangsbo, 1994). Quantifying movement during training and competition in sports such as soccer (Mohr, Krustrup, & Bangsbo, 2003) and Australian Football (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004) has regularly been achieved through techniques such as time-motion analysis. However, the accurate assessment of movement during competition or training was often a laborious and time-consuming process.

In recent years, miniaturisation of player tracking devices has simplified collection of training and in-game data across a wide variety of sports. One such sport is Australian Football, whose governing body, through allowing player tracking devices to be worn during competition, has facilitated a rapid escalation in the amount of data that can be used by clubs. The primary aim of collecting and interpreting this information is to minimise a player's risk of injury while maximising their game day performance.

Analysis of player tracking data has been mainly focussed on the validity of the measures provided by the units (Boyd, Ball, & Aughey, 2011; Coutts & Duffield, 2010), description of physical load encountered by athletes (Boyd et al., 2013; Brewer et al., 2010; Coutts et al., 2015), investigating the link between performance and game day physical output (Bauer, Young, Fahrner, & Harvey, 2015; Hiscock et al., 2012), and describing the development of the physical profile of elite Australian Rules Footballers (Burgess et al., 2012). These investigations have taken on a broad view of the data, looking at cumulative metrics over time periods ranging from minutes to hours, providing many important indicators and useful information that has informed the scientific and sporting population. However none have examined the extremely valuable technique information that can be extracted via a more detailed analysis of inertial sensor data. An important future development is to 'tap into' the more specific movement-based data and to explore in more detail what these data can tell us.

Inertial sensor data have been used to generate some cumulative metrics, and these variables have been examined and validated. For instance, the reliability of the accelerometers within a MinimaxX 2.0 unit (Catapult Sports, Australia) have been assessed for static reliability and dynamic reliability by Boyd, Ball & Aughey (2011). It was found that player load values that are based on accelerometer results (and calculated via the manufacturer's software) were suitable for use in Australian Rules Football as the noise (expressed as a coefficient of variation) was less than the signal (expressed as a smallest worthwhile difference). The player load value is an example of the typical method used to evaluate athlete activity via accelerometers. It is calculated by accumulating the data from three acceleration axes and integrating them to provide a vector magnitude, resulting in a value that is used to determine cumulative load over time. The pattern of acceleration and movement within a step will affect the player load if there is a difference in magnitude of the combined acceleration vector during the step, however there is no direct assessment of the pattern of acceleration during the movement. As a consequence, there is considerable scope for research into the development of analysis methods that utilise accelerometer data obtained from these personal GPS and inertial sensor devices to provide information on the quality of movement during sporting activities.

2.2 Using accelerometers to analyse movement

Accelerometers have proven to be a valuable tool in analysing movement and specific technique for many purposes (such as gait analysis and assessment of sport specific technique) and across a wide range of environments (such as in laboratory conditions, during competitive matches, under water etc.). Gait assessment, whether it be healthy gait (Moe-Nilssen & Helbostad, 2004) or impaired gait (Aminian et al., 1999), has been regularly assessed via accelerometry. Multiple inertial sensors have been used to measure joint kinematics (Picerno, Cereatti, & Cappozzo, 2008) or to identify key temporal characteristics of a stride (Auvinet, Gloria, Renault, & Barrey, 2002). Many types of inertial sensor systems have been used on the leg, shank and foot to identify key characteristics a stride. A review by Rueterbories, Spaich, Larsen, and Andersen (2010) provides an assessment of studies that have used accelerometers and other sensors for gait analysis. There have also been a number of studies that have focussed on a more practical approach using single tri-axial accelerometers mounted on the torso. A single tri-axial accelerometer mounted on the sacrum has been shown to provide accurate measurements of temporal stride characteristics such as stride, step and stance duration in national level runners (Lee, Mellifont, & Burkett, 2010), with good agreement between inertial sensor and infrared camera methods (less than 0.02s difference for most temporal measures). Accelerometers have also been shown to discriminate between different modes of gait and locomotion (Little, Lee, James, & Davison, 2013). Further investigation into the use of accelerometers mounted on the lower back has shown the ability of these techniques to measure vertical stride acceleration, demonstrating near perfect correlation (r=0.96), a small typical error of estimate of 1.84ms^{-2} (with 95% confidence limits of 1.3ms^{-2} to 3.27ms^{-2}) and low mean bias of 0.02 (±0.03) with infrared camera measurements (Lee, Sutter, Askew, & Burkett, 2010). In addition, this study demonstrated that asymmetries in steps taken on the left and right foot could be detected, providing a variable that can be readily used in the applied setting.

The need to incorporate other sensors (such as GPS) into a wearable athlete tracking tool usually requires such athlete tracking devices approved for use during training and competition to be worn on the upper torso to maximise the quality of the GPS signal. As a consequence, given this location has not regularly been freely chosen to assess gait in previous research, it could lead to the assumption that these units are unsuitable for gait assessment. This is particularly noteworthy given the findings of Trost, McIver, and Pate (2005) who suggested that for accurate assessment the placement of the device on the body and the actions subjects are required to perform should be quite strictly controlled. However, there is research to show that placing accelerometers on the upper torso does not preclude a critical analysis of gait. The magnitude of peak accelerations have been validated when a unit is placed on the upper torso (Wundersitz, Gastin, Richter, Robertson, & Netto, 2015) which demonstrates that when placed on the body according to the manufacturers recommendations, filtered data collected by a MinimaxX S4 unit (Catapult Sports, Australia) provides an acceptable means of assessing peak accelerations with a CV of 8.9% when filtered at 10 Hz. Similar units incorporating both GPS and inertial sensors (SPI HPU, GPSports, Canberra, Australia) mounted on the upper torso have been shown to accurately identify temporal stride characteristics when compared to an instrumented treadmill (Buchheit et al., 2015). Contact time was found to be almost perfectly correlated between accelerometer and treadmill measures (r=0.96) and large correlations were found for flight time (r=0.68). Both Wundersitz et al. (2015) and Buchheit et al. (2015) demonstrated that stride variables can be accurately measured using the 100Hz tri-axial accelerometers embedded in units placed on the upper torso.

An important additional finding by Bucheit, Gray and Morin was the ability of a tri-axial accelerometer mounted on the upper torso to identify side to side differences in stride characteristics. Ankle movement was constrained through taping and two of the three variables examined in the study correctly identified side to side differences in stride characteristics, with a 3.7% difference in contact time across taped and tape-free foot measured by the accelerometer being similar to the 4.5% difference measured via the instrumented treadmill. These findings confirm the ability of this and similar units that incorporate GPS and accelerometers to identify small differences in stride characteristics due to physical constraints placed on a subject within a laboratory setting. Extrapolating these results to a field based assessment and providing information on stride characteristics over the course of a training session or competitive game would provide valuable insight for scientists, trainers and coaches into the physical condition of athletes.

Field-based assessments using accelerometers has been a particular focus in swimming, due in part to the difficulties encountered attempting to use video based methods commonly used in other sports. In their review article, Magalhaes, Vannozzi, Gatta, and Fantozzi (2015) identified twenty seven articles that specifically investigated the use of inertial sensors to assess swimming biomechanics that were published in indexed journals and conference proceedings. Their key findings were that inertial sensors including accelerometers and gyroscopes are reliable and can be used for biomechanical performance assessment, they can be used continuously during a whole swimming trial so can increase the amount of data available for technique assessment (allowing modifications due to factors such as fatigue to be assessed) and metrics can be developed to progressively meet the desires of coaches and trainers. These findings can be extrapolated to other sports such as Australian Rules Football that face similar challenges of how technique can be unobtrusively assessed over the course of an entire training session or game to provide metrics desired by coaches and trainers.

The front crawl swimming stroke has regularly been used to assess the suitability of inertial sensors for specific technique assessment. Segment acceleration during a front crawl swimming stroke was assessed against conclusions drawn from video analysis by Callaway, Cobb, and Jones (2009) who concluded that although a swimmer’s performance cannot be determined via the pure acceleration of a body segment, acceleration can be used to show important information within the context of different sections within the stroke. Furthermore, issues to do with the accuracy of the measurement that were at the time limiting the use of accelerometers to inform adjustments to technique were progressively being mitigated by advances in technology and improvements in analysis techniques. Further research into the use of inertial sensors to assess swimming technique by Dadashi et al. (2015) demonstrated that kinematic variability can be assessed through inertial sensor values over a number of cycles, and that variability can be used to discriminate between subject groups of differing skill. Variability in this study referred to the amount of variation in each stroke from a constant speed irrespective of where that variation occurred during the stroke cycle, demonstrating the potential of inertial sensors to capture long periods of data and assess technical aspects of a movement in relation to how those variables change from stroke to stroke.

A key difference in the approaches taken by Dadashi et al. (2015) and Buchheit et al. (2015) is the method used in analysing the cyclical waveform. Key points within the waveform were identified in Buchheit et al. (2015) to output the contact time and flight time of a step. These variables were then collated over the course of the testing session. In Dadashi et al. (2015), the entire waveform representing intra-stroke velocity was evaluated for variance from the overall mean of that particular stroke, and the single variable for variance within the stroke was collated across the testing session. Combining the two methods by analysing gait through accelerometers positioned on the upper torso as per Buchheit et al. (2015) and evaluating the entire waveform as per Dadashi et al. (2015) would provide a method of gait analysis that can be used during training sessions and competitive games that could identify subtle variations within step waveforms.

2.3 Identification of matched sections of data

The assessment of human gait via accelerometers allows assessments that were once confined to laboratory environments to be extended into more practical settings. Stride characteristics in sprinting (Bergamini et al., 2012), and distance running (Auvinet et al., 2002; Wixted, Billing, & James, 2010) have been assessed in field conditions. However, although these studies were conducted in settings that were similar to the normal training or competition environment, data were not extracted from actual training or game situations.

Competition and training data has been assessed in sports such as rowing (Soper & Hume, 2004) and swimming (Dadashi et al., 2015). An advantage that these sports have is that the act of competing and training involves a cyclical and repeatable action that lends itself to longitudinal analysis. In other applications, the data needs to be interrogated to identify periods of matched activity. Accelerometry has previously been used in activity monitoring studies to identify periods of differing activities during a large collection duration (Trost et al., 2005). In a similar way, if field assessments in team sports which do not have consistent cyclical actions are to be conducted, periods of consistent high speed running in one direction without contact from an opponent must be identified, such as was done by Faude, Koch, and Meyer (2012) who identified periods of straight line sprinting in soccer via video-based time motion analysis.

Identifying matched periods of movement during training and competition will ensure that any analysis of gait is performed on strides with matched function and speed.

Validity testing on GPS systems have established that straight line running sections show the lowest variation to a known distance in a simulated team sport game environment (Jennings et al., 2010a), and that activity can be identified in gameplay situations (in Rugby League) before a period of high speed running (Gabbett, 2012). Also, inertial sensors within GPS units can be utilised to identify sport-specific movement patterns during training and gameplay across a wide range of sports (Chambers et al., 2015). Consequently, GPS devices that incorporate inertial sensors are able to accurately identify periods of high speed running, though they are less suitable for identifying short, sharp accelerations (Duffield et al., 2010; Jennings et al., 2010a). It has be concluded that GPS devices that incorporate inertial sensors are able to accurately identify periods of straight line running at high speed during normal training and gameplay.

2.4 Stride variability and pathology

Variability in movement has received much research interest in recent years. The concept of healthy variability in movement, particularly sporting movement was reviewed by Bartlett et al. (2007) and Bartlett (2008) who concluded that there was much still to learn about the effect of movement variability on many aspects of sports biomechanics, in particular whether a certain amount of variability is an indicator of a healthy movement. Indeed, Bartlett et al. (2007) identifies how proponents of different motor control paradigms can interpret movement variability with opposing functions. For instance, Cognitive motor control theorists view movement variability as undesirable, demonstrating a movement error, while Ecological motor control theorists view movement variability as providing flexibility allowing the individual to effectively adapt to changes in the environment.

These seemingly opposing views on the role of movement variability in the control of human movement are the result of two “camps” of scientists (Schmidt, 2003) who have “agreed to disagree” (Newell, 2003). However, Newell also observed that the “deep philosophical and theoretical issues” that are at the heart of these disagreements have not restricted experimentation within motor control and learning, with experiments able to be run as empirical questions “without reference to this important theoretical issue” (Newell, 2003, p. 385).

Studies where the authors have extrapolated results of a discrete experiment to encompass a broader theoretical question on the control of human movement can still aid in the understanding of the phenomenon of movement variability, particularly when results are viewed in the narrow context of the experimental question itself. For instance, Hamill, van Emmerik, Heiderscheit, and Li (1999) demonstrated that individuals with patellofemoral knee pain had reduced movement variability compared to a healthy group, and concluded that lower variability indicates a non-healthy state. The authors then postulated on the wider implications of these results with regard to the overall control of human movement. However, they also observe that lower variability may indicate the presence of an injury (though not the underlying cause of the injury) and that the narrow application of the experimental results may prove extremely useful in the detection of lower extremity running injuries within individuals.

Applying the methods of Hamill et al. (1999) as an effective clinical tool has received some support in subsequent studies such as Heiderscheit (2000b), however there have also been contradictory findings (Cunningham, Mullineaux, Noehren, Shapiro, & Uhl, 2014; Heiderscheit, Hamill, & van Emmerik, 2002) where no difference in movement variability was found between healthy and pathological groups. Although factors that may have influenced the suitability of movement variability as a discriminating factor between experimental groups were identified by the authors in both of these studies, Cunningham et al. (2014) concluded the clinical utility and applicability of coupling angle variability (the measure of movement variability used in their study) are not yet understood or necessarily supported. A key element of these studies is that subjects were separated into healthy and pathological groups. This was done on the assumption (based on theoretical considerations) that low variability in and of itself is an indicator of the underlying pathology.

Importantly, when a within-subject design is used, it has been shown that movement variability can change rapidly as a result of an experimental intervention, and that movement variability may indeed be a useful clinical tool to identify when an individual has a less than optimal movement pattern. Heiderscheit (2000a) demonstrated that movement variability increases in individuals with patellofemoral pain when their pain is reduced through a therapeutic intervention. This supports the suggestions of Hamill et al. (1999) that reduced movement variability may be the result of individuals finding a narrow range of joint angles that allow them to move with the minimum amount of pain, and once that pain is reduced they return to a level of movement variability that is more indicative of their healthy state. There is also evidence to suggest that fatigue can influence movement variability. Cortes, Onate, and Morrison (2014) demonstrated that as fatigue increases, variability in knee kinematics (among other variables) during a cutting manoeuvre increases, leading to a reduced ability to produce a controlled movement.

A theoretical perspective on why in one case movement variability may increase as a result of one intervention yet decrease as a result of a different intervention was presented by Stergiou et al. (2006). The authors proposed that an optimal and individual level of variability exists within the chaotic and highly complex structure of movement, and that increased rigidity (reflected in reduced variability) or instability (which translates to increased variability) is indicative of a system with reduced adaptability are associated with an unhealthy state.

Evidence supporting these theories has come from research into subjects who were ACL deficient (Moraiti, Stergiou, Ristanis, & Georgoulis, 2007) and subjects who had ACL reconstructions (Moraiti, Stergiou, Vasiliadis, Motsis, & Georgoulis, 2010) which showed that stride to stride variability differs from the injured leg to the uninjured leg. Less variability in the injured leg was found to be a characteristic of ACL deficient subjects, while more variability in the injured leg is a characteristic of subjects who has had an ACL reconstruction. Although it was acknowledged that the uninjured leg may not be representative of variability prior to the ACL injury as it has been demonstrated that an injured ACL can affect the step characteristics of the contra-lateral leg, the difference between variability in step waveforms between the injured and uninjured can be used to indicate the relative state of health of the knee joint.

Although motor variability, in particular motor variability in gait, may be an indicator of an unhealthy state, a subject's current physical condition may not be the only reason for a change in an individual's gait variability. One confounding factor for whether observed variability in gait is indicative of healthy or injured individuals is that variability in stride interval in running and walking has been shown to alter with running speed (Jordan, Challis, Cusumano, & Newell, 2009). Minimum values for stride interval variability are found at self-selected speeds (when both running and walking) demonstrating that variability (particularly as it relates to temporal stride characteristics) is not constant but alters with speed. Consequently, to accurately assess whether a movement is more or less variable than would be expected for a subject based on their long term average, the characteristics of the action being investigated must be tightly controlled.

In summary, motor variability exists, even in elite athlete populations who have undergone intensive training in a particular task (Bartlett et al., 2007) and, although it is unclear whether motor variability is a precursor to or an effect of an unhealthy state (Hamill et al., 1999), identifying instances when variability of a motor skill varies from the long term average offers valuable information on the overall health of the individual (Stergiou et al., 2006).

2.5 Measuring movement variability

The measurement technique used to calculate variability in movement is dependent on the underlying metrics. In the analysis of gait, the use of stride characteristics (such as stance duration) require a different analysis of variability compared with joint co-ordination patterns and metrics that interrogate the full waveform rather than specific characteristics of the waveform. Variability in stride characteristics (such as stride time and step width) have commonly been assessed via the coefficient of variation (Heiderscheit et al., 2002; Kadaba et al., 1989), percentage coefficient of variation (Hollman et al., 2010) and standard deviations (Balasubramanian, Neptune, & Kautz, 2009). However, when variability across the waveform of the cyclic movement is assessed, further data reduction must take place to describe the waveform itself before an assessment of the variability of that waveform can take place. Investigations into joint co-ordination have used continuous relative phase (Hamill et al., 1999) and relative motion plots (Heiderscheit et al., 2002) which are then analysed for variability via a coefficient of variation. While these methods do interrogate the entire waveform, they are effectively calculating a stride characteristic (in these cases joint co-ordination) that is then assessed across the trial in the same way as a characteristic such as stride time would be.

Movement variability around a mean has also been used to describe waveform variability. For example, the intra-stroke variability of velocity around a mean for the stroke has been assessed in swimming (Dadashi et al., 2015). This method treats each waveform in isolation and the average of the variability of each isolated waveform is used to describe the overall variability of the trial. Though an effective method to determine the variability around an overall mean, it does not effectively discriminate between differing techniques used to achieve the same outcome. For instance, the position of the peak velocity from stroke to stroke will not cause a change in overall waveform variability as long as the magnitude of the peak is consistent. Methods of examining both temporal aspects and magnitude of a waveform offer greater insight into the overall consistency of a movement.

Autocorrelation procedures have previously been used to describe variability within gait as measured by accelerometers (Moe-Nilssen & Helbostad, 2004). The unbiased autocorrelation method is able to estimate curve similarity through calculating the sum of variables in a time series multiplied by variables at a phase shift equivalent to one stride. It has been shown to be able to discriminate between fit and frail adult populations purely on measurements from trunk mounted accelerometers (Moe-Nilssen & Helbostad, 2005). Methods to correct for different walking speeds using curve fitting to estimate variability at a common speed were demonstrated in the same study. The autocorrelation procedure is an effective method of estimating the repeatability of both stride waveform and stride characteristics of sequential steps.

Non-linear approaches used by Stergiou et al. (2006), based on methods used in previous research into postural control (Harbourne & Stergiou, 2003) assess gait waveforms via the Lyapunov Exponent, which is the slope of the average logarithmic divergence of the trajectories from sequential trials in a three dimensional state space. In gait data, by taking the logarithmic difference at each time point from the previous waveform this method estimates how kinematics vary from one stride to the next given the three dimensional position of the previous stride, a particularly effective method of assessing sequential cyclic waveforms and movements when the position of the previous waveform influences the position of the subsequent waveform at the same point within the movement cycle.

Another method of assessing the repeatability of a waveform within and between testing days is the adjusted co-efficient of multiple determination (Kadaba et al., 1989) which calculates the variance around the mean at each time point in a waveform divided by the variance of all points around the grand mean. An advantage of this method over the Lyapunov Exponent and autocorrelation procedures is that it does not require sequential waveforms to be used to determine the overall variability of the waveforms, and the similarity of a group of waveforms at different times within or even between testing sessions can be evaluated.

The potential for combining waveforms taken from disparate sections of a test session is an important point when examining waveform variability in field based studies, in particular where data and waveforms are extracted from training and competitive game situations. In these circumstances, selecting a statistical tool that requires waveforms to be taken from a continuous time series would considerably reduce the potential number of waveforms available for analysis, particularly as there is the potential for gameplay requirements (such as moving the body to scan for the ball or other players) to contaminate an otherwise useable period of play. Consequently, the adjusted co-efficient of multiple determination (and related adjusted co-efficient of multiple correlation, which is the square root of the co-efficient of multiple determination) appears to be the most appropriate method of analysing waveform variability (in regards to both magnitude and temporal aspects of a waveform) in studies where data from training and games are used. Using this statistical tool will permit the exclusion of strides where gameplay influences have contaminated the movement without having to exclude the entire time series. In addition, it will allow combining the disparate time series from a particular game or training session into one homologous collection of waveforms.

2.6 Advantages and disadvantages of the Coefficient of Multiple Determination and Coefficient of Multiple Correlation

The coefficient of multiple correlation (CMD) and related coefficient of multiple correlation (CMC) has previously been used to analyse many forms of cyclic kinematic and kinetic data that in recent times have ranged from an analysis of kinematic variability in gymnastics (Farana, Jandacka, & Irwin, 2013) to electromyographic, kinematic and kinetic measures of ice hockey skating (Buckeridge, LeVangie, Stetter, Nigg, & Nigg, 2015). The versatility of the CMC as a statistical measure of repeatability is demonstrated when comparing the methods used in these two studies. In the first, waveforms representing different trials in a gymnastic skill were assessed for repeatability. In the second, the variability of individual strokes representing a stroke during the acceleration and steady state phases within a continuous time series of skating on ice were analysed. Both studies used waveforms that were not adjacent, in Farana et al. (2013) due to the fact that only one waveform was generated per trial and in Buckeridge et al. (2015) because the desired comparison was between normalised waveforms generated during different phases of the continuous time series.

Accelerometer data have been evaluated against motion capture data using the CMC (Mayagoitia, Nene, & Veltink, 2002). The authors compared shank angular acceleration and knee linear acceleration (both measured via accelerometers) to motion capture data measuring the same parameters. The CMC and the root of the mean of the squared differences (RMS) between waveforms were used as the statistical tools to compare waveform shapes. Results demonstrated that CMC and RMS both showed a high degree of agreement between waveforms and that both methods were comparable when assessing the similarity of waveform shape. Shank angular acceleration waveform comparisons returned CMC values of above 0.986 and RMS percentage errors of below 7%, while knee linear acceleration waveform comparisons returned CMC values between 0.935 and 0.962 and RMS percentage errors between

11.4% and 14.9%. This demonstrates the value of using CMC as a statistical tool to evaluate the repeatability of waveforms generated via accelerometers.

In a meta-analysis of published gait studies with a focus on between-session repeatability and reliability, McGinley, Baker, Wolfe, and Morris (2009) found that CMC or CMD was used in 8 of the 23 identified studies. However, the authors raised concerns about the suitability of CMC in assessing repeatability in gait kinematics, largely due to the influence of joint range of motion on the magnitude of the CMC, and the adoption of arbitrary values for determining the acceptability of reliability indices. It was recommended that the development of minimum levels of detectable change (MDC) or minimal clinically important differences (MCID) be considered, as well as reporting absolute measures of measurement error in combination with the CMC.

A similarly cautious view of the suitability of CMC in evaluating variability in gait was taken by Røislien, Skare, Opheim, and Rennie (2012) who artificially simulated variability around real gait data and investigated the effects on CMC measurements. They demonstrated several shortcomings in using CMC as a measure of curve similarity for kinematic gait data, with comparisons between joints affected by different ranges of motion, and common data reduction protocols (such as removing marker offsets) having excessive influence over CMC and resulting in overestimation of curve similarity. They conclude that CMC is not an objective statistical measure of curve similarity for kinematic gait data and advise against using it in its current form.

Notwithstanding the concerns raised in the studies outlined previously, there are a number of reasons why the CMC can be an appropriate statistical tool. By limiting the waveform comparisons to longitudinal within-subject analyses, the error introduced when combining two normalised waveforms that represent different ranges of motion is reduced. There are still comparisons between x, y and z direction forces which have quite different ranges of motion, but if these axes are considered in isolation rather than in combination with each other, the risk of misinterpretation of results due to errors resulting from range of motion differences is minimised. In addition, if an individual's longitudinal CMC is combined with an individual minimum detectable change (Haley & Fragala-Pinkham, 2006) as advocated by McGinley et al (2009), individual differences between athletes can be taken into account during analysis, as opposed to making assumptions (based on the group response) on what is a significant level of variability for that individual.

Sampling rate has been shown to affect CMC results in gait, as higher sample rates have the possible effect of overestimating curve similarity due to the adjacent points within a gait cycle being highly correlated (Røislien et al., 2012). The sample rate of accelerometers commonly contained within athlete monitoring devices is 100 Hz, which is low compared to the sampling rates used to investigate gait via trunk mounted accelerometers which range from 100 Hz (Buchheit et al., 2015; Lee, Mellifont, et al., 2010) to 500 Hz (Wixted et al., 2010). The relatively low sample rate regularly used in athlete monitoring devices reduces the risk of overestimating curve similarity.

2.7 Summary

In summary, the analysis of accelerometer data collected by personal GPS devices to investigate the quality of movement has largely been neglected. The analysis of these accelerometer data is an area that offers great possibilities for further investigation, particularly given the widespread use of devices that combine GPS and inertial sensors in elite sport.

Much of the research into using accelerometry to investigate the quality of an athlete's technique has been conducted in sports with a repeatable and cyclical action, such as rowing. For similar data to be extracted from team sport training and gameplay, matched sections of straight line high speed running need to be identified. Research has shown that this is very possible to do with the sensors contained within units combining GPS and inertial sensors.

An effective method of analysing the quality of an athletic technique as it relates to the physical condition of the athlete is through investigating the variability of the action. Research has demonstrated the link between a change in the variability of an action (including variability in gait) and pathology (Hamill, Palmer, & van Emmerik, 2012; Hamill et al., 1999; Heiderscheit et al., 2002; Stergiou & Decker, 2011; Stergiou et al., 2006).

Consequently, an analysis tool that uses accelerometer and GPS data routinely collected in elite sport environments to provide information on the quality of athletic gait is not only possible but could provide vital information within applied settings on the physical condition of an athlete. The development of such an analysis tool, along with investigations as to its efficacy within applied settings will be the subject of subsequent chapters of this thesis.

3 Development of Analysis tool

3.1 Introduction

The development of an analysis tool to extract stride features from accelerometer and GPS data is a complex process made worthwhile by the detailed information on the physical condition of a subject that can be extracted from these data. Advances in wearable sensors have led to these data being routinely collected during training and competition in many team and individual sports. However, the complexities surrounding extraction of information on stride characteristics has generally precluded any thorough examination of these step by step accelerometer data. An analysis tool that quickly and efficiently extracts key features describing stride characteristics that can be used alongside other measures in the longitudinal monitoring of athlete condition could be a particularly valuable tool across many sports.

A single game of Australian Rules Football has a duration of approximately two hours of actual playing time. As GPS is collected at 10 Hz and inertial sensor data is collected at 100 Hz, there is a considerable amount of data to be examined within each game. Consequently, the first stage in the development of the analysis tool is to reduce the amount of data to be examined by establishing parameters for identifying matched sections of running from the data. This is necessary not only for reducing the volume of data and steps to be analysed but also because using sections of data that are closely matched will minimise the stride variability due to activity and gameplay demands. The methods used to identify matched sections of activity utilised GPS data, examine direction (whether or not the athlete is running in a straight line) and velocity. Adjusting the upper and lower limit for valid velocities will substantially affect the amount of data extracted from the file as a whole, and examinations around the establishment of upper and lower limits for velocity will be presented in part 1 and part 4 of this chapter.

Once matched sections have been identified, individual steps need to be extracted from the accelerometer data taken from the matched sections. This procedure includes identification of individual steps, identification of which foot those steps were taken on, removal of outliers, filtering steps for temporal characteristics and using an equal number of steps from each section within a game. Descriptions of these protocols and examinations around some procedures can be found in part 2 of this chapter.

After extracting the step by step waveforms from the accelerometer data those step waveforms can be quantified and described statistically. This can be done in a number of ways, but the method chosen for this analysis tool is to assess the variability of the step waveforms via the coefficient of multiple determination (CMD). This calculation has been previously used in gait data, though not in the specific context of measuring stride characteristics via a single tri-axial accelerometer mounted on the upper torso, as is the case here. It was chosen because it examines the waveform in its entirety rather than at specific points such as at footstrike or toe-off, and therefore accurate identification of specific points within the gait cycle will be less influential on the result of the analysis. Descriptions of how the CMD is calculated as well as the sensitivity of the calculations to pre-selection of the step waveforms, the amount of data available and how the CMD calculation can be applied to waveforms extracted from the same or different games can be found in parts 2, 3, 4 and 5 of this chapter.

3.2 General Aims

1. Establish protocols for selection of matched sections of running for comparison
    a. Establish protocols for matching running velocity (sections 3.4 and 3.7)
    b. Establish protocols for matching activity - straight line running (section 3.4)
2. Establish protocols for extraction of accelerometer waveforms of steps from matched sections
    a. Establish protocols for the classification of steps (section 3.5)
    b. Establish protocols for filtering steps and removal of outliers (section 3.5)
3. Establish methods to quantify and compare waveforms
    a. Describe methods for examining waveform variability within individual football games (section 3.5)
    b. Examine the CMD results when waveforms are excluded from the analysis to simulate games with less data available for analysis (section 3.5)
    c. Perform simulations to examine the CMD results when the amount of data extracted from a single game is reduced (sections 3.6 and 3.7)
    d. Describe methods for examining waveform variability between games (section 3.8)

3.3 General Methods

3.3.1 Subjects

Twenty two professional footballers competing in the Australian Football League (AFL) with an age range of 19 to 28 years old (mean age = 24, mean height = 1.87m, mean mass = 86kg) were used in these studies. This subject cohort represents all athletes who participated in games for the Port Adelaide Football Club during the 2014 Australian Football League season who provided informed consent for their data to be used in this study (details of which can be found in Appendix A). The Human Research Ethics Committee of Victoria University approved the use of human subjects. There was no pre-selection for the position subjects played during a game, or for physical capacity to run at high speeds. Consequently, this cohort provides a comprehensive representation of a typical group of professional AFL footballers that can be found at any AFL club, and is consistent with previous studies encompassing a squad of AFL players (Bauer et al., 2015; Rogalski, Dawson, Heasman, & Gabbett, 2013).

3.3.2 **Software**

The LabVIEW 2014 full development system was used to create the analysis tool. Further analysis of results output from the analysis tool was performed in Microsoft Excel™.

3.3.3 **Data**

Data were collected from 17 competitive games during the 2014 AFL season. Each subject wore a S4 Minimaxx unit (Catapult Sports, Melbourne) fitted into a tight pocket immediately under the collar at the rear of their playing jersey. Subjects were assigned the same unit each game. The data collected and used in these studies were GPS (measured at 10 Hz) and tri-axial accelerometer (measured at 100 Hz). Additional data on the start and end time for quarters within the game, as well as periods spent on the interchange bench was available for some games. Not all games from the season were available for analysis as some games took place in a stadium with a roof, so GPS data were not available for those games. In addition, some data were lost and therefore unavailable when data were collated at the end of the season. Data were de-identified prior to being supplied by the Port Adelaide Football Club.

Data from all available games (n=17) was collated and exported via the raw data export function within the Sprint software package (version 5.1, Catapult Sports, Melbourne), which is the native operating software for the S4 units. The sport selection setting in the software was set to “Team Sports: AFL”. GPS data (smooth speed, latitude and longitude) were exported at 10 Hz, while accelerometer data (forward, sideways and up) were exported separately at 100 Hz. The data was exported separately to aid control of memory allocation in the automated processor software.

3.3.4 **Axis Definitions**

For the purposes of this study the accelerations are defined as follows;

- *x* axis accelerations will be anterior/posterior, with positive accelerations in the anterior direction (which in the data exported from the Sprint software package corresponds to the “forwards” accelerations).
- *y* axis accelerations will be medial/lateral, with positive accelerations being towards the athletes right (which in the data exported from the Sprint software package corresponds to the “sideways” accelerations).
- *z* axis accelerations will be accelerations perpendicular to the transverse plane of the athlete with positive accelerations signifying accelerations towards the top of the athlete’s head (which in the data exported from the Sprint software package corresponds to the “up” accelerations).

3.3.5 **Selection of Variables for Analysis**

The overall goal of the analysis tool was to quickly and efficiently extract descriptions of an athlete’s stride characteristics from normal training and gameplay within an elite team sport environment. An important element of this was to be able to perform this analysis without any additional sensors to the ones normally used in elite sport environments, and without the need for additional tasks during training or games (such as pre-defined pattern runs), thereby maximising the possibilities that this analysis would be adopted in environment that is commonly resistant to any extra requirements for athlete testing. Consequently, the 100 Hz tri-axial accelerometer data collected by personal GPS devices that are commonly worn by elite athletes (particularly team sport athletes) were used. As the location of the GPS device was on the upper back (to optimise the GPS signal strength whilst minimising the risk of impact to the unit), the tri-axial accelerometer was not in a position that is commonly used for gait analysis.

Although the position of the accelerometer may not be in the optimal position for gait analysis, have been some studies which demonstrated that it is possible to determine temporal stride characteristics such as flight time and contact time when the accelerometer is placed on the upper back. Two notable studies that demonstrated the efficacy of using devices similar to a Minimaxx unit to calculate temporal stride characteristics (such as flight time and contact time) are Gaudino, Gaudino, Alberti, and Minetti (2013) and Buchheit et al. (2015).

However, these temporal stride characteristics do not provide a comprehensive description of the stride. It is possible for two strides to have identical temporal characteristics yet have a very different accelerometer waveform. There has also been research which suggests that temporal characteristics alone may not be enough to identify significant differences in an elite athlete's stride characteristics when they are functionally overreached (Fuller et al., 2017). This and other research into the variability of 'end point' measures (metrics that describe the product of the movement) such as stride rate suggests that a more complete analysis of the full accelerometer waveform may provide a more detailed description of an individual's physical state (Hamill et al., 2012; Hausdorff, 2007; Preatoni et al., 2013).

Measures of impulse taken from the step accelerometer waveform could also be considered as an effective means to describing the waveform. However, there are two important reasons why impulse was not used in this study. Firstly it was felt that the important aspect of this analysis was the comparison of the shape of the curve, and a single measure of impulse would not effectively discriminate between two waveforms. For instance, one waveform could have high acceleration in mid-stance and low acceleration at toe off but could record the same impulse as a curve with low acceleration during mid-stance and high acceleration at toe-off. Secondly, the large spike in acceleration at foot contact would cause any small difference between curves during this period to disproportionately affect the overall difference in impulse of the curves.

One approach that has previously been used to indicate the existence (or otherwise) of a pathological state within individual subjects is through examining the coordinative variability of kinematic waveforms. This approach has been used in subjects with patellofemoral pain (Hamill et al., 2012; Hamill et al., 1999; Heiderscheit et al., 2002) and knee ligament injuries (Moraiti et al., 2007; Moraiti et al., 2010). In addition, the concept of an optimal level of coordinative variability in a subject's gait that is indicative of a healthy state within an individual has been proposed (Hamill et al., 2012; Stergiou & Decker, 2011; Stergiou et al., 2006).

There is also research which suggests that the movement variability, measured without conforming to accepted methods for examining coordinative variability such as angle-angle or position-velocity plots as outlined by Preatoni et al. (2013), also has an optimal individual level specific to the movement in question (Bartlett, 2008; Bartlett et al., 2007; Stergiou & Decker, 2011).

An aim of this research is to design an analysis tool that does not require any additional instrumentation to that already has widespread use within applied settings, in particular within elite sport. Consequently, coordinative variability is not a metric that can be readily examined in this environment as it cannot be measured via the instrumentation available. Instead an analysis of movement variability, examining the repeatability of stride trunk acceleration waveforms measured via the tri-axial accelerometer contained within the personal GPS device commonly worn by elite athletes will be used.

By using optimal stride trunk acceleration variability of an individual as the primary variable to be analysed for the current study, there is the potential to identify individuals who have either a higher or lower amount of variability than is normal for them. The underlying cause for the disparity from their normal level of variability is likely to be very different depending on whether there shift is to the higher or lower side, and there is no indication whether the shift is an indicator or cause of a potentially pathological state. However, through indicating when an athlete is outside of their normal healthy state, accelerometer waveform variability can provide an insight into an athlete's current physical condition.

It is important to note here the distinction between the underlying metric describing the variability of the movement itself, and the metric used to determine whether or not an athlete has strayed from their 'normal' amount of variability for the movement in question, thus potentially indicating a pathological state. The former value, describing movement variability, can be any measure that examines how variable an individual's kinematics are on a particular day. The latter value examines variance from a mean, providing context to the movement variability metric which can be used to investigate the underlying physical state of the athlete. Providing context to movement variability metrics is vital, particularly given that the magnitudes of such metrics are commonly specific to not only the individual but the action being examined, rendering a such metrics without context meaningless.

A further advantage in using a metric to describe an individual's variance as the primary variable to be analysed within the current study is that it is not dissimilar from methods regularly used within elite sporting environments to monitor and track athlete wellbeing over the course of a season, as per Rogalski et al. (2013). Consequently, the potential to transfer results and conclusions from this research into the applied setting is quite high.

3.4 Part 1 - Identification of matched sections of running

Stride characteristics naturally vary with different gameplay demands. To identify gameplay and training situations where an individual's stride characteristics have varied from what could be considered their normal, the selection of sections within the match or training to be analysed must represent similar activities. This will minimise the influence of natural variation in stride characteristics during a game. In other words, the strides should be taken from similar situations to minimise the natural variability and maximise the variability due to factors we are interested in such as fatigue and injury, particularly given the random movement patterns characterising the gameplay data being used within this study. Athlete tracking devices incorporating GPS sensors provide an avenue to identify periods of similar movement. By identifying sections where the athlete has run in a straight line over a certain speed, the influence of the natural variation in stride characteristics due to gameplay demand can be minimised.

The magnitude of ground reaction forces has been shown to increase as speed increases (Brughelli, Cronin, & Chaouachi, 2011), so it is expected that running at higher speeds will exacerbate any between-stride variability effects. Additionally, variability in several gait variables increases as speed increases past an individual's preferred running speed (Jordan, Challis, Cusumano, & Newell, 2009). Though an increase in variability with running speed would imply a need to compare strides within a narrow a range of speeds, this will compromise the practical application of this analysis tool by reducing both the total number of sections that satisfy the rules for inclusion in the analysis and the length of those sections.

3.4.1 Aims

- Examine the effects of modifying the maximum change in GPS heading used to define running in a straight line on the average amount of straight line running identified per game
- Examine the effect of reducing the upper velocity limit on the average amount of straight line high speed running that is identified per game
- Examine the average amount of straight line running at high speed that is identified per subject

3.4.2 Methods

3.4.2.1 *Subjects*

A subset of 18 participants from the original cohort of 22 was used in this study. Participants who did not have at least one game where information on playing time (including time spent on the interchange bench), GPS data and inertial sensor data available were excluded from this study.

3.4.2.2 ***Data analysis***

Data from games during the 2014 AFL season were analysed to examine the effects of altering various parameters used to identify periods of straight line high speed (SLHS) running. Player tracking data (both GPS and inertial sensor) captured with a Catapult S4 device (Catapult Sports, Melbourne) and information on playing time (taking into account both the length of the periods within the game and, as players are regularly interchanged during a game of AFL football, the time spent on the interchange bench) were collated. Games were excluded if either playing time, GPS data or inertial sensor data were not present.

3.4.2.2.1 **Straight line running**

Latitude and Longitude positional data were examined point by point to identify periods of straight line running using the following procedure.

1. The instantaneous bearing was calculated for each point using the latitude and longitude between the current point (the 'start point')and the point 1.5 s later (the 'end point')
    a. Instantaneous bearing was calculated using Equation 3-1

Equation 3-1 Equation used to calculate instantaneous bearing from latitude and longitude

$$\theta = atan2(\, sin\Delta\lambda \,*\, cos\varphi_2 \,, cos\varphi_1 \,*\, sin\varphi_2 \,-\, sin\varphi_1 \,*\, cos\varphi_2 \,*\, cos\Delta\lambda)$$

$$where\ \varphi_1, \lambda_1\ is\ the\ start\ point, \varphi_2, \lambda_2\ the\ end\ point\ and\ \Delta\lambda\ the\ difference\ in\ latitude$$

2. The bearing change was calculated by determining the difference in the instantaneous bearing at the current point and the point 1.5 s later
3. If the average bearing change during the subsequent 5 s was between ±0.05 rad then that point was considered to be a valid straight line running point

Varying the time period used to examine average bearing change (initially set at 5 s) and the window of valid angles (initially set at ±0.05 rad) will affect the amount of straight line running points identified. To examine the effects of altering these two variables on the total SLHS time a number of iterations were run, progressively reducing both the time period and window of angles (but leaving the velocity range constant at 4.17 m/s to 6.94 m/s). Tables 3.1 and 3.2 list the options examined for time periods and angle windows. The mean result for each replication was determined, as well as the minimum individual subject mean for each replication when the full data set was divided into individual subjects. These replications were further examined to investigate whether reducing the time period elicited a similar reduction in SLHS time across the angle options. This was done for each angle option by dividing the average

SLHS time at each time option by the SLHS time at the 10 s option. A similar analysis was performed to investigate whether reducing the angle window elicited a similar reduction in SLHS time across the time options.

Table 3.1 Time period options examined

Option	Time Period (s)
1	10
2	7.5
3	5
4	2.5

Table 3.2 Angle window options examined

	Angles	
Option	radians	Degrees
1	±0.1	±5.73
2	±0.075	±4.30
3	±0.05	±2.86
4	±0.025	±1.43

3.4.2.2.2 **High Speed Running**

Periods of high speed running were identified by examining the subject's velocity point by point. Velocity was required to be over 4.17 m/s (15 km/h) to be considered high speed. This speed was chosen as it has been used in previous research to represent the lower velocity limit for high speed running in Australian Rules Football (Brewer et al., 2010). The upper threshold velocity was progressively reduced to examine the effect of narrowing the window of valid velocities on total high speed running instances and time. Although an upper limit of 11.11 m/s is highly unlikely to be achieved, this value was included as it would include all activities over the lower limit without including potential erroneous 'spikes' in the velocity data. Table 3.3 lists the upper velocities examined.

Table 3.3 List of upper velocities examined in section 3.4

	Upper Limit	
Condition	m/s	km/h
1	5.56	20
2	6.25	22.5
3	6.94	25
4	7.64	27.5
5	8.33	30
6	11.11	40

To be considered a valid SLHS section, both straight line and high speed rules need to be satisfied for at least 5 s. The number of valid SLHS sections and total SLHS time were calculated across all upper velocity conditions listed in Table 3.3 with straight line running parameters fixed at 5 s and ±0.05 rad. These straight line variables were selected because they allow some flexibility in the running direction. This flexibility permits small deviations from a perfectly straight line due to measurement error from the GPS and actual deviations in running direction during a straight line running section. The total number of SLHS sections and total SLHS time across all upper velocity limit conditions was calculated for each game and subject. The results from each game and subject were further analysed by calculating the time spent in SLHS at each speed condition as a percentage of the no upper velocity limit condition. Finally, each game and subject were further analysed by calculating the time spent in SLHS at each speed condition as a percentage of the total time spent on the field.

3.4.3 **Results**

Mean SLHS time per game across the four time options and four angle window options is shown in Table 3.4. Minimum individual subject mean across the four time options and four angle window options is shown in Table 3.5. Further analysis of the overall mean (according to the procedures outlined in 3.4.2.2.1) can be found in Tables 3.6 and 3.7. It is pertinent to note that when SLHS time by minimum straight line time is expressed as a percentage of the ±0.1 angle condition, there is a consistent reduction as the angle window is narrowed (Table 3.6). Similarly, when SLHS time by angle window condition is expressed as a percentage of the 2.5 s minimum straight line time option, there is a consistent reduction as the minimum straight line time is reduced. (Table 3.7).

Table 3.4 Mean SLHS time per game across options for minimum time and maximum angle deviation

	Angle Window (rad)			
Minimum Time	±0.025	±0.05	±0.075	±0.1
2.5	207.0	263.3	304.8	340.2
5	150.7	193.4	222.0	241.6
7.5	95.1	119.9	135.8	146.9
10	52.5	64.8	73.5	79.3

Table 3.5 Minimum subject season mean SLHS time per game across options for minimum time and maximum angle deviation

	Angle Window (rad)			
Minimum Time	±0.025	±0.05	±0.075	±0.1
2.5	64.0	91.6	103.9	125.1
5	11.2	51.7	61.1	67.0
7.5	7.6	7.8	8.0	8.2
10	0.0	0.0	0.0	0.0

Table 3.6 Mean SLHS time for minimum straight line time and maximum angle deviation expressed as a percentage of the ±0.1 rad angle condition

	Angle Window (rad)			
Minimum Time	±0.025	±0.05	±0.075	±0.1
2.5	60.8%	77.4%	89.6%	100.0%
5	62.4%	80.0%	91.9%	100.0%
7.5	64.7%	81.6%	92.4%	100.0%
10	66.1%	81.7%	92.7%	100.0%

Table 3.7 Mean SLHS time for minimum straight line time and maximum angle deviation expressed as a percentage of the 2.5 s time condition

	Angle Window (rad)			
Minimum Time	±0.025	±0.05	±0.075	±0.1
2.5	100.0%	100.0%	100.0%	100.0%
5	72.8%	73.4%	72.8%	71.0%
7.5	45.9%	45.5%	44.5%	43.2%
10	25.3%	24.6%	24.1%	23.3%

Results from the analysis of how changing the upper velocity limit affects the number of SLHS sections identified per game as well as the mean SLHS time per game are found in Table 3.8. Further analysis to examine the reduction in mean SLHS time (by expressing the mean SLHS time as a percentage of the no upper limit condition) and the mean SLHS time by upper limit condition as a percentage of time on field can be found in Tables 3.9 and 3.10 respectively. It is worth noting the wide range of results within upper velocity limit conditions (as seen by the differential between maximum and minimum values). The range of individual subject results can also be seen in Figure 3.1 which shows the mean SLHS time broken down into upper velocity limit conditions.

Table 3.8 Mean number of SLHS sections and average SLHS time with varying upper velocity limits (angle window set at ±0.05)

Upper Velocity Limit (m/s)	Number of SLHS Sections			Average SLHS Time (s)		
	Mean	Maximum	Minimum	Mean	Maximum	Minimum
11.11	40.7	65	23	252	402	145
8.33	39.9	63	23	247	389	145
7.64	36.8	56	22	229	350	135
6.94	30.9	45	17	194	286	107
6.25	22.0	30	13	140	193	79
5.56	11.4	17	4	73	109	28

Table 3.9 Mean SLHS time expressed as a percentage of the no upper limit condition

Upper Velocity Limit (m/s)	Mean	Maximum	Minimum
11.11	100.0%	100.0%	100.0%
8.33	98.2%	100.0%	94.8%
7.64	91.1%	100.0%	83.3%
6.94	76.8%	95.0%	64.5%
6.25	55.3%	85.8%	42.2%
5.56	28.4%	55.4%	15.4%

Table 3.10 Mean of SLHS time expressed as a percentage of time on the field

Upper Velocity Limit (m/s)	Mean	Maximum	Minimum
11.11	4.23%	7.04%	2.14%
8.33	4.14%	6.81%	2.12%
7.64	3.83%	6.12%	1.96%
6.94	3.21%	5.00%	1.55%
6.25	2.30%	3.50%	1.14%
5.56	1.17%	1.77%	0.40%

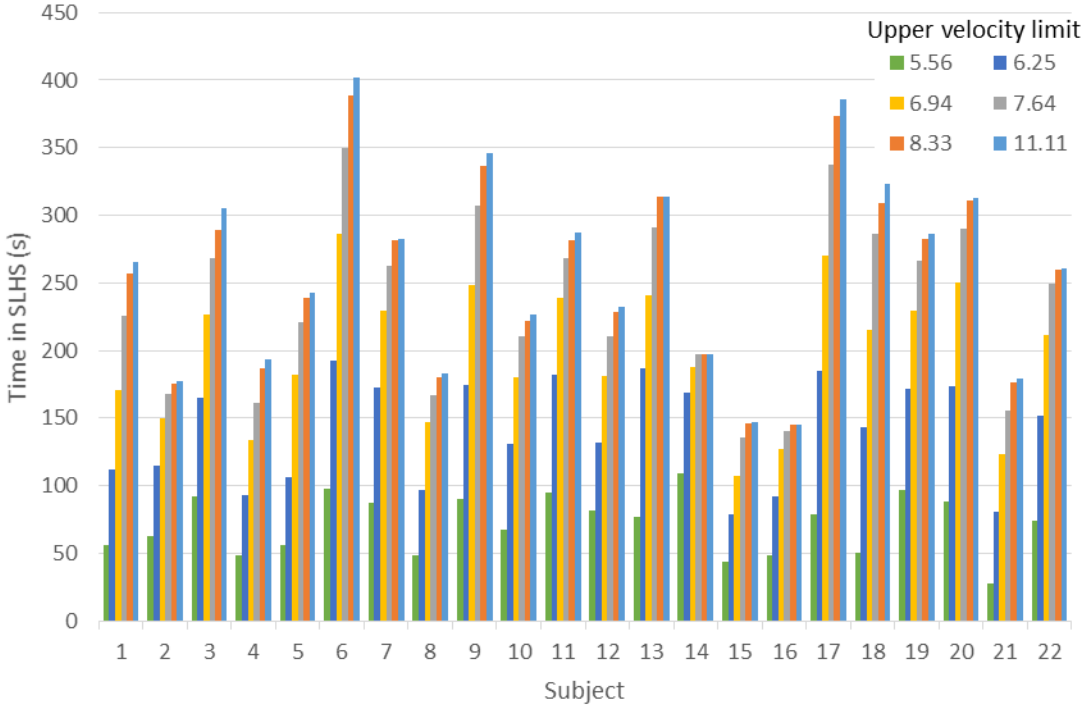


Figure 3-1 Graph displaying subject by subject mean time in SLHS at different upper velocity limits

3.4.4 **Discussion**

As angle window is reduced, the mean SLHS time also reduces. Table 3.5 shows that when this reduction is expressed as a percentage of the maximum angle window condition (±0.1 rad) for the particular minimum straight line time, the reduction in mean SLHS time is consistent across minimum time conditions. Table 3.6 shows that a similar pattern is found in when the mean SLHS time is expressed as a percentage of the minimum straight line time condition (2.5 s). Unsurprisingly, this demonstrates that the most amount of SLHS time results from a wide angle window and short minimum time of straight line running.

Ideally, straight line running sections would comprise small deviations in bearing (which would equate to a narrow angle window), and have a long minimum duration. There needs therefore to be some compromise to allow sufficient SLHS time to be identified within games. A minimum straight line time of 2.5 s will potentially include sections of only 10.4 m in length. Increasing the minimum time to 5 s will increase the minimum possible section length to 20.8 m while reducing the SLHS time by approximately 27%. Reducing the angle window to the narrowest setting (±0.025 rad) will reduce the SLHS time by approximately 37.5%. The next widest angle window (±0.05 rad) will only reduce the SLHS time by approximately 20%. The ideal settings of the narrowest angle window (±0.025) and longest minimum time (10 s) provide an average of 79.3 s of SLHS time which corresponds to approximately 130 stride waveforms per game available for further analysis (based on a mean step time of 0.3 s). Though it could be expected that this number of waveforms would provide adequate opportunity for further analysis, it is the average of all subjects so there will be some subjects with considerably less strides available on average per game. An analysis of the individual subject results was conducted (Table 3.10) and this analysis revealed that the minimum subject mean for SLHS time with an angle window of ±0.025 rad and minimum straight line time of 10 s was 0 s, meaning that these settings are not appropriate for all subjects. Increasing the minimum time to 5 s and widening the angle window to ±0.05 rad provided an average of 193.4 s of SLHS running with a minimum subject mean of 51.7 s (approximately 85 strides). Therefore, a minimum straight line time of 5 s and angle window of ±0.05 seems to provide an acceptable compromise between the ideal parameters and the need to provide enough waveforms for further analysis.

There is a progressive reduction in the number of SLHS sections as the upper velocity limit is reduced. This is to be expected as progressively more efforts that quickly transition from entering the lower limit to exiting the upper limit (which are periods of high acceleration) will be discarded as the upper velocity limit is reduced. Additionally, time spent over the upper velocity limit will be removed from the analysis which will lead to a further reduction in total SLHS time. The smallest reduction occurs between 11.11 m/s and 8.33 m/s, presumably due to the small amount of time spent over 9.03 m/s during a game and the difficulty most subjects will have in reaching speeds over 8.33 m/s. Subsequent steps down in upper velocity limit show progressive increases in the difference in both mean SLHS time and sections. Mean SLHS time reduces by 5 s between the top two upper speed limit conditions, then 18 s between 8.33 m/s and 7.64 m/s conditions, 35 s between 7.64 m/s and 6.94 m/s conditions, 54 s between 6.94 m/s and 6.25 m/s conditions, and 67 s between 6.25 m/s and 5.56 m/s conditions. Table 3.8 shows that at an upper velocity limit of 6.94 m/s, over 75% of the mean SLHS time (as a percentage of the no upper limit condition) is retained (totalling 194 s).

In the context of analysing stride variability, narrowing the velocity window for identifying valid steps is desirable. Previous research has shown an increase in stride variability as velocity increases past a self-selected running speed (Jordan et al., 2009). The implications of this research is that as the upper velocity limit is decreased there is more likelihood of capturing strides with similar underlying characteristics for inclusion in the analysis. Furthermore, as it would be expected that the stride characteristics of an acceleration stride as opposed to a steady state running stride will be different, it would also be desirable to limit the possibility of sections of high acceleration being grouped together with sections of steady state running. This can also be achieved by narrowing the velocity window as sections where the subject crosses the lower speed threshold and then quickly transitions past the upper speed threshold will be excluded due not spending the required time within the high speed window. If high speed or high acceleration strides were grouped together with lower speed steady state strides in the final analysis of stride variability then the amount of variability would be increased not due to any change in the biomechanics of the action but rather the fact that different actions were analysed as if they were the same action. Though identifying variability due to high speed running or periods of high acceleration is a valid method of assessing an athlete's physical condition, there are other perhaps more effective methods (such as simply identifying the amount of high speed or high acceleration events) rather than assessing the variability of stride waveforms. Consequently, for the sole purpose of assessing the variability of stride waveforms, it would be desirable to limit the high speed and high acceleration sections within the final analysis.

Although mean SLHS time is a good indicator of the general effect of reducing the upper velocity limit, the worst case scenario is also very important. This is because the effectiveness of the analysis tool as a practical method of assessing athlete condition will be limited if it can only be applied to a portion of the athlete cohort. Subject by subject results show variations in both total SLHS time and the proportion of time at each upper velocity limit condition (Figure 3.1). The worst case scenario can also be seen in Tables 3.8, 3.9 and 3.10, where the minimum case is shown against all upper velocity conditions. The differential between subjects is likely to be due to gameplay demands of positions, the physical capacities of the subjects being examined and perhaps their game sense or ability to read the play. It is possible that these factors are linked in that players who have less physical capacity to reach high velocity will probably be playing in positions that require less high velocity running unless an enhanced game sense can compensate for their lack of physical ability.

These results have important implications in the development of the overall analysis tool. It is likely that subjects with a reduced capacity to reach high speed running velocities (either through reduced physical capacity or through gameplay demands) will have much less valid SLHS time where valid strides can be extracted for analysis. Conversely, subjects with sufficient capacity to reach high velocities who play in positions that allow them to reach those speeds frequently during games will have more SLHS sections and time to extract a high number of strides for analysis. For those subjects it would be desirable to narrow the gap between upper and lower velocity limits. Identification of the ideal upper velocity limit will therefore depend on the sensitivity of the final stride variability calculation to the different scenarios and how the calculated waveform variability is affected by different amounts of valid data available to be analysed. As this determination requires the development of the remainder of the analysis tool to generate the results, it will be done as the final stage in the development process (section 3.7 within this chapter). Prior to this analysis and for the purposes of further development of the analysis tool, a fixed lower limit of 4.17m/s (15km/h) and upper limit of 6.94m/s (25km/h) will be used.

3.4.5 Conclusion

Narrowing the angle window and reducing the minimum straight line time will decrease the number of waveforms available for further analysis. Settings of ±0.05 rad for maximum deviation and 5 s for minimum straight line time provide an acceptable compromise between ideal settings and the need to provide sufficient waveforms for further analysis.

Reducing the upper velocity limit also reduces the mean SLHS time and number of SLHS sections identified per game, with small reductions from the no upper limit case at 8.33 m/s and 7.64 m/s and larger reductions at other conditions. There were large variations between subjects, most likely due to limits to the physical capacity of subjects to reach high speeds as well as gameplay requirements at different positions on the field. Final selection of the ideal upper velocity limit requires an examination of the effect of reducing the available waveforms on the measured waveform variability which will be discussed later in this chapter (section 3.7 – Part 4).

Overall, the number of steps identified through this process should provide sufficient data for further statistical analysis, a process that will be described in the next section of this chapter (section 3.5 – Part 2). In addition, the sensitivity of the statistical analysis to greater or fewer steps being available for analysis will be investigated later in this chapter (section 3.6 – Part 3).

3.5 Part 2 - Identification of matched steps and calculation of the within-day Coefficient of Multiple Determination

Identifying sections of SLHS running through examination of 10 Hz GPS data allows chunks of data containing strides of similar length and function to be extracted for further analysis. Accelerometer data corresponding to those sections can be analysed with the goal of identifying matched steps that can then be used for the subsequent variability analysis. This is an extremely important element of the procedure as the analysis will be compromised (and variability artificially increased) if strides of differing length and function are grouped together. By extracting strides matched for general pattern via a standardised procedure, stride variability as a function of the process and method will be reduced.

There are a number of procedures that could be used to exclude waveforms in order to increase the homogeneity of stride waveforms extracted from the SLHS segments. Of particular importance are the procedures used to include strides based on matched stride time and other temporal parameters. This part will describe the effect on the number of valid strides identified following various refinement processes. In addition, the effect on the calculated within-day CMD for the different methods used to filter for peak z-axis accelerations will also be examined.

3.5.1 **Aims**

- Describe the processes used to extract step accelerometer waveforms from the SLHS section and determine the average number of steps available for further analysis
- Examine the effects on the number of strides identified of excluding waveforms based on temporal characteristics
- Describe the procedures used to calculate within-day CMD and examine the effect on the within-day CMD of excluding waveforms based on temporal characteristics
- Identify ideal parameters for selection of stride waveforms

3.5.2 **Methods**

3.5.2.1 ***Subjects***

The full cohort of 22 participants was used in this study.

3.5.2.2 ***Procedure***

3.5.2.2.1 **Identification of strides within SLHS section**

Accelerometer waveforms are often used to identify footstrikes in normal gait. As each foot strikes the ground there is a discernible spike in acceleration that can be used to identify the beginning of a stride. The procedure used in this study to determine the general position of the footstrike of each step was to sum the absolute value of accelerations (measured in g) on all 3 axes at each time point then identifying peaks above 4. The sum of all three axes were used because the spike in acceleration at footstrike occurs in all three axes, and by summing the three together there is greater chance of identifying a peak event over a threshold. A sum function was used in preference to resolving the norm of all three accelerations to reduce the computational load of this process. These peaks were used to define the general point where footstrikes occurred. To avoid multiple identification of peaks from the same step (which may occur if there is an acceleration in one axis that is sufficient to produce a second peak), if multiple peaks occurred within 150 ms it is assumed that the first strike is the actual footstrike and any subsequent peaks within the next 150 ms are discarded. There is also a maximum stride length rule used, in that if the gap between three consecutive peaks is greater than 750 ms then the section bounded by the upper and lower peak will be discarded. This is to avoid a footstrike being missed (which will happen if it does not cross the 4g threshold) and an unusually long stride being extracted by effectively including a step from the next stride in the previous stride's data.

The general position of the footstrike is then used to extract step accelerations for further refinement. To standardise the specific position of the footstrike thus allowing for consistent comparison across steps, the position of maximum z axis acceleration is determined for each step. This point is then used as the specific position of footstrike for each step. The z-axis was used in isolation for this procedure because this axis has the most consistent waveform pattern from step to step as well as the most distinct peak in acceleration at footstrike.

Step by step accelerations are finally extracted by clipping the acceleration data from 11ms before the footstrike that marks the beginning of the step to 110 ms before the footstrike that marks the beginning of the next step (at 110 ms it would be expected that the subject would be in the flight phase of a stride). This was done to allow for analysis of movement prior to footstrike that can be used to identify which foot was used for the step and whether the z-axis waveform immediately prior to footstrike is similar to the average waveform from that SLHS section.

3.5.2.2.2 **Preparation of step by step data**

The next stage of the data preparation procedure is to perform a temporal normalisation (to 50 points) for each step. The data were normalised to 50 points (rather than 100 points) because for the estimated mean step time of 300 ms (see section 3.5.2.2.1 page 29), 40% of the data would be estimated when normalising to 50 points as opposed to 70% when normalising to 100 points. Consequently it was felt that

50 was a better number to normalise to. In addition, this is effectively no different to normalising the data to 100% of the stride time (ie. a step on the left and right foot), a technique used in many gait studies such as Bergamini et al. (2012) whose data was collected via trunk mounted inertial sensors, a very similar collection method to the present study.

After the normalisation process, a determination of which foot each step represents is made, and to steps are removed that are clearly different from an individual's standard waveform pattern and were likely to have been affected by some external influence (such as gameplay demands or physical contact with another player). Finally, steps are matched for the point of maximum z axis acceleration to provide multiple data sets for analysis, an unfiltered set and a set that has been filtered for matched maximum z axis accelerations.

3.5.2.2.2.1 **Normalisation**

Step data was normalised to 50 data points using a quintic spline function in the Labview software development system. A quintic spline was selected due to its superior ability to produce accurate acceleration results towards the endpoints of the data (Knudson & Bahamonde, 2001). In general, strides above 4.17 m/s will be 300 ms long (30 data points at 100 Hz), which means the time base of most strides will be stretched by a factor of around 1.67.

3.5.2.2.2.2 **Determination of Steps on Left and Right Foot**

Accelerations in the y-axis were used to discriminate between left and right foot strikes due to the position of footstrike being more lateral than the position of the accelerometer (which is near the sagittal axis of the body). To determine which foot struck the ground in any individual step, the first ten data points in the y axis were examined and if at least six out of the ten were positive then the step is assigned to the left side, and if at least six of the ten were negative then the step is assigned to the right side. A graphical representation of these patterns can be found in Figure 3-2.

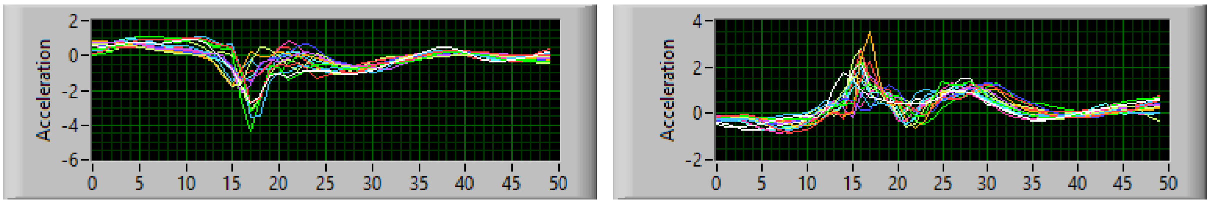


Figure 3-2 Step by step accelerometer waveforms in the y-axis

3.5.2.2.2.3 **Filtering waveforms for torso orientation and function of stride**

For each SLHS section, the mean and standard deviation of the z-axis accelerations from point 5 to 15 of the normalised step data was determined. Any steps whose mean z acceleration from point 5 to 15 falls over 2 standard deviations outside the overall average z acceleration were discarded. This was done as it is likely there were steps where the athlete has altered their torso orientation for gameplay requirements (such as to look what is happening in the play behind them), and those strides should not be included in the analysis as they do not represent the normal running style of the athlete but rather have had external factors influence the accelerometer waveform.

3.5.2.2.2.4 **Step Variability analysis via the Coefficient of Multiple Determination**

Coefficient of multiple determination (CMD) was calculated as per Kabada et al (Kadaba et al., 1989). There are three calculations of variability that can be performed, one to examine the waveform variability within a specific day, one to examine the waveform variability within like sections of SLHS in a game, another to examine the variability between sections of SLHS in a game. In all calculations, higher results indicate less waveform variability.

The equation for the within-section CMD (described by Kadaba et al as within-day CMD as their analysis was on gait data collected across multiple days) is shown in Equations 3-2, 3-3 and 3-4.

Equation 3-2

$$R_a^2 = 1 - \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}(Y_{ijt} - \bar{Y}_{it})^2/MT(N-1)}{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}(Y_{ijt} - \bar{Y}_{i})^2/M(NT-1)}$$

Where M refers to the total number of sections, N refers to the total number of waveforms in each section and T refers to the total time of each waveform (as each waveform is normalised to 50 points, this value is fixed at 50). Y_{ijt} is the *t*th time point of the *j*th waveform in the *i*th section.

$\bar{Y}_{it}$ is the average at time point *t* in the *i*th section, where

Equation 3-3

$$\bar{Y}_{it} = \frac{1}{N}\sum_{j=1}^{N} Y_{ijt}$$

$\bar{Y}_i$ is the grand mean in the *i*th section and is given by

Equation 3-4

$$\bar{Y}_i = \frac{1}{NT}\sum_{j=1}^{N}\sum_{t=1}^{T} Y_{ijt}$$

This equation can be used in two ways, with the only real difference being what is considered a ‘section’. If a section refers to a valid SLHS incident, then T will be equal to the number of sections identified in the game (which will be referred to as a within-section CMD). If a section refers to the game as a whole, then T will be one (as in only one section for the whole game). This will be referred to as a within-day CMD. In practical terms, the within-section CMD will analyse the variability of waveforms within each SLHS section (comparing the shape of those waveforms to the other waveforms found in the immediate area, within the same SLHS section). Those results are then averaged to provide a single number describing waveform variability. The within-day CMD will compare waveforms to all valid waveforms recorded from that day to provide a single number describing waveform variability.

The equation for between-section CMD (described by Kadaba et al. as between-day CMD) is shown in Equation 3-5, 3-6 and 3-7.

Equation 3-5

$$R_a^2 = 1 - \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}(Y_{ijt} - \bar{Y}_t)^2/T(MN-1)}{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T}(Y_{ijt} - \bar{Y})^2/(MNT-1)}$$

$\bar{Y}_t$ is the average at time point *t* over *NM* waveforms,

Equation 3-6

$$\bar{Y}_t = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} Y_{ijt}$$

$\bar{Y}_i$ is the grand mean in the *i*th section and is given by

Equation 3-7

$$\bar{Y} = \frac{1}{MNT}\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} Y_{ijt}$$

The between-section CMD is essentially determining the difference in the mean shape of the waveforms between sections within a day. This offers some valuable information relating to how stride characteristics are changing over the course of the game.

Although previous research has cautioned against isolated interpretation of raw CMD results as high or low (McGinley et al., 2009), as a general guide Garofalo et al. (2009)

described moderate associations between waveforms as having a CMD of between 0.42 and 0.56, good association as between 0.56 and 0.72, very good associations between 0.72 and 0.9, and excellent associations between 0.9 and 1.

3.5.2.2.3 Calculation of season averages

Results for number of strides, number of steps, number of SLHS sections and within-day CMD were generated for each game that contained valid data for each subject. These individual games are then averaged to provide a season mean for each subject. The season averages for all subjects are then averaged once again to form a group mean. Both the group mean and the individual season mean are used in the comparison of various inclusion/exclusion strategies.

3.5.2.2.4 Inclusion and exclusion of steps based on temporal parameters

Steps with differing temporal characteristics were identified by the position of the peak z-axis acceleration. Figure 3-3 displays a graphical representation of the z-axis acceleration. There is a clear peak in acceleration that is in a relatively consistent place in the waveform. The position of this peak is used to select steps with similar temporal characteristics.

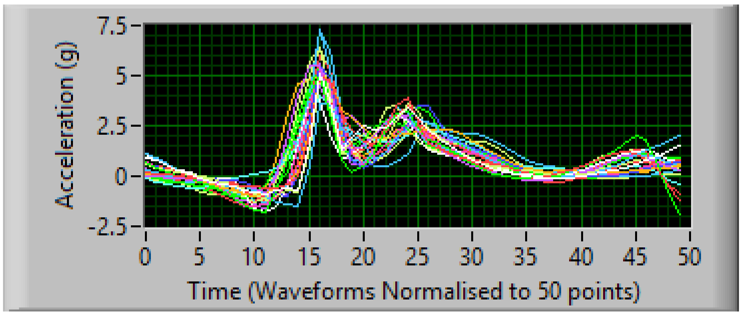


Figure 3-3 z-axis acceleration waveform

The subset of step waveforms that was formed after pre-selecting for temporal characteristics comprised steps whose peak z-axis acceleration was equal to the median peak z-axis acceleration of the entire set of steps. The results from this sub-set of steps were compared to the results generated when all steps were included in the analysis.

3.5.2.2.5 Calculation of mean step time

For each game where a subject had valid data, steps were collated on both side 1 and side 2. The mean and standard deviation of the steps were then calculated for that game. Season averages for mean and standard deviation of step time for each subject were then calculated by averaging the results from the games.

3.5.3 **Results**

The group mean for the number of strides identified and the percent excluded for exceeding the stride length limit of 750 ms (as outlined in 3.5.2.2.1), along with the minimum and maximum individual season average is shown in Table 3-11. Of particular note is the minimum individual season average for total strides (107 strides). The group average for valid steps in each game after inclusion and exclusion of waveforms according to the processes outlined in 3.5.2.2.2.2 and 3.5.2.2.2.3, along with the number remaining after exclusion and inclusion due to temporal parameters described in 3.5.2.2.5 are displayed in Table 3-12. The individual subject season mean for total steps, valid steps and steps matched for temporal parameters are found in Table 3.13 and Figure 3-4. Also found in Table 3-13 are the maximum and minimum steps found in games for individuals. Of particular note in these results is the small number of steps found in some games for some individual subjects. For example, subjects 15 and 16 average only 15 valid steps per game on side 1, which are reduced further when the steps are matched for temporal parameters.

Table 3.11 Group Mean, Maximum and Minimum Strides identified and percent excluded

	Total Strides	Percentage of Strides Excluded	Total Sections
Mean	252	9.0%	30.3
Maximum	380	18.3%	43.6
Minimum	126	6.4%	16.1

Table 3.12 Group mean total steps, valid steps and steps matched for temporal parameters

	Side 1	Side 2
Total Steps	204	213
Valid Steps	86	89
Steps Matched for Temporal Parameters	62	62

Table 3.13 Individual season mean for total steps, valid steps and steps matched for temporal parameters (by side)

Subject	Side 1			Side 2		
	Total Steps	Valid Steps	Steps Matched for Temporal Parameters	Total Steps	Valid Steps	Steps Matched for Temporal Parameters
1	221	104	73	229	107	70
2	165	75	56	175	93	66
3	226	102	75	226	70	46
4	157	91	70	158	88	63
5	204	84	60	206	65	48
6	335	135	97	345	121	82
7	247	111	79	253	104	77
8	129	55	41	117	42	32
9	306	109	83	317	137	94
10	149	65	50	147	60	42
11	262	108	74	278	118	80
12	198	102	71	208	95	64
13	192	81	55	203	98	65
14	187	84	59	191	99	70
15	90	34	27	99	33	24
16	111	33	25	119	44	33
17	288	129	87	309	115	71
18	221	97	67	236	71	50
19	264	108	75	269	135	93
20	237	100	69	257	104	73
21	119	46	32	123	48	32
22	200	58	43	240	87	60

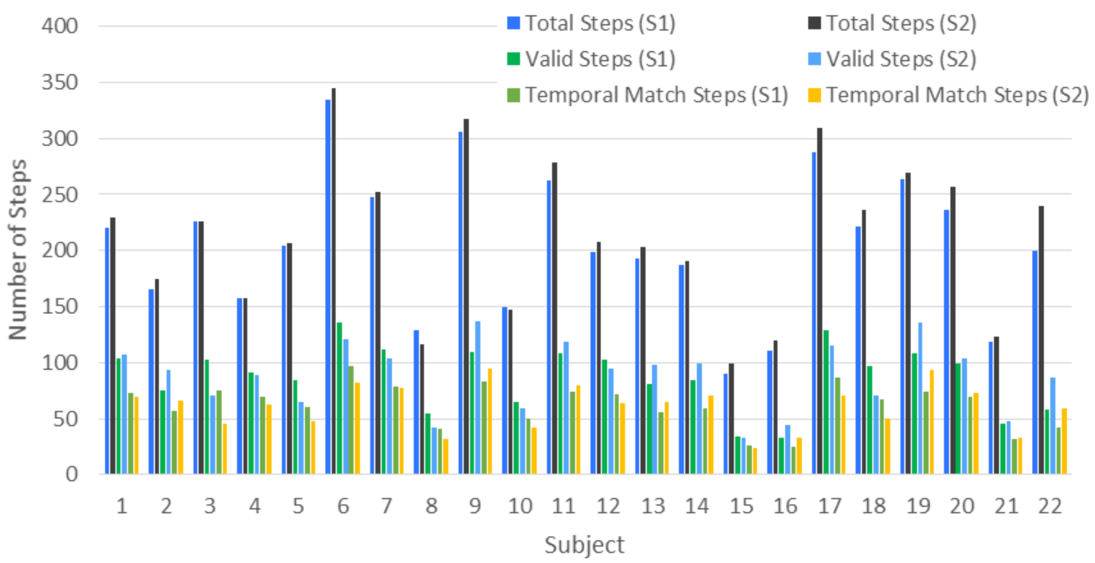


Figure 3-4 Individual season mean for total steps, valid steps and steps matched for temporal parameters (by side)

The group mean within-day CMD results with and without inclusion/exclusion for temporal parameters is shown in Table 3-14. These results are also displayed graphically in Figure 3-5. Of particular note is the increase across all axes on both sides when the exclusion criteria are applied.

Table 3.14 Group mean within-day CMD results for all axes and conditions

		Side 1			Side 2		
		z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
All Steps	Mean	0.692	0.372	0.548	0.701	0.399	0.551
	St Dev	0.040	0.088	0.073	0.037	0.087	0.070
Matched Temporal	Mean	0.817	0.476	0.685	0.825	0.514	0.700
	St Dev	0.039	0.110	0.085	0.037	0.117	0.083

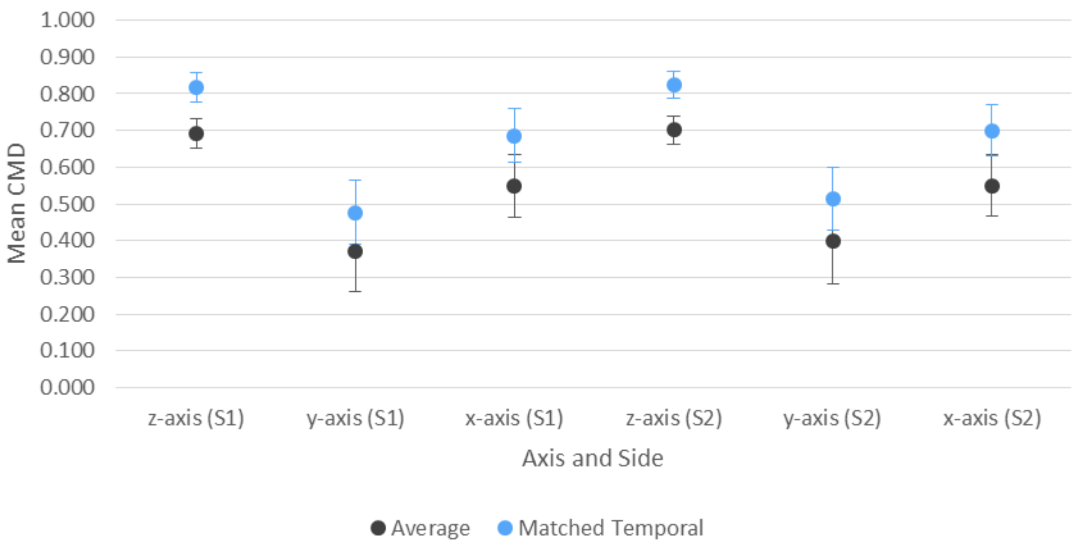


Figure 3-5 Group mean within-CMD results for all axes and conditions. Error bars represent standard deviations.

3.5.4 **Discussion**

The process of automating the extraction of individual step waveforms from the SLHS sections is complicated. The clear peak in acceleration in each step allows some standardisation of the identification of a single point in each step within the overall acceleration trace that can be used to establish its general position, however there is no guarantee that steps identified in this way will be matched for function or temporal characteristics. In addition, when the process is automated to allow for the analysis to occur in a timeframe that makes the tool useable in an applied situation, there also needs to be some control for steps that are inadvertently misidentified.

To control for steps that are misidentified, strides that lasted for longer than 750 ms were eliminated. This was done because a stride time of over 750 ms indicates that it was extremely likely that an acceleration peak was missed which would lead to two strides being combined into one within the analysis. The number of strides discarded after filtering for strides that exceed the 750 ms cut-off was found to be acceptably low, with a maximum individual subject season average of 9.00%. This demonstrates that the method used to automatically identify strides within the overall acceleration trace is effective. Further results from this analysis (displayed in Table 3.11) show that the subject with the minimum strides available per game has considerably fewer strides available for further analysis than the mean of the group (the minimum individual season average was 126 strides as compared to the group mean of 252 strides). This is not unexpected as the results from Part 1 (section 3.4) demonstrated a wide range of SLHS time identified per subject which would be reflected in the number of strides identified. The implications of this is that any further exclusion of strides in an attempt to create a group of waveforms that are matched for parameters other than overall maximum length will necessarily reduce the number of waveforms available for analysis to a point that may influence some subjects more heavily than others.

Excluding steps that are likely to have a different torso orientation or general stride function (as described in section 3.5.2.2.2.3) as well as steps where it is unclear which side of the body the step should be allocated to (as described in section 3.5.2.2.2.2) further reduce the number of steps available for analysis by around 120 steps (Table 3-12) or approximately 57% of the total steps available. Though this is a considerable number of steps, it is felt that this is a necessary process to ensure that only steps of similar function on the same side are grouped together for analysis. The random nature of gameplay including physical contact and tactical considerations will impose further variability onto steps that will be overlaid onto the variability due to an athlete's physical condition. As the goal of the analysis tool is to use step acceleration waveforms to assess an athlete's physical condition, variability due to physical contact or other gameplay considerations would be considered unwanted noise within the signal. Consequently, the reduction of steps, even by as much as 57%, is an acceptable compromise (for the purposes of these analyses) to separate the noise from the signal.

The process of excluding steps based on temporal characteristics will ensure that steps with slight variations to the specific position of peak acceleration will not be analysed together, decreasing the step to step variability of the acceleration. This procedure further reduced the number of steps available for further analysis by, on average, approximately 25 steps per game, resulting in approximately 80% of the steps initially identified being excluded through the two processes of removing noise from the signal and matching temporal characteristics. This will potentially leave a very small set of waveforms for some subjects who are not predisposed to producing a large amount of SLHS time in a game.

Exclusion of steps due to temporal characteristics (which are likely due to strides with different time bases being grouped together for analysis) will ensure that steps with similar time bases will be included in the analysis, thereby reducing another source of noise within the signal (namely variability due to steps of differing time bases being analysed together rather than describing the actual stride to stride variability). However, it could also be argued that removing strides that are slightly different could be considered to be removing a very natural part of the step to step variability that contains valuable information on the physical state of the athlete (and therefore not noise but a very real part of the signal).

The validity of exclusion due to temporal characteristics will revolve around how much variability there is in step length (in time) and how that relates to the calculated within-day CMD. Mean step time is very consistent across the group, as can be seen in Table 3-14, though there are some subjects who tend to have higher mean within game standard deviations for step time. It would be expected that if temporal characteristics influence the within-day CMD then higher variability in step time will lead to a lower CMD (which would represent more variability in the waveform). This is because filtering for matched time of initial peak will remove strides with time bases that are different enough to cause a temporal shift in the waveform after the normalisation process, potentially leading to a proportionally greater increase in within-day CMD in subjects with inconsistent step time.

A post-hoc analysis of the relationship between within-day CMD (and therefore waveform variability) and within-day step variability (measured via the within-day standard deviation of step time) was conducted. Figure 3-6 shows the z-axis within-day CMD differential (temporal exclusion minus unaltered) plotted against within-day step variability for all games available. It would be expected that the CMD differential would show a positive trend given that a set of waveforms with temporal exclusion applied will be more homogenous and consequently would produce less within-day variability, and this is demonstrated by the equation of the linear trendline fit to the data (where $y = 0.004x + 0.0179$). However, this positive trend is weak ($R^2 = 0.0079$) suggesting that although step time variability may have some effect on the overall CMD, it is by no means the only influence.

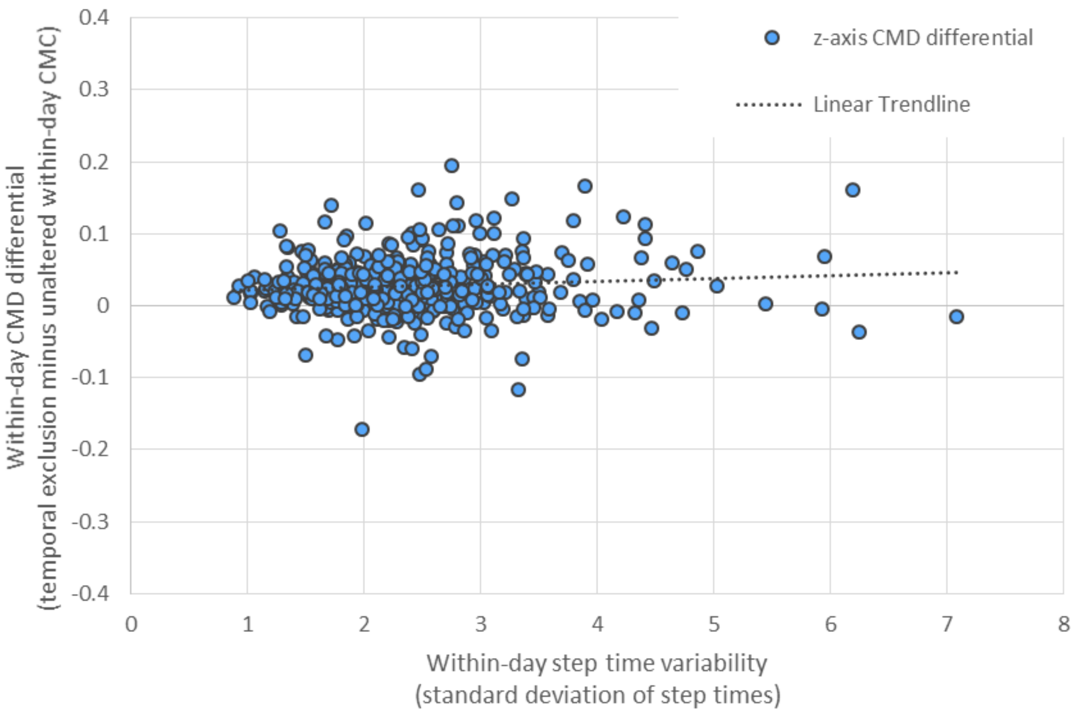


Figure 3-6 Within-day step time variability vs within-day CMD differential

Given the weak relationship between within game stride time standard deviation and z axis CMD differential, it could be assumed that the natural variation within the pattern of the waveform has a greater influence than temporal variability on the overall variability of the step waveforms. Therefore, the natural variation in the temporal aspects of the valid steps should be left in the analysis, and filtering for matched position of initial peak should not occur.

It is worth noting that these conclusions have been reached on data that has already had some inclusion/exclusion for temporal aspects of step waveforms applied (i.e., an upper limit for SLHS was used). The practical effect of this is that steps taken when running over 6.94 m/s, which would tend to be shorter in duration, would already have been eliminated from the analysis. If steps at speeds over 6.94 m/s were retained then the effect of exclusion/inclusion for temporal parameters would likely be greater. For the current data with an upper limit of 6.94m/s on SLHS sections, it is felt that inclusion/exclusion for matched position of initial peak is unwarranted.

Though the use of the inclusion/exclusion criteria is unwarranted, it is still useful to examine the effects of applying those criteria on the resulting within-day CMD. This is valuable as it demonstrates whether the CMD is behaving as expected (in that a more homogenous set of waveforms should produce a higher CMD) and it also shows the sensitivity of the measure across different axes to small adjustments in the set of waveforms. All axes on both sides showed a decrease in waveform variability (Table 3-14) when the criteria were applied, in line with the expected response to the adjusted set of waveforms.

3.5.5 Conclusion

The procedures for identifying matched steps within periods of SLHS running identified a considerable number of strides in the games analysed. Steps tended to be of similar length (in time) and although one third of the steps were excluded because they appear to be influenced by external factors the average number of steps identified for analysis per game was still 62 steps on both sides.

Excluding steps on the basis of temporal characteristics further reduced the average number of steps available to approximately 20% of the original set. This, along with the very weak relationship between waveform variability and step time variability, makes exclusion of strides due to temporal characteristics undesirable.

The within-day CMD was used to analyse whether exclusion due to temporal characteristics is worthwhile. The average results across all axes and conditions demonstrate that a more homogenous set of waveforms (after excluding strides with different temporal characteristics) produces a higher within-day CMD which indicates less variability in the set of waveforms.

These conclusions show that the within-day CMD results match the expected outcomes and that its use in the current situation shows promise. As a consequence, this statistical analysis will be used through the remainder of the thesis.

3.6 Part 3 – Sensitivity of the between-section, within-section and within-day Coefficient of Multiple Determination to the quantity of available data

Results presented in sections 3.4 and 3.5 demonstrate that subjects can vary quite markedly in the amount of valid data available for processing. The range of strides available in a game ranges from a season average of 126 in one subject to 380 in another. This is likely to be due to a combination of gameplay demands that vary by position, game sense and physical capacity. In addition, the average number of valid sections identified per game across the entire subject group was 30.3 sections (Table 3-11). However, the minimum subject season average was 16.1 (Table 3-11) and as this number represents the season average, there will clearly be games where fewer sections are identified.

The effect of a reduction in valid strides (on a within-section and within-day CMD analysis) and sections (on a between-section CMD analysis) is unclear. To further understand the implications of the amount of data available on a particular day, a number of iterations were run to examine the effects of reducing the available data on waveform variability as measured by the between-section and within-section CMD.

3.6.1 **Aims**

- Investigate the effects of reducing the number of waveforms available for a within-day CMD analysis and determine the suitability of this measure with the current data
- Investigate the effects of reducing the number of waveforms available for a within-section CMD analysis and determine the suitability of this measure with the current data
- Investigate the effects of reducing the number of sections available for a between-section CMD analysis and determine the suitability of this measure with the current data

3.6.2 **Methods**

3.6.2.1 ***Subjects***

The full cohort of 22 subjects described in section 3.1.1 above was used in this study.

3.6.2.2 ***Removal of Strides and Sections***

A procedure for removal of strides and sections was performed to progressively reduce the number of sections analysed from a file. By removing sections, chunks of strides are also removed, so each iteration will also result in progressively fewer strides to be analysed.

For each file there were a number of SLHS sections (*S*) identified. A maximum of 25 random sub-sets of *k* sections were selected from the overall collection of SLHS sections (*S*) in a file where *k* ranged from 30% to 90% of S (in increments of 10%). A random selection was used because it was often the case that there were too many possible combinations of sub-sets to be practically analysed. For instance, the 50% case for the average number of sections with upper velocity set at 6.94 m/s (identified in Table 3-8 as 30.9) would create 155,117,520 possible combinations. If there were less than 25 possible combinations (which often occurred in the 90% case) then all possible sub-sets were analysed. This process is further described by the diagrammatic representation seen in Figure 3-7. Each sub-set was then analysed via the process described earlier in 3.5.

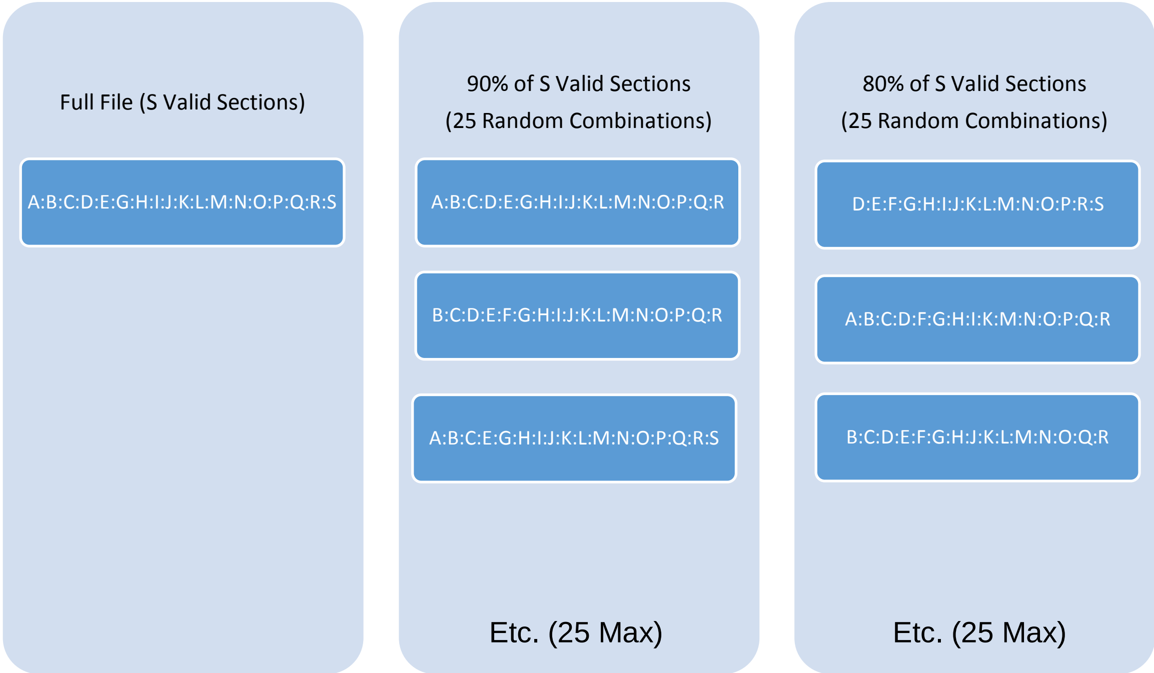


Figure 3-7 Diagrammatic representation of selection of section sub-sets. The process is repeated past 80% of S valid sections, finishing at 30% of S valid sections.

3.6.2.3 ***Data analysis***

Within-day, within-section and between-section CMD were calculated for each repetition. Each repetition of each file was then further processed to determine the difference in the within-day, within-section and between-section CMD between the current repetition and the foundation set of valid SLHS sections from the current file.

This can be best explained by referring back to Figure 3-7, the full file contains the set of sections (A:B:C:D:E…S). The within-day, between-section and within-section CMD for the sub-set of sections was calculated and these results were compared to the results generated for the foundation set of sections. This process was repeated for all sub-sets.

The 30% sub-set (as the worst case scenario) was then investigated further to determine whether there was a critical number of sections required for accuracy in the analysis. Within-day, within-section and between-section CMD results for the 30% sub-set were calculated as a percentage of the CMD results for the full set of sections (the 100% case). These results were then split by number of sections available at the 30% case.

3.6.3 Results

The average within-day, within-section and between-section CMD results of section subsets that comprise different percentages of the 100% case can be found in Table 3-15. Graphical representations of these results can also be found in Figure 3-8 (within-day CMD), Figure 3-9 (within-section CMD) and Figure 3-10 (between-section CMD). It is worth noting the decreasing trend of results in the within-day and between-section results as the percentage (and therefore number) of sections increases. The slope of the linear trendlines found in Figures 3-8, 3-9 and 3-10 can be found in Table 3-16.

Table 3.15 Mean within-day, within-section and between-section CMD results with section sub-sets comprising different percentages of the foundation set of sections

Percent of sections	Side 1 Within-Day	Side 1 Within-Section	Side 1 Between-section	Side 2 Within-day	Side 2 Within-Section	Side 2 Between-Section
30%	0.8027	0.7008	0.8110	0.8077	0.7106	0.8218
40%	0.8025	0.6980	0.8086	0.8078	0.7073	0.8206
50%	0.8024	0.6965	0.8082	0.8077	0.7057	0.8199
60%	0.8024	0.6952	0.8079	0.8076	0.7040	0.8198
70%	0.8019	0.6939	0.8066	0.8077	0.7026	0.8180
80%	0.8022	0.6935	0.8059	0.8075	0.7022	0.8181
90%	0.8044	0.6947	0.8084	0.8099	0.7040	0.8196
100%	0.8020	0.6921	0.8082	0.8060	0.7006	0.8151

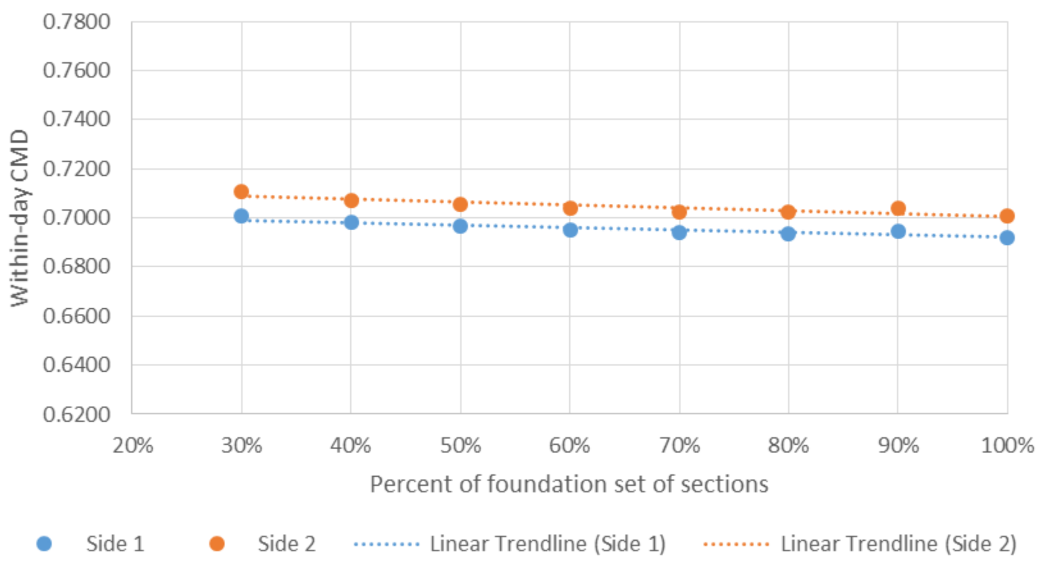


Figure 3-8 Mean within-day CMD of waveform sub-sets comprising different percentages of the foundation set of waveforms

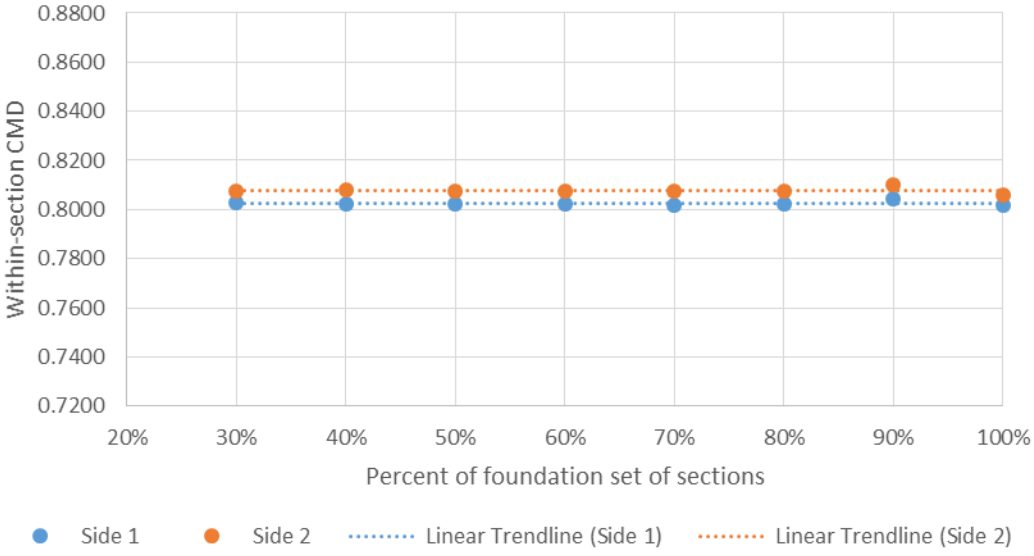


Figure 3-9 Mean within-section CMD of waveform sub-sets comprising different percentages of the foundation set of waveforms

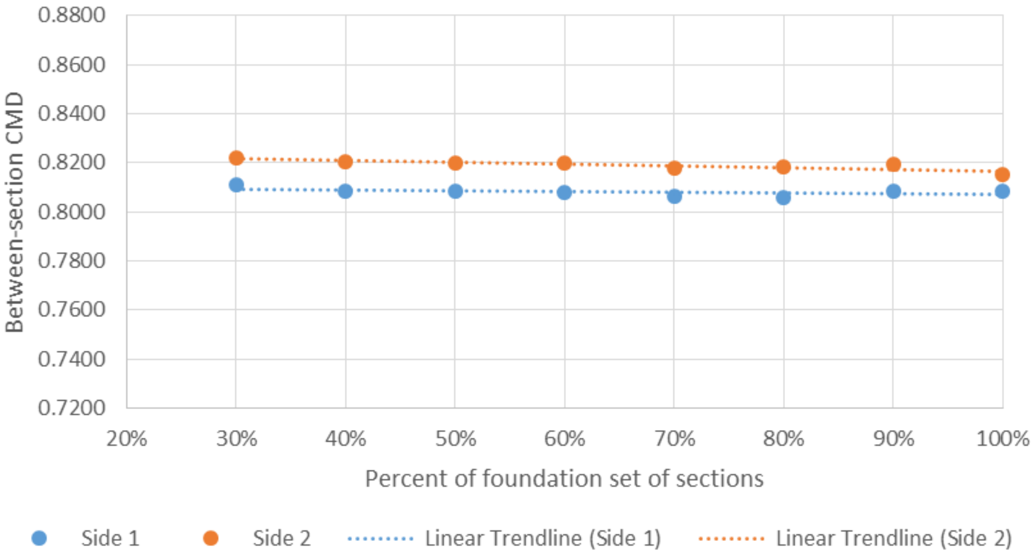


Figure 3-10 Mean between-section CMD of waveform sub-sets comprising different percentages of the foundation set of waveforms

Table 3.16 Slope of linear trendlines found in Figures 3-8, 3-9 and 3-10

	Side 1	Side 2
Within-Section	0.0004	-0.0002
Within-Day	-0.0104	-0.0117
Between-section	-0.0035	-0.0070

Further investigation of the 30% sub-set case can be found in Table 3-17, which shows the average CMD results at the 30% case expressed as a percentage of the CMD results from the full set of sections split by number of sections available at the 30% case. These results are also shown graphically in Figure 3-11 (showing the within-day CMD results), Figure 3-12 (showing the within-section CMD results) and Figure 3-13 (showing the between-section CMD results). It is interesting to note the fall in the between-section graph until the number of sections reaches 6, and the steady fall of the within-day graph.

Table 3.17 Between-section, within-section and within-day CMD at the 30% case split into number of sections and expressed as a percentage of the 100% case

	Within-Day CMD		Within-Section CMD		Between-Section CMD	
Number of sections	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
2	103.63%	105.08%	98.97%	100.02%	101.87%	107.18%
3	103.27%	103.87%	99.57%	98.65%	104.54%	109.70%
4	100.22%	101.46%	99.11%	99.73%	102.76%	102.85%
5	102.77%	102.28%	101.19%	100.49%	101.34%	101.89%
6	102.80%	102.11%	99.56%	100.31%	100.75%	100.31%
7	102.05%	101.45%	100.31%	100.43%	100.13%	100.27%
8	101.51%	101.48%	100.39%	100.58%	100.84%	100.75%
9	101.09%	101.14%	100.06%	100.24%	100.07%	100.63%
10	99.94%	101.16%	99.86%	99.98%	99.60%	101.30%
11	101.39%	101.73%	100.30%	100.28%	100.61%	100.68%
12	100.68%	101.36%	100.19%	100.09%	100.91%	100.02%
13	101.42%	101.94%	100.23%	100.49%	99.63%	99.98%
14	101.01%	100.23%	99.80%	99.41%	99.62%	99.89%
15	103.19%	100.04%	99.77%	99.06%	104.98%	99.06%
16	100.69%	100.39%	99.71%	99.87%	99.68%	99.99%
17	102.38%	102.26%	101.08%	102.06%	100.12%	101.84%
19	100.08%	100.25%	99.74%	100.03%	98.91%	99.33%

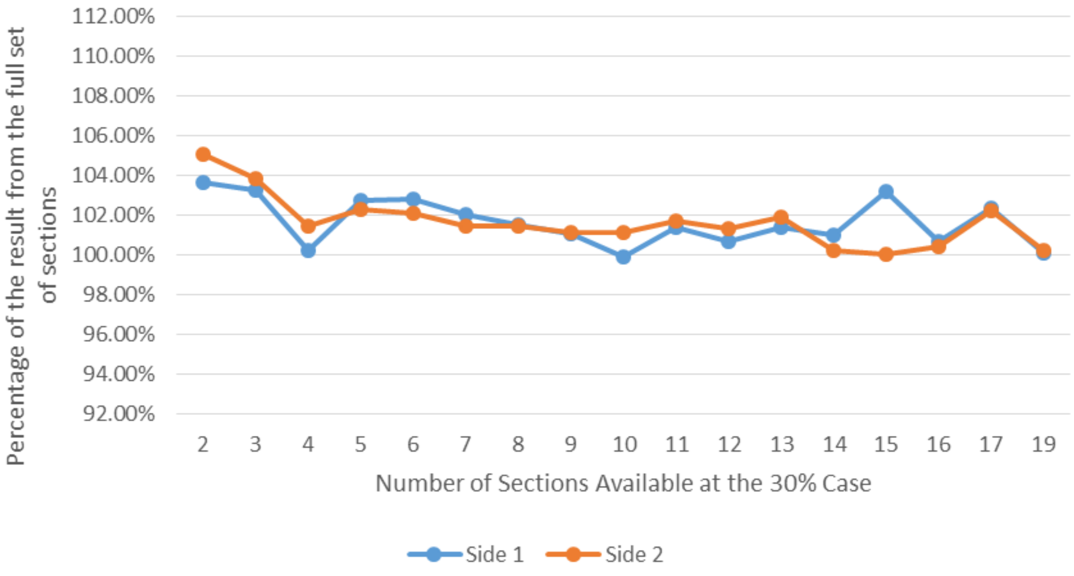


Figure 3-11 Mean within-day CMD at the 30% case expressed as a percentage of the within-day CMD of the full set of sections, broken into number of sections available at the 30% case

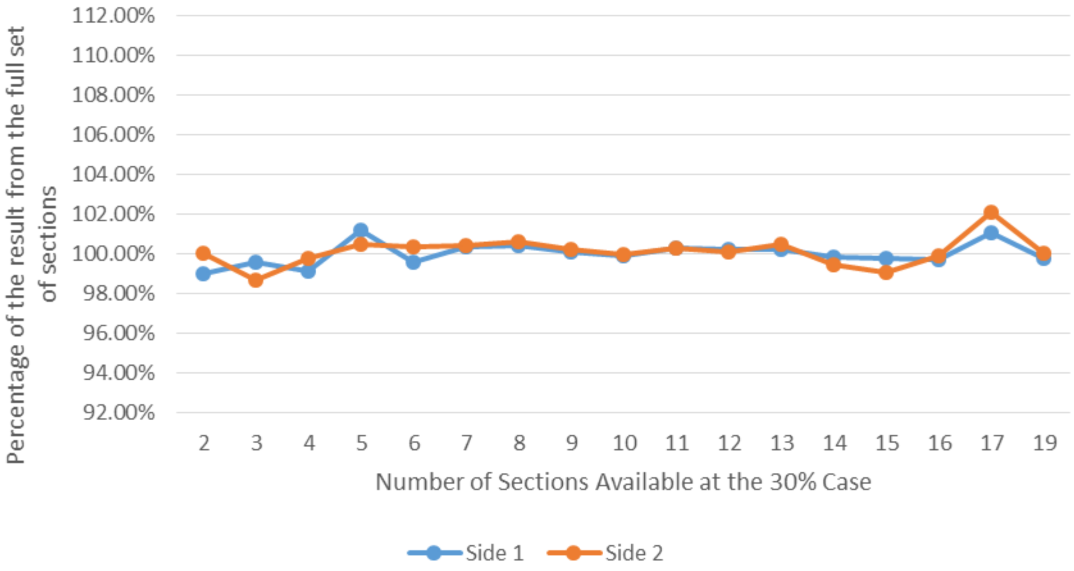


Figure 3-12 Mean within-section CMD at the 30% case expressed as a percentage of the within-section CMD of the full set of sections, broken into number of sections available at the 30% case

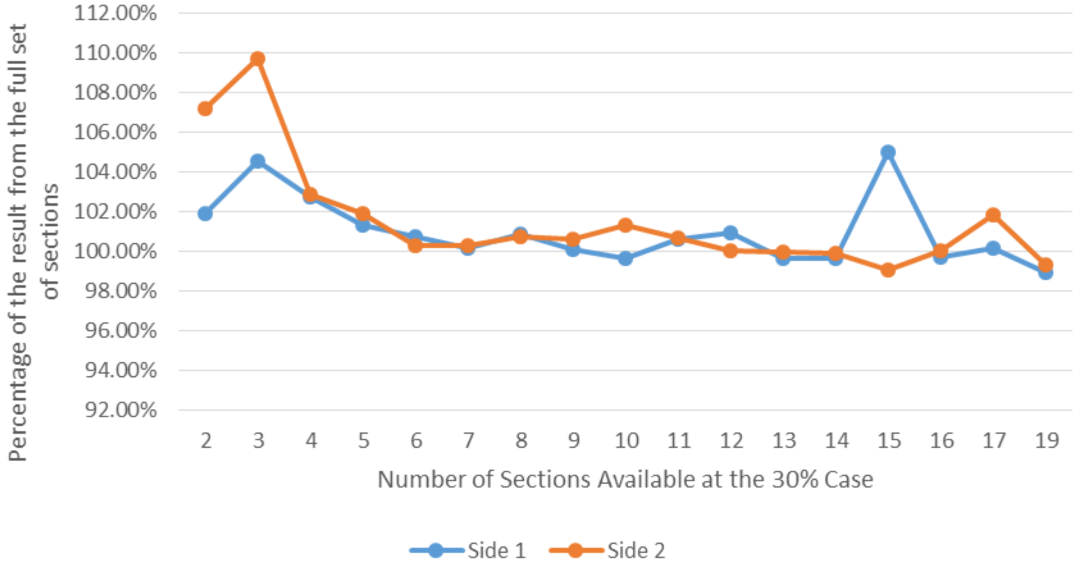


Figure 3-13 Mean between-section CMD at the 30% case expressed as a percentage of the between-section CMD of the full set of sections, broken into number of sections available at the 30% case

3.6.4 **Discussion**

Reducing the sections analysed from each file does not appear to have any impact on the within-section CMD results. Even when the number of sections is reduced to 30% of the foundation set of sections there is no difference between the within-section CMD adjusted for the reduced sections and the within-day CMD of the original file. This can be demonstrated by the linear trendline of results for both sides, which has a slope of 0.0004 on side 1 and -0.0002 on side 2, suggesting that at 50% of the foundation set of sections the within-section CMD would have increased by 0.0002 on side 1 and decreased by 0.0001 on side 2. This provides a great deal of confidence that the within-section CMD is a very robust measure that can be used with equal effectiveness on games where small and large numbers of valid strides have been identified.

However, there is some evidence that the between-section and within-day CMD is influenced by the number of sections available. As the number of valid sections is reduced there is a slight increase in CMD. This essentially means that as the number of sections is reduced, the measured variability in the waveform between all sections becomes smaller (i.e., the waveform variability is reduced). At 50% of the foundation set of sections, the within-day CMD would be expected to have increased by 0.005 and 0.0055 on side 1 and 2 respectively, and the between-section CMD would be expected to have increased by 0.0017 and 0.0035 respectively (when compared to the original set of sections).

The reduction in CMD for the between-section and within-day conditions is still quite small compared to the overall standard deviation of the measures. The standard deviation for z-axis within-day results has previously been established to be 0.04 on side 1 and 0.037 on side 2 (Table 3-14 in section 3.5). Therefore the 50% case described above would change the calculated CMD by 4% of 1 standard deviation on side 1 and 9% of 1 standard deviation on side 2. As a consequence of these results, the between-section and within-day conditions are still appropriate and robust measures, though not as robust as the within-section condition.

The 30% case was investigated further to determine whether there is a break-point where the raw number of sections becomes an important factor in the accuracy of the analysis. The within-section CMD analysis remained consistent as the number of sections available for analysis at the 30% case was reduced, confirming the robustness of this measure as the amount of data available for analysis is reduced. The within-day CMD showed a steady fall as the number of sections available was increased, reflecting the results shown in Figure 3-8. However, the between-section results did not show a consistent fall as the number of sections available increased. Instead there was a sharp decrease until the number of sections reached six (falling from a maximum of 104.54% at three sections to 100.75% at six sections on side 1, and 109.7% to 100.31% on side 2), after which the results remain at 100% ±1% (save for the 10 section case on side 2, the 15 section case on side 1 and the 17 section case on side 2). These results suggest that the between-section CMD should only be used when there are at least six valid sections available for analysis.

3.6.5 **Conclusion**

The results of this study demonstrate that the within-section CMD is a robust measure that can be applied to small numbers of sections and strides within each game. However, the between-section and within-section CMD does appear to be slightly influenced by the number of valid sections within each game, producing higher results (and therefore less measured waveform variability) as the amount of valid data is reduced. Further investigation of the between-section CMD showed that it will be prone to overestimating waveform variability when the number of sections is reduced to fewer than six. Consequently it can be concluded that the within-section CMD is an appropriate measure for the current data set and the between-section CMD may be appropriate if the number of sections available for analysis is sufficient. The within-day CMD may be prone to slightly over-estimating the waveform variability when a small number of steps are identified, so is the least preferred of the three measures to describe waveform variability on a particular day.

As a result of these conclusions, within-section CMD and between-section CMD will be maintained as a statistical tool for the remainder of the thesis, whereas use of the within-day CMD, given it is essentially providing a similar analysis to the within-section CMD (the only difference being the organisation of the available data into one section rather than multiple distinct sections drawn from a training session or game) will not be maintained.

3.7 Part 4 – Sensitivity of Analysis tool to changes in upper velocity limit for Straight Line High Speed Running sections

The final stage in the development of the analysis tool for analysing a single game is to re-examine the sensitivity of both within-section and between-section CMD results to changes in the upper velocity limit for high speed running. In sections 3.5 and 3.6 the upper limit for velocity was set at 6.94 m/s (25km/h). Now that the effects of fewer numbers of strides and sections within games have been identified and ideal procedures discussed, the effects of adjusting the upper velocity limit to reduce the effective velocity window for valid strides can be examined.

The previous section described the effects of reducing valid SLHS sections (and therefore the number of step waveforms analysed) on within-day, within-section and between-section CMD analyses. The number of valid SLHS sections identified in each file will affect the between-section CMD, so the potential effects of changing the upper velocity limit on the number of valid SLHS sections will therefore be investigated in relation to the between-section analysis.

3.7.1 Aims

- Investigate the effect of altering the upper limit for velocity on the number of SLHS sections and total SLHS time identified per game
- Investigate the suitability of the between-section CMD based on the number of SLHS sections available at different upper velocity limits

3.7.2 Methods

3.7.2.1 *Subjects*

A subset of 18 subjects taken from the original cohort of 22 subjects was used in this study. Subjects who did not have at least one game where information on playing time (including time spent on the interchange bench), GPS data and inertial sensor data available were excluded from this study.

3.7.2.2 *Data Processing*

The methods for processing of individual files were the same as was described in section 3.5. However, each individual file was processed a six times, with upper velocity limit for the SLHS sections adjusted each time. The upper velocities analysed are displayed in Table 3-18, and are the same that were originally used in section 3.4. Mean time in SLHS and the mean number of sections of SLHS per game were determined.

Table 3.18 Upper limit velocities examined

	Upper Limit	
Condition	m/s	km/h
1	5.56	20
2	6.25	22.5
3	6.94	25
4	7.64	27.5
5	8.33	30
6	11.11	40

Processor outputs (with regard to the mean amount of SLHS sections per game) were analysed to determine the suitability of a within-section and between-section CMD at the various upper velocity limits. This was done by determining the number of games where at least 10 steps, 20 steps and 30 steps were available on both sides. The number of valid SLHS sections available on both sides was calculated in a similar way, with the number of games (expressed as a percentage of total games) where there were at least 2, 3, 4 6, 8, 10 and 15 SLHS sections available for analysis on both sides identified.

3.7.3 **Results**

The time in SLHS per game was identified and the results displayed in Table 3-19. How this relates to the number of steps available for analysis on both sides was investigated and the results are shown in Table 3-20. It is worth noting the diminishing differential between adjacent velocity conditions, with the greatest differences in percentage of games available occurring between the lower velocity conditions.

Table 3.19 Mean time in SLHS per file by upper velocity limit

Speed (m/s)	Average time in SLHS per file (s)
5.56	73
6.25	140
6.94	194
7.64	229
8.33	247
9.03	252

Table 3.20 Percentage of games where at least 10 steps, 20 steps and 30 steps are available for analysis on both sides by upper velocity limit

Upper Velocity Limit (m/s)	Games with both sides at least 10 steps	Games with both sides at least 20 steps	Games with both sides at least 30 steps
5.56	90%	76%	57%
6.25	97%	93%	85%
6.94	99%	97%	91%
7.64	100%	98%	91%
8.33	100%	98%	93%
9.03	100%	99%	93%

The effect of changing the upper velocity limit on number of SLHS sections available for further analysis on side 1 and side 2 is displayed in Table 3-21. Table 3-22 shows the number of games available as the threshold for number of sections that need to be available on both sides is progressively increased. Again, it is worth noting the diminishing differential between adjacent velocity conditions as upper velocity limit is raised.

Table 3.21 Mean SLHS sections on side 1 and side 2 by upper velocity limit

Upper Velocity Limit (m/s)	Mean SLHS sections on side 1	Mean SLHS sections on side 2
5.56	6.4	6.4
6.25	10.5	10.6
6.94	12.7	12.6
7.64	13.5	13.3
8.33	13.9	13.6
11.11	14.0	13.7

Table 3.22 Percentage of files with at least 2, 3, 4, 6, 8, 10, 12 and 15 sections on both sides by upper velocity limit

	Threshold for the number of sections on both sides							
Upper Velocity Limit (m/s)	2	3	4	6	8	10	12	15
5.56	92%	84%	70%	47%	28%	13%	4%	1%
6.25	98%	96%	92%	78%	64%	44%	30%	16%
6.94	99%	98%	95%	88%	76%	58%	46%	32%
7.64	100%	99%	97%	90%	79%	66%	50%	38%
8.33	100%	99%	97%	91%	82%	70%	52%	39%
11.11	100%	99%	97%	91%	82%	70%	52%	39%

3.7.4 **Discussion**

Previous sections in this chapter (3.5 and 3.6) have identified that more valid sections of SLHS will tend to decrease the within-section and between-section CMD for a file. In section 3.4 the effect of reducing the range of velocities was discussed with reference to previous research showing that it is beneficial to reduce the range of velocities included in SLHS sections. However, results from the current study (as well as section 3.4) demonstrate that as the upper limit velocity is reduced, the number of valid SLHS sections identified in each file is also reduced. We must therefore find a compromise between maximising the validity of the analysis (in terms of identifying stride variability due to factors such as fatigue and injury) and the practical application of this analysis tool.

As upper velocity limit is increased, the number of sections available for analysis also increases. Focusing on six SLHS sections required on both sides (identified in section 3.6 as being a critical number for the validity of the between-section analysis), there is an increase of 31% from an upper velocity limit of 5.56 m/s to 6.25 m/s, 10% from 6.25 m/s to 6.94 m/s, then 2% or less for the subsequent steps in upper velocity limits. The small increases in number of files with at least six sections available on each side after the upper velocity limit passes 6.94 m/s would suggest that there is limited benefit in increasing the upper velocity limit over 6.94 m/s. A similar result is found in Table 3-20, where there are increases of below 2% in the number of files with at least 30 steps available on each side after the upper velocity limit passes 6.94 m/s. Both of these results would indicate that 6.94 m/s is the best compromise between achieving a high number of valid SLHS sections and steps from each file while minimising the velocity window.

These results are very encouraging for the validity of the between-section analysis. Section 3.6 showed that six sections was a critical number of SLHS sections to achieve, and that if there were fewer than six SLHS sections identified there is the potential for the between-section CMD to be elevated not due to a reduction in waveform variability but instead due to the small number of SLHS sections available for analysis. Results shown in Table 3-22 would suggest that only 12% of files would not contain 6 SLHS sections on both sides, which means that there will be limited impact on a longitudinal analysis utilising between-section CMD.

3.7.5 Conclusion

Altering the upper velocity limit does affect the number of SLHS sections and total steps available for further analysis, however once the upper velocity limit goes above 6.94 m/s the gains in both number of sections and total steps are small. As a result, the ideal upper velocity limit as a compromise between extracting enough valid data and minimising the range of velocities used to define high speed running is 6.94 m/s. In addition, the number of sections identified with an upper velocity limit of 6.94 m/s provide confidence that the between-section analysis can be used for a longitudinal analysis of individual subjects. Consequently, an upper velocity limit for high speed running of 6.94 m/s will be used for the remainder of this thesis.

3.8 Part 5 – Between-game analyses

An additional calculation that can be done on the stride waveforms generated in each game is to analyse the similarity of those waveforms across different games. This can be achieved through a variation to the between-section CMD calculation, where whole games are treated as different sections. This is perhaps more in keeping with the CMD analysis as described by Kadaba et al. (1989) with regard to gait data, where the ‘between’ CMD was used to analyse gait variability between testing days.

A between-game CMD analysis has the potential to describe whether the waveforms collated from one game are different to the waveforms collated from another game (over and above the variability normally found in that individual). It could, in essence, detect a change in stride characteristics due to an event that has happened in between the two sessions being analysed.

The large number of waveforms collated from each game provide a difficulty in preparing data for a between-game CMD analysis. As is the case with the between-section CMD, the equation for a between-day CMD analysis requires an equal number of waveforms from the different sections to be analysed (in this case, the different days). This is problematic as it is highly unlikely that the number of waveforms identified in each game will be equal. Consequently, a procedure to equalise the number of waveforms needs to be established. Though this could be seen as imposing an external constraint on the data being analysed, it is necessary given the numerator in the equation to calculate a CMD represents the variance around the mean at the same time point across all sections, and if there were an uneven number of waveforms across sections then one section would be over-represented in the mean (i.e., variance in one section would be weighted more heavily than another in the final calculation). This section will examine the options around data preparation and analysis for the between-day analysis on one subject's data.

3.8.1 Aims

- Identify and describe methods to perform a between-day CMD calculation on the current data
- Determine the optimal procedures for preparing data for a between-day CMD analysis via a case study of one subject.
- Assess the practicality of the identified methods and procedures

3.8.2 Methods

3.8.2.1 *Subject*

One subject whose average number of SLHS sections identified was close to the group mean was selected for analysis in this study.

3.8.2.2 *Data Preparation*

The methods used to select SLHS sections within each file were the same as described in 3.7. An upper velocity limit of 6.94 m/s was applied, and there was no filtering for matched position of footstrike within each file (so all valid steps were exported for further comparison against waveforms collated from a separate day).

There are a number of possible ways to equalise the number of waveforms available for analysis. Ideally, either the subset of waveforms that best represent the waveforms from the day as a whole or the subset of waveforms that provide the highest between-game CMD could be used. Both of these options would require a prohibitively large number of subsets to be tested before the most representative set of waveforms is identified unless only a small number of waveforms are used in the subset (which would also call into question whether the waveform variability has been underestimated due to the small number of waveforms used). An alternative method would be to calculate the between-day CMD on a large number of random samples of subsets. This would assume that accuracy can be achieved through increasing the iterations.

The total number of subsets of waveforms available and the total number of iterations required to test every combination were calculated for all combinations of games. One combination of games was selected to test the iterative approach to calculating between-day CMD. The combination was selected on the basis of having the smallest differential in the number of waveforms on one side (which would produce a small number of waveform combinations when equalising the number of waveforms). This was done because it allowed the effects of the iterative approach to be evaluated on a small number of possible waveform combinations on one side. Between-day CMD calculations on 500 random combinations of waveform subsets were performed, and the maximum between-day CMD was recorded. This process was repeated 40 times. A rolling maximum across 2, 4, 6, 8, 10, 12, 14, 16, 18 and 20 points was calculated on these results to simulate 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000 and 10000 random combinations. The average of the maximum between-day CMD produced by each iteration was then calculated.

3.8.3 Results

The number of waveforms available in all games were identified and the results displayed in Table 3-23. Game numbers refer to the game within the season, so in this case the subject participated in games 2 to 17 but data is not available for games 1 and 9 so these games were skipped in the table. The summary statistics (maximum, minimum and average) for the number of possible waveform sub-sets in each combination of two games on both sides is displayed in Table 3-24.

Table 3.23 Steps available by game

Game	Steps Available Side 1	Steps Available Side 2
2	118	79
3	170	145
4	75	58
5	59	149
6	201	241
7	91	107
8	62	95
10	66	124
11	138	143
12	158	205
13	79	91
14	103	200
15	109	120
16	97	151
17	114	146

Table 3.24 Maximum, minimum and mean possible combinations of waveforms by side

	Maximum		Minimum		Mean
	Value	Game Combination	Value	Game Combination	Value
Side 1	1.70E+59	Game 6/Game 14	37820	Game 5/Game 8	5.07E+57
Side 2	1.81E+71	Game 6/Game 15	146	Game 3/Game 17	3.40E+69

The waveform set for side one, Game 3/Game 17 was used for further analysis. The average of the maximum between-day CMD by number of iterations is displayed in Table 3-25. The z-axis results are displayed graphically in Figure 3-14 (side 1) and Figure 3-15 (side 2). It is worth noting the shape of the graph, and that at fewer iterations there seems to be a rapid increase in the between-day CMD value.

Table 3.25 Maximum between-day CMD by number of random iterations

Number of iterations	z-axis		y-axis		x-axis	
	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
500	0.673	0.705	0.359	0.456	0.599	0.642
1000	0.674	0.706	0.363	0.463	0.603	0.646
2000	0.676	0.708	0.367	0.468	0.607	0.649
3000	0.676	0.709	0.370	0.469	0.608	0.652
4000	0.676	0.709	0.371	0.470	0.609	0.654
5000	0.677	0.710	0.371	0.470	0.609	0.655
6000	0.677	0.710	0.372	0.470	0.609	0.656
7000	0.677	0.710	0.372	0.470	0.610	0.656
8000	0.677	0.711	0.373	0.471	0.610	0.656
9000	0.677	0.711	0.374	0.471	0.610	0.656
10000	0.677	0.711	0.375	0.472	0.610	0.657

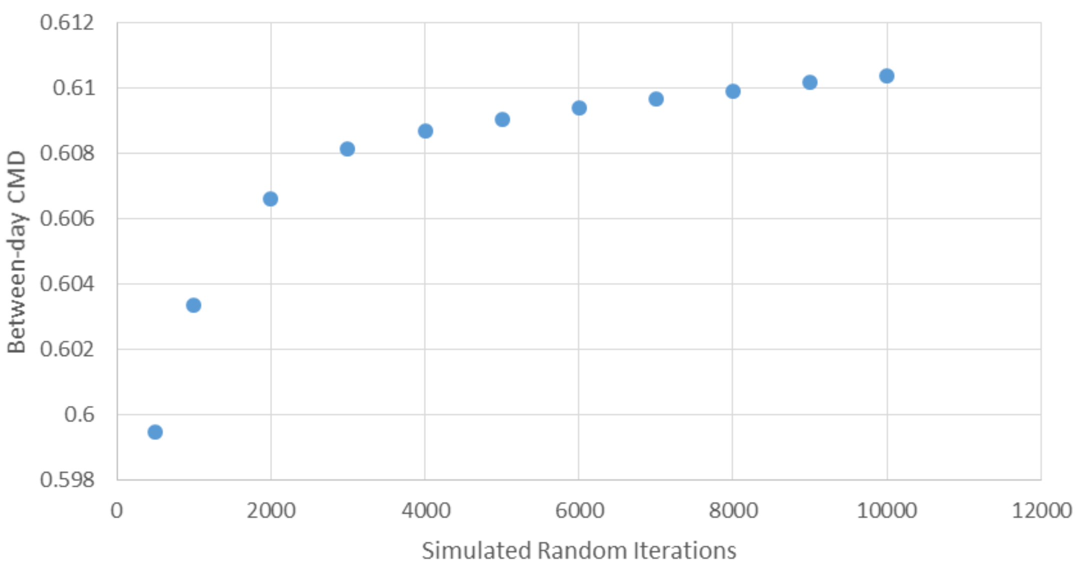


Figure 3-14 Z-axis (side 1) between-day CMD plotted against number of random iterations

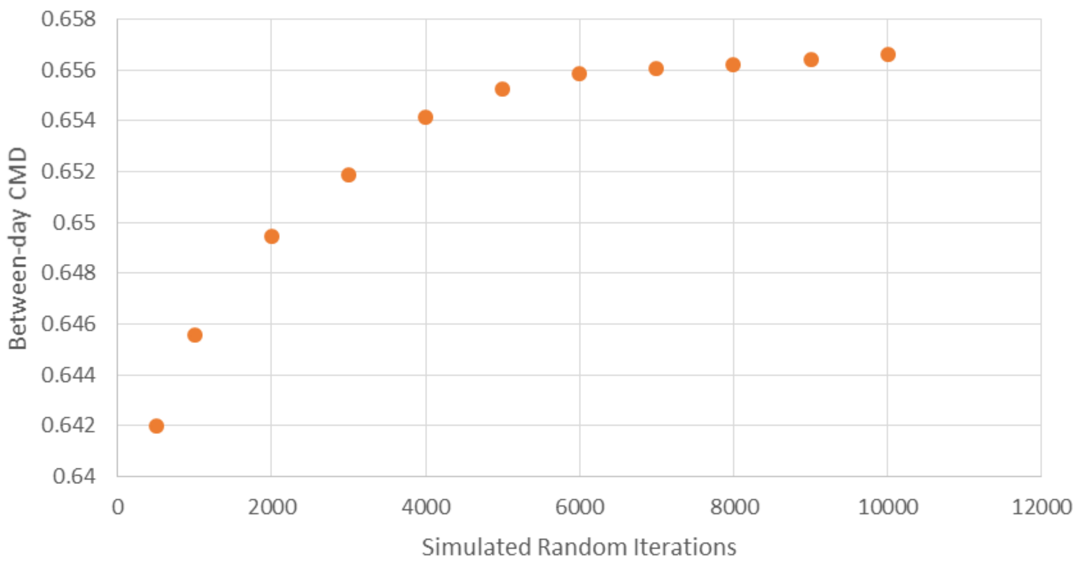


Figure 3-15 Z-axis (side 2) between-day CMD plotted against number of random iterations

3.8.4 **Discussion**

The number of combinations of waveform subsets generated makes testing every case prohibitive. Though there are some games that have fewer combinations, most have too many to analyse practically. We must therefore look for methods of generating a result that justifiably approximates the result that would happen if all waveform sets are processed.

Running a considerable number of iterations using random waveform subsets demonstrated that a small number of iterations will more likely produce a lower between-game CMD that is perhaps not representative of the actual between-game CMD if the most representative subsets of waveforms are used. It appears that after approximately six thousand iterations there is much less change in between-day CMD in comparison to the results from fewer iterations. This is true for both scenarios tested, one with a small number of waveform combinations available (seen in side 1 where the random iterations should encompass most of the possible combinations) and one with a large number of waveform combinations (seen in side 2 where six thousand iterations is nowhere near the total number of possible combinations).

Using 6000 random iterations and selecting the maximum calculated between-day CMD to represent the results between games is still a time consuming process. Currently, 6000 iterations will take approximately 15 minutes to complete on both sides for a single combination of games for one subject. This will likely undermine the practical application of this element of the process, as performing this analysis for just one combination of games on every member of an AFL squad would take approximately 11 hours. Furthermore, there are procedural errors that are likely to be introduced through placement of the units in the uniform on different days. Although there is potential for the unit to move within a game, there is more uncertainty around the repeatability of the placement in the uniform from day to day. The practical usefulness of the between-day CMD is therefore quite limited at the settings required to produce consistent results.

3.8.5 Conclusion

Preparation of data for a between-game CMD calculation provides many challenges. There is currently no consistent method to practically test all possible combinations of waveform subsets that can be used. A compromise of only testing a number of iterations where random waveform subsets are selected from each game can instead be used to generate a between-game CMD that is a close approximation of the best possible result.

At least 6000 random iterations of waveform sub-sets is required to provide confidence that the maximum between-day CMD identified is a fair approximation of the best case scenario. However, this will limit the practical application of the measure as it will take too long to perform this analysis on an entire squad. The optimal settings for this analysis tool will therefore make it impractical in the applied environment.

Given the impracticality of this measure, it was felt that the between-game analysis should be abandoned for the remainder of this thesis. However, this is an area that would be worthy of follow up investigations, particularly when increases in computing power has made the generation of multiple iterations of waveform sub-sets more practical.

3.9 Summary

The development of the analysis tool required a number of different investigations. Factors such as what constitutes a SLHS section, how modifications to the velocity limits change the amount of data available for further analysis, the application and validity of the within-section and between-section CMD calculations to the waveform data, and the preparation of data for a between-game CMD calculation were all discussed. It was identified that an angle window of ±0.05 rad for change in bearing and a velocity window of 4.17 m/s to 6.94 m/s provides the best compromise between theoretical best practice and the extraction of enough valid data to perform analysis on.

Results also suggest that the within-section CMD calculation is a robust measure that can be applied to the waveforms identified in the SLHS sections. However, the within-day CMD calculation appears to be affected by the number of waveforms available for analysis, with less valid waveforms leading to a higher within-day CMD. As the number of waveforms varies between games, there is an inherent error within this calculation that does not appear to affect the within-section CMD. The within-section CMD is therefore the preferred method to quantify waveform variability within a particular day.

The between-section analysis provides insight into variations in waveform shape between sections identified in a game. This is also affected by the number of sections available for analysis, with fewer sections leading to lower variability (especially when the number of valid sections falls to below 6). In most cases the settings for angle window and velocity range that define a SLHS event provide enough valid sections to perform a between-section analysis, so this measure will be included in the overall analysis in subsequent chapters where the value of this measure will be discussed further within the context of its use in the longitudinal analysis of individual subjects.

Data preparation for the between-game CMD analysis provides some challenges but the methods identified can produce justifiable results. However, whether the between-game CMD offers a method of assessing stride variability between games is unclear, as there are many confounding elements to the final analysis of data (such as differing placement of the unit from game to game). For these reasons the between-game CMD analysis will not be included in the overall analysis in subsequent chapters.

The optimal settings for the analysis tool as identified in this chapter will be used in subsequent chapters to analyse the stride variability of a squad of Australian Rules Football Players for the length of a normal Australian Football League season.

4 Application of analysis tool

4.1 Introduction

The development of the analysis tool in Chapter 3 was undertaken to provide the means to evaluate stride variability over the course of a season. It was considered that analysing results generated by this tool would provide an effective method to examine the physical condition of athletes over the course of a season. The processes performed to extract the most amount of data to be analysed while still maintaining validity with reference to previous research and general principles will have implications for the practical application of the analysis tool.

The application of analysis tools based on monitoring an athlete's physical condition is predominantly done to gain insight into how individual athletes are coping with a particular stress that they are being subjected to (Colby, Dawson, Heasman, Rogalski, & Gabbett, 2014; Rogalski et al., 2013) or their game performance (Bauer et al., 2015). The frequent examination of these data at an individual level is standard practice within the applied environment (Cummins, Orr, O'Connor, & West, 2013; Ehrmann, Duncan, Sindhusake, Franzsen, & Greene, 2016).

This chapter evaluates the practical use of the analysis tool by re-analysing data presented in the previous chapter in the context of individual subjects. The general methodology is outlined, then investigations into how the overall season averages vary between subjects (section 4.4), how results vary week to week in the average subject (section 4.5) and the worst case scenario subject in terms of amount of SLHS sections identified (section 4.6) are described.

4.2 General Aims

- Describe the season average results obtained by using the analysis tool on game data obtained from professional AFL players over the course of a season (section 4.4)
- Investigate the applicability of the analysis tool to longitudinal analyses of professional AFL footballers over the course of a season (section 4.4, 4.5, and 4.6)

4.3 General Methods

4.3.1 Subjects

The participant cohort was the same as that used in Chapter 3 (section 3.3.1, page 15), that being 22 professional AFL footballers with age range of 19 to 28 years old. No preselection for position played or physical capacity took place.

4.3.2 Data

Data collection and preparation procedures were the same as was used in Chapter 3 (section 3.3.3, page 16). Briefly repeating for the sake of clarity, GPS and accelerometer data (acquired via a S4 minimaxx unit) were collected from 17 competitive games during the 2014 AFL season.

4.3.3 Axis Definitions

Axis definitions were as outlined in Chapter 3 (section 3.3.4, page 16).

4.3.4 Analysis tool

The analysis tool developed and evaluated in Chapter 3 was applied in this chapter. Straight line high speed (SLHS) running was identified through the processes outlined in Chapter 3 (section 3.4 page 17), with the angle window for the straight line component set to ±0.05 rad and velocity window set from 4.17 m/s to 6.94 m/s. Extraction of step waveforms and analysis via the Co-efficient of Multiple Determination (CMD) was conducted in accordance with the procedures outlined in Chapter 3 (section 3.5, page 26).

4.4 Part 1 – Group results from the 2014 season

A number of different approaches can be taken to assess the performance of the analysis tool over the course of a season of competitive matches. This section will focus on a broad view approach, looking at the season average results to describe the performance of the analysis tool across the group as a whole. This is an important step as not only will these results have some potentially important implications that can be examined further when they are linked to results from missed and modified training and game activity (such as whether there are any implications for subjects who have different levels of waveform variability between sides in the same axis, or whether raw CMD scores have any significance for injury risk), but it will also provide a valuable overview as to the performance of the analysis tool with respect to the group as a whole.

4.4.1 Aims

- Describe the raw season average within-section CMD and between-section CMD results
- Identify instances where significant differences occur between sides within axes and analysis condition for individual subjects
- Describe the processes used to convert within-section CMD and between-section CMD results to individual z-scores
- Identify and describe the distribution of z-scores
- Identify the instances where subjects' individual game z-scores were significant at different confidence levels

4.4.2 Methods

4.4.2.1 *Subjects*

The full cohort of 22 participants was used in this section.

4.4.2.2 *Data preparation and processing*

Data were prepared and processed in accordance with the procedures outlined in the general methods, section 4.3.

4.4.2.3 *Data analysis*

Parameters generated by the analysis tool for each game were:

- Valid strides per game – the total number of strides identified within straight line high speed sections of running through analysis of accelerometer data to locate footstrike events
- Valid steps on both sides – the total number of steps remaining after removing instances where the z-axis accelerations suggest a non-standard body orientation or step function (such as looking over a shoulder to locate the ball)
- Valid SLHS sections on both sides – the number of sections of straight line high speed running identified per game that contain at least three valid steps
- Within-section CMD on all three axes for both sides – calculated on all valid steps
- Between-section CMD on all three axes for both sides – calculated on the three most representative steps from each section of straight line high speed running.

The results were collated by subject, and a season average (mean) and standard deviation for all key parameters was calculated for every subject. Season averages for valid strides, valid steps and valid SLHS sections facilitated comparisons of the capacity for each subject to generate those parameters over a season. Season average within-section and between-section CMD results were evaluated for side to side differences.

4.4.2.3.1 Identification of subject specific significant side to side differences in season average within-section and between-section co-efficient of multiple determination

For each subject, the confidence intervals for within-section and between-section CMD results were determined by performing an empirical bootstrapping procedure as per Ball (2006). A bootstrapping procedure was appropriate with these data because the CMD results available for each individual were not necessarily normally distributed and the number of games available for each individual varied considerably across the cohort. Consequently, using a bootstrapping procedure maximised the validity of the confidence intervals that were generated (Ball, Best, & Wrigley, 2003; Thompson, 1993).

The bootstrapping method employed entailed resampling the data from each individual to form 100000 'new' datasets (with replacement) from the set of data from a single condition, calculating the mean of each sample and the difference of that to the mean of the original sample, sorting the results, then determining the 0.5% and 99.5% value for the 99% confidence interval as well as determining the 2.5% and 97.5% value for the 95% confidence interval. This was repeated for each condition (CMD analysis, axis and side) for each individual subject to create confidence intervals specific to the samples in each condition and subject. For each subject and condition, season average results that were significantly different from the season average of the opposite side (at the 99% and 95% confidence level) were identified. In addition, incidents where the 99% confidence intervals of both sides did not overlap were identified by subject, CMD analysis and axis.

4.4.2.3.2 Calculation of z-scores

The within-section CMD and between-section CMD results were re-analysed within the context of each individual subject's season average and standard deviation to convert the raw score into a z-score, where the z-score is the distance from the subject's season average expressed in standard deviations (Haley & Fragala-Pinkham, 2006). The calculation of z-scores allows raw CMD results to be analysed within a specific context, namely how the raw CMD (both within-section and between-section) compares to the average for the individual subject on that particular side within that particular axis. Previous research has identified that when investigating gait data, CMD values should not be compared across joints and planes as each have different interpretations (Røislien et al., 2012). Researchers have also advocated establishing the development of minimum levels of detectable change or minimal clinically important differences when analysing three-dimensional kinematic gait data, especially in the context of using CMD in the statistical analysis (McGinley et al., 2009). Converting the raw scores to z-scores satisfies those conditions.

4.4.2.3.3 Analysis of z-scores

The distribution of z-scores across the subject group were investigated through calculating the degree of skewness and kurtosis in Excel (Microsoft, USA). All within-section and between-section z-scores were collated by axis (so side 1 and side 2 were combined on each axis), then the skewness and kurtosis was calculated, and significance was measured against the standard error of skewness and standard error of kurtosis respectively. A histogram was also generated for each condition to aid in the visual analysis of the distribution of z-scores.

Confidence intervals for z-scores were established to identify the number of games where a significant z-score occurred per subject. Confidence intervals were also used to identify the total number of games across all subjects where a significant negative z-score occurred in any analysis condition and axis, a significant positive z-score occurred in any condition, and both a significant positive and significant negative z-score occurred. Confidence intervals were established at 99%, 95%, 90% and 80% by implementing a bootstrapping procedure. The z-scores for side 1 and side 2 were collated for each axis and analysis condition, producing six sets of 526 points. Each underlying set was resampled (with replacement) 1000 times, with each of those resampled sets sorted and confidence intervals determined by identifying the 5th and 995th point (for the 99% confidence level), the 25th and 975th point (for the 95% confidence level), the 50th and 100th point (for the 90% confidence interval), and the 100th and 900th point (for the 80% confidence level). The confidence intervals were then averaged across the 1000 iterations to determine the final confidence intervals for that underlying set of data.

Correlations of z-scores across side, axis and analysis condition were calculated via a bootstrapping procedure. Data were resampled (with replacement) 1000 times and the average correlation across all replications was calculated.

4.4.3 **Results**

Summary statistics for all subjects (including total games, valid steps per game, valid steps and valid sections) for all subjects can be found in Table 4-1. The average, maximum and minimum results are highlighted in Table 4-2. It is worth noting the minimum number of average SLHS sections available (5.1 on side 1, 5.4 on side 2), as well as the number of subjects who have at least one side with fewer than six sections available (subjects 15 and 16). Subject by subject results for z-axis, y-axis and x-axis within-section CMD are shown in Tables 4-3, 4-4 and 4-5 respectively. These results are also displayed graphically in Figures 4-1 (z-axis), 4-2 (y-axis) and 4-3 (x-axis). Results where the difference in average CMD is significant to a confidence level of 0.95 and 0.99 are denoted. The same results for the between-section analysis can be found in Tables 4-6, 4-7 and 4-8 and are also displayed graphically in Figures 4-1, 4-2 and 4-3. The y-axis range displayed on all figures is 0.5 for z-axis and x-axis results and 0.8 for y-axis results. Tighter ranges were used for the z-axis and x-axis figures to assist in the identification of instances where 99% confidence bands (displayed as error bars in the figures) do not overlap.

Table 4.1 Summary statistics (by subject) for total games, valid strides, valid steps and valid sections per game

			Side 1		Side 2	
Subject (ID)	Total Games	Valid strides per game	Valid Steps[1]	Valid Sections	Valid Steps	Valid Sections
1	12	240	104	13.8	107	12.8
2	14	185	75	9.6	93	11.1
3	14	258	102	15.7	70	11.7
4	9	165	91	11.7	88	11.0
5	6	222	84	12.3	65	10.0
6	11	351	135	17.7	121	15.1
7	15	270	111	16.1	104	15.5
8	13	148	55	8.7	42	7.4
9	15	329	109	15.1	137	18.5
10	11	171	65	10.4	60	9.8
11	15	282	108	15.3	118	16.1
12	15	217	102	13.4	95	12.5
13	7	214	81	11.7	98	13.3
14	15	199	84	12.1	99	14.4
15	14	107	34	5.1	33	5.4
16	11	141	33	5.8	44	6.5
17	8	341	129	17.6	115	17.8
18	6	256	97	14.8	71	11.0
19	13	276	108	14.8	135	17.9
20	11	295	100	15.0	104	13.7
21	14	138	46	7.4	48	7.6
22	14	259	58	10.4	87	11.9

Table 4.2 Mean, maximum and minimum summary statistics for total games, valid strides, valid steps and valid sections of straight line high speed running per game

			Side 1		Side 2	
	Total Games	Valid strides per game[1]	Valid Steps[1]	Valid Sections	Valid Steps[1]	Valid Sections
Mean	12	230	87	12.5	88	12.3
Maximum	15	351	135	17.7	137	18.5
Minimum	6	107	33	5.1	33	5.4

[1] The number of valid steps on side 1 and side 2 will not add up to the number of valid strides per game as strides have no pre-selection changes in body orientation or step function, whereas steps do have this procedure imposed. Without eliminating steps with different functions and body orientations the number of steps would be equal to the number of strides. Refer to section 3.5.2.2.2.3 for a detailed description of the process.

*Table 4.3 Mean and standard deviation of z-axis within-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Mean	St Dev	Mean	St Dev
1	0.843	0.028	0.844	0.017
2	0.761**	0.034	0.802**	0.026
3	0.813**	0.033	0.79**	0.029
4	0.831	0.035	0.815	0.029
5	0.819	0.037	0.815	0.018
6	0.814	0.022	0.818	0.038
7	0.799	0.019	0.804	0.034
8	0.786	0.046	0.772	0.031
9	0.813	0.028	0.818	0.031
10	0.817**	0.017	0.787**	0.020
11	0.878**	0.024	0.896**	0.012
12	0.836	0.018	0.835	0.028
13	0.850	0.027	0.844	0.021
14	0.797**	0.044	0.819	0.032
15	0.714	0.059	0.723	0.051
16	0.677	0.046	0.688	0.042
17	0.779	0.043	0.768	0.045
18	0.828	0.031	0.811	0.030
19	0.805**	0.019	0.843**	0.012
20	0.806	0.016	0.798	0.022
21	0.779	0.040	0.781	0.028
22	0.825**	0.021	0.844**	0.020

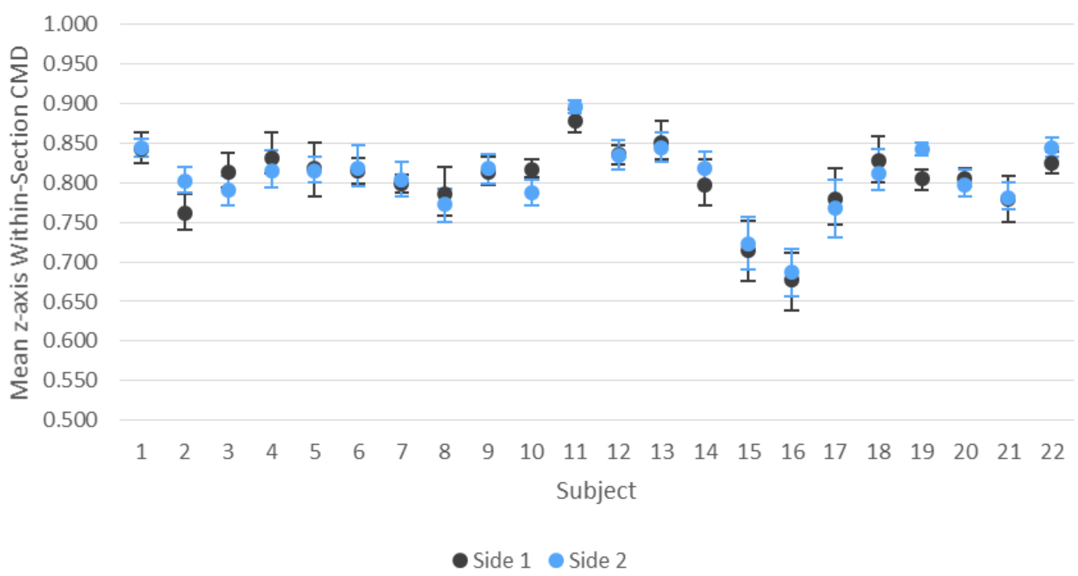


Figure 4-1 Graphical representation of average z-axis within-section CMD results. Confidence intervals (99%) are displayed as error bars.

*Table 4.4 Mean and standard deviation of y-axis within-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Mean	St Dev	Mean	St Dev
1	0.472**	0.028	0.587**	0.017
2	0.457**	0.034	0.664**	0.026
3	0.477	0.033	0.438	0.029
4	0.499**	0.035	0.62**	0.029
5	0.521	0.037	0.499	0.018
6	0.48**	0.022	0.582**	0.038
7	0.609**	0.019	0.553**	0.034
8	0.494**	0.046	0.325**	0.031
9	0.524**	0.028	0.602*	0.031
10	0.53**	0.017	0.41**	0.020
11	0.605	0.024	0.619	0.012
12	0.629	0.018	0.634	0.028
13	0.609**	0.027	0.505**	0.021
14	0.583	0.044	0.580	0.032
15	0.417	0.059	0.399	0.051
16	0.338**	0.046	0.414**	0.042
17	0.496**	0.043	0.336**	0.045
18	0.567**	0.031	0.352**	0.030
19	0.612*	0.019	0.573**	0.012
20	0.487	0.016	0.498	0.022
21	0.484**	0.040	0.39**	0.028
22	0.459**	0.021	0.652**	0.020

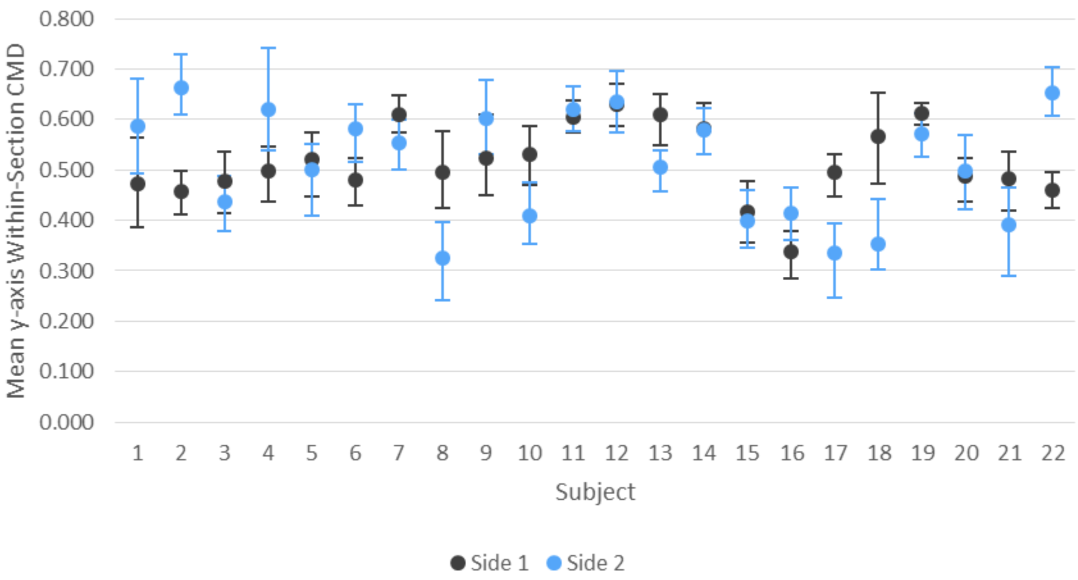


Figure 4-2 Graphical representation of average y-axis within-section CMD results. Confidence intervals (99%) are displayed as error bars.

*Table 4.5 Mean and standard deviation of x-axis within-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Mean	St Dev	Mean	St Dev
1	0.718**	0.028	0.678**	0.017
2	0.575**	0.034	0.751**	0.026
3	0.706**	0.033	0.633**	0.029
4	0.769*	0.035	0.724**	0.029
5	0.635	0.037	0.602	0.018
6	0.691	0.022	0.671	0.038
7	0.736	0.019	0.717**	0.034
8	0.648**	0.046	0.61*	0.031
9	0.759*	0.028	0.746	0.031
10	0.736**	0.017	0.692**	0.020
11	0.700	0.024	0.686	0.012
12	0.677	0.018	0.687	0.028
13	0.685*	0.027	0.710	0.021
14	0.711*	0.044	0.745*	0.032
15	0.643	0.059	0.651	0.051
16	0.655	0.046	0.629*	0.042
17	0.713**	0.043	0.625**	0.045
18	0.650	0.031	0.596**	0.030
19	0.641**	0.019	0.715**	0.012
20	0.734	0.016	0.732	0.022
21	0.714	0.040	0.704	0.028
22	0.686	0.021	0.696	0.020

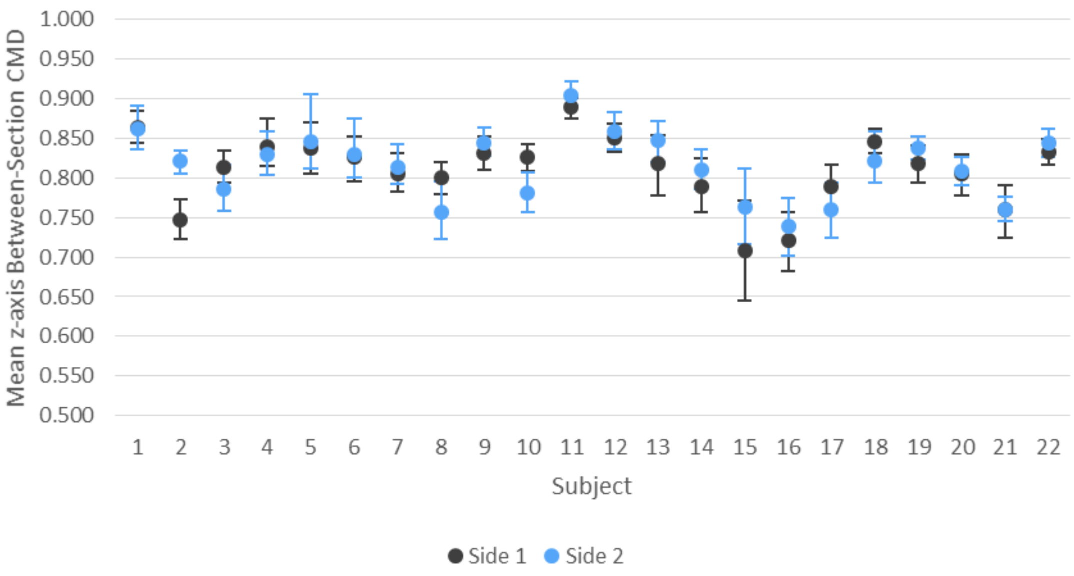


Figure 4-3 Graphical representation of average x-axis within-section CMD results. Confidence intervals (99%) are displayed as error bars.

*Table 4.6 Mean and standard deviation of z-axis between-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Mean	St Dev	Mean	St Dev
1	0.864	0.028	0.862	0.017
2	0.746**	0.034	0.821**	0.026
3	0.813*	0.033	0.786**	0.029
4	0.839	0.035	0.829	0.029
5	0.838	0.037	0.846	0.018
6	0.826	0.022	0.830	0.038
7	0.805	0.019	0.814	0.034
8	0.801**	0.046	0.757**	0.031
9	0.83*	0.028	0.844	0.031
10	0.825**	0.017	0.78**	0.020
11	0.889**	0.024	0.904**	0.012
12	0.850	0.018	0.859	0.028
13	0.819**	0.027	0.847*	0.021
14	0.789*	0.044	0.810	0.032
15	0.708**	0.059	0.763*	0.051
16	0.722	0.046	0.739	0.042
17	0.788*	0.043	0.76**	0.045
18	0.846	0.031	0.822**	0.030
19	0.818**	0.019	0.837*	0.012
20	0.806	0.016	0.808	0.022
21	0.760	0.040	0.760	0.028
22	0.833	0.021	0.844	0.020

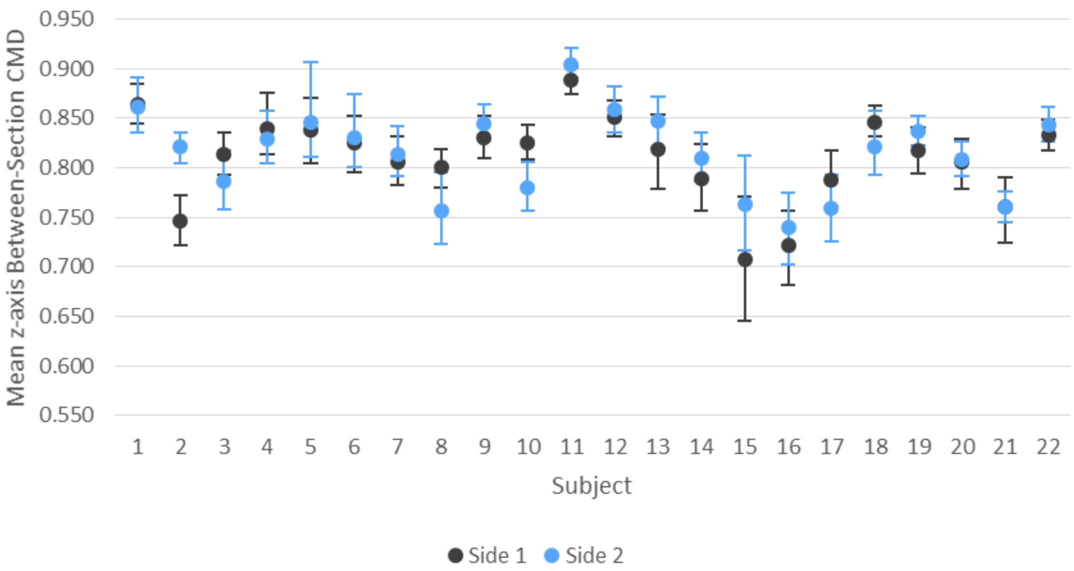


Figure 4-4 Graphical representation of average z-axis between-section CMD results. Confidence intervals (99%) are displayed as error bars.

*Table 4.7 Average and standard deviation of y-axis between-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Average	St Dev	Average	St Dev
1	0.447*	0.028	0.576**	0.017
2	0.374**	0.034	0.684**	0.026
3	0.404	0.033	0.404	0.029
4	0.441**	0.035	0.61**	0.029
5	0.575	0.037	0.555	0.018
6	0.464**	0.022	0.607**	0.038
7	0.618**	0.019	0.55**	0.034
8	0.533**	0.046	0.203**	0.031
9	0.492**	0.028	0.602**	0.031
10	0.458**	0.017	0.32**	0.020
11	0.573	0.024	0.599	0.012
12	0.615*	0.018	0.672*	0.028
13	0.543*	0.027	0.43**	0.021
14	0.546*	0.044	0.483**	0.032
15	0.37*	0.059	0.425	0.051
16	0.147**	0.046	0.344**	0.042
17	0.442**	0.043	0.237**	0.045
18	0.574**	0.031	0.421**	0.030
19	0.607**	0.019	0.523**	0.012
20	0.347*	0.016	0.43*	0.022
21	0.388	0.040	0.347	0.028
22	0.246**	0.021	0.545**	0.020

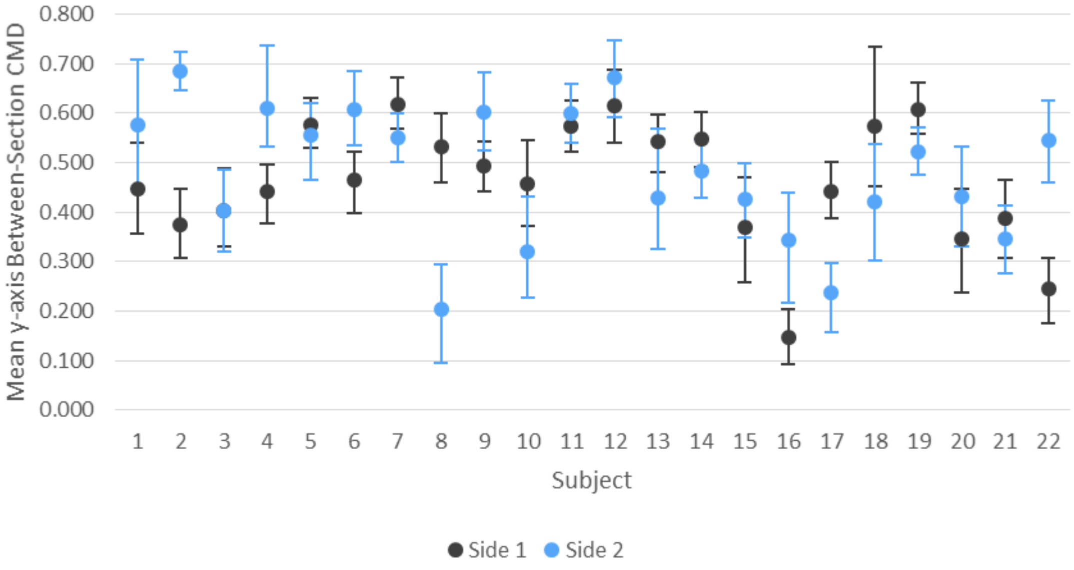


Figure 4-5 Graphical representation of average y-axis between-section CMD results. Confidence intervals (99%) are displayed as error bars.

*Table 4.8 Mean and standard deviation of x-axis between-section CMD by subject. Results where the difference in the averages is significant at a confidence level of 0.95 are marked *, if results are significant at a confidence level of 0.99 they are marked ***

	Side 1		Side 2	
Subject	Mean	St Dev	Average	St Dev
1	0.710	0.028	0.672**	0.017
2	0.511**	0.034	0.747**	0.026
3	0.689**	0.033	0.591**	0.029
4	0.787**	0.035	0.739**	0.029
5	0.632	0.037	0.661	0.018
6	0.681	0.022	0.666	0.038
7	0.729	0.019	0.741	0.034
8	0.604	0.046	0.607	0.031
9	0.741	0.028	0.753	0.031
10	0.755**	0.017	0.688**	0.020
11	0.674	0.024	0.661	0.012
12	0.627*	0.018	0.692	0.028
13	0.616**	0.027	0.670	0.021
14	0.683	0.044	0.708	0.032
15	0.628	0.059	0.647	0.051
16	0.621	0.046	0.648	0.042
17	0.71**	0.043	0.606**	0.045
18	0.67**	0.031	0.608**	0.030
19	0.626**	0.019	0.702**	0.012
20	0.726	0.016	0.744	0.022
21	0.617	0.040	0.637	0.028
22	0.661	0.021	0.668	0.020

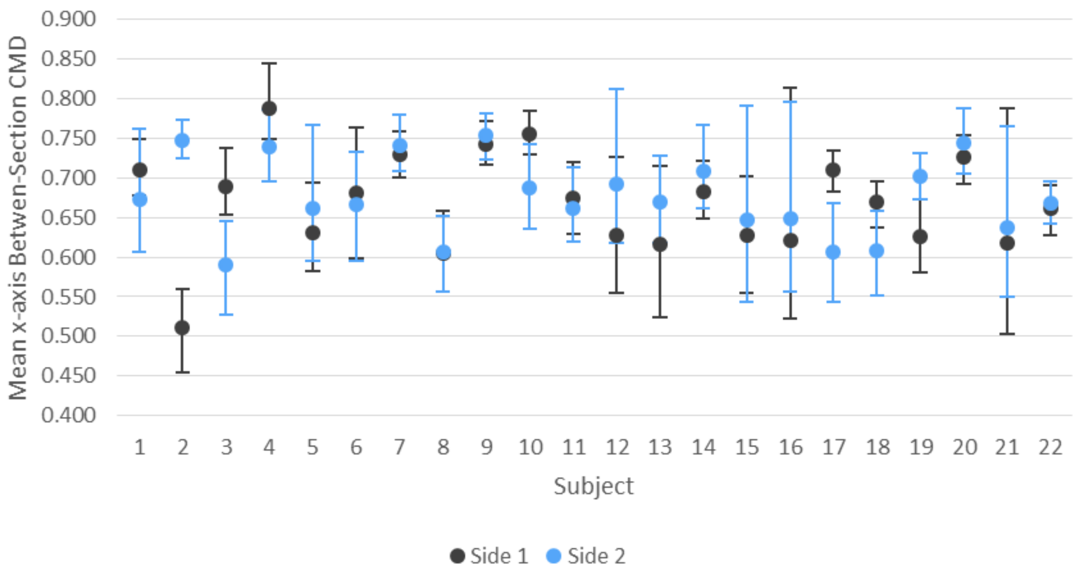


Figure 4-6 Graphical representation of average x-axis between-section CMD results. Confidence intervals (99%) are displayed as error bars.

Instances where the difference between season averages are different between sides within an axis for each subject are seen in Table 4-9. If the averages are different to a confidence level of 0.95 then the cell is marked with an 'x'. If the averages are different to a confidence level of 0.99 then the cell has a black background. These results are collated by axis in Table 4-10. It is interesting to note the relatively high number of significant results (at both confidence intervals) within the y-axis, as well as subject 2 who has significant differences to a confidence interval of 0.99 in all but three conditions. The number of incidents where 99% confidence intervals do not overlap are shown in Table 4-11.

Table 4.9 Instances of absolute difference in average result within the same axis being significantly different at a confidence level of 0.95 side (marked with x), and instances where the absolute difference in average result is different at a confidence level of 0.99 are shaded black.

	Within-Section						Between-Section					
	Side 1			Side 2			Side 1			Side 2		
Subject	z	y	x	z	y	x	z	y	x	z	y	x
1		x	x		x	x		x			x	x
2	x	x	x	x	x	x	x	x	x	x	x	x
3	x		x	x		x	x		x	x		x
4		x	x		x	x		x	x		x	x
5												
6		x			x			x			x	
7		x			x	x		x			x	
8		x	x		x	x	x	x		x	x	
9		x	x		x			x			x	
10	x	x	x	x	x	x	x	x	x	x	x	x
11	x			x			x			x		
12								x	x		x	
13		x	x		x		x	x	x	x	x	
14	x		x			x	x	x			x	
15							x	x		x		
16		x			x	x		x			x	
17		x	x		x	x	x	x	x	x	x	x
18		X			x	x		x	x	x	x	x
19	x	x	x	x	x	x	x	x	x	x	x	x
20								x			x	
21		x			x							
22	x	x		x	x			x			x	

Table 4.10 Percent of results within each axis where the difference between sides is significant to a confidence level of 95% and 99% (cells with no instances are left blank)

	95% Confidence Level			99% Confidence Level		
Subject	z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
1		100%	75%		75%	75%
2	100%	100%	100%	100%	100%	100%
3	100%		100%	100%		75%
4		100%	100%		100%	75%
5						
6		100%			100%	
7		100%	25%		100%	25%
8	50%	100%	50%	50%	100%	25%
9		100%	25%		100%	
10	100%	100%	100%	100%	100%	100%
11	100%			100%		
12		50%	25%			
13	50%	100%	50%	25%	75%	25%
14	50%	50%	50%	25%	25%	
15	50%	25%		25%		
16		100%	25%		100%	
17	50%	100%	100%	25%	100%	100%
18	25%	100%	75%	25%	100%	75%
19	100%	100%	100%	75%	100%	100%
20		50%				
21		50%			50%	
22	50%	100%		50%	100%	

Table 4.11 Incidents where 99% confidence intervals for season averages do not overlap by subject.

	Within-Section			Between-Section		
Subject	z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
1						
2	x	x	x	x	x	x
3			x			x
4					x	
5						
6					x	
7						
8		x			x	
9						
10	x			x		
11						
12						
13		x				
14						
15						
16					x	
17		x	x		x	x
18		x				
19	x		x			x
20						
21						
22		x			x	

Skewness and kurtosis measures for z-scores collated by axis (both sides combined) are shown in Table 4-12. These data sets are displayed graphically as histograms in Figures 4-7 and 4-8. It is worth noting the degree of skewness of the data, with all but the y-axis between-section results with a negative skew. The results from the bootstrapping procedure to generate confidence intervals on z-scores can be found in Table 4-13. Correlations between collated z-scores for within-section, between-section and across both within and between-section results are shown in Table 4-14, 4-15 and 4-16 respectively. The generally high correlation between z-axis and x-axis results across all conditions is of interest in these results.

*Table 4.12 Skewness and kurtosis measurements for within-section and between-section individual z-scores by axis. Skewness measures marked * are outside the standard error of skewness (SES), and kurtosis measures marked * are outside of the standard error of kurtosis (SEK).*

	Within-Section			Between-Section		
	z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
Skewness	-0.37*	-0.16	-0.67*	-0.29*	0.05	-0.25*
Kurtosis	-0.22	-0.54*	0.50*	-0.47*	-0.36	-0.31

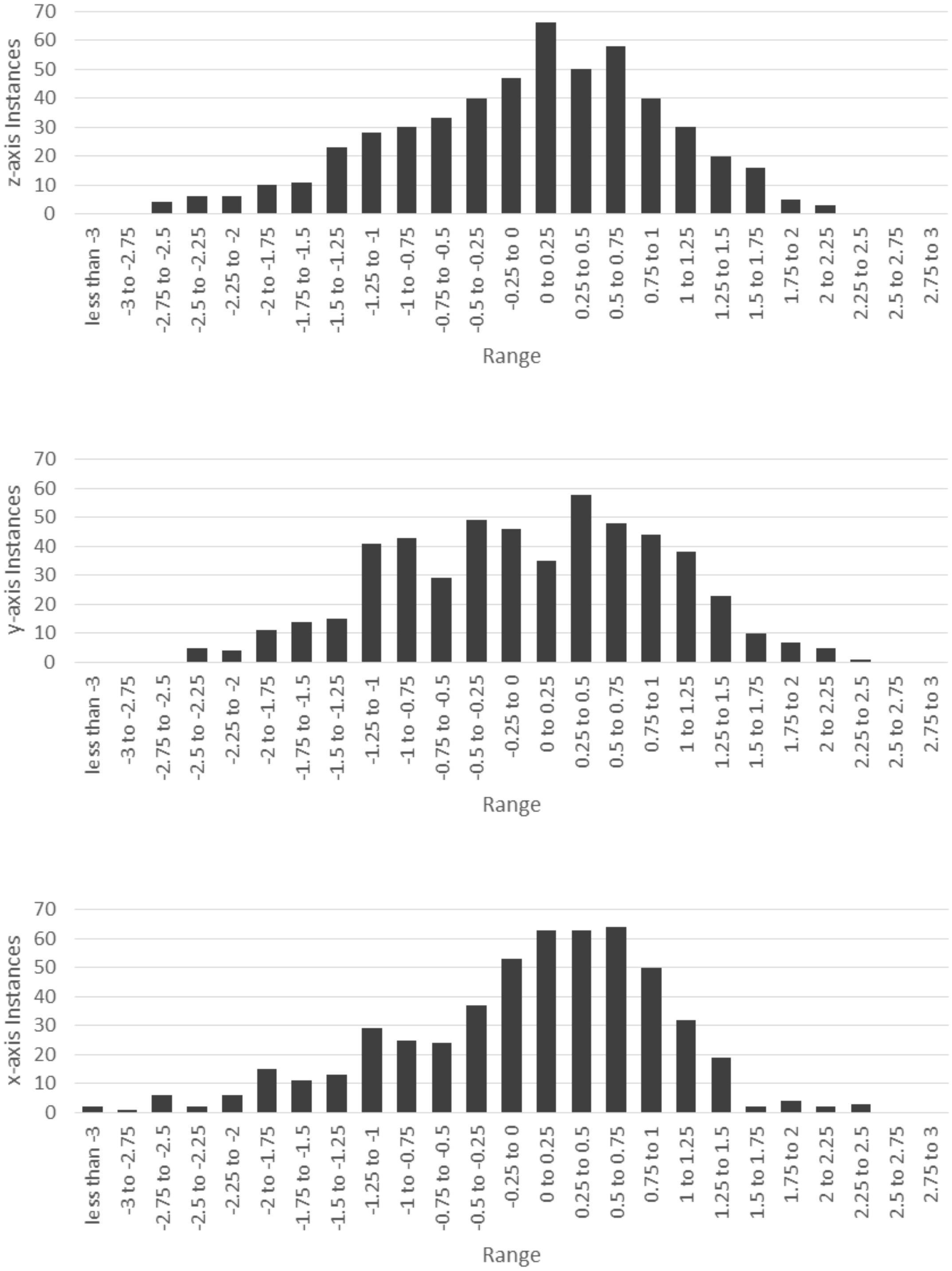


Figure 4-7 Histograms displaying z-score distributions for within-section CMD measurements in the z-axis (top), y-axis (middle) and x-axis (bottom)

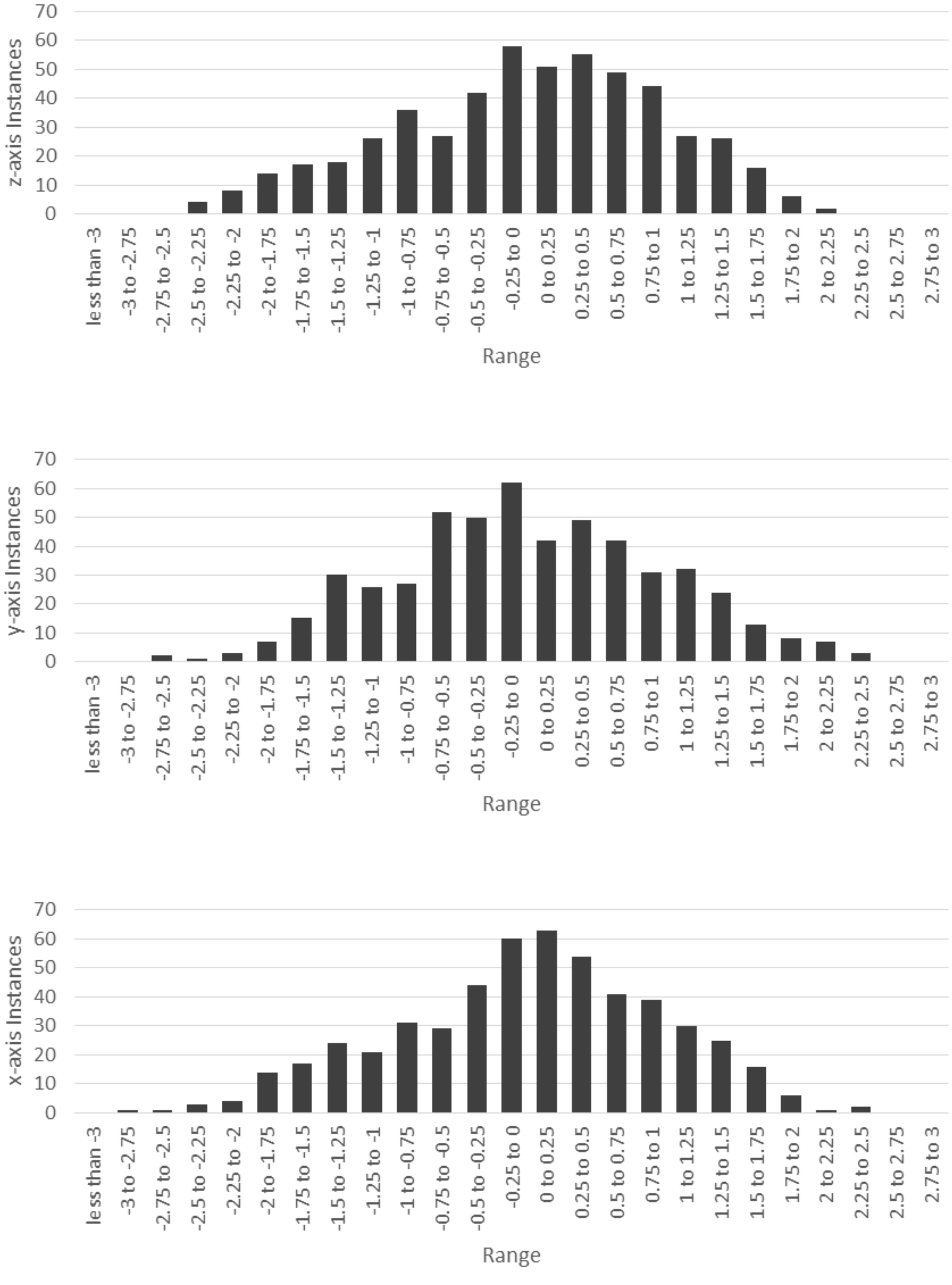


Figure 4-8 Histograms displaying z-score distributions for between-section CMD measurements in the z-axis (top), y-axis (middle) and x-axis (bottom)

Table 4.13 Correlation (r) of within-section z-scores between sides and axes

		Side 1			Side 2		
		z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
Side 1	z-axis		0.517	0.651	0.519	0.269	0.291
	y-axis			0.362	0.346	-0.056	0.214
	x-axis				0.362	0.253	0.278
Side 2	z-axis					0.485	0.622
	y-axis						0.371
	x-axis						

Table 4.14 Correlation (r) of between-section z-scores between sides and axes

		Side 1			Side 2		
		z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
Side 1	z-axis		0.383	0.606	0.267	0.194	0.191
	y-axis			0.179	0.124	-0.111	0.096
	x-axis				0.166	0.237	0.249
Side 2	z-axis					0.445	0.650
	y-axis						0.365
	x-axis						

Table 4.15 Correlation (r) across within-section and between-section z-scores

			Within Section					
			Side 1			Side 2		
			z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
Between Section	Side 1	z-axis	0.570	0.304	0.442	0.399	0.203	0.259
		y-axis	0.232	0.485	0.088	0.143	-0.216	0.077
		x-axis	0.415	0.118	0.625	0.222	0.207	0.207
	Side 2	z-axis	0.343	0.228	0.245	0.470	0.303	0.359
		y-axis	0.192	-0.132	0.203	0.278	0.624	0.198
		x-axis	0.192	0.120	0.181	0.285	0.201	0.549

Table 4.16 Z-score confidence intervals by axis and CMD analysis as generated by bootstrapping procedure

Confidence Level	Limit	Within-Section z-axis	Within-Section y-axis	Within-Section x-axis	Between-Section z-axis	Between-Section y-axis	Between-Section x-axis
99%	Low	-2.25	-2.11	-2.39	-2.45	-2.26	-2.73
	High	1.87	2.20	2.07	1.88	2.02	2.03
95%	Low	-1.75	-1.55	-1.70	-1.71	-1.63	-1.85
	High	1.46	1.57	1.44	1.48	1.47	1.30
90%	Low	-1.35	-1.29	-1.37	-1.30	-1.23	-1.34
	High	1.23	1.29	1.19	1.17	1.20	1.05
80%	Low	-0.87	-0.80	-0.86	-0.83	-0.92	-0.80
	High	0.84	0.85	0.81	0.83	0.87	0.79

The z-scores are broken down by individual subject in Table 4-17, with the number of instances identified where a z-score in any condition exceeds a confidence interval of 99%, 95%, 90% and 80%. These results are broken down further in Table 4-18 into the percentage of games to show where at least one condition is significantly higher than the long term average, at least one condition is significantly lower than the long term average, and where there is at least one condition higher and one condition lower in the same game.

Table 4.17 Number of games where the z-score for any condition of within-section CMD or between-section CMD on any side and axis exceeds the corresponding confidence level

		Confidence Level			
Subject	Total Games	99%	95%	90%	80%
1	12	1	3	6	10
2	14	3	7	10	12
3	14	2	5	8	11
4	9	2	2	2	5
5	6	0	2	4	5
6	11	1	3	6	8
7	15	1	5	10	12
8	13	1	4	8	12
9	15	3	6	8	13
10	11	0	3	8	10
11	15	2	7	8	12
12	15	1	3	9	13
13	7	0	2	3	4
14	15	2	5	11	12
15	14	1	4	7	12
16	11	2	6	6	9
17	8	1	3	4	7
18	6	0	1	3	4
19	13	0	4	7	11
20	11	2	3	6	8
21	14	4	6	10	12
22	14	2	7	9	12
Total	263	31	91	153	214
Percentage		11.8%	34.6%	58.2%	81.4%

Table 4.18 Percentage of total files with at least one condition significantly higher, at least one condition significantly lower and both one condition higher and one condition lower

Confidence Level	At least one condition significantly higher	At least one condition significantly lower	At least one condition higher and one condition lower
99%	6.5%	5.3%	0.0%
95%	19.4%	17.9%	2.7%
90%	35.0%	29.7%	6.5%
80%	52.1%	48.3%	19.0%

4.4.4 **Discussion**

Nineteen of the 22 subjects showed a difference in season average between side 1 and side 2 on an axis in either the within-section or between-section CMD that is significantly different at a confidence level of 99% (Table 4-10). Two of those subjects (subjects 2 and 10) have all conditions where the difference is significant and one subject (subject 19) has all but two conditions significant to 99% (the remaining conditions were significantly different to 0.95). Relating these results back to Figures 4-1 to 4-6, subject 2 has significantly lower results (and consequently more variability) on side 1 than side 2, subject 10 has significantly lower results on side 2 than side 1, and subject 19 has significantly lower results on side 1 than side 2 except for the y axis where side 2 is lower than side 1. When the significant differences are collated by axis, there were more subjects with significant differences in the y-axis (16 subjects) than the z-axis (11 subjects) or the x-axis (12 subjects). Of the subjects who had a significant results in the y-axis, 12 subjects had significant differences in all CMD measures on the y-axis. The causes and implications of these differences are currently unknown, and will be investigated further in section 4-7, however it is encouraging for the performance of the analysis tool that there are specific instances where a significant difference occurs that can be linked to information on the athlete's overall history of training and game participation so that inferences can be made as to the cause of such differences.

When the confidence level for inferring significance is reduced to 95% there are more significant differences identified (52.3% of conditions were significant at 95% while 43.9% of conditions were significant at 99%). It is interesting to note that although there are a lot of significant results, some subjects (such as subject 2) have very large discrepancies between sides in a number of different conditions. This can be seen in Table 4-11 where the number of incidents where the 99% confidence intervals overlapped, as well as Figures 4-1 to 4-6 where the distance between averages and the 99% confidence intervals have been plotted. This is perhaps a better indication of subjects whose difference in waveform variability between sides may be of clinical significance.

There are many possible reasons for a difference in stride variability across left and right sides, and the clinical significance (or lack of significance) of a difference for an individual would need to take into account their personal activity and injury history. Despite the large number of possible causes, this area is still worthy of further investigation, particularly to see if there are any common features in the group of individuals that display a side to side difference.

The distribution of z-scores is significantly negatively skewed in all but the y-axis between-section CMD (significance was measured against the standard error of skewness and standard error of kurtosis). This is not surprising given the number of influences that will tend to decrease the CMD value (such as natural variation, contact with an opponent, gameplay considerations etc.). In contrast, to achieve high values for CMD the subject must produce waveforms that are almost perfectly matched. It is, in effect, much easier to produce highly variable waveforms than it is to produce perfectly matched waveforms. Consequently the distribution of the z-scores will tend to be negatively skewed with a longer tail of negative values. The practical implications of these results are that confidence intervals associated with normally distributed z-scores are invalid. However, this was mitigated by the use of the bootstrapping procedure which calculated confidence intervals with respect to the data currently being analysed.

The subject by subject analysis of the number of games where z-scores were significant within axis, side and CMD condition at various confidence levels (Table 4-13) shows that there are 11.8% of games where there was at least one significant result at the 99% confidence level. At the 95% confidence level, there are 34.6% of games where there was at least one significant result. The practical application of these results may be that games where a significant results occurs at the 99% confidence level should be treated as a ‘red flag’ and followed up with specific diagnostic tests, whereas games significant at the 95% confidence level would indicate that there is possibly a problem that should be investigated with diagnostic tests if other athlete wellness measures also indicate a potential issue. At confidence levels above 95%, there are less than 2.7% of games where both a significant positive and negative event occur. This is a good indication that at high confidence levels there is more clarity in identifying a general increase or decrease in waveform variability that pervades across all conditions of side, axis and CMD calculation. That is not to say that positive and negative z-scores should not occur in the same game, as an increase in stride variability in one axis does not preclude uniformity in another axis. Instances of both high and low significant results will be investigated further in sections 4.5, 4.6 and 4.7.

The average number of SLHS sections available is 12.5 on side 1 and 12.3 on side 2 (Table 4-2) which exceeded the threshold of six established in Chapter 3 (section 3.6, page 39) for the minimum number required. When individual subjects were examined it was found that 20 of the 22 subjects recorded a season average for number of SLHS per game greater than six. However, the subject with the fewest number of valid SLHS sections available (subject 15) had an average of only 5.1 SLHS sections on side 1 and 5.4 SLHS sections on side 2. There was also one other subject with a similar average number of sections available (subject 16, 5.8 SLHS sections on side 1 and 6.5 SLHS sections on side 2), and two other subjects (subject 8 and subject 21) who had less than 10 SLHS sections available on average on both sides. Given that these are the average results, there is a very real potential that there will be many games where the number of SLHS sections is much lower than six.

The low number of SLHS sections in some subjects could be due to factors discussed during the development of the analysis tool such as a limited physical capacity to achieve high running speeds and limited opportunities to run at high speed in straight lines during a game due to gameplay demands. A post-hoc analysis was conducted to determine the season average for maximum straight line running speeds achieved during games. Subjects were ranked from highest to lowest, and the two subjects who had the fewest number of SLHS sections were ranked 19th (subject 15) and 21st (subject 16) of the 22 subjects, suggesting that capacity to achieve high running speeds did affect the amount of SLHS sections identified in a game. Interestingly, the subject who ranked 22nd in the post-hoc analysis of maximum speeds achieved was subject 22 who was able to generate an average of 10.4 SLHS sections on side 1 and 11.9 SLHS sections on side 2, much closer to the group average than subjects 15 and 16. This demonstrates that although a factor, reduced capacity to achieve high speeds does not necessarily reduce the amount of SLHS sections per game to a level where the accuracy of between-section analyses may be questionable.

Another factor that could reduce the amount of SLHS sections identified is reduced game time, as files analysed in this section were not pre-selected for games where it was known that the subject completed the entire game without substitution or injury. It is likely that there would be some games included in this analysis where a subject did not take part in the full game because in addition to the interchange that normally occurs in a game in the AFL, the 2014 season had a substitute available who did not take part in the game until he was substituted in, which would consequently mean there was also a player who was substituted out of the game. In both cases, the subject would not have taken part in the full game so would have less opportunity to generate SLHS sections. These games were left in the analysis as the reason for the reduced game time is unknown. These games may provide valuable information on stride characteristics that precede an injury event (if the reason the subject did not compete the full game was because of injury), or the subject may have been used as a substitute if it was felt they would not be able to play the full game without exposing themselves to the risk of injury. Whatever the case, these games are still valuable additions to the analysis. The practical effects of only having a small average number of SLHS sections is not immediately clear and will be investigated further in section 4.5 where a longitudinal analysis will be performed on subject 15.

4.4.5 **Conclusion**

Season average raw CMD results were calculated and the number of significant differences between sides within the same analysis condition and axis were identified. The y-axis produced the most number of subjects who had significant differences between sides at a confidence level of 0.99. There were two subjects who had significant differences across all conditions and axes.

Individual subject raw CMD results were converted to z-scores. The overall distribution of these z-scores when collated across the subject group were negatively skewed in the z and x axes. When analysed by subject there were roughly one third of games where at least one condition was significantly different from the long term average at a confidence level of 95%. There were also variations between subjects in the number of games with a significant z-score.

Overall, the use of z-scores to provide a means for longitudinal analysis of results within analysis condition and axis of measurement for individuals shows great promise. The practical implications of all these results will be investigated further in sections 4.5, 4.6 and 4.7.

4.5 **Part 2 – Longitudinal analysis of the average subject**

Group average results presented in section 4.4 show the season-long average (mean) results for the group and individual subjects. These results provide information on long term trends within the results that may offer some insight into the overall physical condition of the athlete (such as chronic imbalances between steps on left and right legs). Another way (and perhaps a more typical way) these results would be analysed within the practical setting of a professional sporting club would be to calculate CMD results weekly (or even after every training session) and add those results to a longitudinal analysis within each subject that is being analysed in order to develop a reference range individual to that athlete. This section does not include a comprehensive investigation into the relationship between incidents where athletes have exhibited a variability outside of their normal range and incidents of missed or modified training (this will be presented in Chapter 5). Instead, in order to demonstrate the practical application of the analysis tool, this section will describe an individual style of analysis with reference to a single subject to explore the application of results to individual subjects, an important element in the eventual application of the analysis tool within elite sporting environments.

4.5.1 Aims

- Identify an average subject and describe their results across the season

4.5.2 Methods

4.5.2.1 *Subject*

One subject was selected to represent the average subject within the group based on the results presented in section 4.4. Subjects were ranked (in ascending order) on the absolute difference from the group mean to their score within the following categories:

- The number of games available for analysis
- The mean number of strides identified per game
- The mean number of valid SLHS sections identified on side 1 and side 2
- The mean number of valid steps identified on side 1 and side 2
- The number of instances where their season mean is significantly different between sides within the same axis
- The number of games where a significant difference from the season mean within side and axis were identified.

An overall ranking was then calculated by averaging the rankings in the aforementioned categories and then determining the overall ascending rank of those averages.

The description of the personal characteristics (such as age, mass etc.) of the chosen subject is problematic given the subjects were de-identified, suffice to say that the subject chosen fell within the overall range of characteristics described in section 4.3.1 and that their results in the key variables described earlier in this section suggested they were most appropriate to use as a representative subject for the whole cohort.

4.5.2.2 *Data preparation and processing*

Data were prepared and processed in accordance with the procedures outlined in the general methods, section 4.3.

4.5.2.3 *Data analysis*

Results from each game available for the selected subject were collated. Key variables extracted from each game were:

- Valid strides per game
- Valid steps on both sides
- Valid SLHS sections on both sides
- Within-section CMD on all three axes for both sides
- Between-section CMD on all three axes for both sides

The within-section CMD and between-section CMD results were converted to z-scores within side, axis, and between-section or within-section condition. In each of the 12 separate conditions (three axes by two sides by two CMD analysis conditions), the season average and standard deviation of results was calculated and used to convert raw scores to z-scores. Significance at the 99% and 95% confidence intervals was assessed using the confidence intervals calculated in the previous section (Table 4-16).

4.5.3 Results

The average of category rankings and overall subject rank used to determine the average subject are displayed in Table 4-19. Subject 1 was determined to be the most representative of the group average across all categories. A summary of games available for subject 1, as well as the number of valid steps and sections identified per game are found in Table 4-20. It is worth noting the small number of sections identified in game 14.

Table 4.19 Average ranking in absolute difference from group mean in categories used to determine the average subject and the overall ranking by subject

Subject	Average of Category Rank	Overall Rank
1	5.3	1
2	10.4	11
3	8.4	6
4	7.6	4
5	10.1	10
6	12.6	15
7	10.9	12
8	14.0	16
9	14.8	19
10	12.5	14
11	11.5	13
12	7.6	4
13	8.4	6
14	7.1	3
15	17.5	22
16	14.4	18
17	15.1	20
18	9.3	8
19	14.3	17
20	9.9	9
21	16.6	21
22	6.9	2

Table 4.20 Summary of valid strides, valid steps and valid SLHS sections by game for subject 1.

Game	Total Strides	Valid Steps		Valid Sections	
		Side 1	Side 2	Side 1	Side 2
1	195	66	74	10	11
2	226	126	106	17	14
4	178	87	90	12	9
5	280	138	122	16	15
8	297	123	107	17	13
10	327	135	130	17	14
11	262	86	125	13	16
12	240	87	101	14	10
13	262	111	120	14	12
14	160	40	54	5	8
15	304	170	168	21	19
17	146	76	92	9	12
Mean	240	104	107	14	13

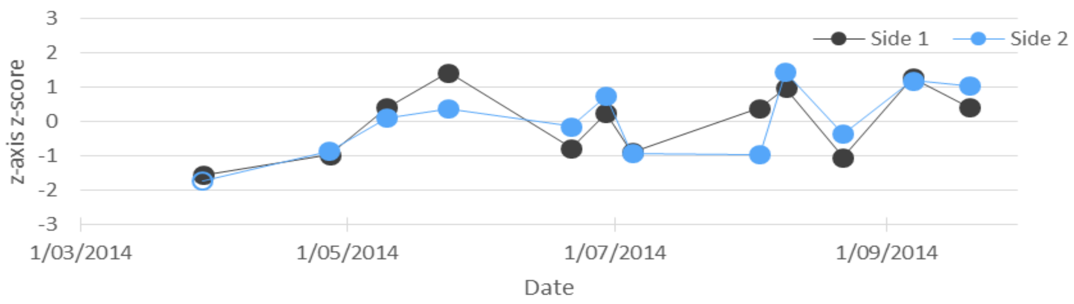
Longitudinal results for the raw within-section CMD analysis can be found in Table 4-21 and z-scores displayed in Table 4-22. Graphical representations of these results can also be found in Figure 4-9. Longitudinal results for the between-section CMD analysis can be found in table 4-23, and z-scores displayed in Table 4-24. Graphical representations of these results are found in Figure 4-10. It is worth noting the significant results at the 95% confidence level in the between-section results, and the lack of significance in the corresponding results in the within-section results. In particular, the between-section results in game 1 showed significant results to a confidence level of 99% for side 2 in the z-axis and to a confidence level of 95% for side 2 in the x-axis, with no significant results for the within-section category. Similarly, for game 11 there were significant results to a confidence level of 95% in the between-section category (side 1 in the z-axis and side 1 in the x-axis) with no significant results in the within-section category.

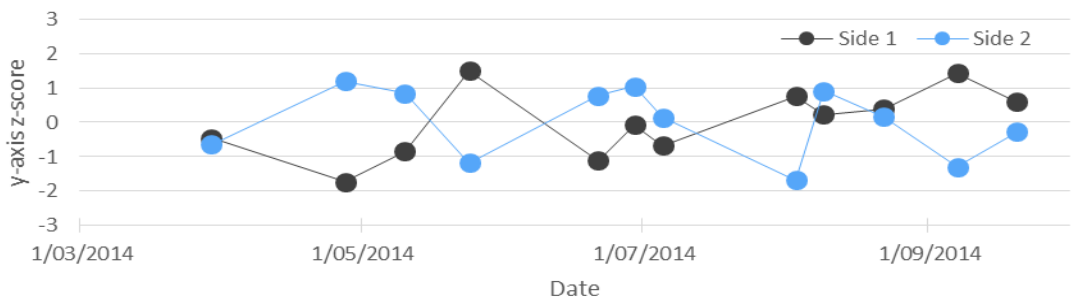
Table 4.21 Longitudinal within-section CMD analysis for subject 1

	z-axis CMD		y-axis CMD		x axis-CMD	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.800	0.814	0.411	0.498	0.654	0.606
2	0.816	0.829	0.245	0.757	0.715	0.713
4	0.855	0.846	0.362	0.705	0.803	0.738
5	0.883	0.851	0.669	0.421	0.786	0.618
8	0.822	0.841	0.326	0.696	0.677	0.731
10	0.850	0.857	0.462	0.735	0.753	0.690
11	0.819	0.828	0.382	0.606	0.653	0.672
12	0.854	0.828	0.573	0.351	0.646	0.608
13	0.870	0.868	0.502	0.717	0.776	0.675
14	0.814	0.838	0.524	0.611	0.639	0.735
15	0.879	0.864	0.659	0.405	0.773	0.692
17	0.854	0.862	0.550	0.549	0.739	0.659

Table 4.22 Within-section z-scores by game for subject 1.

	z-axis		y-axis		x-axis	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	-1.54	-1.74	-0.46	-0.63	-1.04	-1.50
2	-0.97	-0.87	-1.72	1.19	-0.04	0.72
4	0.41	0.13	-0.84	0.83	1.39	1.24
5	1.43	0.39	1.50	-1.18	1.11	-1.26
8	-0.76	-0.14	-1.11	0.77	-0.67	1.10
10	0.26	0.75	-0.08	1.04	0.58	0.25
11	-0.88	-0.92	-0.68	0.13	-1.06	-0.12
12	0.40	-0.94	0.76	-1.67	-1.17	-1.46
13	0.98	1.44	0.23	0.91	0.95	-0.06
14	-1.04	-0.35	0.39	0.16	-1.29	1.19
15	1.29	1.20	1.42	-1.29	0.90	0.29
17	0.41	1.05	0.59	-0.27	0.34	-0.40





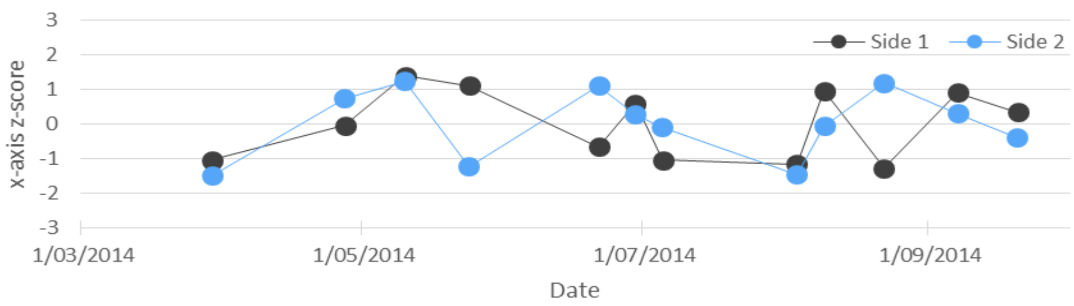


Figure 4-9 Graphs of the longitudinal within-section z-scores for subject 1 in the z-axis (top), y-axis (middle), and x-axis (bottom).

Table 4.23 Longitudinal between-section analysis for subject 1.

	z axis CMD		y axis CMD		x axis CMD	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.837	0.750	0.546	0.308	0.671	0.396
2	0.841	0.895	0.271	0.776	0.730	0.771
4	0.869	0.912	0.330	0.832	0.787	0.778
5	0.915	0.833	0.619	0.355	0.766	0.502
8	0.840	0.828	0.215	0.729	0.734	0.635
10	0.876	0.861	0.447	0.720	0.743	0.693
11	0.804	0.837	0.225	0.571	0.585	0.647
12	0.879	0.883	0.597	0.335	0.641	0.742
13	0.884	0.906	0.455	0.846	0.765	0.709
14	0.849	0.864	0.554	0.483	0.652	0.765
15	0.880	0.889	0.586	0.356	0.727	0.721
17	0.890	0.881	0.521	0.594	0.720	0.710

*Table 4.24 Between-section z-scores for subject 1. Significant results at a confidence level of 99% are marked **, significant results at a confidence level of 95% are marked *.*

	z-axis		y-axis		x-axis	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	-0.87	-2.48**	0.66	-1.31	-0.65	-2.39*
2	-0.75	0.74	-1.18	0.98	0.33	0.85
4	0.19	1.11	-0.78	1.26	1.28	0.91
5	1.7*	-0.63	1.15	-1.08	0.92	-1.48
8	-0.79	-0.76	-1.55	0.75	0.40	-0.32
10	0.41	-0.01	0.00	0.71	0.55	0.18
11	-1.99*	-0.55	-1.49	-0.02	-2.08*	-0.22
12	0.50	0.47	1.00	-1.18	-1.15	0.60
13	0.66	0.99	0.05	1.32	0.92	0.32
14	-0.49	0.05	0.72	-0.45	-0.97	0.80
15	0.55	0.62	0.93	-1.07	0.28	0.42
17	0.87	0.43	0.49	0.09	0.16	0.33

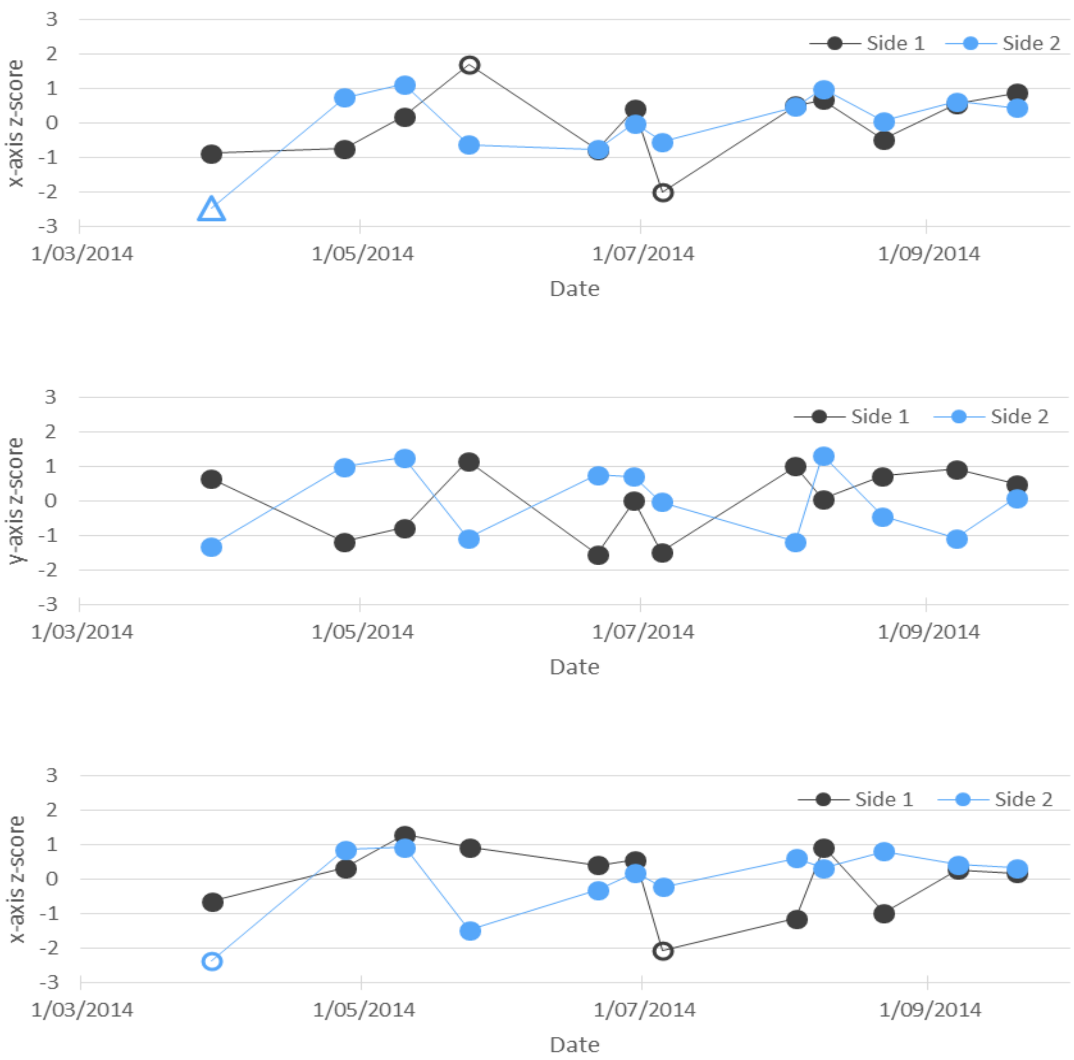


Figure 4-10 Graphs of the longitudinal between-section z-scores for subject 1 in the z-axis (top), y-axis (middle), and x-axis (bottom). Significant values at a confidence level of 99% are represented with a hollow triangle, significance at a confidence level of 95% is marked with a hollow circle.

4.5.4 **Discussion**

Examination of the number of sections available per game reveals one game (game 14) where there were only five valid SLHS sections identified on side 1 and eight valid SLHS sections identified on side 2. This is important as it was identified in the previous chapter that if fewer than six SLHS sections were available for analysis then the between-section analysis can be inflated. However, there does not appear to be any sudden increase in CMD in the between-section CMD results, and there are no significant results in any between-section condition for that game. Also, as it was identified in the previous chapter that within-section CMD is not affected by a small number of SLHS sections available, it is worthwhile noting that there were not any significant results in the within-section condition as well. Although the absence of significant results in both the within-section and between-section analyses does not necessarily mean that a greater number of sections available for a between-section analysis would not have produced a significant result in the between-section condition, the agreement between both analysis conditions would indicate that it is more likely that the small number of sections did not produce an unexpected result in the between-section analysis. This would suggest that the small number of sections available for analysis had a limited effect on the between-section CMD results.

There are no instances in the within-section results that are significantly different from the season average at a confidence level of 95%, indicating that this subject did not have any extreme variations away from the season average result in individual games. In isolation, these results are not particularly informative as it is unknown whether this subject should have had events that the analysis tool identified during the season (in which case the analysis tool is of little benefit) or whether the subject maintained a relatively constant physical condition during the season (which would indicate that the analysis tool is providing useful information). Both of these possibilities will be examined further in Chapter 5 where results generated by the analysis tool will be examined in conjunction with instances of missed and modified trainings and games during the season.

Although not significant in terms of difference from the season average, there are some results that are worthwhile investigating as they are quite low as far as the raw CMD value is concerned (indicating a high amount of variability in the waveforms). The result for side 1 in the y-axis in game 2 (0.245) indicates a very high amount of waveform variability and although it is not significantly different from the season average, it would be worth investigating to determine the cause of this variability.

The between-section results have some significant events, including events that are significant at a confidence level of 99%. Game 1 had two significant results, side 2 was significant to 99% in the z-axis (z-score of -2.48) and to 95% in the x axis (z-score of -2.39). Game 5 had a significant result to 95% (side 1 in the z-axis had a z-score of 1.7) and game 11 had a further two significant events to 95% (side 1 in the z-axis had a z-score of -1.99 and side 1 in the x-axis had a z-score of -2.08). It is interesting to note that there are significant results that are positive and negative z-scores. Though the implications of these events cannot be determined without more information on the effect they had on modifications to the normal game and training activity (which will be examined in Chapter 5, where information on missed and modified training and game activity is investigated in combination with the z-scores), they clearly indicate a need for a follow up investigation. In a practical sense, a significant result could indicate the need for follow up investigation by medical and scientific staff within a professional club (through medical examination, video analysis or other diagnostic tool) to determine whether this significant event could provide forewarning of an injury or other event that could lead to reduced athletic performance.

The lack of significant results in the within-section analysis but some significant results in the between-section analysis is of particular interest in the longitudinal analysis of subject 1. The difference between the method used to calculate these two variables would suggest that there are some games where this subject varies his step waveform over the course of the game, but in the individual sections within the game there is a non-significant amount of waveform variability. In other words there was possibly an event, perhaps injury related, perhaps fatigue related, that has caused a change in the stride waveform at some stage in the game, but within the individual sections identified throughout the game there is no change to the normal amount of waveform variability.

4.5.5 Conclusion

The subject whose season averages best approximated the group average across a range of criteria was identified as subject 1. A longitudinal analysis of his within-section and between-section CMD results was conducted. A number of potentially important events were identified through evaluating z-scores with respect to the confidence limits identified in section 4.4.

Results from this section demonstrate that the practical use of the results produced by the analysis tool will be best achieved by combining analysis of raw scores and z-scores to identify potentially important events. How potentially significant events highlighted through these analysis relate to the athlete’s physical condition will be investigated further in Chapter 5.

4.6 Part 3 – Longitudinal analysis of the subject with the fewest amount of SLHS sections

Previous sections have identified that the analysis tool can identify incidents within a season that require follow up investigation to determine whether those incidents indicate a heightened risk of an adverse event (such as a modification to training or game activity due to injury). However, the performance of the analysis tool for the subject with the least amount of SLHS running will influence its usefulness in a practical setting. If the analysis tool is unsuitable for a proportion of subjects who do not achieve a certain amount of SLHS running due to physical limitations or gameplay considerations then its application in a practical setting will be limited. This section will analyse the results of the subject with the fewest number of SLHS incidents identified to determine whether potentially critical incidents can be detected.

4.6.1 Aims

- Describe the number of SLHS incidents as well as the within-section and between-section CMD results across the course of the season for the subject with the lowest season average for SLHS incidents per game
- Determine whether potentially critical incidents can be effectively identified given the low number of SLHS incidents per game

4.6.2 Methods

4.6.2.1 *Subject*

One participant, subject 15, was used for this analysis. This subject was identified as having the lowest season average for number of SLHS incidents identified per game (Table 4.1). They also had the worst average ranking in absolute difference from group mean in categories used to determine the overall ranking by subject (Table 4-19) so based on the current data they represent the worst case scenario.

4.6.2.2 *Data preparation and analysis*

Data were prepared and processed in accordance with the procedures outlined in the general methods, section 4.3. The same procedures as for the previous section (outlined in 4.5.2.3) were used to analyse the data. In addition, correlations were calculated between within-section and between-section CMD results within side and axis via a bootstrapping procedure. Each underlying pair of data sets was resampled (with replacement) 1000 times and correlations were calculated on each resampled pair. The average of all correlations was calculated as the final correlation for each pair of underlying data sets.

4.6.3 Results

A summary of the games available for analysis for subject 15 is shown in Table 4-25. Note there are only five of the 14 games where at least five SLHS sections are identified on both sides. Longitudinal within-section CMD results are shown in Table 4-26, and between-section CMD results are shown in 4-27. These results are also displayed as z-scores in Table 4-28 for within-section analysis and Table 4-29 for between-section analysis. It is worth noting the occasional value in the between-section results that is extremely low (such as game 5, x-axis, side 2). The correlation between results in the corresponding side and axis between within-section and between-section CMD results (after bootstrapping) is shown in Table 4.30. Large differences between individual subject results and group averages (in particular in the x-axis and y-axis on side 2) are particularly noteworthy.

Table 4.25 Game by game summary of total strides, valid steps identified and valid SLHS sections identified for subject 15

Game	Total Strides	Valid Steps		Valid Sections	
		Side 1	Side 2	Side 1	Side 2
1	39	14	15	3	2
2	127	52	23	7	3
4	191	83	45	12	9
5	62	6	19	1	3
6	176	82	82	10	9
7	68	37	28	6	5
8	95	22	36	3	7
10	82	20	34	3	5
12	122	23	35	3	8
13	121	26	26	6	6
14	155	59	51	8	8
15	86	16	31	3	5
16	112	15	24	2	2
17	55	16	18	4	4
Mean	107	34	33	5	5

Table 4.26 Longitudinal within-section CMD analysis for subject 15.

	z axis CMD		y axis CMD		x axis CMD	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.755	0.732	0.517	0.228	0.729	0.737
2	0.789	0.679	0.472	0.479	0.696	0.662
4	0.740	0.742	0.453	0.362	0.652	0.691
5	0.664	0.676	0.407	0.380	0.604	0.616
8	0.776	0.783	0.546	0.479	0.734	0.716
10	0.703	0.781	0.440	0.504	0.640	0.750
11	0.597	0.634	0.296	0.361	0.518	0.553
12	0.683	0.639	0.284	0.288	0.596	0.531
13	0.675	0.740	0.342	0.387	0.649	0.556
14	0.711	0.735	0.392	0.459	0.635	0.684
15	0.721	0.758	0.387	0.452	0.571	0.684
17	0.642	0.716	0.304	0.323	0.507	0.633

Table 4.27 Longitudinal between-section CMD analysis for subject 15.

	z axis CMD		y axis CMD		x axis CMD	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.749	0.773	0.421	0.552	0.710	0.826
2	0.800	0.709	0.367	0.529	0.665	0.754
4	0.707	0.751	0.381	0.388	0.576	0.701
5	0.580	0.590	0.322	0.226	0.493	0.080
8	0.780	0.835	0.543	0.568	0.726	0.794
10	0.813	0.778	0.636	0.506	0.788	0.745
11	0.564	0.700	0.151	0.398	0.458	0.666
12	0.571	0.793	0.309	0.214	0.449	0.734
13	0.818	0.760	0.422	0.439	0.736	0.605
14	0.562	0.666	0.038	0.349	0.535	0.592
15	0.813	0.811	0.526	0.600	0.759	0.763
17	0.628	0.812	0.262	0.328	0.485	0.759

*Table 4.28 Within-section z-scores by game for subject 15. Significant results at a confidence level of 95% are marked **

	z-axis		y-axis		x-axis	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.69	0.17	1.08	-1.95*	1.09	1.06
2	1.27	-0.86	0.59	0.90	0.67	0.14
4	0.43	0.38	0.39	-0.42	0.11	0.50
5	-0.85	-0.91	-0.10	-0.23	-0.51	-0.44
8	1.05	1.19	1.40	0.90	1.16	0.81
10	-0.18	1.14	0.25	1.18	-0.04	1.22
11	-2.00	-1.74	-1.31	-0.43	-1.60	-1.22
12	-0.54	-1.64	-1.44	-1.26	-0.60	-1.49
13	-0.67	0.33	-0.81	-0.14	0.07	-1.18
14	-0.06	0.24	-0.27	0.68	-0.11	0.40
15	0.12	0.69	-0.33	0.60	-0.93	0.41
17	-1.23	-0.13	-1.23	-0.87	-1.74	-0.22

*Table 4.29 Between-section z-scores by game for subject 15. Significant results at a confidence level of 99% are marked **, significant results at a confidence level of 95% are marked **

	z-axis		y-axis		x-axis	
Game	Side 1	Side 2	Side 1	Side 2	Side 1	Side 2
1	0.37	0.12	0.27	1.06	0.65	0.83
2	0.82	-0.70	-0.01	0.87	0.29	0.50
4	-0.01	-0.16	0.06	-0.31	-0.41	0.25
5	-1.14	-2.24*	-0.26	-1.66	-1.07	-2.64**
8	0.65	0.92	0.93	1.19	0.78	0.68
10	0.93	0.19	1.44	0.67	1.27	0.46
11	-1.28	-0.82	-1.18	-0.23	-1.35	0.09
12	-1.22	0.38	-0.33	-1.76	-1.42	0.41
13	0.99	-0.05	0.28	0.12	0.86	-0.20
14	-1.30	-1.25	-1.79	-0.63	-0.74	-0.26
15	0.94	0.61	0.84	1.46	1.04	0.54
17	-0.72	0.63	-0.58	-0.81	-1.14	0.52

Table 4.30 Correlations between within-section and between-section results after the application of bootstrapping procedures

	Side 1			Side 2		
	z-axis	y-axis	x-axis	z-axis	y-axis	x-axis
subject 15	0.63	0.57	0.59	0.41	0.40	0.00
Group Average	0.57	0.49	0.62	0.47	0.62	0.55

4.6.4 **Discussion**

Results presented in the previous chapter (section 4.6) demonstrated that a low number of SLHS sections and steps identified makes the application of the between-section CMD problematic. Although most subjects have enough sections to alleviate these concerns, subject 15 was identified as having an average number of SLHS sections that would likely mean there were games during the season where the between-section CMD analysis would be inappropriate.

In examining the number of SLHS sections identified per game (Table 4.24), this is definitely the case. One game has only one section identified, which makes a between-section analysis impossible. There is still a between-section CMD reported for this game, although this will simply represent the waveform variability of the three most representative waveforms from the single section available. There are other games where only two sections are identified, and although this does permit a between-section analysis this is well below the threshold identified in section 4.6 for confidence that the between-section result is not artificially inflated due to the number of sections identified. With only two sections available for analysis and consequently fewer waveforms to compare (especially as there is pre-selection to identify the three most representative waveforms from each section) the between-section CMD will be higher than if more waveforms were available for analysis with the same underlying physical qualities (as was demonstrated in section 4.6).

A further confounding factor with few SLHS sections identified is that with no control for when those sections occurred during the game, the validity of the measure is questionable. If only two sections were available for analysis, those sections could have occurred in close succession, limiting the influence of factors such as fatigue which would affect the between-section result in games where the sections are distributed throughout the game. Consequently, it would be prudent to discard these results from a longitudinal analysis purely on theoretical grounds. Expanding this argument, standardising the number of sections drawn from each section of the game could enhance the validity of the between-section measure, ensuring that between-section measures are generated from similar data each game. This could provide confidence that a longitudinal analysis was more indicative of the underlying physical condition of the athlete. Although this was not possible with the current data as information on periods during the game was only available for a limited number of games, adding a control for when SLHS sections occurred during a game would be a worthwhile follow up investigation. A confounding factor that would need to be taken into account in any follow up investigation would be not only the period of play that the SLHS section occurred in but also how long the player had spent on the field before the section occurred. In Australian Rules Football, players are regularly interchanged so they often have periods of rest during each quarter of the game. If the position of SLHS sections during the game are controlled for, then time on the field after a period of rest should also be taken into account (perhaps limiting the SLHS sections that are included in between-section analyses to those that occurred within a certain time after returning to the field).

The correlations presented in Table 4-29 are important because it has been shown in the previous chapter (section 4.6) that the within-section CMD analysis is not affected by the number of SLHS sections identified, and consequently if the between-section results for this subject are not confounded by the small number of SLHS sections identified then there should be a consistent difference in correlation to the group average across all conditions. The correlations between within-section and between-section results shows that subject 15 is more highly correlated than the group average in two of the six categories (z-axis and y-axis on side 1), only slightly below the group average in two categories (x-axis on side 1 and z-axis on side 2), and much lower in two categories (y-axis and x-axis on side 2). Of the two axes that are less correlated in subject 15 than the group average, it is the x-axis on side 2 that is most interesting. The group average for the x-axis on side 2 is 0.55, while subject 15 has a correlation of 0.00. When looking back to the raw results, it is this axis and side that had one result that was extremely low (between-section CMD for the x-axis on side 2 was 0.08 in game 5). However, the bootstrapping procedure applied to the data should have corrected for a single outlier. In addition, when looking across the between-section z-scores there are more significantly low results on the same side (the z-axis is significant to 0.99 and the y-axis is significant to 0.95). These results are not significant in the corresponding within-section results, which could be an indication that the between-section results have been affected across all conditions either by the low number of sections available for analysis (3 sections for that side and game were available for analysis) or by a real change in stride characteristics between the sections identified. The difference in correlations between subject 15 and the group average for all axes on side 2 would indicate that the small number of sections identified have had an effect on the between-section results, and consequently their use in a longitudinal analysis would not be recommended.

4.6.5 Conclusion

The number of SLHS sections identified per game for subject 15 are often below the threshold identified previously for the number of SLHS sections required for confidence in the between-section CMD analysis. The combination of theoretical considerations and the correlation of results from within-section to between-section analyses on side 2 suggests that the low number of SLHS sections identified would preclude the between-section analysis for that game being used in a longitudinal analysis. These principles can be extrapolated to the entire subject group.

The practical implications of these results are that the number of steps and sections identified from a training session or game must be taken into consideration, in particular when examining the between-section CMD results.

4.7 General Discussion

Four methods of analysing the longitudinal data have been presented in this chapter. The first method identified in section 4.4 is differences in the season long averages between sides within an axis and analysis condition. There were two subjects where significant differences between sides were found in all conditions at the 99%

confidence level (subjects 2 and 10) as well as one additional subject (subject 19) who recorded significant differences in ten of the twelve categories significant at 99% and the remaining two categories were significant at 95%). For one of these subjects (subject 2) the 99% confidence intervals did not overlap in any condition. A strict interpretation of these results would be to say that for these subjects there is more waveform variability on one side than the other. A more speculative approach would be to suggest there could be some imbalance between sides, possibly indicating a risk of injury or even repercussions from a previous injury. The possibility of a link to an injury incurred during the season being analysed will be examined in chapter 5 through matching information on missed or modified training and game activity during the season.

Significant differences between sides in the y-axis were found in 19 of the 22 subjects which, unless virtually the whole squad was troubled by injuries that could manifest in high y-axis waveform variability (such as leg adductor injuries), would indicate this measure is not an effective discriminator of an injured (or at high risk of injury) population. However, the magnitude of some average y-axis CMD results would indicate a very high level of waveform variability. This is the second method of analysis identified, and further examination of this method through linking high levels of waveform variability (both chronic and acute) and missed and modified training (including the reasons for any alterations to a normal training program) is required to assess its validity and use in a practical setting.

In the two methods of analysis described above, there was no correction to the level of significance (such as a Bonferroni or Holmes correction) for the number of statistical tests conducted. This was done to ensure an inclusive rather than exclusive criteria was used to highlight the outputs from the analysis tool that showed promise as metrics that could be worthy of follow up research in applied settings. It was felt that the use of a correction, particularly a Bonferroni correction as demonstrated by Perneger (1998), would be too harsh a treatment on the data and lead to the erroneous dismissal of analysis conditions as not worthy of follow up research.

Converting raw scores to z-scores is the third method of analysis identified. This method places results into the context of the individual subject, analysis condition and axis, allowing measures to be effectively compared between subjects and conditions while limiting the exposure of the analysis to errors stemming from the individual nature (in terms of both subject and analysis condition) of the CMD analysis that have previously been identified as limitations of using CMD as a statistical tool (McGinley et al., 2009; Røislien et al., 2012). Using z-scores also allows results to be collated between subjects rather than assessed individually, and it is these collated results that will be examined further in Chapter five.

The fourth method of analysis identified in section 4.5 was identifying significant z-scores over the course of a season. The practical application of this method could be problematic as although taking the normal game to game variation of results into account to establish a level of significance for any individual value will aid in highlighting values that are clearly different from the long term average, there is no guarantee that the point of statistical significance at a particular confidence level coincides with the point where clinical significance is achieved (and therefore requiring a practical change in behaviour to avoid an injury or other adverse event). Indeed, there is also no guarantee that there is an actual point of clinical significance as opposed to a continuum of risk of an adverse event that is amplified as distance from the long term average increases. Perhaps a more practical application of this method would be to allow the applied scientist implementing the analysis tool to view results that take into account the game to game variation while not necessarily imposing a strict criteria for significance. The statistical elements of this method will be investigated further in later chapters by linking incidents of significant z-scores to incidents of missed and modified training, however it is unlikely that there is enough data in the current set to determine any individualised level of clinical significance.

4.8 General Conclusions

Results generated by the analysis tool were analysed in the context of the season as a whole and as individual longitudinal analyses. Four methods of analysing the data were identified, and the link between results generated from the analysis methods identified and incidents of missed or modified training and game activity will be investigated in Chapter 5.

5 Exploration of use of the analysis tool in predicting injury

5.1 Introduction

The results from chapter four highlighted four methods of analysing the results generated by the analysis tool. This chapter will examine all four methods with respect to incidents during the season where subjects have modified their training or game activity. This will identify the potential of the analysis tool to provide practical information that can reduce the risk of injury and maximise training and competition performance.

5.2 General Aims

- Identify the influence of incidents of missed or modified training on results generated by the analysis tool

5.3 General Methods

5.3.1 Subjects

The participant cohort was the same as that used in Chapter 3 (section 3.3.1, page 15) with the exception of one participant who could not be contacted to provide consent for his data to be used in this study. Briefly repeating here for clarity, 22 professional AFL footballers with age range of 19 to 28 years old were used in these studies. No preselection of subjects for position played or physical capacity took place.

5.3.2 Data

5.3.2.1 *GPS and Accelerometer data*

Procedures for the collection of GPS and accelerometer data were the same as was outlined in Chapter 3 (section 3.3.3, page 16).

5.3.2.2 *Missed and modified training and game activity*

Data on missed and modified training or game activity were collected during the 2014 AFL season. Instances where a subject had missed a training session or game, had their activity modified from what was previously planned (but still took part in the activity) for a training session or game, and the reason for any missed or modified session were recorded. Descriptions of the reason for a modification to a session were detailed but not extensive. For instance, a soft tissue injury to the hamstrings would be described as “hamstrings”, but details such as the cause, severity, specific location and other similar specific descriptions of the injury were not recorded. Similarly, an injury to the ankle would be described as “ankle”, but no details were recorded on the type of strain, or even if it was a ligament strain or some other injury.

Data were collated for further analysis into the following five categories that described the reason for the modification to normal activity:

- Modifications due to “load”, meaning the subject’s training or game participation was altered because it was felt he was at a high risk of further injury because of the accumulated training and game activity.
- Modifications due to “groin”, meaning the subject’s training or game participation was altered because of soreness in an area roughly defined as the “groin”. This could include any injury that would manifest in soreness in the groin area.
- Modifications due to a leg soft tissue injury other than “groin”, meaning any injury described as “hamstrings”, “calf”, or any other description that would loosely refer to a muscle group in the leg.
- Modified solely due to a leg structural injury, meaning any injury described as “ankle”, “heel”, or any other description that would loosely refer to a joint or bone in the leg.
- Other modification, which includes any other reason for a modification such as “virus”, an injury to an area other than the leg, or a combination of reasons both prior and post the game being analysed that cannot be placed into a single category (such as a “groin” description in the week preceding the game and a “load” description in the week after the game).

This classification system, although developed for the use at a single professional AFL club, will share many similarities with similar classification systems used in other environments. For example Rogalski et al. (2013) investigated the relationship between training load and injury risk in an elite AFL population, and a similar classification method was described for the AFL club who provided the subjects for the study. Categories that will be consistent (or could be reasonably resolved from records that are generally kept) will be modifications due to “load”, “soft tissue” and “structural”. Modifications due to “groin” may differ slightly given this can often include both musculoskeletal strains and other injuries such as osteitis pubis that could be recorded separately or in combination. In this study, these injuries are combined within the “groin” condition which is in accordance with the report on injuries during the AFL season published by the league itself (Orchard, Seward, & Orchard, 2014). In addition, overall indicators of missed and modified training and game activity will be consistent between teams so the findings here are more widely generalised.

A further advantage of the general injury categories used within this study is that by using broad categories there is less dilution of the number of instances prescribed to each category. With more specific categorisation there is the potential that too few instances will be assigned to groups, decreasing the statistical power of the data.

These data were de-identified prior to being supplied by the Port Adelaide Football Club, with individual subject codes matched between GPS data and missed or modified training data.

5.3.2.3 *Axis definitions*

Axis definitions remain as per previous chapters, outlined in Chapter 3 (section 3.3.4, page 17)

5.3.3 Analysis Tool

The analysis tool used was the same as described in Chapter 3 and used in Chapter 4 (section 4.3.4, page 60). Repeating the key variables in the interests of clarity, the angle window for the straight line running component was set to ±0.05 rad and velocity window set from 4.17 m/s to 6.94 m/s.

5.4 Part 1 – Average z-scores with and without incidents of missed or modified training

The first method to be examined of analysing the results generated by the analysis tool with respect to instances of missed and modified training and game activity is comparing the average z-scores from games classified as “load”, “groin”, “structural”, “soft tissue” and “other” reasons for modifying normal activity to those games where no modification was present. This will determine whether there are responses in the z-scores that can be linked to a certain reason for a modification to the normal training program.

5.4.1 Aims

- Identify instances of missed and modified training and games from the 2014 AFL season in the week preceding and following games where GPS and accelerometer data is available for a subject
- Collate and classify instances of missed and modified training and games by reason for the modification to normal activity

- Compare if stride variability differed between classifications of modified activity and unmodified training
- Identify practical applications of these methods for reducing the incidence of injury and maximising athletic performance within a team sport environment

5.4.2 Methods

5.4.2.1 *Subjects*

All participants within the cohort described in section 5.3.1 (General Methods) were used for this study.

5.4.2.2 *Data collection*

GPS and accelerometer data were collected in accordance with the procedures outlined in General Methods, section 5.3.2.1. Missed and modified training information was collected and collated in accordance with the procedures outlined in General Methods, section 5.3.2.2.

5.4.2.3 *Data analysis via the analysis tool*

Data were analysed in accordance with the procedures outlined in General Methods, section 5.3.3

5.4.2.4 *Missed and Modified Training and Game activity*

For each game available for each subject, the missed and modified game information was examined and if there were any instances where training or game activity was modified in the week preceding or following the game then this was recorded, along with the reason given for the modification. Games that fell into the various missed and modified classifications were collated across the subject group, and average z-scores were calculated in the following categories:

- z-axis within - the mean of the z-axis within-section z-scores
- y-axis within - the mean of the y-axis within-section z-scores
- x-axis within - the mean of the x-axis within-section z-scores
- z-axis between - the mean of the z-axis between-section z-scores
- y-axis between - the mean of the y-axis between-section z-scores
- x-axis between - the mean of the x-axis between-section z-scores
- z-axis average - the mean of the z-axis between-section and within-section z-scores

- y-axis average - the mean of the y-axis between-section and within-section z-scores
- x-axis average - the mean of the x-axis between-section and within-section z-scores
- average of all – the mean of all axes between-section and within-section z-scores.

5.4.2.5 ***Determination of confidence intervals and p values***

Confidence intervals for the set of games with no modification to training in the week preceding or following each game were determined via an empirical bootstrapping procedure (Ball, 2006). This entailed (for each condition outlined in 5.4.2.4) performing 100000 resamples with replacement, calculating the mean of each sample and the difference of that to the mean of the original sample, sorting the results, then determining the 0.5% and 99.5% value for the 99% confidence interval (as well as determining the 2.5% and 97.5% value for the 95% confidence interval). This was done to create confidence intervals specific to the samples in each condition.

The confidence level where the average of a sub-set of data (such as games where any load modification was present in the week preceding or following the date of the game) is different from the average of the no modification set of data was determined via a separate empirical bootstrapping procedure. The p-values were determined via a bootstrap permutation procedure, using the studentized t-statistic (Efron & Tibshirani, 1994, pp. 220-223). This method determines the probability that data set A is the same as data set B. In the current study, 100000 replications (with replacement) were generated to determine the probability that two data sets are different (for instance, CMD values for where there was no training modification compared to CMD values for where there was a training modification prior to the game where the CMD was determined).

5.4.3 **Results**

There were 255 total player games analysed, and within those games there were 107 instances where modification to normal training activity occurred. These instances where modifications took place are broken down by category in Table 5-1. Modifications are separated into any modifications, a modification in the preceding week, modifications in the following week, and modifications in both the preceding and following week. These data (in the “any modification” classification) are also shown by subject in Table 5-2.

Table 5.1 Instances of modifications to the normal training activity for games where GPS and accelerometer data is available, split into classifications for the cause of the modification.

Categories	Instances	Modification Prior	Modification Post	Both Prior and Post
Total Games	255	-	-	-
Any Modification	107	43	42	22
Load Modification	24	8	14	2
Groin Modification	28	8	8	12
Leg Soft Tissue Modification	4	3	1	-
Leg Structural Modificaiton	41	18	18	5
Other or mixed reason	10	6	1	3^

^ There was one instance of a structural cause prior and a load cause post, one instance of a load cause prior and a soft tissue cause post, and one instance of a groin cause prior and a soft tissue post

Table 5.2 Incidents of games with GPS and accelerometer data available where a modification was present by subject.

Subject	Games	Modification in the preceding week	Modification in the following week	Modified both preceding and following	No Modifications
1	12	6	1	1	4
2	14	3	4	0	7
3	14	2	4	0	8
4	9	3	3	1	2
5	6	1	1	0	4
6	11	3	2	2	4
7	15	3	3	0	9
8	13	1	4	1	7
9	15	4	2	0	9
10	10	2	1	7	0
11	15	0	1	0	14
12	15	1	2	1	11
13	15	1	2	2	10
14	14	2	2	0	10
15	11	3	0	1	7
16	8	1	1	3	3
17	6	1	0	0	5
18	13	0	2	1	10
19	11	3	1	0	7
20	14	4	3	2	5
21	14	0	2	0	12
Total	255	44	41	22	148

Mean z-scores as well as values corresponding to 99% and 95% confidence intervals for the set of “unmodified” games are reported in Table 5-3. Mean z-scores for instances where any modifications, modifications due to “load”, modifications due to “groin”, modifications due to “leg structural”, modifications due to “leg soft tissue” and modifications due to “other” are shown in Tables 5-4, 5-5, 5-6, 5-7, 5-8 and 5-9 respectively. Estimations for p values (determined via the bootstrap permutation procedure) in each condition and classification (compared to the “no modification” set) are also shown in these tables. Graphical representations of the “any modification”, “load”, “groin” and “leg structural” results can be found in Figures 5-1 to 5-4 (the “both prior and post” condition has been removed from Figure 5-2 because there were only two files included in this classification). No p values were calculated for the “leg soft tissue” and “other” classifications (Tables 5-8 and 5-9) due to the small number of instances in each category.

Table 5.3 Mean and confidence intervals at the 99% and 95% confidence level for z-scores of games where no modification in training occurred.

		99%		95%	
	Mean	Low CI	High CI	Low CI	High CI
z-axis within	0.036212	-0.134	0.203	-0.091	0.155
y-axis within	0.010906	-0.126	0.159	-0.101	0.117
x-axis within	0.033343	-0.122	0.192	-0.092	0.16
z-axis between	-0.0152	-0.186	0.154	-0.145	0.103
y-axis between	-0.02371	-0.173	0.111	-0.136	0.085
x-axis between	-0.02587	-0.185	0.144	-0.145	0.103
z-axis average	0.010508	-0.162	0.174	-0.113	0.13
y-axis average	-0.0064	-0.131	0.108	-0.096	0.089
x-axis average	0.003734	-0.138	0.156	-0.104	0.112
average of all	0.002613	-0.109	0.129	-0.085	0.101

Table 5.4 Mean z-scores for instances where modifications are present.

	Any Modification		Modification Prior		Modification Post		Modification Both Prior and Post	
	Mean	*p*	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	-0.067	0.19	0.136	0.23	-0.147	0.11	-0.276	0.04
y-axis within	-0.017	0.38	0.024	0.45	0.008	0.49	-0.187	0.09
x-axis within	-0.006	0.36	-0.023	0.33	-0.025	0.35	-0.119	0.20
z-axis between	0.034	0.32	0.082	0.23	0.054	0.31	-0.179	0.17
y-axis between	0.003	0.38	0.014	0.37	0.049	0.27	-0.008	0.46
x-axis between	0.096	0.13	0.009	0.40	0.185	0.05	-0.139	0.26
z-axis average	-0.016	0.40	0.109	0.21	-0.046	0.33	-0.228	0.07
y-axis average	-0.007	0.50	0.019	0.40	0.029	0.36	-0.098	0.23
x-axis average	0.045	0.33	-0.007	0.46	0.080	0.27	-0.129	0.20
average of all	0.007	0.48	0.040	0.35	0.021	0.43	-0.151	0.12

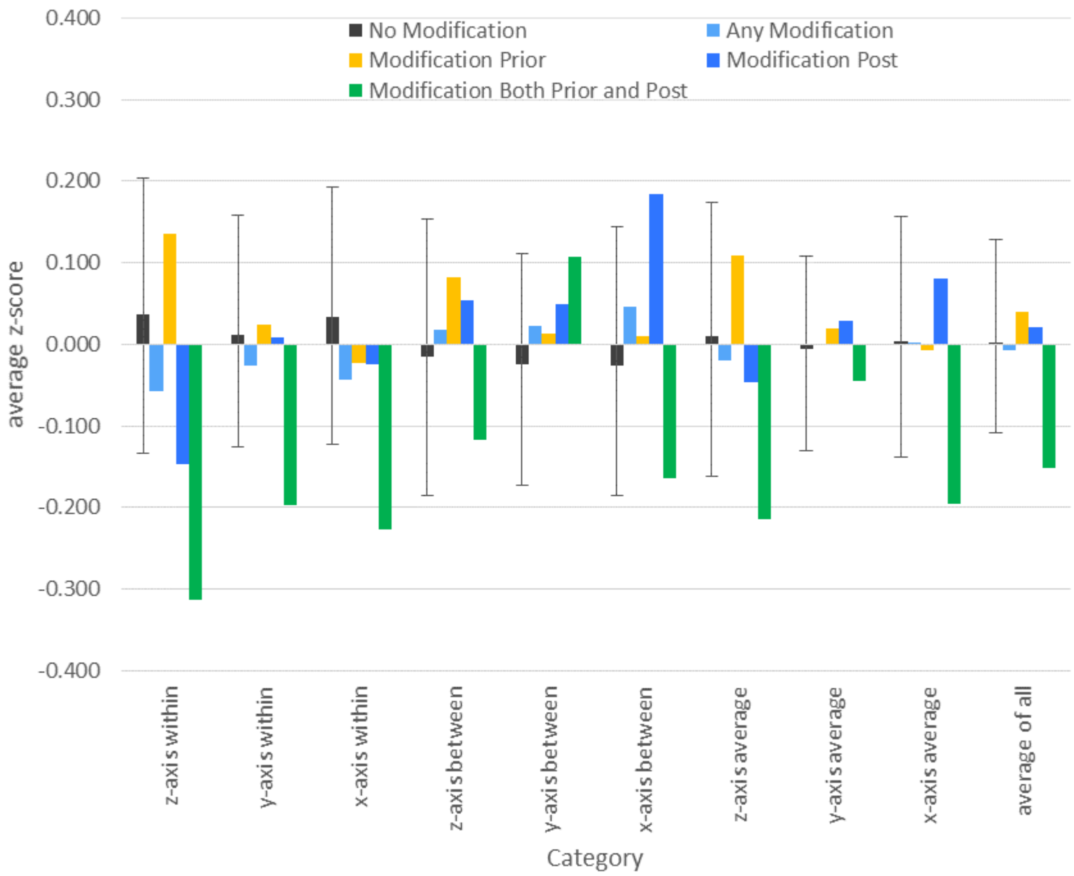


Figure 5-1 Graphical representation of mean z-scores where a modification is present. Error bars on the no modification data represent the 99% confidence interval.

Table 5.5 Mean z-scores for instances where modifications classified as "load" are present.

	Any Load Modification		Load Prior		Load Post		Load Both Prior and Post	
	Mean	*p*	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	-0.331	0.02	-0.298	0.13	-0.320	0.06	-0.807	-
y-axis within	-0.167	0.11	-0.255	0.14	-0.055	0.36	-0.597	-
x-axis within	-0.090	0.23	-0.216	0.18	-0.104	0.27	-0.329	-
z-axis between	-0.095	0.31	-0.125	0.34	-0.061	0.41	-0.110	-
y-axis between	-0.108	0.27	-0.184	0.26	-0.038	0.47	-0.003	-
x-axis between	0.021	0.38	0.006	0.47	0.018	0.42	-0.135	-
z-axis average	-0.213	0.08	-0.212	0.20	-0.190	0.16	-0.459	-
y-axis average	-0.138	0.14	-0.219	0.15	-0.046	0.40	-0.300	-
x-axis average	-0.034	0.39	-0.105	0.33	-0.043	0.40	-0.232	-
average of all	-0.128	0.15	-0.179	0.20	-0.093	0.28	-0.330	-

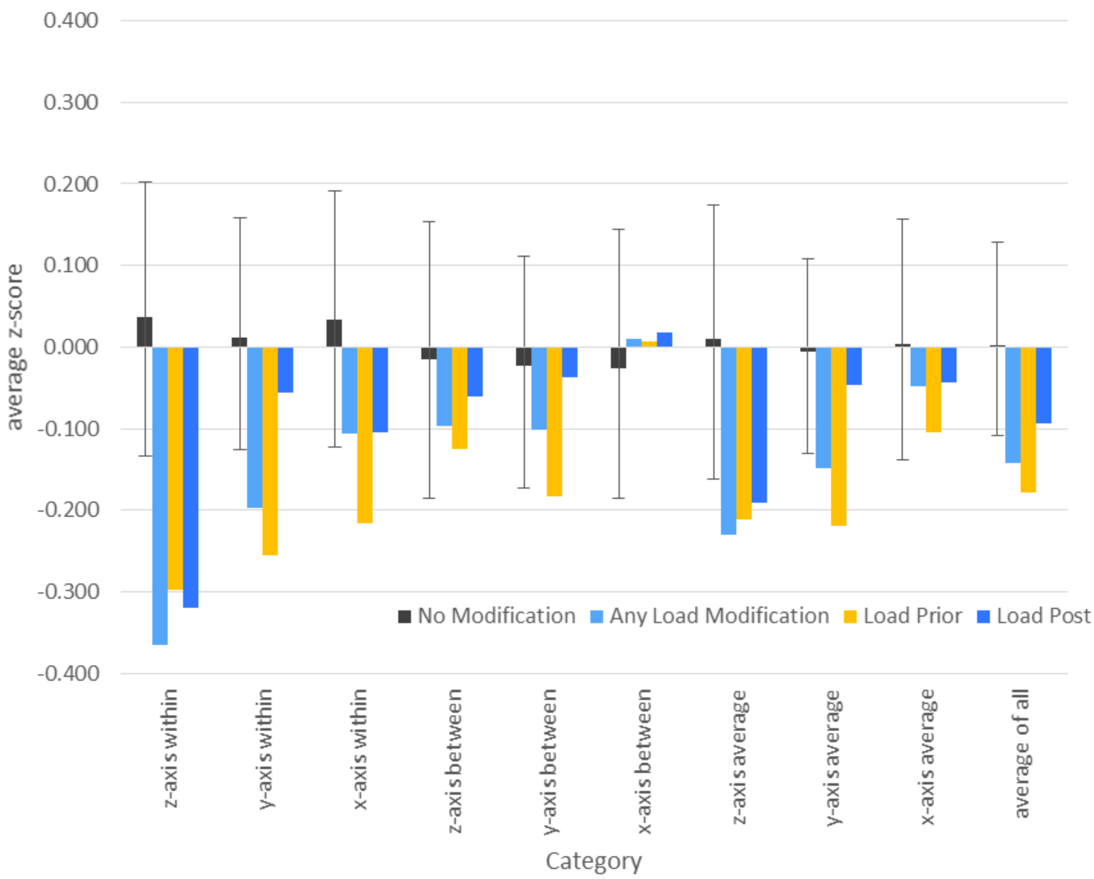


Figure 5-2 Graphical representation of mean z-scores where a modification classified as "load" is present. Error bars on the no modification data represent the 99% confidence interval.

Table 5.6 Mean z-scores for instances where modifications classified as “groin” are present

	Any Groin Modification		Groin Prior		Groin Post		Groin Both Prior and Post	
	Mean	*p*	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	0.014	0.45	0.273	0.21	0.031	0.49	-0.169	0.19
y-axis within	0.027	0.45	0.183	0.23	0.175	0.25	-0.171	0.18
x-axis within	0.041	0.48	0.150	0.34	0.311	0.16	-0.222	0.14
z-axis between	0.104	0.22	0.367	0.08	0.013	0.47	0.107	0.30
y-axis between	-0.020	0.49	-0.027	0.49	0.002	0.46	0.086	0.30
x-axis between	0.097	0.22	0.141	0.28	0.249	0.15	0.012	0.45
z-axis average	0.059	0.36	0.320	0.11	0.022	0.49	-0.031	0.42
y-axis average	0.004	0.46	0.078	0.34	0.089	0.32	-0.043	0.41
x-axis average	0.069	0.32	0.145	0.29	0.280	0.13	-0.105	0.30
average of all	0.044	0.36	0.181	0.20	0.130	0.28	-0.060	0.35

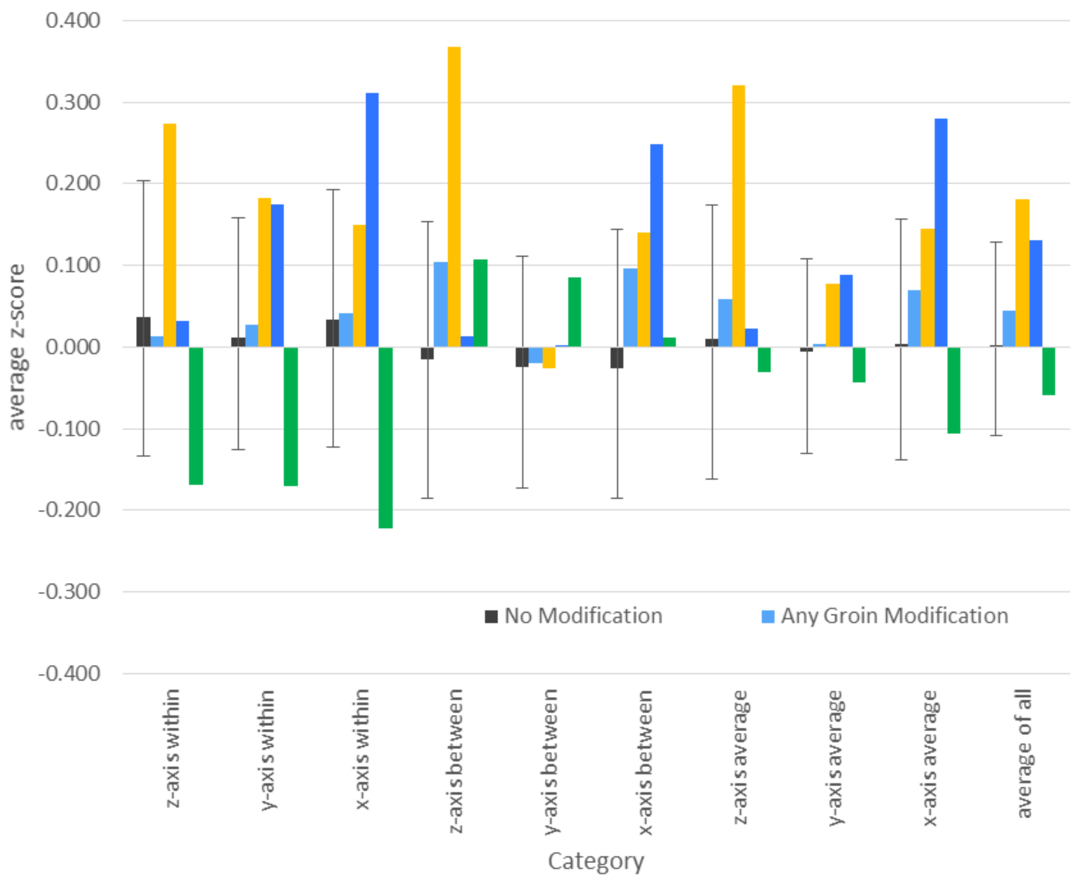


Figure 5-3 Graphical representation of mean z-scores where a modification classified as “groin” is present. Error bars on the no modification data represent the 99% confidence interval.

Table 5.7 Mean z-scores for instances where modifications classified as "leg structural" are present.

	Any Structural Modification		Structural Prior		Structural Post		Structural Both Prior and Post	
	Mean	*p*	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	0.054	0.45	0.127	0.32	0.119	0.34	-0.459	0.09
y-axis within	0.063	0.32	0.057	0.39	0.116	0.27	-0.102	0.36
x-axis within	0.031	0.50	0.069	0.42	0.054	0.46	-0.196	0.25
z-axis between	0.027	0.38	-0.043	0.44	0.291	0.06	-0.658	0.04
y-axis between	0.141	0.07	0.013	0.41	0.258	0.04	0.205	0.23
x-axis between	0.085	0.21	-0.005	0.47	0.371	0.01	-0.599	0.06
z-axis average	0.040	0.41	0.042	0.43	0.205	0.14	-0.559	0.05
y-axis average	0.102	0.13	0.035	0.38	0.187	0.08	0.051	0.41
x-axis average	0.058	0.33	0.032	0.43	0.213	0.11	-0.398	0.11
average of all	0.067	0.26	0.036	0.41	0.202	0.09	-0.302	0.13

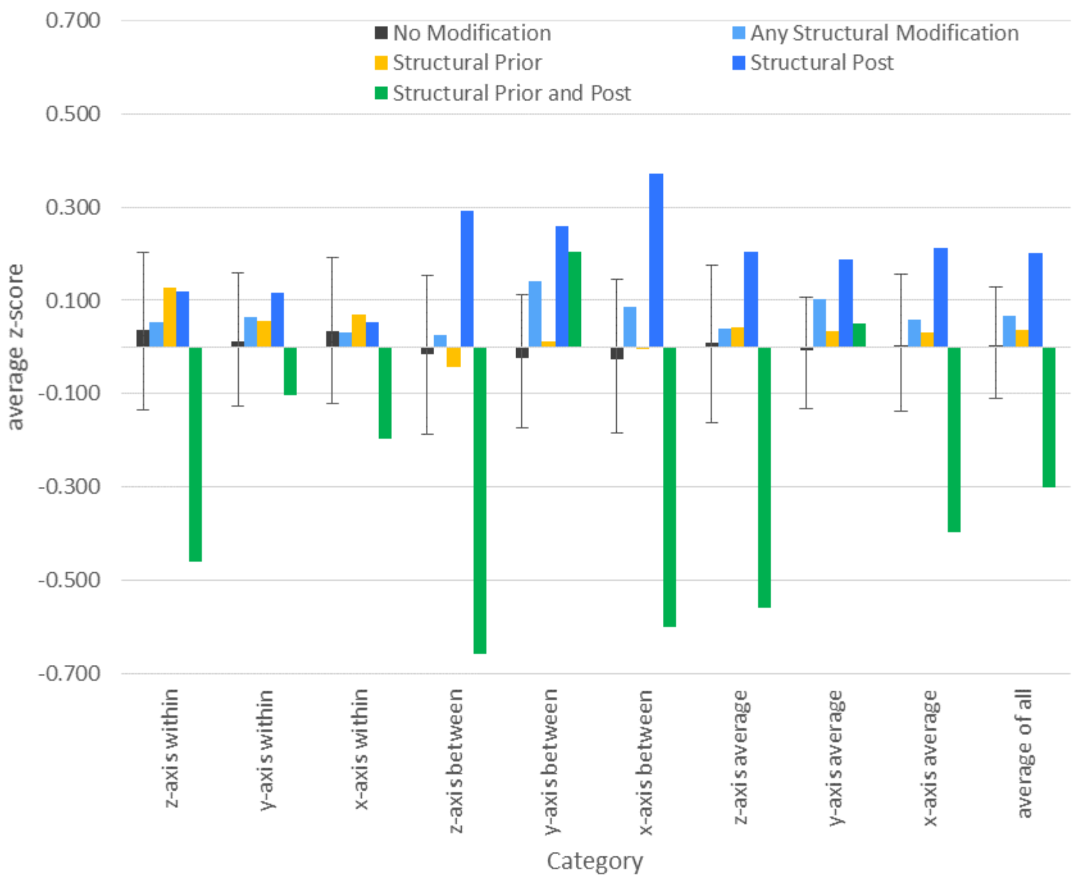


Figure 5-4 Graphical representation of average z-scores where a modification classified as "leg structural" is present. Error bars on the no modification data represent the 99% confidence interval. Note, the scale on the y-axis is different to Figures 5-1, 5-2 and 5-3 to accommodate results in the Structural Prior and Post condition.

Table 5.8 Mean z-scores for instances where modifications classified as "leg soft tissue" are present

	Any Soft Tissue Modification		Soft Tissue Prior		Soft Tissue Post	
	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	-0.253	-	0.026	-	-1.091	-
y-axis within	-0.258	-	0.106	-	-1.351	-
x-axis within	-0.408	-	-0.196	-	-1.044	-
z-axis between	-0.005	-	0.134	-	-0.420	-
y-axis between	0.003	-	0.352	-	-1.043	-
x-axis between	-0.077	-	0.066	-	-0.507	-
z-axis average	-0.129	-	0.080	-	-0.756	-
y-axis average	-0.128	-	0.229	-	-1.197	-
x-axis average	-0.243	-	-0.065	-	-0.776	-
average of all	-0.166	-	0.081	-	-0.910	-

Table 5.9 Average z-scores for instances where modifications classified as "other reason" are present.

	Any Other Modification		Other Prior		Other Post		Mixed Reason	
	Mean	*p*	Mean	*p*	Mean	*p*	Mean	*p*
z-axis within	0.040	0.50	0.026	-	-1.801	-	-0.047	-
y-axis within	-0.177	0.20	0.106	-	-1.632	-	-0.123	-
x-axis within	-0.074	0.33	-0.196	-	-1.766	-	0.563	-
z-axis between	-0.138	0.31	0.134	-	-0.363	-	-0.569	-
y-axis between	-0.287	0.12	0.352	-	-0.370	-	-0.739	-
x-axis between	-0.127	0.32	0.066	-	-0.391	-	0.026	-
z-axis average	-0.049	0.39	0.080	-	-1.082	-	-0.308	-
y-axis average	-0.232	0.11	0.229	-	-1.001	-	-0.431	-
x-axis average	-0.100	0.32	-0.065	-	-1.078	-	0.294	-
average of all	-0.127	0.24	0.081	-	-1.054	-	-0.148	-

5.4.4 **Discussion**

Using z-scores to investigate the influence of classifications of modified training on stride variability as measured by the analysis tool produced a number of interesting results. Modifications due to "load" showed generally increased stride variability (lower z-scores), as did "soft tissue" modifications following a game and most injury categories when modifications were present both preceding and following a game. Generally decreased stride variability (higher z-scores) were characteristics of "leg structural" classifications (particularly in between-section analyses), and "groin" classifications. There was generally good agreement between axes within classifications, in that if one axis produced a high z-score then the other two were likely to also have high z-scores.

Approximately 40% of the games available for analysis had some form of modification to the planned training activity in the week preceding or following. As would be expected, the number of modifications varied per subject. For instance, subject 11 has a modification in only one of his 15 games, whereas subject 10 has a modification in all of his games available for analysis. This will affect the potential to establish significance in the way z-scores respond to different modifications in that for some subjects the average and standard deviation for the raw results (on which the z-score is based) will be reflective of the "no modification" condition, and for other subjects (such as subject 10) the average and standard deviation will instead be reflective of the "modification" condition. In other words, in some subjects the deviation from the norm is accurately reflected by a z-score, while in others the deviation becomes the norm and the real (uninjured) norm cannot be established. That is not to say there is no potential for subject 10 to record significant results, it is simply that a significant result for subject 10 would be the equivalent of a very significant result for subject 11. Also, when results are averaged across the group it is likely that the contribution of subject 10 to the group average will skew results (and tend to make them less significant) as their zero z-score is potentially equal to a significantly positive or negative score in another subject. Despite these concerns, the z-score still represents the best method of comparing and collating CMD results across the group as previous research has demonstrated that each axis and analysis condition (within-section or between-section) needs to be analysed in the context of the specific subject and condition (McGinley et al., 2009), and the z-score provides the best method of performing the analysis in this way while still allowing comparison and collation of results across subjects and analysis condition.

When examining the average of all games with modifications (regardless of the reason for the incident of modified activity) there is only one instance where the p-value is below 0.05, in the within-section analysis for games where a modification was present both preceding and following the game (z-axis p=0.04. This would suggest that when the subject is going through a period of extended training modification, the variability of the stride waveform is higher than when no modification is present. The absence of any further highly significant results is likely due to some categories of activity modifications eliciting an increase in waveform variability and others a decrease and when all modifications are grouped together the significant results effectively cancel each other out. This is borne out when the data are separated into the reason for the activity modification.

There is one value in the "load modification" classification that has a p-value below 0.05, being the z-axis within-section condition in the "any load modification" classification which has a p-value of 0.02. This indicates that higher waveform variability could be a characteristic common to subjects who are in a period of activity modification due to “load” reasons. When this result is broken down further, it is when training is modified following the game where the z-axis within value has the lowest p-value ($p=0.06$), along with the both prior and post condition which had an average z-score of -0.807 (this classification only comprised two instances so p-values were not calculated). Having a low p-value in the “load modified post” condition is important as this would allow a low z-score in a particular week to be used as a predictor of the need to modify activity in the following week.

Although the mechanism underlying this increase in variability is currently unclear, it is roughly in agreement with theories presented by Hamill et al. (2012) and Stergiou et al. (2006), who suggest that a shift away from an individual’s optimal level of variability is indicative of a pathological state. A shift to an increased level of variability could be a sign of a noisy and irregular system, demonstrated by Stergiou and Decker (2011) to be a characteristic of individuals who had undergone knee reconstructions to repair a damaged anterior cruciate ligament (possibly due to not being able to restore the proprioceptive pathways found in a healthy knee). Fatigue may also be a factor that leads to an increase in variability, as per (Cortes et al., 2014). In addition, Fuller et al. (2017) expected to see impaired regulation and sequencing of movement in functionally overreached athletes though a change in their stride-interval correlation properties (in effect, a change in the variability of the temporal properties of their stride). Though there was no mean reduction in stride-interval long-range correlation strength following the overreaching protocol, participants who were most affected by the overreaching protocol (as measured by their time trial performance) experienced the greatest reduction in long-range correlation strength (ie. higher variability).

There is a high practical value to these findings as predictive tools are particularly valuable in the elite sport environment. The ability to identify times when an athlete is at risk of injury or requires a training modification to maximise their performance in subsequent activities (whether that be a reduction or increase to their training load) is crucial in the preparation of athletes for competition. Current metrics do have the ability to predict injury risk, especially when examining cumulative load measures (Colby et al., 2014). The difference in the measures outlined in the current study is that predictions are able to be made from physical symptoms rather than inferred from cumulative data. It therefore has the potential to identify athletes who are displaying physical symptoms that would indicate the need to modify training without satisfying the criteria established via cumulative metrics. Conversely, it may be able to identify athletes who do satisfy cumulative criteria but are showing no physical symptoms who therefore may not need training modifications. Combining both methods is likely to enhance the predictive ability of both and become a very powerful tool within elite sport environments, and further investigations into this are warranted.

The “leg structural” classification has low p-values in the between-section categories of the modified post sub-set (the z-axis had a p-value of 0.06, the y-axis had a p-value of 0.04 and the x-axis also had a p-value of 0.01). These findings are also in line with those of Hamill et al. (1999), who suggested that subjects in their study with patellofemoral pain demonstrated decreased variability of joint couplings in order to run while minimising the pain from their injury. It is interesting that the within-section results have a much higher p-value than the between-section results in the “structural pre” and “structural post” classifications. One possible explanation of this could be that the constraint imposed on the movement to reduce variability does not allow the stride to naturally vary during the course of the game as fatigue and other factors would normally affect the stride (causing an increase in the between-section CMD), but it may allow the normal stride to stride variability within the small window of time that comprises each section (which is evaluated with the within-section CMD).

Another interesting observation from the “structural post” classification is that although the between-section measures have z-scores that are above the average of the unmodified set of games, the average z-scores are below the unmodified average in eight out of ten categories in the “structural pre and post” classification. Furthermore, the z-axis between-section average of -0.658 had a p-value of 0.04, and the x-axis between-section average was -0.599 with a p-value of 0.06.This could possibly an indication that if a training modification was required both before and after a game the subject may have been carrying an injury from one week to the next, and that in the “up” and “forwards” planes stride waveform variability is increased as the subject is searching for an effective method of creating propulsion. Although these are speculative conclusions, the response of the analysis tool to athletes recovering from or trying to play with an injury would be worthy of further research.

Although the “leg soft tissue” classification does not have many instances (three with alterations preceding the game, one with an alteration following the game), there are some interesting results that are worthy of further investigation with a larger sample size. The z-scores in within-section analysis conditions for the single instance of modification post were all below -1 (and all other categories were below -0.4) which, although not low enough to be statistically significant in their own right, indicated a higher than normal amount of step waveform variability. In addition, the average of the three instances where the training modification preceded the game was below -0.25 for all three axes in the within-section analysis condition and the x-axis was below -0.4, which indicates a generally high amount of step waveform variability compared to the normal situation. If these results were replicated with a larger sample size then high waveform variability in the within-section condition across all three axes may be an extremely valuable tool in predicting future soft tissue injuries as well as identifying when an athlete has recovered from a previous injury and is ready to return to training and competition.

The “groin modification” classification has no analysis categories with a p-value below 0.05, and only one analysis category with a p-value below 0.1 (the z-axis between-section value for games where activity was modified in the week preceding the game which had a p-value of 0.08). With the lack of any highly significant results, the “groin modification” category does not seem to be of value, though perhaps a more specific categorisation (dividing the general “groin” category into soft tissue injuries to the adductor muscle group and more overuse type injuries such as osteitis pubis) could elicit some more meaningful results in follow up research. It is interesting that the average x-axis z-scores for this sub-set are positive, while the average x-axis z-scores for the “load” sub-sets tended to be negative. A positive z-score would indicate reduced variability, and this result is not unexpected for an acute injury. Stergiou & Decker (2011) observed that ACL deficient patients have less step to step variability in walking gait, inferring that they are being more “careful” when they were walking, trying to eliminate extraneous movements. A similar phenomenon could be displayed in the current results, in that subjects may attempting to constrain movements and reduce step to step variability when modifications due to “groin” are required.

5.4.5 **Conclusion**

Instances of missed or modified training and game activity in the week preceding or following a game with valid GPS and accelerometer data available for analysis were identified. These instances were sorted into six classifications, including five categories where a modification took place and one category where there was no modification to normal activity. Season average z-scores were collated for ten categories of analysis within the six classifications. High waveform variability was indicative of modifications due to “load”, with the within-section z-axis showing promise as a predictor of the need to modify activity. Low waveform variability in the between-section results appears to be a good indicator of the need for activity modification due to “leg structural”. Results from other classifications were promising (including the “groin” classification, where there was moderately significant results for z-axis between-section results), though further research with a larger sample size and perhaps more descriptive injury definitions needs to be conducted on some classifications to confirm the results presented here.

Overall, the performance of the analysis tool as a whole (from identification of steps to extraction of waveforms to statistical analysis) shows great promise, particularly in its ability to critically evaluate the physical condition of athletes with regard to their readiness to play and train.

5.5 Part 1a – Average z-scores after a bye in competitive matches.

In section 5.4, missed and modified training and game activity was divided into classifications according to incidents where modifications occurred due to an injury or other event that changed the normal training schedule. One classification that does not fit that description but is still of interest is games where GPS and accelerometer data is available and there was a bye (rest week with no match played) in the previous round (so the player has not participated in a competitive match for approximately two weeks). This section will investigate the response of the average z-scores when there has been a bye round in the week preceding a game with valid data.

5.5.1 Aims

- Identify and collate instances where no modification to the training program took place but there was a bye in the previous round
- Compare the average z-scores within the “no modification and bye” to identify significant differences to the unmodified and no bye training classification

5.5.2 Methods

The methods used were as per the previous section (section 5.4.2), except for a variation to the classification of missed and modified data (section 5.4.2.4). The instances classified as “no modification” in the previous section were divided into “with bye” (for when there was no competitive game in the previous round) and “without bye” (for all other instances of the “no modification” classification). The “without bye” set was then used as the baseline set, and confidence intervals were calculated on these data using the same bootstrapping procedure outlined in section 5.4.2.5.

5.5.3 **Results**

There were two bye rounds during the season in which the data for this study was collected. The number of instances in the "without bye" and "with bye" classifications are shown in Table 5-10. Confidence intervals on the "without bye" set of data are found in Table 5-11. Averages for both "with bye" and "without bye" classifications, as well as p-values for the "with bye" classification are found in Table 5-12. The lowest p-values were found in the x-axis results, particularly in the between-section ($p= 0.02$) and average between and within results ($p=0.02$). There are also low p-values found in the x-axis within-section ($p=0.05$). The z-score averages for all these categories are all negative, meaning there is higher waveform variability following a bye.

Table 5.10 Instances of no modification with bye and no modification without bye

Categories	Instances	Without Bye	With Bye
Total Games	255		
No Modification	148	125	23

Table 5.11 Confidence intervals of the without bye set of data

		99%		95%	
	Mean	Low CI	High CI	Low CI	High CI
z-axis within	0.028	-0.155	0.212	-0.111	0.175
y-axis within	0.019	-0.131	0.158	-0.094	0.132
x-axis within	0.077	-0.091	0.245	-0.045	0.205
z-axis between	0.000	-0.178	0.172	-0.129	0.134
y-axis between	0.004	-0.162	0.172	-0.114	0.123
x-axis between	0.032	-0.123	0.183	-0.081	0.165
z-axis average	0.014	-0.147	0.188	-0.110	0.138
y-axis average	0.012	-0.110	0.136	-0.082	0.109
x-axis average	0.055	-0.100	0.180	-0.055	0.161
average of all	0.027	-0.102	0.165	-0.073	0.124

Table 5.12 Mean z-scores in the no bye and with bye classifications.

	No Bye	With Bye	
	Average	Average	*P*
z-axis within	0.028	0.064	0.42
y-axis within	0.019	-0.034	0.36
x-axis within	0.077	-0.213	0.05
z-axis between	0.000	-0.093	0.30
y-axis between	0.004	-0.169	0.13
x-axis between	0.032	-0.340	0.02
z-axis average	0.014	-0.015	0.42
y-axis average	0.012	-0.101	0.19
x-axis average	0.055	-0.277	0.02
average of all	0.027	-0.131	0.12

5.5.4 **Discussion**

It is interesting that there are no low p-values in the z-axis. It could be reasonably assumed that a bye would help to reduce the physical load on a subject (providing there was not a commensurate increase in training intensity or volume), so it is quite reasonable given the results from the previous section where periods of rest due to load were characterised by high z-axis variability that after a bye week the z-axis waveform variability would approximate towards season average (with a z-score close to zero). It is also interesting to note that the x-axis between-section results in the "load" classification are very close to the average for the unmodified data set and have the highest p-values for the "any load modification" sub-set. The practical application of these findings would be that if a subject is reporting z-axis waveform variability that is increasing and x-axis waveform variability that is decreasing, they are more likely to require an alteration to training. If their z-axis waveform variability is decreasing and their x-axis waveform variability is increasing then it could be an indicator that they are getting "fresher" and do not require any reduction in training load. It could also indicate it is an appropriate time to increase training load. A flexible training plan could incorporate these findings to identify periods where athletes have coped well with the current training load and would be able to tolerate an increase with the goal of maximising the training effects without causing any adverse effects emanating from too much training load.

The ability to identify periods requiring training modification due to "load" as well as periods where it is expected that an athlete will be "fresh" would have implications for the ongoing assessment of training programs within an elite environment. Both individual and group results could be examined for this analysis. Group results would provide an overall picture of the condition of the squad which would be able to be matched to the training plan. If the group results were as predicted by the training plan then it would not raise any concerns. However, if the group results were to suggest a different physical condition to that predicted by the training plan then further investigation would be warranted. Similarly, if an individual result were to be different from the group or what was expected from that individual's recent physical output then further investigation into the cause of the discrepancy would be required.

5.5.5 Conclusion

Instances of a bye in the preceding week were identified, and data where the training program was otherwise unmodified were collated. Some low p-values were identified, suggesting that x-axis waveform variability increases when the subject has a bye in the previous week. This, along with results from section 5.4 that showed z-axis waveform variability increased when a modification due to "load" occurred, may provide a valuable indicator as to the physical condition of an athlete. This could be particularly useful in the applied setting to not only identify when athletes are under physical pressure but also when they are coping well with the physical load they are currently experiencing.

5.6 Part 2 – Significant z-scores in weeks adjacent to incidents of missed or modified training

The longitudinal analysis of z-scores within each subject demonstrated that there are instances within a season where z-scores show a significant deviation from the mean (section 4.4.3, Tables 4-17 and 4-18, page 77). The link between these scores and instances of missed and modified training and games will determine whether this style of analysis has any practical use in the prediction of when normal activity needs to be modified. This would be a key benefit to the use of this analysis tool, particularly in applied environments to identify instances where an athlete's physical load should be modified.

5.6.1 Aims

- Identify whether incidents of missed or modified training and game activity are linked to incidents where a significant z-score is found within an analysis category

5.6.2 Methods

5.6.2.1 *Subjects*

All participants within the cohort described in section 5.3.1 (General Methods) were used for this study.

5.6.2.2 *Data collection*

GPS and accelerometer data were collected in accordance with the procedures outlined in General Methods, section 5.3.2.1. Missed and modified training information was collected and collated in accordance with the procedures outlined in General Methods, section 5.3.2.2.

5.6.2.3 *Data analysis via the analysis tool*

Data were analysed in accordance with the procedures outlined in General Methods, section 5.3.3

5.6.2.4 *Missed and Modified Training and Game activity*

Incidents of missed and modified training and game activity were identified as per the methods outlined in section 5.4.2.4

5.6.2.5 *Identification of significant z-scores*

All games available for analysis were examined for the presence of significant z-scores as per the procedures outlined in Chapter 4 (section 4.4.2.3, page 71). These data were then collated with the missed and modified training and game activity data to determine the number of games where there was both a training modification and at least one analysis category that contained a significant z-score at the 99%, 95%, 90% and 80% confidence levels. This was repeated for the sub-sets of games with modified activity under the classifications of “structural”, “groin”, “load” and “soft tissue”. The percentage of the total games for each set of data was calculated.

5.6.3 Results

The total number of games with training modifications and the total number of games with a significant z-score in any category are found in Table 5-13 and 5-14 respectively. The results in Table 5-14 are presented as percentage of the overall set of games in Table 5-15. It is interesting to note the agreement between the two categories at all confidence levels. The missed and modified training instances at different confidence intervals are shown by category in Table 5-16, and as percentages of the total games at different confidence levels in Table 5-17.

Table 5.13 Baseline figures for total games and games with any modification to normal activity in the preceding or following week

	Instances
Total Games	255
Total games with modifications	107
Percent games with modifications	42%

Table 5.14 Instances of at least one significant z-score and both a significant z-score and a training modification at different confidence levels

Confidence Level	Total games with at least one significant z-score	One significant z-score and a training modification	
		Total Games	Percent of one significant z-score sub-set
0.99	31	14	45%
0.95	88	38	43%
0.9	149	60	40%
0.8	209	87	42%

Table 5.15 Instances of at least one significant z-score as a percentage of total games, and the percentage of games with training modifications within the sub-set of games with a significant z-score at different confidence levels

Confidence Level	Games with at least one significant z-score as a percentage of total games	Games with at least one significant z-score and a training modification as a percentage of games with at least one significant z-score
0.99	12%	13%
0.95	35%	36%
0.90	58%	56%
0.80	82%	81%

Table 5.16 Instances of modified training by reason for the modification within the sub-set of games with a significant z-score at different confidence levels

Classification	Total Instances	Confidence level of significant z-score sub-set			
		99%	95%	90%	80%
Structural	42	8	18	27	37
Groin	29	1	9	18	25
Load	26	5	10	14	20
Soft Tissue	6	0	1	4	6

Table 5.17 Percentage of games by reason for modification of all games that were modified within different sub-sets of significant z-scores at different confidence levels

		Confidence level of significant z-score sub-set			
Classification	Total Instances	99%	95%	90%	80%
Structural	41%	57%	47%	43%	42%
Groin	28%	7%	24%	29%	28%
Load	25%	36%	26%	22%	23%
Soft Tissue	6%	0%	3%	6%	7%

5.6.4 **Discussion**

As the confidence level reduces from 99% to 80%, the number of games with at least one significant z-score and the number of games within that subset where a training modification occurred naturally increases. Interestingly, the percentage of games with both a training modification and at least one significant z-score remains consistent across confidence levels (Table 5-14). What this indicates is that the presence of a significant z-score does not indicate any extra chance of a training modification being present, and consequently demonstrates that the presence of a significant z-score cannot be used to predict the need for training modification either preceding or following a game. Although this is not an encouraging result for the practical application of the analysis tool, it re-enforces the argument made in section 4.7 that the presence of statistical significance in an individual is not guaranteed to indicate clinical significance. In this case, statistical significance is clearly not an indicator of clinical significance (rendering this method of analysis for the current data ineffective), but that is not to say that if a z-score that indicates clinical significance were determined for each individual subject this method of analysis would not be of use. In addition, as identified in section 5.4.4, the differing number of incidents of missed or modified training and game activity per subject (Table 5-2) mean that there are likely to be some subjects whose long term average and standard deviation of raw scores do not represent an uninjured condition. The consequence of this is that the raw scores that equate to a z-score of zero may actually be significant if an uninjured average raw score were established.

Although not possible with the data available for this study, a method to ensure an uninjured average and standard deviation for raw scores would enhance the validity of these results. One method would be to use training sessions with a known training load in the preceding week and no training modifications in the preceding month. For instance, if there is a period of reduced load during a pre-season as part of a periodised training program then the two weeks that follow the week of reduced training could be used to establish the baseline values.

When looking at the different classifications of modified training, “structural” is over-represented in the set of games where there was a significant z-score at the 99% confidence level (57% of all instances were “structural” the 99% confidence level while only 41% of instances were “structural” when the full data set was examined). The over-representation of the “structural” classification was offset by the under-representation of the “groin” classification (7% in the 99% confidence level set compared to 28% in the full set). In practical terms, alterations to stride variability due to “structural” injuries are of greater magnitude than due to “groin” injuries, especially given both classifications approximate towards the percentages present in the full set of games when the set is expanded to the 90% confidence level. This could indicate this method of using the analysis tool will be better suited to identifying “structural” injuries as opposed to “groin” injuries. Even so, this does not alter the conclusion that in the current data set using an individual incident of a significant z-score does not provide any value for predicting an incident of missed or modified training or game activity.

5.6.5 Conclusion

The results indicate that there does not appear to be a link between incidents of missed or modified training and game activity and individual incidents of significant z-scores within an analysis category. Consequently, this method of analysing the data extracted by the analysis tool has no practical benefit at this time, though it is an area that would be appropriate for further investigation with other data or data with better defined ‘healthy’ values, particularly given the practical benefits this analysis could provide in applied environments.

5.7 Part 3 – Significant side to side differences adjacent to incidents of missed and modified training

In section 4.4, a number of subjects were identified as having significant differences between season averages on side 1 and side 2 in multiple axes (Table 4-9 and 4-10). The link between these results and the propensity for these subjects to record incidents of missed or modified training will be examined in this section.

5.7.1 Aims

- Investigate the link between a significant difference between side 1 and side 2 within an axis and CMD condition and subjects whose training was modified for "load" or "groin" reasons

5.7.2 Methods

5.7.2.1 *Subjects*

All participants within the cohort described in section 5.3.1 (General Methods) were used for this study.

5.7.2.2 *Data collection*

GPS and accelerometer data were collected in accordance with the procedures outlined in General Methods, section 5.3.2.1. Missed and modified training information was collected and collated in accordance with the procedures outlined in General Methods, section 5.3.2.2.

5.7.2.3 *Data analysis via the analysis tool*

Data were analysed in accordance with the procedures outlined in General Methods, section 5.3.3

5.7.2.4 *Missed and Modified Training and Game activity*

Incidents of missed and modified training and game activity were identified as per the methods outlined in section 5.4.2.4

5.7.2.5 *Season average within-section and between-section co-efficient of multiple determination results*

Season average within-section and between-section CMD results were calculated and subjects whose season averages were significantly different from side 1 to side 2 were identified as per the methods outlined in section 4.4.2.3.

5.7.2.6 *Data Analysis*

Subjects who recorded an instance of modified training or game activity due to a "load" or "groin" reason at any stage during the season were identified. Only the "load" and "groin" classifications will be examined as modifications due to these reasons are in general long term issues as opposed to the "structural" classification which included many acute ligament sprains (especially ankle sprains). The "soft tissue" category was excluded due to the small number of instances (four) that were identified throughout the year. These results were then compared to the subjects who were identified as having a significant difference in their average CMD values between side 1 and side 2 within an axis and CMD analysis condition. The link between a significant difference between sides within an axis and CMD analysis condition and the presence of an incident of “load” or “groin” modification was examined by classifying each subject as a true positive, false positive, true negative and false negative where the presence of a significant difference in season average CMD represented the condition and the existence of an incident of training modification due to “load” or “groin” represented the test. These combinations of condition and test result are further outlined in Table 5-18. For the test element to be positive within an axis either within-section or between-section analysis conditions must have a significant difference on both sides (i.e. the average of side 1 needed to be outside the 99% confidence interval for the average of side 2 and the average of side 2 needed to be outside the 99% confidence interval of side 1). The test condition was determined for all three axes.

Table 5.18 Combinations of condition and test result

	Side to side difference in season average CMD	Instance of Training Modification
False positive	Yes	No
True Negative	No	No
False negative	No	Yes
True Positive	Yes	Yes

5.7.3 **Results**

The total number subjects with modified training or game activity at any time during the year by reason for the modification are shown in Table 5-19. These are broken down further by instances where the test (a significant difference in season average CMD) has predicted the condition (the presence of a training or game modification) in Table 5-20 for training or game modifications due to “load”, and Table 5-21 for training or game modifications due to “groin”. The overall number of subjects where the test correctly predicted the condition (i.e. true positive or true negative results) is shown in Table 5-22.

Table 5.19 Number of subjects with modified and unmodified training by reason for modification

	Modified	Unmodified
Load	10	11
Groin	9	12

Table 5.20 Condition and test result for "load" modifications

	z-axis	y-axis	x-axis
True Positive	50%	60%	30%
True Negative	82%	27%	55%
False positive	18%	73%	45%
False negative	50%	40%	70%

Table 5.21 Condition and test result for "groin" modifications

	z-axis	y-axis	x-axis
True Positive	56%	78%	67%
True Negative	75%	42%	92%
False positive	25%	58%	8%
False negative	44%	22%	33%

Table 5.22 Overall instances (out of 21) where the test has correctly predicted the condition

	z-axis	y-axis	x-axis
Correct Load	14	9	9
Correct Groin	14	12	15

5.7.4 **Discussion**

Overall, the presence of a significant difference in season average CMD between sides within an axis and analysis condition does not appear to be an effective test for whether there will be a training modification at any time during the year for reasons of “load” or “groin”. Though a side to side difference in the z-axis correctly predicted the presence of a training modification in 66% of all subjects, this would not be an effective practical tool if used in isolation to definitively indicate the risk of the need for a training modification over the course of a season, especially given the high number of false negative results. The fewest number of false negative results were found in the y-axis “groin” (two false negative results) and the x-axis “groin” (three false negative results), indicating this method used in isolation is poor at correctly identifying subjects who were at an increased risk of requiring a training modification due to either “groin” or “load” reasons during the year. It is possible that when used in combination with other testing and monitoring tools that the predictive power of this method will enhanced, and that it could be integrated into a barrage of tests that when used together reliably predict “groin” and “load” training modifications during the season.

There were, however, some very encouraging results when the false positive results are examined. There was only one subject who required an activity modification for “groin” reasons who did not have a significant difference between sides on in the x-axis. This would indicate that this method of analysing the season long results has some merit for identifying subjects who are at a reduced risk of requiring an activity modification due to “groin”. In addition, there were only two of eleven subjects who recorded a false positive result for “load” modifications in the z-axis, and three of twelve subjects who recorded a false positive result for “groin” in the z-axis, indicating that the lack of significant differences in the z-axis may potentially have some practical use in identifying subjects at a reduced risk of requiring “groin” or “load” modifications during the season. There are a number of practical implications for these results. Predicting a reduced likelihood of the need to modify training would be extremely useful information to have when designing training programs. It would also be beneficial when combined with other testing and screening tools in the diagnosis of injury when pain is reported. There are also implications for recruitment of athletes, in that if this information were available prior to recruitment it could aid in the selection of athletes who are most likely to be available for selection more often, a significant issue when considering the return on investment in both the athlete and support staff for professional sporting clubs.

It must be noted that all subjects with available data were used for this study, and there was no exclusion for subjects who may have had significant differences between sides within an axis for reasons such as a previous anterior cruciate ligament (ACL) reconstruction (as discussed in section 4.4). There may be some merit in excluding subjects with previous ACL reconstructions to aid in identifying subjects at a reduced risk of an activity modification due to “groin” or “load” as excluding subjects who already have a side to side difference will reduce the proportion of subjects who have a positive test, which has the potential to reduce the number of false positive and true positive results. For instance, by excluding subjects who had a side to side difference in at least 90% of all analysis conditions (subjects 2, 10 and 19) two false positive results would be excluded in each axis of the “load” condition and one false positive result would be excluded in each axis of the “groin” condition. The net result of this is that in the “load” condition, the z-axis predicts 100% of true negative results, and in the “groin” condition the x-axis predicts 100% of the true negative results. There would consequently be merit in conducting further research to establish whether exclusion due to criteria such as a previous ACL reconstruction would enhance the ability of this analysis method to identify subjects who were at a reduced risk of requiring a training modification due to “load” or “groin”.

5.7.5 Conclusion

The link between a significant difference between side 1 and side 2 within an axis and CMD condition and subjects whose training was modified for “load” or “groin” reasons was investigated, and it was found that this analysis method has some merit in identifying subjects who were at reduced risk of requiring a training modification, particularly in the x-axis for “groin” modifications. These findings are amplified if subjects with difference in stride variability from side to side across at least 90% of analysis conditions are excluded.

When used in isolation this method does not appear to be able to identify subjects who were at an increased risk of requiring a training modification, however further investigation may identify enhanced predictive value when this tool is combined with other athlete screening and monitoring tools.

5.8 Part 4 – Low raw Coefficient of Multiple Correlation values and incidents of missed and modified training and game activity

A number of subjects have previously been identified as having very low season average CMD values, particularly in the y-axis (section 4.4, Tables 4-4 and 4-7). A low CMD value indicates high waveform variability, which has previously been linked to possible injury concerns (Stergiou & Decker, 2011). The link between these results and incidents of missed or modified training will be examined in this section.

5.8.1 Aims

- Investigate the link between low y-axis CMD values and incidents of training modification

5.8.2 Methods

5.8.2.1 *Subjects*

All participants within the cohort described in section 5.3.1 (General Methods) were used for this study.

5.8.2.2 ***Data collection***

GPS and accelerometer data were collected in accordance with the procedures outlined in General Methods, section 5.3.2.1. Missed and modified training information was collected and collated in accordance with the procedures outlined in General Methods, section 5.3.2.2.

5.8.2.3 ***Data analysis via the analysis tool***

Data were analysed in accordance with the procedures outlined in General Methods, section 5.3.3

5.8.2.4 ***Missed and Modified Training and Game activity***

Incidents of missed and modified training and game activity were identified as per the methods outlined in section 5.4.2.4. Only incidents of modification due to “groin” or “load” were analysed, as the y-axis CMD scores returned by far the greatest number of low CMD scores, and anecdotal reports from staff at the Port Adelaide Football Club indicated a high degree of interest in whether low CMD scores in the side to side accelerations (in this case the y-axis accelerations) were more prevalent in individual athletes who presented with groin or load related issues.

5.8.2.5 ***Data Analysis***

Season average y-axis CMD results were collated, and the number of subjects whose minimum value across all conditions in the y-axis was below a threshold of 0.3, 0.35, 0.4 and 0.45 were identified. Raw CMD values under 0.4225 have previously been described as demonstrating less than moderate repeatability (Garofalo et al., 2009) so CMD values below that could be considered low, and 0.45 could be considered at the lower end of a ‘moderate’ level. Those subjects who were identified at each threshold were then divided into those who had an incident of modified activity classified as “groin” or “load” and those that didn’t. Only the “groin” and “load” classifications were analysed in this way for the reasons outlined in section 5.7.2.6, namely that these classifications are generally chronic rather than acute. This process was repeated, substituting an average of all y-axis conditions, an average of within-section y-axis conditions and an average of between-section y-axis conditions for the minimum y-axis value used in the initial analysis.

The number of games where a single y-axis CMD value was below a threshold of 0.2, 0.25, 0.3, 0.35, 0.4 and 0.45 were identified. These sub-sets were then examined to identify the number of instances where a training modification was present. This procedure was repeated using the average of all y-axis CMD values, the average of within-section CMD values and the average of between-section CMD values.

5.8.3 Results

The number of subjects whose minimum y-axis season average across all conditions is below a threshold value, as well as the number of subjects within that sub-set who recorded an incident of modified activity classified as "groin" or "load" at any time during the season are shown in Table 5-23. The number of subjects whose average of all y-axis conditions is below a threshold value are shown in Table 5-24. The number of subjects whose average of y-axis within-section and between-section season average CMD is below a threshold value (along with the number who recorded a "groin" modification during the season) are shown in Tables 5-25 and 5-26 respectively.

Table 5.23 Subjects whose minimum y-axis value is below a threshold, and the instances of modification due to "groin" or "load" within that sub-set

Threshold	Instances	Load Modification	Groin Modification
0.3	4	2	2
0.35	7	2	3
0.4	10	3	4
0.45	13	5	7

Table 5.24 Subjects whose average y-axis value is below a threshold, and the instances of modification due to "groin" or "load" within that sub-set

Threshold	Instances	Load Modification	Groin Modification
0.3			
0.35	1		
0.4	3	1	2
0.45	8	2	4

Table 5.25 Subjects whose average y-axis within-section value is below a threshold, and the instances of modification due to "groin" or "load" within that sub-set

Threshold	Instances	Load Modification	Groin Modification
0.3			
0.35			
0.4	1		
0.45	5	2	2

Table 5.26 Subjects whose average y-axis between-section value is below a threshold, and the instances of modification due to "groin" or "load" within that sub-set

Threshold	Instances	Load Modification	Groin Modification
0.3	1		
0.35	2	1	1
0.4	8	3	3
0.45	9	4	4

The number of games across all subjects where one y-axis CMD value was below a threshold, as well as the percentage of instances where a modification to activity is present is shown in Table 5-27. Similar analyses are shown in Table 5-28, 5-29 and 5-30 where instances below threshold for the average across all y-axis categories, the within-section y-axis average and between-section y-axis average are presented.

Table 5.27 Number of games where one y-axis CMD value is below a threshold, and the percentage of those games where a training modification is present.

Threshold	Games	Load Percentage	Groin Percentage	Soft Tissue Percentage	Structural Percentage
0.2	40	10.0%	15.0%	2.5%	10.0%
0.25	40	10.0%	15.0%	2.5%	10.0%
0.3	82	6.1%	13.4%	3.7%	17.1%
0.35	110	7.3%	12.7%	3.6%	17.3%
0.4	138	8.0%	15.2%	2.9%	18.1%
0.45	173	10.4%	12.7%	2.9%	19.7%

Table 5.28 Number of games where the average y-axis CMD is below a threshold, and the percentage of those games where a training modification is present.

Threshold	Games	Load Percentage	Groin Percentage	Soft Tissue Percentage	Structural Percentage
0.2	0	0.0%	0.0%	0.0%	0.0%
0.25	2	0.0%	0.0%	0.0%	0.0%
0.3	7	0.0%	0.0%	14.3%	14.3%
0.35	28	17.9%	17.9%	7.1%	14.3%
0.4	54	9.3%	14.8%	5.6%	18.5%
0.45	81	7.4%	18.5%	3.7%	14.8%

Table 5.29 Number of games where the average within-section y-axis CMD is below a threshold, and the number of those games where a training modification is present.

Threshold	Games	Load Percentage	Groin Percentage	Soft Tissue Percentage	Structural Percentage
0.2	0	0.0%	0.0%	0.0%	0.0%
0.25	1	0.0%	0.0%	0.0%	0.0%
0.3	3	33.3%	0.0%	33.3%	0.0%
0.35	12	25.0%	0.0%	8.3%	16.7%
0.4	32	9.4%	12.5%	6.3%	18.8%
0.45	65	7.7%	13.8%	3.1%	16.9%

Table 5.30 Number of games where the average between-section y-axis CMD is below a threshold, and the number of those games where a training modification classified as "groin" or "load" are present.

Threshold	Games	Load Percentage	Groin Percentage	Soft Tissue Percentage	Structural Percentage
0.2	7	14.3%	28.6%	14.3%	0.0%
0.25	15	13.3%	13.3%	6.7%	6.7%
0.3	28	10.7%	14.3%	7.1%	14.3%
0.35	49	8.2%	16.3%	4.1%	16.3%
0.4	68	7.4%	17.6%	2.9%	14.7%
0.45	94	7.4%	14.9%	3.2%	14.9%

5.8.4 **Discussion**

The results demonstrate that a low season average CMD does not necessarily mean a training modification classified as "groin" or "load" would have occurred during the season. At the lowest threshold for minimum y-axis CMD, there are two of the four subjects who did not have a "groin" training modification during the year. This ratio is roughly consistent as the threshold is increased, and is also consistent when the average of all y-axis conditions (rather than the minimum) is used. Similar results were found for "load" modifications. These results are re-enforced when individual games are analysed. The percent of games where training modifications are present is slightly higher in the sub-sets of instances where a low CMD value is present than for the entire set of games, however the maximum percentage of games that accurately predicted a "groin" modification is only 28.6% (two out of seven instances at a threshold of 0.2 for the average between-section y-axis CMD) and the maximum percentage for "load" classifications was 33% (one out of three instances at a threshold of 0.3 for the average within-section y-axis CMD). This demonstrates that a low average CMD value does not necessarily mean an increase in risk of requiring a training modification due to "load", "groin", "structural" or "soft tissue".

This is not a surprising result, given the nature of CMD as a statistical tool. Although there is some evidence to show that low CMD results are possibly linked to injury (Stergiou & Decker, 2011), further research (McGinley et al., 2009; Røislien et al., 2012) demonstrated that it is not the raw CMD result that is potentially important but the CMD result within the context of what is expected for the particular subject, movement, joint (or in this case the position of the accelerometer on the body) and axis. Consequently, though there are some instances of very low CMD results within the data, for those results to be meaningful they should be analysed within the context of what is the expected result for that particular datum, as has been done in other sections within this chapter.

5.8.5 Conclusion

Based on the low percentage of instances where a low raw CMD value occurs adjacent to a training modification, there does not appear to be a link between low y-axis CMD results and training modifications. This demonstrates that this method of analysis when used in isolation is ineffective and has no practical benefit. Furthermore, given the caution around analysing raw CMD scores for these sort of data advocated in previous research, this area is not particularly worthy of further investigation.

5.9 General Discussion

Results from this study have demonstrated a number of outputs from the analysis tool that appear to be influenced by instances of missed or modified training or game activity. Key findings include;

- High z-axis within-section waveform variability when training is modified for “load” (p=0.02)
- Low x-axis (p=0.01) and y-axis (p=0.04) between-section waveform variability when training is modified for “structural” in the week following the game being analysed
- High x-axis between-section waveform variability in the week following a bye (p=0.02)
- Generally high waveform variability if a soft tissue injury occurred in the week following the game being analysed
- Absence of training modifications due to “load” in individual subjects predicted by an absence of side to side differences in season average raw CMD results in z-axis conditions (82% correct prediction).

- Absence of training modifications due to “groin” in individual subjects predicted by an absence of side to side differences in season average raw CMD results in x-axis conditions (92% correct prediction)

No corrections were used on these data to account for the large number of statistical tests and the potential effect that has on the appropriate level of significance that should be employed. However, as per the previous chapter, this was done to ensure an inclusive rather than exclusive criteria was used in regards to highlighting outputs from the analysis tool that showed promise. In a practical sense, this approach will assist in identifying elements of the analysis tool that are worthy of follow up research. It also identified areas that showed little promise that were not recommended (the un-adjusted p-value would not affect any of these that were $p>0.05$). Further testing using the more promising tools is needed to determine to what extent these might be significant.

The results presented in sections 5.4 and 5.5 have important implications for the practical application of results extracted by the analysis tool. Section 5.4 showed that within-section z-scores are reduced (and waveform variability increased) when a modification to normal training activity for “load” reasons was present. In contrast, x-axis between-section z-scores approximated towards zero in the same sub-set of games. In section 5.5, x-axis between-section z-scores were shown to be reduced when there was a bye in the week preceding the game being analysed, whereas z-axis within-section z-score approximated towards zero. The implications of these results is that if a reduction in z-axis within section z-scores is observed in the longitudinal analysis of both individual or group average z-scores without a concurrent reduction in between-section x-axis z-scores then it could be concluded that the individual or group may require a reduction in training load. Conversely, if the opposite pattern is observed with a decrease in x-axis between-section z-score and a z-axis within-section z-score that is approximating to zero then it could be concluded that the athlete can tolerate an increased training load (or are at least approaching a period of low general fatigue). This information can be incorporated with other athlete monitoring tools to increase the precision in prescribing training load for individuals or groups.

Low waveform variability in the between-section analysis is a characteristic found in the “structural post” classification. All axes have p-values smaller than 0.14, and both the x-axis ($p=0.02$) and y-axis ($p=0.04$) have p-values below 0.05, indicating that the mean of the sub-set is significantly higher than the mean of the unmodified set of games to a high level of confidence. The low waveform variability may be an indicator of constraints placed on the system due to the structural injury, where variability that is normally present as the game progresses is diminished due to the subject placing constraints on the movement. A practical application of these results may be in the identification of athletes who will need training modification in the week following a game where an injury has occurred. In addition, there may be a possibility of using this analysis to identify athletes who are ready to return to normal activity in that when their between-section variability returns to their long term average the effect of the injury has diminished.

When the side to side differences in season average raw CMD scores within axis and analysis condition were collated with the instances of modified activity, subjects with no difference between side 1 and side 2 in the z-axis were very unlikely to require a training modification classified as “load” (only two out of eleven subjects with no significant side to side difference in the z-axis required a modification due to “load” throughout the season), and subjects with no difference between side 1 and side 2 in the x-axis were very unlikely to require a training modification classified as “groin” (one out of ten subjects was incorrectly classified using this method). This provides extremely valuable practical information on an athlete’s risk of requiring a training modification during the season, which can be incorporated with other monitoring tools to assess overall risk of injury when designing a training program.

Other methods of analysing the data extracted by the analysis tool do not appear to provide practical benefits. Individual instances of significant z-scores do not appear to have any link to instances of missed or modified training, although establishing individual confidence intervals that indicate clinically significant z-scores rather than using statistical tools to establish confidence intervals may aid make this form of analysis more effective. In addition, as some subjects had more incidents of modified activity during the year, there is no guarantee that an accurate baseline z-score that represents an uninjured state can be established across the subject group. By using an expanded set of data to establish a baseline average and standard deviation that represents the un-injured state of an individual there may be more merit in using individual instances of significant z-scores to predict when a training modification is required. Similarly, low raw CMD results do not appear have any value in predicting instances of modified activity. Although the predictive value of this method may be improved if full medical profiles are used to identify subjects whose performance is hampered by an injury, if training or game activity does not require modification as a result of an injury the practical impact of that injury must be questioned. Consequently, although further research could reveal more practical benefits from these forms of analysis, the current data does not advocate the use of these analysis techniques.

5.10 General Conclusions

Instances of missed and modified training and game activity were identified and collated with results generated by the analysis tool. Analysis of group average z-scores revealed within-section z-axis z-scores appear to have some value in predicting instances where training requires modification due to “load”, and between-section x-axis z-scores appear to have some value in predicting instances where physical load has been reduced due to a bye in the previous round of games. Season average differences in raw CMD value between side 1 and side 2 within axis and analysis condition also appear to have some predictive value in identifying subjects who are at reduced risk of requiring a training modification due to “load” or “groin” during the season. Other methods of analysis do not appear to have any practical application.

6 General Discussion and Conclusions

This research outlined a technique to extract stride accelerometer waveforms from athlete tracking data collected with a device with integrated GPS and accelerometer sensors. Although previous research has demonstrated that movement patterns can be identified and stride characteristics can be extracted from data collected with similar devices (Buchheit et al., 2015), to the author's knowledge this is the first time a method has been outlined that combines both an identification of movement pattern to limit the analysis to periods of common activity (namely straight line running at high speed) and then extracts full-stride waveforms (as opposed to metrics describing specific aspects of the stride such as stride time) to examine their consistency across an entire game or training session. In addition, as the data used to develop the model was collected during competitive games and not from specially designed activities, the ability of the tool to extract data and provide information to scientists, coaches and trainers in the applied environment is assured.

The extraction of matched sections of running is an important element of this study. In a similar vein to Gabbett (2012) who used GPS to identify periods of sprinting in competitive rugby league matches, as well as Spencer, Bishop, Dawson, and Goodman (2005) and Faude et al. (2012) who used video-based time motion analysis to identify periods of sprint running during competitive hockey and football games respectively, the current study used GPS to identify periods of high speed running in a straight line. This process allows data from normal matchplay and training to be analysed rather than requiring data to be collected from specially designed drills or pattern runs. This will ensure that data to be analysed is taken from sections of running where the athlete is less focussed on maintaining correct technique and more focussed on the gameplay implications of their actions, thereby maximising the ecological validity of the process.

Instances where training and game activity was modified influenced the outputs from the analysis tool were identified. These results have many practical applications in professional sporting clubs. The ability to predict the need for modifying normal activity is a much sought after goal of applied scientists, coaches and trainers who are endeavouring to maintain athletes at their optimal physical condition over the course of a season. In this respect, identifying trends in individual results that would indicate a heightened possibility of the need to modify normal activity provides crucial insight.

Another possible application would be to use group average results from training sessions and games to help identify when the group as a whole is experiencing periods of high or low physical load. This could be especially useful in times of specific training such as during the pre-season where much of the squad is experiencing similar training loads as the random element of gameplay is not present to the same degree as during the regular competitive season and physical conditioning is generally tightly controlled. By analysing longitudinal trends of the group average results insights can be gained into the overall effect the training program is having on the group's physical condition which can then be compared with the expected outcome given the training load that has been prescribed.

As there appears to be some clear increases in between-section results when a "structural" injury has been identified, there is a possibility that this analysis tool can be used as an indicator of when the effect of the injury has subsided and the athlete is ready to return to training or competitive games. Healthy baseline values could be used as a reference for return to play, and criteria could be established that indicate when variability is close enough to the baseline value to indicate they were ready to return to normal activity.

A particular benefit provided by the methods presented in this study is the ability to generate results without any extra effort in terms of data collection or specialised activity. The analysis tool uses data that is routinely collected during training and competitive games, and extracts the key sections to be analysed from normal game activities. This is an important point because there are many competing demands on the limited training time available at a professional sporting club, and requiring specialised testing often renders a test or metric unusable due to an unwillingness to alter normal training activities to accommodate the specialised test or equipment. One of the key criteria in the overall design of the analysis tool was to maximise its practical usefulness, and a fundamental part of that was to only use data that is routinely collected currently rather than rely on a specific test that may encounter resistance in its application. This study demonstrated that the analysis tool not only is able to extract sufficient data from normal competitive gameplay, but results generated by the analysis tool have real practical outcomes for the prediction of modifications to normal activity. In addition, results in this study have been generated from a small number of games in comparison to the total number of games and training sessions that are prescribed during a normal season. It is therefore encouraging that significant results have been identified with such a limited set of data.

Data from competitive games were used in this study as it was thought that competitive games would provide the greatest weekly physical stress to the subjects. It was assumed that the greatest physical stress would also provide the greatest chance of the analysis tool uncovering characteristics that could be used as predictors of injury. However the analysis tool can be extended to be used with training data as well. The amount of SLHS sections that are able to be identified within a standard training session is currently unknown. It is possible that given the reduced duration of training compared to games there would be fewer SLHS sections which may compromise the accuracy of the between-section measures. However, as training sessions are often interspersed with periods of physical conditioning that often involve straight line running at high speed there is the possibility that an adequate number of sections of SLHS running can be identified. If needed there is also the possibility of incorporating the need to generate straight line high speed running during training into the design of training drills, allowing for more valid data to be available. Further research into the applicability of the analysis tool to training data needs to be conducted before its worth in identifying important aspects of an athlete's physical condition from training data can be established.

An additional benefit to including training data within the analysis would be that a more complete time series of data would be available. In the current data the time between data points is irregular in that games available for analysis are often separated by a number of weeks. This does not allow for an analysis of how results change over small time periods. Analysis of training data could possibly uncover associations and more stable transitions from high to low z-scores (and vice versa) as time progresses. More detailed data on the physical condition of the athlete may identify subtle variations in athlete condition that can be identified and predicted by outputs from the analysis tool, thus strengthening results presented in this study.

Another aspect of the underlying data that could be investigated further is the time during the game where sections of SLHS running occurred. The selection of sections used in the between-section analysis (with respect to when those sections occurred during the game) was not controlled, resulting in the likelihood that sections within games used for between-section analysis overly represent periods within games. Also, the time within a game that sections of straight line high speed running occurred will be inconsistent across the season. A more detailed data set may provide further clarity on results and conclusions presented in the current study and may offer insights into how outputs from the analysis tool change during the course of the game. These findings would provide useful practical information in relation to an athlete's ability to maintain physical condition throughout the course of a game.

The predictive value of results generated by the analysis tool is likely to be enhanced when combined with other parameters regularly collected in professional clubs. Adding information on stride waveform variability to other measures and procedures such as medical screening, tests for power and strength, general physiological measures, session ratings of perceived exertion and more traditional GPS measures like cumulative distance or player load would likely enhance the applicability and predictive power of all metrics. This approach has been demonstrated in the past by Colby et al. (2014), who investigated injury risk predicted by physical workload. Injury was defined in a very similar style to the current study in that instances of modified training in a professional AFL team were used as indicators of injury incidents. Another similarity was the use of custom analysis tools developed by the authors, similar to the analysis tool developed for the current study. Incorporating the analysis tool from the current study into the methods used by Colby et al. would likely result in a predictive model that is more powerful than if the analysis methods were used in isolation. The results from the analysis tool developed for this study can be used as a piece of the overall puzzle as well as providing important insights in their own right.

An absence in side to side difference in z-axis within-section results and a reduced possibility of requiring training modification due to "load", as well as a similar finding where an absence in side to side differences in x-axis between-section results reduces the possibility of requiring a training modification due to "groin" have implications for the management of athletes within professional sporting clubs. If side to side differences are present in an athlete then more monitoring, medical screening and other preventative and diagnostic measures should be implemented. This is not to imply that athletes with no side to side differences should be ignored as far as testing and monitoring for "load" and "groin" issues goes, simply that given the reduced probability found in this group would help to direct time and energy towards a group with a higher probability of requiring training modifications. Additionally, if player tracking data were available on potential recruits, identification (or non-identification) of side to side differences may aid in the recruitment of athletes to minimise the possibilities of recruiting athletes that may require some training modifications (and perhaps miss games due to injury) during the season.

Overall, the influence of instances of missed or modified training on results generated by the analysis tool generally supports previous research. A shift away from an athlete's optimal amount of movement variability (ie. their normal 'healthy' state) has been associated with a pathological state (Cortes et al., 2014; Hamill et al., 2012; Hamill et al., 1999; Heiderscheit et al., 2002; Stergiou & Decker, 2011; Stergiou et al., 2006). Athletes demonstrated a shift to decreased variability in some situations (such as in the week following a 'leg structural' injury) and a shift to increased waveform variability in other situations (such as in the week following a training modification for 'load', suggesting the training staff felt the athlete was fatigued or in danger of becoming functionally over-reached). This pattern is in agreement with Hamill et al. (2012), who suggested that a higher or lower level of coordinative variability was indicative of an injured state. Indeed, as was suggested by Stergiou et al. (2006), an overly rigid system (characterised by too little variability) and an overly chaotic system (characterised by too much variability) can both be indicators of a pathological state.

The indications of a pathological state are statistical variance from a mean value that reflects a 'normal' amount of movement variability for an athlete. Changes within the underlying movement variability displayed by the athlete is reflected in the variance from their mean value. This is a common technique used in elite sporting environments, as outlined by (Rogalski et al., 2013).

The practical application of this analysis tool may go some way to enabling movement variability to be used in applied situations to identify athletes progression towards and recovery from an injured state. There are many benefits to using this analysis tool in elite sporting environments. There is no extra equipment required over and above the instrumentation already worn in most training and game situations, reducing the need for acquisition of the instrumentation, compliance from both the athletes to wear the units and staff to manage the administration of the units (including administration of the data produced by the units), and regulatory obligations with governing bodies who control what instrumentation can be worn during competition. It is hoped that the analysis tool presented in this research will be an effective addition to the applied sport scientist's toolkit, and that movement variability can be used, as envisioned by Hamill et al. (2012), to help track progression towards or recovery from an injured state, thereby assisting athletes to perform at their peak.

Although not possible in this study due to ethics requirements and conditions in the informed consent provided by subjects, it would be interesting to discover whether subjects with large side to side differences in season average CMD results had a history of ACL injury as suggested by Moraiti et al. (2007) and Moraiti et al. (2010). If this were the case, it would enhance the possibilities of the methods presented in this study to further the theoretical discussions on movement variability by providing methods to unobtrusively examine variability during times of physical stress in the field, thus maximising ecological validity. Using data from actual gameplay situations will allow for theoretical concepts developed in laboratory and more controlled field testing to be tested in competitive settings. These applications will require further investigation to confirm the results obtained *in situ* can be replicated in more controlled settings (for instance by comparing results generated by the analysis tool when running on a treadmill to running in competitive situations), however the possibilities presented when analysing stride variability in competitive settings may provide new avenues to resolve questions on the role of movement variability in injured and non-injured athlete populations. In addition, research into the cause of results presented in this study would improve the power of the predictive model through enhancing the theoretical base for the results presented here.

The use of this analysis tool need not be restricted to the population used in the current study (elite AFL footballers). Straight line sprinting has been shown to be present in other sports (Faude et al., 2012; Gabbett, 2012) and is regularly used in testing batteries for elite athletes (Brown, Vescovi, & van Heest, 2004). In some instances, no changes in parameters used in identifying valid sections of data would be necessary before the analysis tool could be used to measure step waveform variability in other sports. In other cases some adjustments may be required to maximise the amount of valid data available. Further applications of the methods used in this study can be found in other cyclical sports. An example of this could be rowing or kayaking, where boat acceleration is regularly measured in competition and training (Janssen & Sachlikidis, 2010; Soper & Hume, 2004), though external factors such as weather conditions would need to be controlled for. Another sport where movement variability has already been investigated is swimming (Dadashi et al., 2015), where inertial sensors very similar to the units used in the current study (Slawson et al., 2009) could be used to examine movement variability in swimming strokes. The methods in this study could also be used in the examination of non-athletic populations, one example being movement variability and healthy gait in elderly subjects which has received some research interest in the past (Moe-Nilssen & Helbostad, 2005).

In many aspects, this study fits the description of a predictive model as described by Shmueli (2010). The influence of incidents of missed training on stride variability is not intended to imply any causative link. Although previous research has indicated that movement variability away from an optimal individual level may be indicative of some pathology (Stergiou & Decker, 2011), the mechanism that is the initial cause of the movement variability has not been investigated in this study. The analysis of data in this study is only partially based on a theoretical construct, in that an analysis of movement variability had the potential to uncover associations between the data and practical implications. Any possible associations identified can be used to predict new observations and are in this sense prospective.

Further elements of this study also conform to what could be considered characteristics of predictive models. Empirical precision was a high priority in the development of the analysis tool, providing sufficient data within the straight-line high-speed running sections for an effective statistical analysis was a key goal of identifying parameters for the analysis tool. Also, the analyses that have not been found to display a direct relationship with instances of missed or modified training (such as the magnitude of the raw CMD score in the y-axis, and incidents of significantly high or low z-scores) may, when combined with other models, provide a strong predictive relationship.

Investigations undertaken during the development of the analysis tool identified a number of parameters that could be modified to maximise the amount of valid data available for further analysis while maintaining best practice with regard to theoretical principles. Optimal values defining what constitutes both high speed and straight line running were established, and minimum amounts of valid data for analysis conditions were identified. However, given the similarities the current study has with predictive modelling studies, further investigations should be undertaken to address weaknesses in design that are common to predictive modelling research. To ascertain whether parameters identified and developed for this analysis tool are universally acceptable the performance of the analysis tool should be tested with a new set of data. In addition, results demonstrating a strong influence of incidents of missed or modified training on outputs from the analysis tool should also be tested against a new set of data generated from new subjects with new assessors deciding when normal activity should be modified (as well as the reason for that modification).

The key aspect of the results presented in this study is that they can be readily practically applied. Recent research into intra-stride accelerations (Buchheit et al., 2015) has demonstrated some of the possibilities afforded when these data are analysed. Providing another alternative method of analysing intra-step accelerations, in particular analysing the entire step waveform rather than stride characteristics generated from specific points within the waveform as well as reporting movement variability within games will aid scientists, coaches and trainers to utilise aspects of data being collected on a daily basis in sporting clubs worldwide. These data have hitherto remained largely untouched and the analysis presented in this study will aid in the accurate assessment and prescription of physical activity to maximise the physical condition of athletes. Combining methods presented in this study with other methods of analysing athlete tracking data will enhance the power of previous predictive approaches as well as increasing the clarity of conclusions drawn from retrospective analyses of player tracking data.

7 References

Aminian, K., Rezakhanlou, K., De Andres, E., Fritsch, C., Leyvraz, P., & Robert, P. (1999). Temporal feature estimation during walking using miniature accelerometers: an analysis of gait improvement after hip arthroplasty. *Medical & biological engineering & computing, 37*(6), 686-691.

Auvinet, B., Gloria, E., Renault, G., & Barrey, E. (2002). Runner's stride analysis: comparison of kinematic and kinetic analyses under field conditions. *Science & Sports, 17*(2), 92-94.

Balasubramanian, C. K., Neptune, R. R., & Kautz, S. A. (2009). Variability in spatiotemporal step characteristics and its relationship to walking performance post-stroke. *Gait & posture, 29*(3), 408-414.

Ball, K. (2006). *Weight transfer styles in the golf swing: Individual and group analysis.* (Doctoral Dissertation, Victoria University, Melbourne, Australia), Retrieved from http://vuir.vu.edu.au/1432

Ball, K., Best, R., & Wrigley, T. (2003). Body sway, aim point fluctuation and performance in rifle shooters: inter-and intra-individual analysis. *Journal of Sports Sciences, 21*(7), 559-566.

Bangsbo, J. (1994). The physiology of soccer--with special reference to intense intermittent exercise. *Acta Physiologica Scandinavica. Supplementum, 619*, 1-155.

Bartlett, R. (2008). Movement variability and its implications for sports scientists and practitioners: an overview. *International Journal of Sports Science and Coaching, 3*(1), 113-124.

Bartlett, R., Wheat, J., & Robins, M. (2007). Is movement variability important for sports biomechanists? *Sports Biomechanics, 6*(2), 224-243. doi:10.1080/14763140701322994

Bauer, A. M., Young, W., Fahrner, B., & Harvey, J. (2015). GPS variables most related to match performance in an elite Australian football team. *International Journal of Performance Analysis in Sport, 15*(1), 187-202.

Bergamini, E., Picerno, P., Pillet, H., Natta, F., Thoreux, P., & Camomilla, V. (2012). Estimation of temporal parameters during sprint running using a trunk-mounted inertial measurement unit. *Journal of biomechanics, 45*(6), 1123-1126.

Boyd, L. J., Ball, K., & Aughey, R. J. (2011). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *International Journal of Sports Physiology and Performance, 6*(3), 311-321.

Boyd, L. J., Ball, K., & Aughey, R. J. (2013). Quantifying external load in Australian football matches and training using accelerometers. *International Journal of Sports Physiology and Performance, 2013*(8), 44-51.

Brewer, C., Dawson, B., Heasman, J., Stewart, G., & Cormack, S. (2010). Movement pattern comparisons in elite (AFL) and sub-elite (WAFL) Australian football games using GPS. *Journal of Science and Medicine in Sport, 13*(5), 531-536.

Brown, T. D., Vescovi, J. D., & van Heest, J. L. (2004). Assessment of linear sprinting performance: a theoretical paradigm. *J. Sports Sci. Med, 3*, 203-210.

Buchheit, M., Gray, A., & Morin, J. B. (2015). Assessing Stride Variables and Vertical Stiffness with GPS-Embedded Accelerometers: Preliminary Insights for the Monitoring of Neuromuscular Fatigue on the Field. *Journal of sports science & medicine, 14*(4), 698.

Buckeridge, E., LeVangie, M. C., Stetter, B., Nigg, S. R., & Nigg, B. M. (2015). An On-Ice Measurement Approach to Analyse the Biomechanics of Ice Hockey Skating.

Burgess, D., Naughton, G., & Norton, K. (2012). Quantifying the gap between under 18 and senior AFL football: 2003-2009. *International Journal of Sports Physiology and Performance, 7*(1), 53.

Callaway, A., Cobb, J., & Jones, I. (2009). A comparison of video and accelerometer based approaches applied to performance monitoring in swimming. *International Journal of Sports Science and Coaching, 4*(1), 139-153.
Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine, 45*(7), 1065-1081.
Colby, M. J., Dawson, B., Heasman, J., Rogalski, B., & Gabbett, T. J. (2014). Accelerometer and GPS-derived running loads and injury risk in elite Australian footballers. *The Journal of Strength & Conditioning Research, 28*(8), 2244-2252.
Cortes, N., Onate, J., & Morrison, S. (2014). Differential effects of fatigue on movement variability. *Gait & posture, 39*(3), 888-893. doi:http://dx.doi.org/10.1016/j.gaitpost.2013.11.020
Coutts, A. J., & Duffield, R. (2010). Validity and reliability of GPS devices for measuring movement demands of team sports. *Journal of Science and Medicine in Sport, 13*(1), 133-135.
Coutts, A. J., Kempton, T., Sullivan, C., Bilsborough, J., Cordy, J., & Rampinini, E. (2015). Metabolic power and energetic costs of professional Australian Football match-play. *Journal of Science and Medicine in Sport, 18*(2), 219-224.
Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports Medicine, 43*(10), 1025-1042.
Cunningham, T. J., Mullineaux, D. R., Noehren, B., Shapiro, R., & Uhl, T. L. (2014). Coupling angle variability in healthy and patellofemoral pain runners. *Clinical Biomechanics, 29*(3), 317-322. doi:http://dx.doi.org/10.1016/j.clinbiomech.2013.12.008
Dadashi, F., Millet, G. P., & Aminian, K. (2015). Front-crawl stroke descriptors variability assessment for skill characterisation. *Journal of Sports Sciences*, 1-8. doi:10.1080/02640414.2015.1114134
Dawson, B., Hopkinson, R., Appleby, B., Stewart, G., & Roberts, C. (2004). Player movement patterns and game activities in the Australian Football League. *Journal of Science and Medicine in Sport, 7*(3), 278-291. doi:http://dx.doi.org/10.1016/S1440-2440(04)80023-9
Duffield, R., Reid, M., Baker, J., & Spratford, W. (2010). Accuracy and reliability of GPS devices for measurement of movement patterns in confined spaces for court-based sports. *Journal of Science and Medicine in Sport, 13*(5), 523-525.
Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. New York: Chapman and Hall.
Ehrmann, F. E., Duncan, C. S., Sindhusake, D., Franzsen, W. N., & Greene, D. A. (2016). GPS and injury prevention in professional soccer. *The Journal of Strength & Conditioning Research, 30*(2), 360-367.
Farana, R., Jandacka, D., & Irwin, G. (2013). Influence of different hand positions on impact forces and elbow loading during the round off in gymnastics: A case study. *Science of Gymnastics Journal, 5*(2), 5-14.
Faude, O., Koch, T., & Meyer, T. (2012). Straight sprinting is the most frequent action in goal situations in professional football. *Journal of Sports Sciences, 30*(7), 625-631.
Fuller, J. T., Bellenger, C. R., Thewlis, D., Arnold, J., Thomson, R. L., Tsiros, M. D., Robertson, E. Y., & Buckley, J. D. (2017). Tracking Performance Changes With Running-Stride Variability When Athletes Are Functionally Overreached. *International Journal of Sports Physiology and Performance, 12*(3), 357-363.
Gabbett, T. J. (2012). Sprinting Patterns of National Rugby League Competition. *The Journal of Strength & Conditioning Research, 26*(1), 121-130. doi:10.1519/JSC.0b013e31821e4c60

Garofalo, P., Cutti, A. G., Filippi, M. V., Cavazza, S., Ferrari, A., Cappello, A., & Davalli, A. (2009). Inter-operator reliability and prediction bands of a novel protocol to measure the coordinated movements of shoulder-girdle and humerus in clinical settings. *Medical & biological engineering & computing, 47*(5), 475-486. doi:10.1007/s11517-009-0454-z

Gaudino, P., Gaudino, C., Alberti, G., & Minetti, A. E. (2013). Biomechanics and predicted energetics of sprinting on sand: Hints for soccer training. *Journal of Science and Medicine in Sport, 16*(3), 271-275. doi:http://dx.doi.org/10.1016/j.jsams.2012.07.003

Haley, S. M., & Fragala-Pinkham, M. A. (2006). Interpreting change scores of tests and measures used in physical therapy. *Physical Therapy, 86*(5), 735-743.

Hamill, J., Palmer, C., & van Emmerik, R. E. A. (2012). Coordinative variability and overuse injury. *BMC Sports Science, Medicine and Rehabilitation, 4*(1), 45.

Hamill, J., van Emmerik, R. E. A., Heiderscheit, B. C., & Li, L. (1999). A dynamical systems approach to lower extremity running injuries. *Clinical Biomechanics, 14*(5), 297-308. doi:http://dx.doi.org/10.1016/S0268-0033(98)90092-4

Harbourne, R. T., & Stergiou, N. (2003). Nonlinear analysis of the development of sitting postural control. *Developmental Psychobiology, 42*(4), 368-377.

Hausdorff, J. M. (2007). Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking. *Human movement science, 26*(4), 555-589. doi:http://dx.doi.org/10.1016/j.humov.2007.05.003

Heiderscheit, B. C. (2000a). *Locomotion variability and joint pain.* (Doctoral Dissertation), Available from Proquest (AAI9988797)

Heiderscheit, B. C. (2000b). Movement Variability As a Clinical Measure for Locomotion. *Journal of Applied Biomechanics, 16*(4), 419.

Heiderscheit, B. C., Hamill, J., & van Emmerik, R. E. A. (2002). Variability of Stride Characteristics and Joint Coordination Among Individuals With Unilateral Patellofemoral Pain. *Journal of Applied Biomechanics, 18*(2), 110-121.

Hiscock, D., Dawson, B., Heasman, J., & Peeling, P. (2012). Game movements and player performance in the Australian Football League. *International Journal of Performance Analysis in Sport, 12*(3), 531-545.

Hollman, J. H., Childs, K. B., McNeil, M. L., Mueller, A. C., Quilter, C. M., & Youdas, J. W. (2010). Number of strides required for reliable measurements of pace, rhythm and variability parameters of gait during normal and dual task walking in older individuals. *Gait & posture, 32*(1), 23-28.

Janssen, I., & Sachlikidis, A. (2010). Validity and reliability of intra-stroke kayak velocity and acceleration using a GPS-based accelerometer. *Sports Biomechanics, 9*(1), 47-56.

Jennings, D., Cormack, S., Coutts, A. J., Boyd, L., & Aughey, R. J. (2010a). The Validity and Reliability of GPS Units for Measuring Distance in Team Sport Specific Running Patterns. *International Journal of Sports Physiology & Performance, 5*(3).

Jennings, D., Cormack, S., Coutts, A. J., Boyd, L. J., & Aughey, R. J. (2010b). Variability of GPS units for measuring distance in team sport movements. *International Journal of Sports Physiology and Performance*.

Jordan, K., Challis, J. H., Cusumano, J. P., & Newell, K. M. (2009). Stability and the time-dependent structure of gait variability in walking and running. *Human movement science, 28*(1), 113-128.

Kadaba, M., Ramakrishnan, H., Wootten, M., Gainey, J., Gorton, G., & Cochran, G. (1989). Repeatability of kinematic, kinetic, and electromyographic data in normal adult gait. *Journal of Orthopaedic Research, 7*(6), 849-860.

Kavanagh, J. J., Morrison, S., James, D. A., & Barrett, R. (2006). Reliability of segmental accelerations measured using a new wireless gait analysis system. *Journal of biomechanics, 39*(15), 2863-2872.

Knudson, D., & Bahamonde, R. (2001). Effect of endpoint conditions on position and velocity near impact in tennis. *Journal of Sports Sciences, 19*(11), 839-844.

Lee, J. B., Mellifont, R. B., & Burkett, B. J. (2010). The use of a single inertial sensor to identify stride, step, and stance durations of running gait. *Journal of Science and Medicine in Sport, 13*(2), 270-273.

Lee, J. B., Sutter, K. J., Askew, C. D., & Burkett, B. J. (2010). Identifying symmetry in running gait using a single inertial sensor. *Journal of Science and Medicine in Sport, 13*(5), 559-563.

Little, C., Lee, J. B., James, D. A., & Davison, K. (2013). An evaluation of inertial sensor technology in the discrimination of human gait. *Journal of Sports Sciences, 31*(12), 1312-1318. doi:10.1080/02640414.2013.779739

Magalhaes, F. A. d., Vannozzi, G., Gatta, G., & Fantozzi, S. (2015). Wearable inertial sensors in swimming motion analysis: a systematic review. *Journal of Sports Sciences, 33*(7), 732-745. doi:10.1080/02640414.2014.962574

Mayagoitia, R. E., Nene, A. V., & Veltink, P. H. (2002). Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems. *Journal of biomechanics, 35*(4), 537-542.

McGinley, J. L., Baker, R., Wolfe, R., & Morris, M. E. (2009). The reliability of three-dimensional kinematic gait measurements: a systematic review. *Gait & posture, 29*(3), 360-369.

Moe-Nilssen, R., & Helbostad, J. L. (2004). Estimation of gait cycle characteristics by trunk accelerometry. *Journal of biomechanics, 37*(1), 121-126.

Moe-Nilssen, R., & Helbostad, J. L. (2005). Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults. *Gait & posture, 21*(2), 164-170.

Mohr, M., Krustrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of Sports Sciences, 21*(7), 519-528. doi:10.1080/0264041031000071182

Moraiti, C., Stergiou, N., Ristanis, S., & Georgoulis, A. (2007). ACL deficiency affects stride-to-stride variability as measured using nonlinear methodology. *Knee Surgery, Sports Traumatology, Arthroscopy, 15*(12), 1406-1413.

Moraiti, C., Stergiou, N., Vasiliadis, H. S., Motsis, E., & Georgoulis, A. (2010). Anterior cruciate ligament reconstruction results in alterations in gait variability. *Gait & posture, 32*(2), 169-175.

Newell, K. M. (2003). Schema Theory (1975): Retrospectives and Prospectives. *Research Quarterly for Exercise and Sport, 74*(4), 383-388. doi:10.1080/02701367.2003.10609108

Orchard, J., Seward, H., & Orchard, J. (2014). *2014 AFL Injury Report*. Retrieved from http://s.afl.com.au/staticfile/AFL%20Tenant/AFL/Files/2014-AFL-Injury-Report.pdf

Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R., & Di Prampero, P. E. (2010). Energy cost and metabolic power in elite soccer: a new match analysis approach. *Med Sci Sports Exerc, 42*(1), 170-178.

Perneger, T. V. (1998). What's wrong with Bonferroni adjustments. *BMJ: British Medical Journal, 316*(7139), 1236.

Picerno, P., Cereatti, A., & Cappozzo, A. (2008). Joint kinematics estimate using wearable inertial and magnetic sensing modules. *Gait & posture, 28*(4), 588-595.

Polglaze, T., Dawson, B., & Peeling, P. (2015). Gold Standard or Fool's Gold? The Efficacy of Displacement Variables as Indicators of Energy Expenditure in Team Sports. *Sports Medicine, 46*(5), 657-670. doi:10.1007/s40279-015-0449-x

Preatoni, E., Hamill, J., Harrison, A. J., Hayes, K., van Emmerik, R. E. A., Wilson, C., & Rodano, R. (2013). Movement variability and skills monitoring in sports. *Sports Biomechanics, 12*(2), 69-92.

Rogalski, B., Dawson, B., Heasman, J., & Gabbett, T. J. (2013). Training and game loads and injury risk in elite Australian footballers. *Journal of Science and Medicine in Sport, 16*(6), 499-503.

Røislien, J., Skare, Ø., Opheim, A., & Rennie, L. (2012). Evaluating the properties of the coefficient of multiple correlation (CMC) for kinematic gait data. *Journal of biomechanics, 45*(11), 2014-2018.

Rueterbories, J., Spaich, E. G., Larsen, B., & Andersen, O. K. (2010). Methods for gait event detection and analysis in ambulatory systems. *Medical engineering & physics, 32*(6), 545-552.

Schmidt, R. A. (2003). Motor schema theory after 27 years: reflections and implications for a new theory. *Research Quarterly for Exercise & Sport, 74*(4), 366-375.

Shmueli, G. (2010). To Explain or to Predict? *Statistical Science, 25*(3), 289-310.

Slawson, S., Justham, L., West, A., Conway, P., Caine, M., & Harrison, R. (2009). Accelerometer profile recognition of swimming strokes (p17). In *The Engineering of Sport 7* (pp. 81-87): Springer.

Soper, C., & Hume, P. A. (2004). Towards an ideal rowing technique for performance. *Sports Medicine, 34*(12), 825-848.

Spencer, M., Bishop, D., Dawson, B., & Goodman, C. (2005). Physiological and Metabolic Responses of Repeated-Sprint Activities: Specific to Field-Based Team Sports. *Sports Medicine, 35*(12), 1025-1044.

Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Human movement science, 30*(5), 869-888.

Stergiou, N., Harbourne, R. T., & Cavanaugh, J. T. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of Neurologic Physical Therapy, 30*(3), 120-129.

Thompson, B. (1993). The Use of Statistical Significance Tests in Research: Bootstrap and Other Alternatives. *The Journal of Experimental Education, 61*(4), 361-377.

Trost, S. G., McIver, K. L., & Pate, R. R. (2005). Conducting accelerometer-based activity assessments in field-based research. *Medicine and science in sports and exercise, 37*(11), S531.

Wixted, A. J., Billing, D., & James, D. A. (2010). Validation of trunk mounted inertial sensors for analysing running biomechanics under field conditions, using synchronously collected foot contact data. *Sports Engineering, 12*(4), 207-212.

Wundersitz, D. W., Gastin, P. B., Richter, C., Robertson, S. J., & Netto, K. J. (2015). Validity of a trunk-mounted accelerometer to assess peak accelerations during walking, jogging and running. *European journal of sport science, 15*(5), 382-390.