Discovering the Movement Sequences of Elite and Junior Elite Netball Athletes

by

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DOCTORATE OF PHILOSOPHY

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ABSTRACT

This thesis investigated the movement sequences of elite and junior-elite female netball athletes using a local positioning system (LPS). Study one determined the indoor validity of an LPS, specifically the Wireless ad hoc System for Positioning (WASP), for measuring distance, velocity and angular velocity whilst sprinting and walking five non-linear courses. The criterion measure used to assess WASP validity was Vicon, a motion analysis system. During all sprinting and walking drills, WASP had an acceptable accuracy for measuring total distance covered (coefficient of variation, CV; < 5.2%). Similarly, WASP had an acceptable accuracy across all sprinting and walking drills for measuring mean velocity (CV; < 6.5%). During all sprinting drills, WASP had acceptable accuracy for measuring mean and peak angular velocity (CV; < 3%). A increased bias was observed during all walking drills, compared to sprinting, likely due to radio-frequency (RF) interference from the metal-clad indoor stadium where validation trials were conducted. Researchers and practitioners may use WASP to accurately quantify the non-linear movement of athletes during indoor court-based sports although should be aware of the increased bias during walking movement.

Spatiotemporal data, obtained by WASP, was analysed for the movement sequences performed during competitive netball matches in study two. Traditional analysis of team-sport athlete match activity typically bins velocities and accelerations into different zones. These zones are discretised using threshold values that are usually based on other research, determined arbitarily or from proprietary software. In study two, *k*-means clustering was used to identify four velocity, three acceleration and four angular velocity clusters from netball athlete spatiotemporal data collected by WASP. The frequently recurring latent patterns of athlete movement across a quarter of netball were identified with sprinting, acceleration and deceleration a common feature.

Study three investigated the movement sequences performed by each of the seven netball playing positions, during competitive matches at the elite level. A total of 10 frequently recurring combinations of movement were discovered with only the wing attack (WA), goal attack (GA) and goal defence (GD) closely related. According to the frequently recurring latent movement sequences performed, the goal shooter (GS) and GD were the least similar netball playing positions at the elite level. Discovering the relative frequency of recurring movement sequences calculates a characteristic signature that differentiates each of the seven netball playing positions. Rather than structuring training around time spent in pre-determined velocity or acceleration zones, the developed movement sequencing technique allows practitioners to focus on training the specific movement patterns performed by each playing position.

Study four investigated the movement sequences performed by elite and junior-elite female netball athletes during competitive matches. A total of 11 frequently recurring combinations of movement were discovered, with the GS and goal keeper (GK) the most closely related netball playing positions across both standards. Pairwise comparisons revealed large differences across playing standards, suggesting that specific physical training may be required for athletes to move up a playing standard. The playing positions of netball, at the elite and junior-elite level, may have individualised training programs to target the specific movement sequences performed. To gain a further understanding of netball athlete movement and to apply the methdoology to spatiotemporal data from other team-sports, more matches should be incorporated to train and test the technique.

The findings of this thesis identify that the WASP can accurately quantify the non-linear movement of athletes indoors. Spatiotemporal data can be analysed for the movement sequences performed by athletes, according to playing position and standard. Junior-elite netball athletes may require specific conditioning to perform the different movement patterns of elite netball athletes.

STUDENT DECLARATION

"I, Alice J. Sweeting, declare that the PhD thesis entitled "Discovering the Movement Sequences of Elite and Junior Elite Netball Athletes" 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: [redacted]

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ABBREVIATIONS

3D	Three-dimensional
AFL	Australian Football League
AIS	Australian Institute of Sport
AU	Arbitrary Units
C	Centre
CO_2	Carbon dioxide
COD	Change of Direction
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CV	Coefficient of Variation
$deg \cdot s^{-1}$	Degrees per second
FFT	Fast Fourier Transform
FFT	Fast Fourier Transform
GA	Goal Attack
GD	Goal Defence
GK	Goal Keeper
GPS	Global Positioning Systems
GS	Goal Shooter
HIR	High Intensity-Running
Hz	Hertz
ICC	Intraclass Correlation Coefficient

LCS	Longest Common Substring
LPS	Local Positioning Systems
$m \cdot min^{-1}$	Metres per minute
$m \cdot s^{-1}$	Metres per second
$m \cdot s^{-2}$	Metres per second squared
MAS	Maximal Aerobic Speed
O_2	Oxygen
RF	Radio Frequency
RMS	Root Mean Squared
SEE	Standard Error of the Estimate
SEM	Standard Error of Measurement
SOM	Self-Organising Maps
TE	Typical Error
TTNC	Trans-Tasman Netball Competition
$\dot{V}O_2$	Maximum Rate of Oxygen Consumption
VT_2	Second Ventilatory Threshold
WA	Wing Attack
WASP	Wireless ad hoc System for Positioning
WD	Wing Defence

PUBLICATIONS

The following work has been presented at scientific meetings and/ or published in peer reviewed journals in support of this thesis:

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2. **Sweeting, A. J.,** Cormack, S. J., Morgan, S., and Aughey, R. J. (2016). The Accuracy of a Radio-Frequency Tracking System for Indoor Court Sports. *Currently being prepared for submission to International Journal of Sports Physiology and Performance.* (Chapter 4)

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PUBLICATIONS ARISING DURING CANDIDATURE

The following work has been presented at scientific meetings and/ or published in peer reviewed journals during candidature but are outside the scope of this thesis:

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3. **Sweeting, A.J.,** Billaut, F., Varley, M.C., Rodriguez, R.F., Hopkins, W.G. and Aughey, R.J. (2017). Variations in Hypoxia Impairs Muscle Oxygenation and Performance during Simulated Team-Sport Running. *Frontiers in Physiology*,*8*.

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CHAPTER 1 – INTRODUCTION

The external load of a team-sport athlete can be captured, via tracking technologies, during competition or training. An athlete's displacement, velocity and acceleration over time, termed activity profile, can then be calculated. Research on the activity profiles of elite team-sport athletes has typically focused on the distance covered or time spent at varying velocities. Threshold values are used to bin these velocities into different categories, each with a qualitative descriptor. However, conjecture exists regarding which thresholds should be used to classify the velocity and acceleration of a team-sport athlete. Multiple threshold values exist, even within a single sport, making the comparison between studies difficult for researchers and practitioners. Threshold values have also been arbitarily determined or as instructed by properitary software from manufacturers of tracking systems. Velocity thresholds have been individualised (Abt & Lovell, 2009) although linear running during physiological tests to exhausation do not account for the energetic cost of accelerated or decelerated running, a feature of team-sport activity (Carling, 2013). Alternatively, sophisticated analytical methods such as data mining may be a useful approach to examine team-sport athlete external load.

Data mining, a subfield of computer science, is a problem-solving methodology that finds a logical or mathematical description of patterns within a data set (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). In elite sport, athletic performance has been examined via data mining techniques including clustering (Ofoghi, Zeleznikow, Dwyer, & Macmahon, 2013a). Clustering is a data mining technique that detects and organises data into groups based on similarity. Clustering was used to group acclerometer derived activity profile data from the seven playing positions of netball (Young, Gastin, Sanders, Mackey, & Dwyer, 2016). Athletes were classified based on their match external load output, which may result in specific training strategies for separate clusters or groups. The position of different body parts has been extracted from wearable sensor data via clustering (Ghasemzadeh, Loseu, & Jafari, 2010). Each velocity and acceleration movement was represented by a sequence of characters. A distance metric was then used to find the similarity between two character sequences (Ghasemzadeh et al., 2010). Human movement from wearable sensors was therefore classified and compared without the requirement of an arbitrary velocity or acceleration threshold. Together, the data mining techniques of clustering and sequence matching present an oppportunity to ascertain the movement of team-sport athletes, without the requirement of arbitrary or physiologically defined thresholds. Information on the movement sequences performed by team-sport athletes, the *how* part of activity profile, is currently missing from the literature. Using data mining techniques, this thesis will develop a method to examine the movement sequences performed by elite team-sport athletes during matches.

Research on team-sport match activity profiles has typically focused on field-based male athletes (Aughey, 2011a). Female athletes are underrepresented in sport research (Costello, Bieuzen, & Bleakley, 2014). There is also limited information on the activity profile of court-based team-sports, including netball. At the elite level, netball matches and training are held indoors. The lack of research on court-based team-sports, including netball, is likely due to limitations in technologies available for this type of analysis. Radio-frequency (RF) tracking systems, orignally deployed for use in underground mines, may have application for indoor sports (Hedley et al., 2010). To date, no study has examined the accuracy of this system, against a criterion, for measuring movement representative of court-based team-sports. This thesis will therefore investigate the accuracy of an RF tracking system for indoor court-based team-sport use. This technology will be used to collect the external load of elite female netball athletes during competitive matches. Using data mining techniques, the frequently recurring movement sequences of netball athletes will be uncovered. These sequences will then be examined according to similarities between the seven netball playing positions and two playing standards, elite versus junior elite. This method derives the latent movement patterns of elite and junior-elite netball athletes. Future application of this methodology, including generalisation to all elite and junior-elite netball athletes, requires testing on a much larger dataset.

CHAPTER 2 - REVIEW OF LITERATURE

2.1 Athlete Tracking Technologies

The movement of a team-sport athlete can be captured during training or matches via athlete tracking technologies including global positioning systems (GPS), local positioning systems (LPS) or optical player tracking systems. These technologies estimate an athlete's position relative to the local coordinates of a playing area. Athlete displacement, velocity and acceleration are then calculated over a specified time epoch. The analysis of these variables is termed activity profile (Aughey, 2011a). Measuring an athlete's activity profile allows for the design of specific training drills (Boyd, Ball, & Aughey, 2013). Activity profiles can also be used to monitor change during a season or tournament (Bradley et al., 2009; Jennings, Cormack, Coutts, & Aughey, 2012a). Whilst extensive research exists on those competing in field-based team-sports (Aughey, 2011a; Jennings et al., 2012a; Mooney et al., 2011), the activity profile of court-based athletes remains largely unknown. This is likely due to limitations in tracking technologies to capture external load in these environments.

Large datasets are collected from athlete tracking technologies, resulting in a multitude of external load analysis techniques (Aughey, 2011a). Due to the variety of technologies and techniques within the literature, the comparison of activity profiles is difficult. A detailed review of the various activity profile analysis techniques is discussed in Chapter Three. An added limitation is the differing validity and reliability of athlete tracking systems used to collect activity profiles. Tracking technologies, and their commercially developed software, are often released with limited information on accuracy and precision (Edgecomb & Norton, 2006). Researchers are therefore required to quantify the validity and reliability of tracking systems before they are used in specific sports. Commercial tracking systems should be independently and scientifically validated before release for use in a practical setting. Quantifying the accuracy and precision of an athlete tracking system allows for meaningful change in activity profile to be measured.

2.1.1 Validity and Reliability of Athlete Tracking Systems

Validity is the ability of equipment to reflect what it is designed to measure (Atkinson & Nevill, 1998). Tracking technologies should accurately quantify an athlete's position plus the resulting displacement, velocity and acceleration when compared to a criterion measure. A variety of criterion measures are used when validating athlete tracking technologies, including pre-defined courses (Coutts & Duffield, 2010; Gray, Jenkins, Andrews, Taaffe, & Glover, 2010). The distance of a pre-defined course is quantified with a measuring tape (Coutts & Duffield, 2010; Frencken, Lemmink, & Delleman, 2010). Cones are typically used to indicate the start, turning point and end of each course although the exact path travelled by an athlete is unable to be quantified. Small but critical deviations in an athlete's position may therefore go undetected. Speed, calculated by the total distance of the pre-measured course divided by the time taken to complete, is used as a comparison measure. Fluctuations in speed are therefore unable to be quantified using this approach. Accurately measuring the fluctuation or range of speeds performed by a team-sport athlete is critical for the analysis of activity profile (Aughey, 2011a). As this cannot be quantified, pre-defined courses are therefore an inadequate criterion measure for validating athlete tracking systems. Criterion measures that can accurately quantify position, displacement and speed should instead be utilised.

Infra-red timing gates, together with pre-defined courses, are often used as a criterion when validating athlete tracking systems (Castellano, Casamichana, Calleja-González, San Román, & Ostojic, 2011; Di Salvo, Collins, McNeill, & Cardinale, 2006; Frencken et al., 2010; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010a). Timing gates are placed at the start, end and evenly distributed throughout a pre-defined course to obtain split times. Although easy to setup, average speed is partly dependent upon the number of timing gates in use. A continuous measure of speed is also unable to be quantified via timing gates. Instead, a system that can accurately quantify instantaneous speed should be used as a criterion measure when validating athlete-tracking systems.

An alternate criterion to timing gates is laser devices. During validity trials, a laser is typically positioned on a tripod and aligned with the centre of a participant's back (Varley, Fairweather, & Aughey, 2012). A narrow beacon of light is omitted and then reflected off the participant, allowing for a nonintrusive continuous measurement of distance and velocity (Harrison, Jensen, & Donoghue, 2005). Compared to video-based systems, laser devices produce valid and reliable estimates of distance and velocity (Harrison et al., 2005). Laser devices also possess a high sample rate, typically > 50 Hz, allowing for the collection of instantaneous velocity (Harrison et al., 2005). Laser was used as a criterion measure to determine the validity and reliability of GPS devices during linear accelerated running (Varley et al., 2012). However, the validity and reliability of laser during non-linear running is currently unknown. If an athlete tracking system is to be valid and reliable at measuring non-linear activity, the criterion should accurately quantify such movements. Laser is therefore extremely limited as a criterion measure for assessing distance covered and instantaneous velocity during non-linear movements.

The current accepted criterion for assessing human movement during linear and non-linear trials is three-dimensional (3D) motion analysis systems, including Vicon (Richards, 1999). These systems consist of multiple, high-resolution cameras that operate at a high sampling rate, usually > 100 Hz (Duffield, Reid, Baker, & Spratford, 2010; Stevens et al., 2014). These high-definition cameras capture a visual record of light-reflective markers that are positioned on anatomical landmarks (Richards, 1999). Multiple frames of these markers are then digitised to calculate position, displacement and velocity. Vicon, a brand of 3D motion analysis systems, has an error range of within one millimeter dependent upon the number plus configuration of cameras, the calibration procedure, marker properties and sampling rate (Windolf, Götzen, &

Morlock, 2008). Vicon was utilised as a criterion for validating athlete tracking systems including GPS (Duffield et al., 2010) and radio-frequency (RF) based LPS (Ogris et al., 2012; Stevens et al., 2014). Whilst LPS measures have been compared with Vicon during soccer-specific courses (Ogris et al., 2012; Stevens et al., 2014), an LPS has not been validated during court-based sport movement. The only criterion to accurately detect non-linear movement, Vicon must be utilised when validating a LPS for court-based sport use.

The statistical analysis used to determine the precision of an athlete tracking system also varies. The standard error of the estimate (SEE), standard error of the measurement (SEM), the correlation coefficient (r) and the Bland-Altman plot are commonly utilised. Pearson's correlation coefficient measures a linear relationship between two variables. Two measures may be highly ($r > 0.80$) correlated however, substantial differences may be present across a range of values (Hopkins, 2004). The Bland-Altman plot was developed to highlight such dissimilarities between measures (Y axis) over their range (X axis) of values. Systematic bias and random error can be observed by the direction and magnitude of scatter around the zero line (Atkinson & Nevill, 1998). The 95% limits of agreement are formed on the plot by bias and random error lines. If a new individual from the proposed population were to be investigated, the difference between any two tests should be within the limits of agreement (Atkinson & Nevill, 1998). However, the plot incorrectly portrays that there are systematic differences or bias in the relationship between two measures (Hopkins, 2004). An alternate approach is linear regression. If bias is present, linear regression contains an equation to correct the raw values (Hopkins, 2004). A transformation for the re-calibration of instrumentation is also provided (Hopkins, 2004). Linear regression should be used to understand the error associated with an athlete tracking technology, when compared to a criterion.

Reliability is the capacity of a measurement tool to provide consistent values (Atkinson & Nevill, 1998). Athlete tracking technologies must be reliable so changes in the external load of individual athletes can be monitored over time. Reliability is calculated over repeated trials and reported as a correlation or the typical error (TE) expressed as a coefficient of variation (CV). Systems that involve the subjective tracking of athletes must report intra- or inter-observer reliability. Intra-observer reliability is the within reproducibility of results for tracking a single match (Carling, Bloomfield, Nelsen, & Reilly, 2008). Inter-observer reliability is the variability of independently measured results as recorded by two or more individuals (Drust, Atkinson, & Reilly, 2007). The following sections will critique the validity and reliability (where applicable) of different tracking systems used to collect the external load of team-sport athletes.

2.1.1.1 Notational Analysis

Notational analysis was the first method of athlete tracking. Human observers subjectively determined individual athlete or team activity during a live match (Knowles & Brooke, 1974). Estimates of distance covered in pre-defined categories, including standing, walking, jogging or sprinting, were recorded by pen and paper. Each activity was recorded in one minute epochs that referred to 4.6 m of distance travelled (Knowles & Brooke, 1974). The frequency, total and relative distance for each coded activity was then calculated (Knowles & Brooke, 1974). Inter-observer reliability for total distance travelled per minute and the number of sprints performed had coefficients of 0.61 and 0.98, respectively (Knowles & Brooke, 1974). Although minimal equipment is required, the displacement plus speed of an athlete is subjectively recorded. Due to this subjective interpretation, the validity of notational analysis has not been reported. For validity to occur, values from notional analysis must be close to the true measurement. Since validity has not been examined, notational analysis is inappropriate for the activity profiling of elite team-sport athletes. A tracking system that can accurately quantify the position plus displacement and speed of team-sport athletes should instead be used.

2.1.1.2 Manual Video Analysis

Filming a match or training allows for footage to be replayed and paused, overcoming the live recall method of notational analysis. Filming or manual video analysis is an inexpensive method of estimating athlete activity (Barris & Button, 2008). Athlete movement during rugby (Duthie, Pyne, & Hooper, 2003), Australian Rules football (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004), soccer (Mohr, Krustrup, & Bangsbo, 2003) and netball (Davidson & Trewartha, 2008; Fox, Spittle, Otago, & Saunders, 2013; Otago, 1983) matches have been estimated via manual video analysis. In netball, broadcast footage was used to estimate elite athlete activity during matches (Otago, 1983). However, only a small number of athletes involved with the ball were analysed, with athletes in a different court area to the broadcast footage excluded. These athletes were assumed to be inactive, due to not being directly involved with the play (Otago, 1983). Despite not being in camera view, team-sport athletes may still perform preliminary movements to create position, move towards the ball or away from opponents (Faude, Koch, & Meyer, 2012). These movements must be captured to ensure the entire external load is analysed. Broadcast footage is therefore extremely limited in capturing the global external load of team-sport athletes and should not be used. A tracking system that can accurately capture the entire external load of all athletes should instead be utilised.

Recognising the limitations of broadcast footage for estimating athlete activity, a team-sport match or training session can be directly filmed by a camera operator. A single camera is used to track and zoom in on individual players (Davidson & Trewartha, 2008). The duration and frequency of athlete activity is then recorded (Barris & Button, 2008). Since multiple cameras and human operators are required, only a limited number of players can be tracked, resulting in a small sample size. Tracking a small number of players during a match does not account for individual variation in playing position or style, important when analysing athlete movement (Carling et al., 2008). As multiple players are unable to be monitored, the use of a single camera to capture the external load of team-sport athletes is ineffective. Single cameras should therefore not be used due to the limitations in capturing an entire team or positional group of players.

An alternative to tracking individual athletes via a single camera is the use of multiple cameras. Each camera is positioned so the entire playing area can be viewed, allowing for a greater number of athletes to be monitored (Spencer et al., 2004). An important consideration is camera positioning since zoom quality, lighting, distance from the playing area and capture angle may impact footage quality (Carling et al., 2008). When a large number of players are clustered together, it may be difficult to determine an individual's identity and position (Barris & Button, 2008). This subsequently impacts upon the quantity and quality of analysis. These limitations are further amplified when matches are held at different venues, resulting in a different camera setup. Although non-intrusive, manual video tracking requires substantial human input for setup and capture, which may introduce error and impact analysis.

The activity of team-sport athletes, obtained via manual video tracking, have been analysed via numerous techniques. The activity of elite soccer players during seven competitive matches was classified into eight locomotor categories (Mohr et al., 2003). Across each match, the frequency, distance covered and time spent in each locomotor activity was estimated by one experienced observer (Mohr et al., 2003). Similar approaches have been conducted in Australian Rules football (Dawson et al., 2004), basketball (Klusemann, Pyne, Hopkins, & Drinkwater, 2013) and netball (Davidson & Trewartha, 2008; Fox et al., 2013). However, there are inconsistencies in the definition and classification of athlete activity, throughout the literature, when using this methodology. This issue is examined further in Chapter Three. Tracking team-sport athletes via manual video analysis requires substantial human input to capture plus categorise movements. Consequently, human error may be introduced at any processing stage. The capacity of a human user to consistently reproduce results is also a major limitation of manual video analysis (Duthie et al., 2003).

Inter- and intra-observer reliability are commonly reported when using manual video analysis. Elite rugby union athletes were individually tracked by a single researcher on two occasions, separated by a one month period (Duthie et al., 2003). The mean duration of time spent in varying locomotor categories was considered moderate (7.1% to 9.3% TEM), concluding that manual video analysis was a reasonably reliable tool. In the repeated analysis of elite netball athlete footage, a substantial agreement was noted within (k = 0.908) and between (k = 0.857) observers (Fox et al., 2013). However, only one playing position across a single quarter was analysed. Human observers have difficulty in classifying high-intensity, short-duration activity (Withers, Maricic, Wasilewski, & Kelly, 1982), movement that is representative of court-based team-sports (Póvoas et al., 2012). Manual video analysis is therefore considerably limited in quantifying the external load of court-based team-sport athletes. Although portable and inexpensive, there is a substantial time demand to setup, collect and post-process data. An added limitation is that validity is rarely established and no criterion exists for the subjective classification of athlete activity. Athlete tracking systems should be validated against a criterion to understand the error of measurement. Considering the substantial limitations in classifying short, high-intensity activity and non-reporting of validity, manual video analysis is a poor method which should not be used to capture team-sport athlete external load.

2.1.1.3 Semi-automated Vision-based Tracking Systems

Semi-automated vision tracking systems were designed to monitor athlete activity without a human needing to manually film. Consequently, the laborious coding associated with manual video analysis is removed. Semi-automatic tracking systems comprise of multiple, fixed cameras positioned around a playing area. Each area is covered by at least two cameras to ensure overlap and improve accuracy. Post collection, all cameras are synchronised before each video is automatically tracked. The post-processing phase comprises of image detection and filtering (Barris & Button, 2008). Athlete position is then predicted relative to the playing area and the continuous trajectories of each athlete are subsequently determined (Di Salvo et al., 2006). Trajectory data is presented in X and Y coordinates relative to a survey point (Di Salvo et al., 2006) or the line markings of a playing area (Wei et al., 2015). Athlete velocity and acceleration can then be calculated.

A range of commercially available semi-automated systems, including ProZone™ (Di Salvo et al., 2006) and Amisco™ (Castellano, Alvarez-Pastor, & Bradley, 2014) can capture and detect the position of multiple team-sport athletes. The validity of Prozone™ for measuring athlete speed was assessed during sprinting and change of direction movement at two outdoor stadiums (Di Salvo et al., 2006). Six recreationally active individuals performed four different courses, including 60 m straight, 50 m angled, 15 m straight and 20 m straight with a 90° turn. Prozone™ speed was compared with infra-red timing gates (Di Salvo et al., 2006). The average speed obtained during 60 m and 50 m sprints was correlated ($r = 0.999$) with timing gate data (Di Salvo et al., 2006). Similarly, maximal sprinting over a 15 m course had a strong ($r = 0.970$) correlation (Di Salvo et al., 2006). However, the criterion measure, infra-red timing gates, produced an average and not a continuous change in speed. As team-sport athletes perform many changes in speed during a match (Varley & Aughey, 2013), a tracking system must be able to accurately detect instantaneous speed. To obtain a true known error, athlete tracking systems must therefore be compared with a criterion measure that provides instantaneous data on displacement and velocity.

Semi-automated tracking systems have been used during indoor, court-based team-sports. Throughout a competitive match, the trajectories of handball athletes were collected by two fixed, overlapping cameras positioned on top of the court (Perš & Kovačič, 2000). Three different algorithms, including motion detection, template and colour tracking, were used to obtain athlete trajectories (Perš & Kovačič, 2000). The motion detection tracking had less noise but involved a substantial input from the human operator, resulting in a slower processing time (Perš & Kovačič, 2000). Combining colour and motion detection tracking resulted in less noise and input from the human supervisor (Perš & Kovačič, 2000). Relying on colour detection algorithms may be problematic if athlete uniforms and the court surface are similar in colour. Variation in colour pixels is required to delineate an athlete and their position on the court (Perš & Kovačič, 2000). Semi-automatic methods may have enhanced validity when compared to manual video tracking although the required specialised equipment is expensive. Tracking is also non-portable as cameras must be installed and calibrated prior to each use. Athlete activity is therefore unable to be captured in stadia without the elaborate setup. Human input, which may introduce error, is still required and the *post-hoc* analysis can be a time consuming process (Barris & Button, 2008). An added limitation of vision-based tracking systems is the capture of athlete movement in an assumed two-dimensional plane. Changes in position from vertical movement including jumping, a feature of court-based team-sports such as netball (Cormack, Smith, Mooney, Young, & O'Brien, 2014), are consequently unable to be quantified. Despite advances from manual vision tracking, semi-automatic methods are expensive, time-consuming and may underestimate some athletic movement. Due to the non-portable setup, semi-automatic tracking is unable to be used across multiple environments. This is extremely unsuitable for teams who may train or compete at numerous venues. The time-intensive post-processing phase is also impractical for teams who have a congested match fixture or compete in tournaments and require a quick turnaround on analysis. Semi-automatic tracking is therefore an extremely limited tool for collecting team-sport athlete external load.

In contrast to video estimates of movement, wearable sensors that directly measure an athlete's external load are portable, less expensive and quick to setup. These devices directly quantify athlete movement, as opposed to estimation from video. Wearable devices, including accelerometers, GPS and LPS, are practical tools to quantify team-sport athlete external load. These systems should be utilised instead of video analysis and semi-automatic detection.

2.1.1.4 Accelerometers

The frequency and magnitude of athletic movement in three dimensions, including the medio-lateral, anterior-posterior and longitudinal planes, can be measured by accelerometers (Boyd et al., 2013). Accelerometers typically sample at 100 Hz and provide a high-resolution measure of the totality of mechanical stress on an athlete (Barrett, Midgley, & Lovell, 2014). Accelerometers are small, often 88 x 50 x 19 mm in size (dependent upon brand) and lightweight (~ 67 g), with an internal battery (Boyd, Ball, & Aughey, 2011). Accelerometers are usually worn in a custom-built vest and located between the athlete's scapulae (Boyd et al., 2013; Cormack, Money, Morgan, & McGuigan, 2012; Walker, McAinch, Sweeting, & Aughey, 2015). The energy expenditure during daily living (Bouten, Koekkoek, Verduin, Kodde, & Janssen, 1997) and sporting activities (Walker et al., 2015) have been estimated from accelerometers.

An accelerometer-derived variable of interest to researchers and practitioners is PlayerLoad™. This is the square root of the sum of the squared instantaneous rate of change of acceleration, derived from three dimensions, divided by 100 (the sample rate) and expressed in arbitrary units (AU). The technical reliability of PlayerLoad™ to measure activity was investigated in a laboratory and field setting (Boyd et al., 2011). The within- (0.91 to 1.05% CV) and between- (1.02 to 1.10% CV) unit laboratory reliability was performed in a mechanical shaker, designed to mimic typical acceleration ranges of Australian Rules athletes (Boyd et al., 2011). In a field setting, between unit reliability (1.90% CV) was assessed by athletes wearing two accelerometers fixed together, to ensure axis alignment, across nine matches (Boyd et al., 2011). The test-retest reliability of PlayerLoad™ has also been examined during a standardised bout of treadmill running (Barrett et al., 2014). When the accelerometer was worn at the scapulae, a moderate to high test-retest reliability (ICC; 0.80 to 0.93, 5.3 to 14.8% CV) was observed across varying treadmill speeds (Barrett et al., 2014). When assessing repeated PlayerLoad™ measures, the same unit should be worn to avoid between-unit bias.

The external load of Australian Rules (Boyd et al., 2013), rugby league (Gabbett, 2015a) and union (Cunniffe, Proctor, Baker, & Davies, 2009) athletes have been captured via accelerometers. Athlete activity during court-based sports, including netball (Cormack et al., 2014; Young et al., 2016), basketball (Montgomery, Pyne, & Minahan, 2010) and handball (Barbero, Granda-Vera, Calleja-González, & Del Coso, 2014), have been captured by accelerometers. In netball, accelerometer derived load can differentiate between competition standard and provide a breakdown of athlete movement in the three planes (Cormack et al., 2014). However, accelerometers do not give the position of the athlete with respect to a playing area. Displacement and velocity therefore cannot be quantified. Measuring athlete displacement allows for the calculation of time spent and distance covered at varying velocities. This information can be used to monitor change within training and matches, across a competitive season or tournament (Bradley et al., 2009; Jennings et al., 2012a). To account for a global profile of external load, displacement and velocity should be examined. For this reason, accelerometers have been incorporated into micro-technology positioning sensors, such as global positioning systems (GPS).

2.1.1.5 Global Positioning Systems

The global positioning system (GPS) comprises a radio signal travelling from a satellite to a receiver on Earth. Position is triangulated when a minimum of four satellites are in communication with the GPS receiver (Aughey, 2011a). Displacement is calculated from changes in GPS position over a specified time epoch. Velocity and acceleration can then be quantified from position. To profile this movement during team-sport matches or training, a GPS unit typically measuring 88 x 50 x 19 mm and weighing 67 g (dependent upon brand and model) is positioned between the scapulae of an athlete and housed in a custom built vest (Aughey, 2011a).

The validity and reliability of GPS during movements representative of team-sport activity is well documented. In elite Australian Rules footballers, the validity and reliability of 1 and 5 Hz GPS was assessed during linear and non-linear courses at varying speeds (Jennings et al., 2010a). Despite the higher sample rate improving validity, GPS accuracy decreased as movement speed increased (Jennings et al., 2010a). Criterion and GPS distance differed by 9% to 32%, although infrared timing gates, used as the criterion measure, could not measure the exact course performed (Jennings et al., 2010a). As timing gates only report mean speed, their usefulness as a criterion measure is severely limited. Instead, criterions that report a continuous measure of speed, such as laser, should be utilised when assessing GPS.

The validity and reliability of instantaneous velocity from 5 and 10 Hz GPS has been assessed against laser (Varley et al., 2012). The higher GPS sampling rate was up to three times more accurate (3.1% to 11.3% CV) during linear running (Varley et al., 2012). During decelerated running, GPS overestimated changes in velocity by up to 19.3% (Varley et al., 2012). Consequently, GPS units are considerably limited in assessing short, high-intensity movements, irrespective of sample rate. Caution should therefore be used when analysing these movements from GPS data.

In confined spaces, where court-based sports are played, GPS is poor in detecting athlete movement. The accuracy of GPS to quantify movement representative of court-based sports was assessed against Vicon, the current accepted criterion for measuring human movement (Duffield et al., 2010). During five movement drills, GPS distance and speed was underestimated by up to 25% (Duffield et al., 2010). For court-based sports, GPS is consequently an unsuitable tool. Despite this, GPS has still been used to quantify athlete external load during outdoor handball (Barbero et al., 2014; Corvino, Tessitore, Minganti, & Sibila, 2014) and netball (Chee Yong, Wylde, Choong, & Lim-Prasad, 2016; Higgins, Naughton, & Burgess, 2009) activity. Considering the poor accuracy of GPS to quantify short, high-intensity movements in confined outdoor spaces (Duffield et al., 2010), these studies should be interpreted with extreme caution. Research on netball activity has also utilised 1 Hz GPS units (Higgins et al., 2009), that have a large (77.2%) CV when measuring short sprint efforts (Jennings et al., 2010a). These units are substantially limited in measuring single sprints or small changes in velocity. Studies utilising 1 Hz GPS units to measure sprint or acceleration efforts should therefore be interpreted with extreme caution.

Elite court-based team-sports, including netball, are held indoors where GPS has no satellite reception. Since GPS is limited to outdoor use and has poor accuracy in quantifying short, high-intensity movements (Duffield et al., 2010), it is a poor tool to quantify athlete external load during court-based team-sports. A tracking system that can operate indoors and is accurate in quantifying short-high intensity movements should instead be utilised.

2.1.1.6 Local Positioning Systems

Local positioning systems (LPS) can measure athlete position indoors. Radio-frequency (RF) is used to communicate the range between LPS mobile nodes, worn by athletes, and anchor nodes that are positioned around a playing area (Hedley et al., 2010). A survey is conducted to obtain the distance between each anchor node and a relative coordinate, for example, the middle of a court. An athlete's position, displacement, velocity and acceleration can then be quantified. Since LPS utilise a portable setup, opposed to the global satellite infrastructure of GPS, athlete tracking can occur outdoors and indoors.

Comparison of LPS validity and reliability is difficult due to methodological differences. A summary of methods used to assess LPS valdity for measuring distance covered, speed and acceleration is presented in Table 2-1.

The accuracy of an LPS, over four soccer-specific courses, was compared to timing gates (Frencken et al., 2010). Distance covered during three non-linear courses, including 45° turn, 90° turn and combined changes of direction, was underestimated (0.6 to 2%) by the LPS (Frencken et al., 2010). An increased course length and turning angle resulted in an increased mean difference between LPS and criterion measures of distance (Frencken et al., 2010). The CV for walking and sprinting speed ranged from 1.4 to 3.9% and absolute mean speed differed by more than 0.4 $km \cdot h^{-1}$ (Frencken et al., 2010). The three individuals who participated in the 30 trials were not elite athletes. Higher velocities and accelerations may be produced by elite athletes during sport-specific courses. If an LPS is to track the movement of elite athletes during matches, it should therefore be validated using a comparable movement profile. Infra-red timing gates do not measure continuous speed (Frencken et al., 2010). Timing gates and pre-defined courses are poor measures to assess the change in speed and position of a participant during a validity trial. Instead a high-resolution motion analysis system that can consistently quantify position (Richards, 1999) should be used as a criterion.

Study	LPS Model	Sample Rate (Hz)	Participants	Movement Task	Repetitions	Criterion	Variable Assessed
Frencken et al., (2010)	Inmotio Object Tracking	45	3 males	Four soccer specific courses	5 walking 5 sprinting	Timing gates	Distance Average speed
Ogris et al., (2012)	LPM, Abatec, Austria	45.45	6 moderately trained males	Straight, 45° and 90° courses 10 small sided games	6 different speeds 3 different constraints	Vicon	Position Speed
Sathyan et al., (2012)	WASP	10	6 elite male and 4 elite female athletes	One linear (I and O) One non-linear (I and O)	1 trial per course n = 160 trials	N/A	Distance Position
Stevens et al., (2014)	Inmotio, version 05.30R	45.45	12 amateur male soccer players	8 movements, including 90° and 180° COD	3 intensities including jog, submaximal and maximal	Vicon	Distance Average speed Peak speed Acceleration

Table 2-1. Summary of the validation studies assessing local positioning systems and their suitability for team-sports.

* I = Indoor, O = Outdoor, COD = Change of Direction.

The accuracy of LPS for measuring position during six different speeds was quantified over linear and non-linear courses (Ogris et al., 2012). Six moderately trained male soccer players performed a total of 276 trials plus 10 small-sided games whilst wearing LPS mobile nodes (Ogris et al., 2012). Vicon motion analysis system was the criterion. The absolute mean error of LPS position estimates was 23.4 ± 20.7 cm during all trials (Ogris et al., 2012). During maximum velocities, there was a mean relative difference of up to 10% or 2.71 $km \cdot h^{-1}$ indicating that the LPS was less accurate in quantifying position during dynamic movements (Ogris et al., 2012). The accuracy of an LPS to capture changes in velocity was investigated during soccer-specific movements (Stevens et al., 2014). Twelve amateur male soccer players performed eight drills, including linear running and 90° or 180° turns. Drills were performed at three movement intensities; jogging, submaximal and maximal running (Stevens et al., 2014). Vicon was the criterion measure for distance, average and peak velocity plus acceleration (Stevens et al., 2014). During 180° turn drills, LPS understimated distance and velocity by up to 7% (Stevens et al., 2014). In the same drill, average acceleration and deceleration were also underestimated by up to 9% (Stevens et al., 2014). During 90° turns, the LPS overestimated average acceleration and deceleration by up to 16%. The greatest difference was during a 90° turn combined with linear running, where peak acceleration was overestimated by up to 41% (Stevens et al., 2014). These large discrepancies were potentially due to the LPS position delayed relative to the participant's actual position. Due to the Kalman filter used, the detection of a sudden acceleration from a standing start is delayed by the LPS. When standing still, the Kalman filter receives no input data of a future movement. When there is a sudden acceleration, the LPS attempts to draw near the actual position and consequently, a higher acceleration is shown than what really occurred (Stevens et al., 2014). The Kalman filtering may potentially explain fluctuations during constant running, with accelerations below 1.5 $m \cdot s^{-2}$ unable to be accurately quantified (Stevens et al., 2014).

Although LPS have been validated during soccer specific movements (Frencken et al., 2010; Stevens et al., 2014), to date, the accuracy of a LPS for measuring movements representative of court-based team-sports is yet to be quantified.

The Wireless ad-hoc System for Positioning (WASP) is an LPS originally developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) for tracking vehicles in underground mines (Hedley et al., 2010). For sport purposes, CSIRO in conjunction with the Australian Institute of Sport (AIS) developed WASP into a suitable hardware for tracking athletes during training and matches. The location of each WASP mobile node, worn by an athlete, is measured relative to a survey position on the playing area. The resulting displacement and velocity can be quantified outdoors and indoors (Sathyan, Shuttleworth, Hedley, & Davids, 2012). Time of arrival (TOA) measurement from WASP is used on the entire 125 MHz bandwith available in the 5.8 GHz frequency band allocated to industry (Hedley et al., 2010). The exchange of transmit and receive time between each node is determined, allowing athletes wearing mobile nodes to be located (Hedley et al., 2010). A Kalman filter is then used to predict position based on a dynamic weighting of previous measurements in combination with the current value (Hedley, Sathyan, & Mackintosh, 2011).

The validity and reliability of WASP for measuring elite athlete indoor position was quantified relative to an outdoor venue (Sathyan et al., 2012). An absolute position error of 11.9 cm was obtained during static indoors measures, compared with 12.1 cm outdoors (Sathyan et al., 2012). During a 28 m linear and 27.6 m non-linear course, WASP had a 2.2% and 2.7% mean distance error, respectively (Sathyan et al., 2012). The non-linear course was an agility test used by the Australian Football League (AFL) to benchmark field-based athletes. Movements representative of indoor court-based team-sports were not examined. The indoor accuracy of WASP should be calculated during movements that are representative of elite court-based team-sports, such as netball. A criterion system has also not been used to validate WASP. The accuracy of

WASP to quantify distance and velocity during short non-linear movements, representative of court-based team-sports, is presented in Chapter Four.

2.1.1.7 Summary

The movement of team-sport athletes can be captured via time-motion analysis (Knowles & Brooke, 1974). Time-motion analysis is a poor tool as athlete displacement plus speed is subjectively recorded. Whilst filming matches or training allows footage of athletes to be replayed or paused, overcoming the live recall method, the validity of time-motion analysis is not reported. Team-sport athlete activity has been analysed from broadcast footage (Otago, 1983), although athletes not in camera view were excluded from analysis. Since athletes may be performing preliminary moves to create position, sprint towards the ball or away from the opposition (Faude et al., 2012), broadcast footage is extremely limited in capturing the global activity of court-based team-sport athletes. Directly filming individual athletes allows for the duration and frequency of locomotor plus game-related activities to be estimated (Barris & Button, 2008). However multiple cameras and human operators are required. Substantial human input is also required to capture and categorise movements. Humans have difficulty in accurately classifying short-duration high-intensity activity, movement representative of court-based team-sports (Barris & Button, 2008). Validity is not established due to the lack of a criterion for the subjective classification of athlete activity. Manual video analysis is therefore an extremely poor method to capture the external load of team-sport athletes.

Semi-automatic tracking was designed to remove the time-intensive coding associated with manual video analysis however, these systems are non-portable and expensive. Tracking athletes at multiple venues is therefore substantially limited. In contrast, wearable sensors are portable, quick to setup and require minimal human input for collection. Accelerometers are wearable sensors that directly measure the load of an athlete in three planes (Boyd et al., 2011). Although accelerometer derived load can differentiate between netball playing standard (Cormack et al., 2014), an athlete's position on the court cannot be quantified. Meausuring an athlete's position, displacement, velocity and acceleration during matches is important for training design and load monitoring (Aughey, 2011a). Athlete position can be quantified during training and matches by GPS. There is extensive research on the activity profiles of field-based team-sport athletes, collected by GPS (Aughey, 2011a). However, limited research exists in court-based sports, likely due to matches and training being held indoors where GPS has no satellite reception. Short, high-intensity movements, representative of court-based sports, are also unable to be accurately quantified by GPS (Duffield et al., 2010). Alternatively, LPS operate indoors and are accurate at measuring athlete position (Sathyan et al., 2012). The activity profiles of athletes participating in court-based sports, such as netball, should therefore be quantified using LPS.

2.2 Netball

Netball is a court-based team-sport with a large participation rate in Commonwealth countries (Steele & Chad, 1991a). The aim of netball is to outscore the opposition by shooting a ball through a ring atop a 3.05 m high pole. Players must pass or shoot the ball within three seconds of catching. Players are only permitted to take one step when in possession of the ball. A defending player must also be at least 0.9 m away from a player holding the ball (The-All-Australia-Netball-Association, 2012). In Australia, elite netball comprises international representation (elite) and state/ territory representation at the junior level (junior-elite).

At the elite and junior-elite level, netball matches consist of 15 minute quarters contested on a 30.5 x 15.25 m indoor court dived into thirds. The substitution of players is only permitted during quarter and half-time breaks or if an injury time-out is called (The-All-Australia-Netball-Association, 2012). Players are assigned one of seven positions, each with a unique role. The main role of the goal shooter (GS) is to score. Goal scoring responsibilities are shared with the goal attack (GA), who assists in feeding the ball into the goal circle. The wing attack (WA) is primarily responsible for delivering the ball to the GS and GA whilst assisting the centre (C). The C must deliver the centre pass and contribute in attack plus defence. The wing defence (WD) is required to defend the opposition WA and support the C in transitioning the ball to the scoring end. The primary task of the goal defence (GD) is to counter the opposition GA's moves and prevent goals from being scored. The GD also assists the goal keeper (GK), whose main role is to stop the opposing GS from scoring.

The court area available for netball athletes to move within is restricted according to their playing position (Figure 2-1). A penalty is awarded if an athlete moves into an area of the court other than that defined by their playing position (The-All-Australia-Netball-Association, 2012). To avoid penalty and maximise their team's ability to score, it is critical that netball athletes remain within their designated court area.

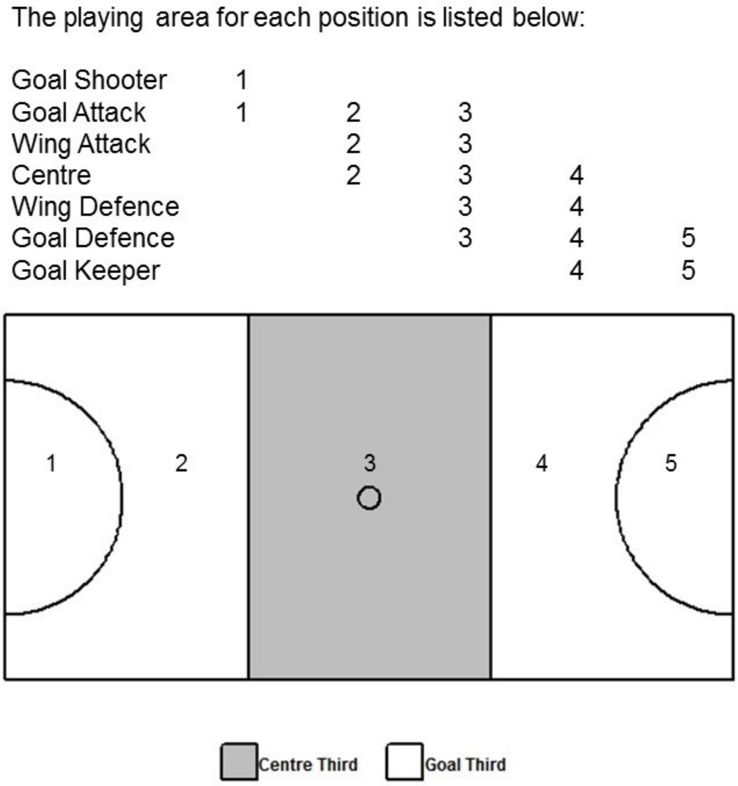

Figure 2-1. Court availability for each netball playing position. Modified from: Association, A. A. N. (2012). *Official Rules of Netball*. Melbourne, Australia: All Australia Netball Association.

During matches, athlete external load may be influenced by a restriction in playing space (Rampinini et al., 2007). This variation in external load must be accounted for between playing positions (Carling, Le Gall, & Dupont, 2012). Analysis on the differences or similarities between positions allows for the prescription of specific training programs for each individual athlete (Boyd et al., 2013). Since playing position determines the court space available, the variation in external load between the seven netball positions may be greater than other court-based team-sports.

2.2.1 Movement Analysis in Netball

The majority of research on the activity profiles of netball athletes utilises television footage or video analysis. Research has typically focused on the number of actions performed and time spent in different movement categories (Otago, 1983; Steele &

Chad, 1991a). Activity during elite netball matches, captured by television footage, was categorised into “sprint”, “shuffle”, “defend” and “jump” movements (Otago, 1983). Most activities were less than 10 seconds in duration, interspersed with at least 30 seconds of recovery (Otago, 1983). Athletes were excluded from analysis if they were not in the broadcast footage on the assumption that no activity was performed when out of camera view (Otago, 1983). Athletes can still be performing activity despite not appearing in ball-centric footage. As highlighted in Chapter 2.1, television footage is an extremely limited athlete tracking tool. Caution should therefore be used when interpreting the results of this study due to the substantial limitations of broadcast footage for assessing athlete movement.

An alternative to television footage is the live capture of team-sport matches. Netball athlete movement was filmed during sub-elite matches and activity was binned into six locomotor categories, modified from other classification systems (Docherty, Wenger, & Neary, 1988; Mayhew & Wenger, 1985). Thirteen non-locomotor activities, including shooting, passing, catching and defending, were also used (Steele & Chad, 1991a). The majority of locomotor movements were brief in duration, ranging from 5.4 seconds for standing to 0.3 seconds for sprinting (Steele & Chad, 1991a). Sprinting, defined as running at maximum speed and full effort, accounted for less than 1% of total match time across all positions. Given the subjective coding of athlete movement by a human operator and the non-reporting of validity, this total percentage of time is likely to be highly innacurate. There was no difference between positions in the number of sprint efforts performed yet only four players per position were analysed (Steele & Chad, 1991a). Each individual athlete should be monitored throughout a match for a complete analysis of athlete external load. Considering the limited positions investigated, restrictions of notational analysis as an athlete tracking tool and the lack of validity, results from this study should be intepreted with caution. Research on the activity profiles of netballers should examine more players per position and not use subjective recall to capture athlete movement.

Video analysis has been used widely in netball research (Davidson & Trewartha, 2008; Fox et al., 2013). During three matches, six athletes in the English Superleague were filmed by four cameras with footage coded *post-hoc* via a computerised analysis system (Sportscode, Australia). Only three positions, including C, GS and GK, were analysed (Davidson & Trewartha, 2008). Activity was classified into six categories including standing, walking, jogging, running, sprinting and shuffling (Davidson & Trewartha, 2008). This study was the first to report the total distances covered by netball athletes in each movement category over a match, with distance predicted by a time and speed equation (Davidson & Trewartha, 2008). Mean speed was measured via electronic timing gates, spread over a 10 m course, during three repetitions of each movement activity. Given the constraints on court area according to playing position, it is unlikely that netball athletes will cover a linear 10 m course at maximum speed during a match. Although a novel approach to estimate distance covered, athlete movement in each category was still subjectively classified by a human user and therefore prone to error (Barris & Button, 2008). A further limitation of notational analysis is the descriptive and arbitrary classifications of movement that vary greatly across studies. For example, the movement of elite netball athletes during three international matches was classified into 13 skill and activity based categories (Fox et al., 2013). Although each court position was examined, the number of categories (13) differed to the 6 used for sub-elite athletes (Davidson & Trewartha, 2008) and 19 for those at the state league level (Steele & Chad, 1991a). International level athletes were up to four times more active, a descriptor based on the combination of all five movement and eight game-based classifications, than their sub-elite counterparts (Steele & Chad, 1991a). This variability is however very likely due to differences in the descriptive estimation of activity, rather than meaningful differences between playing standards. External load should be directly captured by microtechnology sensors to accurately measure external load and remove the error associated with estimations from video.

External load has been quantified in netball via accelerometers (Cormack et al., 2014). Compared to other tracking methodologies used in netball (Davidson & Trewartha, 2008; Otago, 1983; Steele & Chad, 1991a), accelerometers directly quantify movement, including jumping and body contacts, in three planes (Boyd et al., 2013). Accelerometers are also reliable in measuring the external load of team-sport athletes (Boyd et al., 2011). During five matches, accelerometer profile or Load™·min^{-1} (AU), was on average 31% greater in state level compared to recreational level athletes (Cormack et al., 2014). Differences also extended to positions, with a 90% *likely* practical difference between individual positions across playing standards (Cormack et al., 2014). Centres had an 82% *likely* greater match Load™·min^{-1} than defenders at the lower standard of play (Cormack et al., 2014). In contrast, there were no clear differences when comparing other positions within playing standards (Cormack et al., 2014). When transitioning from a lower to higher standard of netball, athletes may need to develop specific physical capacities in order to sustain the increased activity profile associated with a higher standard of play.

The accelerometer load of netball athletes during training and matches has recently been examined in an elite cohort competing within the trans-tasman netball competition or TTNC (Young et al., 2016). There were clear differences in PlayerLoad™ across all seven playing positions. The C, WD, WA and GA positions had the highest playing intensity and the lowest proportion of match time in the low intensity zone (Young et al., 2016). In contrast, the GS, GK and GD spent the highest proprotion of match time in the low intensity zone (Young et al., 2016). A unique feature of this study was the use of *k*-means clustering to uncover similarities in PlayerLoad™ between each playing position (Young et al., 2016). Unknown patterns and classifications within a dataset can be discovered using *k*-means clustering, a data mining technique. Unfortunately, only one playing group was investigated with little generalisation to other standards of play. Whilst accelerometers provide detail on the global load of an athlete, including movement in all three planes, the position of a player relative to a court and team-members or opposing players is unknown. Information on an athlete's position with respect to their direct opponent may provide coaching staff a unique opportunity to further explore the influence of match tactics on athlete output. Athlete positional data, obtained from an LPS, may allow for displacement, velocity and acceleration to be calculated in netball.

Limited research exists on the activity profile of elite netball athletes, with no information on the external load of junior-elite players. It is difficult to compare studies on netball athlete activity profiles due to differences in match duration, with research on games comprising 20 minute halves (Steele & Chad, 1991a) compared to 15 minute quarters (Fox et al., 2013). Only three standards of play have been investigated and a variety of techology utilised including broadcast television footage (Otago, 1983), video analysis (Davidson & Trewartha, 2008; Fox et al., 2013) and accelerometers (Cormack et al., 2014). The categories of movement used to analyse activity also make for a complex comparison. No information exists on how to approporiately classify athlete external load in court-based team-sports, including netball. The subsequent analysis of activity profile is therefore difficult.

There are a range of velocity and accelerations thresholds, even within a single sport, by which to categorise athlete movement. Thresholds have been determined from physiological tests, examined in Chapter Three, although it is currently unclear if these tests reflect the accelerations within team-sport activity. No research has examined the external load of court-based athletes using a physiologically defined threshold. Alternatively, data mining and knowledge discovery is an approach to derive patterns from large datasets without the use of thresholds. Data mining could gain further insight into team-sport athlete activity profiles. Consequently, athlete external load could be analysed without the requirement of an arbitrary or physiologically defined threshold. Data mining techniques will therefore be used in this thesis to examine netball athlete load across playing position and standard, without the requirement of velocity and acceleration thresholds.

CHAPTER 3 – A REVIEW OF THE ANALYSIS OF TEAM-SPORT ATHLETE ACTIVITY PROFILE

3.1 Introduction

Team-sport athlete external load can be quantified using accelerometers, global positioning systems (GPS), local positioning systems (LPS) and optical tracking systems. Except for accelerometers, these systems calculate displacement, velocity and acceleration over time. The analysis of external load over a match or training session is termed activity profile (Aughey, 2011a). Information from the activity profile is used to monitor change across a competitive season or tournament (Bradley et al., 2009; Jennings et al., 2012a) and allow for the design of specific training drills (Boyd et al., 2013).

The activity profile of field-based team-sport athletes is well-documented (Aughey, 2011a; Bradley et al., 2013; Jennings, Cormack, Coutts, & Aughey, 2012b; Mooney et al., 2011). Activity profile analysis typically includes time spent in velocity or acceleration zones. These zones are defined according to threshold values and determined arbitarily, by the properitary software of tracking systems or expressed relative to a physiological test. Currently, there is no consensus on how to determine a velocity or acceleration threshold. Large discrepancies exist in the classification of a sprint effort. The comparison of activity profiles across and within team-sports is consequently difficult.

This chapter describes the velocity and acceleration thresholds used to analyse team-sport athlete external load. Applying a global velocity or acceleration threshold may allow for the examination of positional and individual differences over time. Whilst thresholds can be individualised, physiological tests comprising continuous or linear movement do not reflect changes of direction and acceleration. The current techniques used to analyse external load are therefore inappropriate. Alternate methods, including unsupervised data mining techniques, are considered. These techniques find trends within external data and may be useful in informing thresholds.

3.2 Distance Covered

A common athlete activity profile measure is the total distance covered. English Premier League athletes cover an average of 10,714 m during matches (Bradley et al., 2009), less than One Day International (ODI) cricketers at 15,903 m per match (Petersen, Pyne, Portus, Karppinen, & Dawson, 2009). Elite Australian footballers may record total distances of up to 12,939 m (Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010). The total distance covered during matches varies across athlete age (Buchheit, Mendez-Villanueva, Simpson, & Bourdon, 2010a), position and competition level (Jennings et al., 2012b). When total distance covered is expressed per minute of match duration, soccer athletes may cover 104 $m \cdot min^{-1}$ (Varley, Gabbett, & Aughey, 2013b) and up to 130 $m \cdot min^{-1}$ (Carling, Espié, Le Gall, Bloomfield, & Jullien, 2010). In soccer, the metres per minute of match duration varies across athlete age and playing position (Buchheit et al., 2010a). Australian footballers may average between 127 $m \cdot min^{-1}$ (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015b) and 157 $m \cdot min^{-1}$ (Aughey, 2011b), whilst elite rugby league players may cover 97 $m \cdot min^{-1}$ (Varley et al., 2013b) and up to 120 $m \cdot min^{-1}$ (Austin & Kelly, 2013). Sport-specific constraints, including positional or tactical roles, may contribute to these differences. The higher total distance in Australian football may be attributed to the unlimited interchange policy (removed in 2015), and the smaller field size available to soccer and rugby league athletes (Varley et al., 2013b). The total distance covered should be presented per minute of match duration or time spent on field/ in a training drill (Aughey, 2011a).

Court-based athletes have a smaller playing area compared to their field-based counterparts, yet cover similar metres per minute. There is limited activity profile research on court-based athletes. State-level female basketballers cover 127 to 136 $m \cdot min^{-1}$ during matches (Scanlan, Dascombe, Reaburn, & Dalbo, 2012), higher than junior males (115 $m \cdot min^{-1}$) and similar to state- (126 to 132 $m \cdot min^{-1}$) and national (130 to 133 $m \cdot min^{-1}$) male basketballers (Scanlan, Dascombe, & Reaburn, 2011). In semi-elite netball, centre (C) athletes cover up to 133 $m \cdot min^{-1}$ compared to goal keepers (GK) and goal shooters (GS), who average 71 $m \cdot min^{-1}$ and 70 $m \cdot min^{-1}$, respectively (Davidson & Trewartha, 2008). These differences could be due to the spatial restrictions imposed by each playing position although manually estimating distance covered from video may also provide unreliable estimates (Barris & Button, 2008).

In court-based sports, the ball may frequently and chaotically change direction. Court-based athletes must be responsive to movement of the ball, their team-mates and opposition in a small area. Athletes may change direction and complete short, high-intensity movements to cover or create space. Although there are more spatial limitations compared to field-based sports, the high frequency of these actions performed by court-based athletes may result in a comparable metres per minute profile. Whilst reporting metres per minute gives an understanding of intensity, granular periods of activity at different velocities are lost by aggregating to the total distance covered. Quantifying the time spent and distance covered at varying velocities may be useful in programming training and monitoring load.

3.3 Velocity Thresholds

During matches or training, the instantaenous velocity of an athlete is binned into different zones via threshold values. Velocity thresholds are defined by proprietary software providers (Cunniffe et al., 2009), modified from published research (Jennings et al., 2012a) or determined arbitrarily (Mohr et al., 2003). There is no consensus on how to determine a velocity threshold and large discrepancies exist, even within a single team-sport (Table 3-1). The comparison of activity profile research is consequently difficult.

Reference	Cohort	Zone 1		Zone 2		Zone 3		Zone 4		Zone 5		Zone 6	
		Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor
Rugby Union													
Clarke et al. (2014)	Elite females	< 2	Low	> 3.5	Moderate					> 5	High-intensity		
Suárez-Arrones et al. (2012)	Elite males	0.03 to 1.64	Standing and walking	1.66 to 3.31	Jogging	3.33 to 3.86	Cruising	3.89 to 4.98	Striding	5 to 5.53	High-intensity	> 5.56	Sprinting
Combined – Soccer, rugby league and Australian football													
Varley et al. (2013b)	Elite males	0 to 5.4	Low-intensity							≥ 5.5 to 10	High-velocity	≥ 7 to 10	Sprinting
Australian Rules football													
Sullivan et al. (2013)	Elite males									> 4	High-speed		
Aughey et al. (2010)	Elite males	0.10 to 4.17	Low-intensity							4.17 to 10	High-intensity		

Table 3-1. Classification of athlete movement, according to speed zones, in a variety of field-based team-sports.

Reference	Cohort	Zone 1		Zone 2		Zone 3		Zone 4		Zone 5		Zone 6	
		Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor	Speed ($m \cdot s^{-1}$)	Descriptor
Hockey													
Jennings et al. (2012a)	Elite males	0.10 to 4.17	Low-speed							> 4.17	High-speed		
Macutkiewicz et al. (2011)	Elite females	0 to 0.17	Standing	0.19 to 1.67	Walking	1.69 to 3.06	Jogging	3.08 to 4.17	Running	4.19 to 5.28	Fast-running	> 5.28	Sprinting
Rugby League													
Johnston et al. (2013)	Sub-elite males	0 to 4.72	Low-speed							> 4.75	High-speed		
Kempton et al. (2015a)	Elite males							> 4	High-speed	> 5.03	Very high-speed	> 6.67	Sprinting
Soccer													
Buchheit et al. (2010a)	Youth males	< 3.61	Low-intensity					3.64 to 4.44	High-intensity	4.47 to 5.28	Very high	> 5.31	Sprinting
Carling et al. (2012)	Elite males	< 0.17	Standing	1.94 to 1.97	Walking	2 to 3.97	Jogging	4 to 5.47	Running	> 5.5	High-intensity		

Table 3-1 (continued). Classification of athlete movement, according to speed zones, in a variety of field-based team-sports.

The inconsistency between velocity thresholds extends to qualitative descriptors. For example, activity may be labeled as low-velocity or low-intensity movement. Low-velocity movement, including walking and jogging, could be activity between 0 and up to 5.40 $m \cdot s^{-1}$ (Varley et al., 2013b). Yet in the same sport, activity > 4.00 $m \cdot s^{-1}$ was classed as high-speed running (Sullivan et al., 2013). The classification of high-velocity or high-intensity movement is also without consistent definition. The varying definitions make for a difficult comparison between studies. In Australian football, sprint efforts have been defined as activity > 4.00 $m \cdot s^{-1}$ (Sullivan et al., 2013) while a threshold of > 4.17 $m \cdot s^{-1}$ has also been utilised (Aughey, 2010; Mooney et al., 2011). The presentation of thresholds as a single > or < value, with ambiguous descriptors, is confusing when velocity data falls between two thresholds. For example, running by professional soccer athletes is described as velocities between 4.00 to 5.47 $m \cdot s^{-1}$ whilst activity > 5.50 $m \cdot s^{-1}$ was considered high-intensity movement (Carling et al., 2012). It is unclear if velocities within the 0.03 $m \cdot s^{-1}$ upper and lower ranges of the two classifications were removed from analysis. Deletion of these values may influence the frequencies and durations reported. Research describing thresholds in this manner should detail how instantaenous velocities are binned into different zones. If researchers use discrete values, it is recommended that thresholds be presented as ≥ or ≤ values.

The confusion in velocity thresholds also extends to the duration of a sprint. In elite female rugby union (Clarke et al., 2014), hockey (Vescovi, 2014) and professional male soccer (Carling et al., 2012) matches, sprinting must occur for a minimum of one second. However, in other studies (Buchheit et al., 2010a; Jennings et al., 2012a; Kempton et al., 2015b; Varley et al., 2013b), the minimum duration is not stated. It is unclear what effect these inconsistent minimum threshold durations have on the activity profile. Researchers should state the minimum duration required to record a sprint effort. The inconsistency of sprint thresholds in the literature is likely due to values being arbitrarily determined or taken from proprietary software.

3.4 Acceleration Thresholds

Acceleration is a metabolically demanding activity, requiring more energy than constant running (Osgnach, Poser, Bernardini, Rinaldo, & Di Prampero, 2010). During team-sport matches, a large number of high intensity efforts are short in duration and commence from a low velocity. In elite soccer matches, more than 85% of maximal accelerations did not exceed the high-speed (4.17 $m \cdot s^{-1}$) threshold (Varley & Aughey, 2013). Maximal accelerations (> 2.78 $m \cdot s^{-2}$) occurred eight times more than sprinting, classified as > 6.94 $m \cdot s^{-1}$ but < 10.00 $m \cdot s^{-1}$ (Varley & Aughey, 2013). The starting velocity is critical when measuring accelerations or decelerations, although quantification of these variables is dependent upon the validity and reliability of athlete tracking systems.

Large variations exist in GPS estimates of accelerations and decelerations, between models and units from the same manufacturer (Buchheit et al., 2014). During simultaneous capture of a sled dragging exercise, small to very large between-model and unit differences were observed in 15 Hz GPS units (Buchheit et al., 2014). These units were manufactured with a 10 Hz GPS but upsampled to 15 Hz (Aughey, 2011a). In 10 Hz GPS, acceleration and deceleration movements have a large between-unit coefficient of variation (CV) of 31% to 56% (Varley et al., 2012). A variety of factors may influence GPS measures of acceleration and velocity. The accuracy of GPS to measure instantaneous velocity is limited by unit processing speed, location, antenna volume and chipset capacity. Quantification of instantaneous velocity is up to three times more accurate in 10 Hz GPS units compared to 5 Hz (Varley et al., 2012). When measuring acceleration and deceleration, 10 Hz units still differ by ~10% when compared to a laser device (Varley et al., 2012). However, laser devices are limited to quantifying instantaneous velocity during linear movement only. In contrast, high-resolution motion analysis systems including Vicon, can accurately detect instantaneous velocity during non-linear activity (Richards, 1999). Local position systems (LPS) sample at up to 1000 Hz with generally superior accuracy compared to GPS (Stevens et al., 2014). During varying speed and change of direction movement, the average acceleration and deceleration derived from LPS was within 2% of Vicon (Stevens et al., 2014). Although accuracy for peak acceleration and deceleration is limited, LPS can measure average change in velocity or time spent in various acceleration thresholds.

There are large inconsistencies between acceleration thresholds used throughout the literature. In field-based team-sports, accelerations have been classified as > 1.11 $m \cdot s^{-2}$ (Wisbey, Montgomery, Pyne, & Rattray, 2010), 2.78 $m \cdot s^{-2}$ (Varley, Gabbett, & Aughey, 2013a), 3.00 $m \cdot s^{-2}$ (Hodgson, Akenhead, & Thomas, 2014) and 4.00 $m \cdot s^{-2}$ (Farrow, Pyne, & Gabbett, 2008). Accelerations have also been categorised into moderate (2.00 to 4.00 $m \cdot s^{-2}$) or high (> 4.00 $m \cdot s^{-2}$) zones, with a minimum duration of 0.40 s (Higham, Pyne, Anson, & Eddy, 2012). The rationale used to select these zones is unknown. The 2.78 $m \cdot s^{-2}$ threshold used in soccer (Varley & Aughey, 2013) and Australian Football (Aughey, 2010) originated from a standing start maximal acceleration of between 2.50 and 2.70 $m \cdot s^{-2}$, performed by non-athletes (Varley et al., 2012). Since elite Australian Football athletes often maximally accelerate from a moving start during matches (Aughey & Falloon, 2008), a 4.00 $m \cdot s^{-2}$ threshold was considered too high and 1.11 $m \cdot s^{-2}$ too low (Aughey, 2010). It appears the threshold of 2.78 $m \cdot s^{-2}$ was determined arbitrarily (Aughey, 2010). Acceleration thresholds of 1.50 $m \cdot s^{-2}$, 3.00 $m \cdot s^{-2}$ and 4.00 $m \cdot s^{-2}$ have been used in a single study (Buchheit et al., 2014). Specifying thresholds in this manner has implications for quantifying activity profile and monitoring change over time, particularly when large variations in the measurement of acceleration are common between GPS models from the same manufacturer (Buchheit et al., 2014).

The velocity distribution of elite field-based team-sport athletes was used to create sport-specific threshold values (Dwyer & Gabbett, 2012). Match data from five elite female and male soccer, hockey and professional male Australian Football athletes were collected from GPS sampling at 1 Hz (Dwyer & Gabbett, 2012). A frequency distribution of speed (0 to 7 m·s-1) in 0.1 $m \cdot s^{-1}$ increments was computed from the 25 data sets and an average distribution calculated (Dwyer & Gabbett, 2012). Four normally distributed Gaussian curves were then fitted to the averaged velocity distribution curves and the intersecting points used to determine thresholds for each sport (Dwyer & Gabbett, 2012). A frequency distribution of acceleration from each data set was calculated and a threshold was based on the highest 5% of accelerations performed (Dwyer & Gabbett, 2012). This threshold was then calculated for each pre-determined velocity range and used to identify sprints (Dwyer & Gabbett, 2012). The average velocity distribution for all field-based team-sports was similar. Differences between sexes from the same sport were larger than differences across sports (Dwyer & Gabbett, 2012). Six additional sprints, of a short duration, would not have been recorded using the traditional threshold (Dwyer & Gabbett, 2012). While the decision to include five movement categories comprising standing, walking, jogging, running and sprinting, appear to have been arbitrarily determined, this is a novel idea compared to the traditional analysis of athlete velocity. This approach was utilised to profile the activity of national level lacrosse (Polley, Cormack, Gabbett, & Polglaze, 2015) and youth female field hockey (Vescovi, 2014) athletes. However, the 1 Hz GPS units used have a very large (77.2%) CV when measuring short sprint efforts (Jennings et al., 2010a). Consequently, data obtained from 1 Hz GPS during these movements, and the results presented, should be interpreted with extreme caution. The small sample size is also limited in detecting meaningful change across and between sports. Decelerations or negative changes in velocity were also removed from the analysis, likely due to the poor capacity of GPS to accurately quantify these movements (Buchheit et al., 2014).

The ability to reduce velocity is termed deceleration. An athlete's capacity to efficiently decelerate is important for changing direction (Kovacs, Roetert, & Ellenbecker, 2008). The major components of deceleration include dynamic balance, power, reactive and eccentric strength (Kovacs et al., 2008). In elite team-sport athletes, the substantial eccentric loading during repeated decelerations is likely to have a detrimental effect on subsequent 40 m sprint test performance (Lakomy & Haydon, 2004). In collegiate team-sport athletes, muscle damage was induced post 15 x 30 m repeated sprints with a rapid deceleration, interspersed with 60 seconds of passive recovery (Howatson & Milak, 2009). Increased muscle soreness, swelling, creatine kinase efflux and decreased maximum isometric contract was also observed 48 to 72 hours post (Howatson & Milak, 2009). Collectively, these results demonstrate the magnitude of muscle and performance damage when team-sport athletes perform repeated deceleration efforts.

Investigation into the decelerations of team-sport athletes during matches is limited. In elite male rugby sevens matches, decelerations were classified as moderate (-4.00 to -2.00 $m \cdot s^{-2}$) or high (> -4.00 $m \cdot s^{-2}$) and occurred for a minimum of 0.40 s (Higham et al., 2012). It is unclear why these zones were chosen. A 35% and 25% difference in moderate and high decelerations, respectively, existed between standards of play (Higham et al., 2012). The large error of 5 Hz GPS to accurately quantify these movements may account for the difference between playing levels. The deceleration of professional rugby league athletes were investigated during two competitive seasons (Delaney et al., 2015). Differences in the maximum value recorded over a rolling average, from one to ten minutes in duration, was compared across playing positions (Delaney et al., 2015). Compared with a 10 minute rolling average, a large effect was observed for acceleration and decelerations of one to two minutes. A moderate to small effect for three to seven minute duration was also recorded (Delaney et al., 2015). While this approach presents the maximum load of an athlete over varying durations, all acceleration and deceleration measures were modified to estimate the total number of accelerations performed (Delaney et al., 2015). This approach could be misleading as energetically, the ability to accelerate and decelerate is different. Using this approach, the specific training prescription of deceleration is consequently limited.

The deceleration output of court-based team-sport athletes remains largely unknown. Decelerations, and their distribution over varying epochs, should be included in the activity profiles of court-based team-sport athletes. The inconsistency previously described in defining velocity thresholds is also evident in research on decelerations. There is currently no consensus on how to define acceleration or deceleration thresholds. While presenting the acceleration frequency of team-sport athletes provides a global representation of high-intensity movements, limited research exists on the individualisation of acceleration thresholds. The classification of accelerations is also dependent upon the sampling epoch utilised, which may alter the magnitude of frequencies reported.

3.5 Filtering of Data

Athlete tracking data may be filtered during the post-processing phase. Filtering involves the smoothing of position and reduction of noise using various mathematical algorithms (Carling et al., 2008). Noise can be removed by numerous techniques, each with different results. Curve fitting involves a low-order polynomial curve fitted to raw trajectory data. Although this technique is best for repetitive movements including jumping, error may be introduced through poor selection of specific points that the curve is fitted to (Winter, 2009). These points are determined from the raw data and consequently, are influenced by the very noise the filter is trying to eliminate (Winter, 2009). Bandpass filtering converts raw data from the spatial to the time domain, typically using a Fast Fourier Transform (FFT). High-frequency signal, uncharacterise of normal human movement, is eliminated before data is converted back into the spatial domain through an inverse FFT (Wundersitz, Gastin, Robertson, Davey, & Netto, 2015a). However, the threshold used as the optimal cut-off frequency is arbitrary and typically chosen via visual inspection (Wundersitz et al., 2015a). Digital filtering analyses the frequency spectrum of both signal and noise. The signal typically occupies the lower end of a frequency spectrum and overlaps with the noise, which is typically observed at a higher frequency (Winter, 2009). A low-pass filter permits the lower frequency signals while consequently reducing the higher frequency noise. Low-pass filtering can be used when analysing trajectory data (Winter, 2009).

The filtering of athlete external load data is dependent upon the tracking system utilised. Filtering may occur on raw positional data at the instruction of the tracking system manufacturer (Stevens et al., 2014). Derived measures, including metabolic power from GPS (Di Prampero et al., 2005; Osgnach et al., 2010) are also filtered at unspecified frequencies during the post-processing stage. Butterworth (Stevens et al., 2014) and Kalman (Sathyan et al., 2012) filters are typically used for LPS data. There is limited information on how filters are used in optical player tracking systems and GPS. Filtering may account for the 24% difference in sprint distance between real-time and post-match Australian football GPS data (Aughey & Falloon, 2010) although no detail was presented on how the manufacturer explains these discrepancies. It is important to know how the manufacturer of an athlete tracking system filters raw data, particularly when inferences from external load are used to make decisions on programming training (Borresen & Lambert, 2009; Rogalski, Dawson, Heasman, & Gabbett, 2013). The filtering of accelerometer data has recently been examined (Boyd et al., 2011). Only one of the 13 filters was strongly related (mean bias; -0.01 ± 0.27 g; CV 5.5%) to the criterion measure, Vicon (Wundersitz et al., 2015a). Information on filtering is rarely presented from GPS or LPS data when time spent or distance covered in velocity bands are reported. The filtering of raw data from an athlete tracking system has a substantial impact on the frequencies and distances covered in velocity or acceleration zones. Prior to reporting team-sport athlete activity profiles, researchers should detail the type of filtering applied to raw data.

3.6 Individualised Thresholds

Activity profile data reported as an average across a team (Aughey, 2011b) or position (Mooney et al., 2011; Varley & Aughey, 2013) does not account for differences in individual physical capacity. The use of a single sprinting or high-velocity threshold, for all athletes within a team, also does not consider the differences between individual athletes. Although team-sport matches are contested at an absolute level, the same external load calculated by a high-velocity or sprinting threshold, for two athletes could represent a different internal load based on individual characteristics (Impellizzeri, Rampinini, Coutts, Sassi, & Marcora, 2004). Athlete movement may be expressed relative to a physiologically defined variable. High-intensity activity can be classified as greater than the second ventilatory threshold (VT_2), obtained during a maximal aerobic capacity ($\dot{V}O_{2max}$) test. The VT_2 is the point where CO_2 production exceeds O_2 consumption during exercise (Davis, 1985). It is assumed that activity beyond this point cannot be sustained for prolonged periods due to the athlete no longer being in a steady state (Davis, 1985). During team-sport matches, activity below the VT_2 can likely be continued for a prolonged duration. In male soccer athletes, distance covered at or greater than vVT_2 was 167% higher or a *very large* effect when compared to a threshold of 5.50 $m{\cdot}s^{-1}$ (Abt & Lovell, 2009). A 44% variation in athlete rank, calculated by distance covered at high-speed, was observed between the two thresholds (Abt & Lovell, 2009). Individual VT_2 has also been measured in professional soccer athletes (Lovell & Abt, 2012). The resulting vVT_2 was compared to an arbitrary velocity (4.00 $m{\cdot}s^{-1}$) threshold (Lovell & Abt, 2012). High-speed running distance was overestimated by 9% when arbitrary thresholds were used (Lovell & Abt, 2012). For individual athletes, this range could be between 22% lower and 33% higher (Lovell & Abt, 2012). In elite female rugby sevens athletes, a physiologically-defined threshold corresponding to treadmill speed at VT_2 was compared to a cohort average (3.50 $m{\cdot}s^{-1}$) value (Clarke et al., 2014). When individualised thresholds were used, high-intensity running was up to 14% over or under-estimated compared to the cohort mean VT_2 derived threshold (Clarke et al., 2014). Distance covered at high-speed may therefore be underestimated by traditional thresholds.

While the individualisation of velocity thresholds is a well-reasoned approach to assess external load, conjecture exists on the implementation of an incremental treadmill protocol, conducted within a laboratory, and its application to team-sports. The individualisation of velocity thresholds, derived from a continuous running protocol, does not consider the change of direction and acceleration movements, frequent in team-sports (Lovell & Abt, 2012). Whilst speed thresholds have been individualised in field-based team-sports (Abt & Lovell, 2009; Clarke et al., 2014; Lovell & Abt, 2012), limited research exists on court-based team-sports.

Athlete thresholds for external load can be expressed relative to maximum speed attained during sprint testing. The external load of junior-elite male soccer athletes was compared using absolute (> 5.27 $m \cdot s^{-1}$) or individual thresholds by obtaining the peak running velocity during the fastest 10 m split of a 40 m sprint (Buchheit, Mendez-villanueva, Simpson, & Bourdon, 2010b). Athletes in the highest playing standard (U18 years of age) performed more repeated-sprint efforts when activity was assessed using absolute thresholds (Buchheit et al., 2010b). Younger players (U13 and U14 years of age) recorded more sprinting activity with individualised thresholds (Buchheit et al., 2010b). In junior male rugby league athletes, when an individualised threshold of peak velocity obtained during the final 20 m of a 40 m sprint test was compared with absolute speed (> 5.00 $m \cdot s^{-1}$) thresholds, younger athletes (U13) performed *likely* (effect size = 0.43 to 0.58) greater high-speed running compared to their older (U14 and U15 years of age) counterparts (Gabbett, 2015b). The total high-intensity running performed by junior athletes may be altered when expressed relative to a movement threshold obtained during maximal sprinting (Buchheit et al., 2010b; Gabbett, 2015b). Inconsistencies therefore exist in the recorded sprinting distance according to the velocity threshold used.

Expressing a team-sport athlete's data relative to a physiologically defined threshold is an individualised approach that may benefit the training prescription for players.

Although an advancement on the use of arbitrarily derived velocity thresholds, limited research exists on how to individualise accelerations. Accelerations require more energy than constant velocity. Without information on how to classify accelerations, individualised thresholds are therefore limited in their use for team-sport athletes, including those who participate in court-based sports.

3.7 Relationship of High-Intensity Activity to Match Performance

The capacity to accelerate and sprint is important for team-sport match performance. In junior-elite Australian Football, athletes faster over a 5 m and 20 m split acquired the most kicks and disposals during matches, compared with their slower counterparts (Young & Pryor, 2007). During elite matches, a relationship exists between athlete physical capacity and the number of disposals. This relationship is mediated by the amount of high intensity-running (HIR) $m \cdot min^{-1}$ or distance travelled at > 4.17 $m \cdot s^{-1}$ (Mooney et al., 2011). Sophisticated modelling techniques may therefore be able examine the effect of contextual and match-related factors on team-sport athlete running intensity.

The relationship between physical capacity and match performance in professional soccer was examined across three top English leagues (Bradley et al., 2013). Total distance covered and HIR > 5.50 $m \cdot s^{-1}$ was captured via semi-automatic tracking (Bradley et al., 2013). Less total and HIR distance occurred at a higher than a lower playing standard. Physical capacity, defined as score on the Yo-Yo intermittent recovery two (IR2) test, was correlated with HIR distance (Bradley et al., 2013). In junior-elite male soccer athletes, the relationship between external load, defined as movement > 4.47 $m \cdot s^{-1}$ and physical capacity, quantified as score on the Yo-Yo IR1, was position dependent. Poor correlations were observed between match running performance and athlete physical capacity in all positions except strikers. However, the 1 Hz GPS units used have poor validity (CV% of 11 to 30%) for assessing HIR (Coutts & Duffield, 2010). To truly quantify the relationship between athlete match external load and physical capacity, tracking technologies that are accurate at detecting movement within a range of intensities should also be used. Although the relationship between match outcomes, athlete performance and external load have been examined, research has applied a mean velocity threshold to all athletes within a team. The justification for these thresholds is typically based on other literature or arbitarily determined. Individualising velocity thresholds may allow for a detailed analysis of the relationship between athlete external load and match outcome, although physiologically defined thresholds are limited in their application for defining accelerations. The majority of research on the relationship between athlete performance and external load has focused on males competing in team-sports, with limited information on female athletes.

3.8 Thresholds for Male and Female Team-Sport Athletes

Men and women compete in team-sports at an elite level. Tracking technologies, including GPS, are used to collect the activity profiles of male and female team-sport athletes (Dwyer & Gabbett, 2012; Gabbett & Mulvey, 2008; Vescovi, 2014). There are differences in physiological capacities between sexes, including aerobic fitness and absolute sprinting ability (Mujika, Santisteban, Impellizzeri, & Castagna, 2009). Consequently, the physiological cost of high-speed running may be substantially different for male and female team-sport athletes. Although lower speed thresholds are suggested for female team-sport athletes (Dwyer & Gabbett, 2012), limited research exists on the application of these thresholds. An under- or over-estimation of external load may occur if female athletes use thresholds initially developed for male athletes.

Thresholds developed for male team-sport athletes have been applied to female external load data. During international female hockey matches, the average number (17) of sprints completed was lower than the mean number (30) performed by male athletes (Macutkiewicz & Sunderland, 2011). However a sprinting threshold of 5.2 $m \cdot s^{-1}$, adapted from research on male soccer athletes (Bangsbo, 1992), was applied to female match data. Since there are sex differences in sprinting speed (Mujika et al., 2009), the reduction in mean sprints observed during international female hockey could be due to the inappropriate use of a velocity threshold designed for males. In soccer, male velocity thresholds have also been applied to female external load data (Krustrup, Mohr, Ellingsgaard, & Bangsbo, 2005; Mohr, Krustrup, Andersson, Kirkendal, & Bangsbo, 2008). However, the sprinting speed of female soccer athletes varies across age (Vescovi, Rupf, Brown, & Marques, 2011) and differs compared to males (Mujika et al., 2009). To develop female specific values, varying velocity thresholds have been used in soccer (Vescovi, 2012). During competitive matches, sprinting by professional female soccer athletes accounts for 5.3% of total distance covered when categorised as activity > 5.0 m·s-1 (Vescovi, 2012). However, if the threshold is increased to > 6.9 $m \cdot s^{-1}$, similar to thresholds used for male team-sport athletes (Varley et al., 2013b), little to no sprinting is recorded (Vescovi, 2012). A ceiling effect may therefore be present when using thresholds originally developed for male team-sport athletes. Although the use of varying velocity thresholds is a guide in the development of sprinting values for female soccer, this approach does not consider the individual physiological differences between athletes.

The individualisation of velocity thresholds for female athletes has recently been examined. In elite female rugby sevens athletes, a male velocity threshold (5.0 $m \cdot s^{-1}$), individual and cohort mean vVT2 speed, was used to determine distance covered at high-intensity (Clarke et al., 2014). The absolute amount of match high-intensity running was understimated by up to 30% when using a velocity threshold designed for male athletes (Clarke et al., 2014). The individualised threshold under- or over-estimated high-intensity running by up to 14% when compared to the cohort mean vVT2 speed threshold of 3.5 $m \cdot s^{-1}$ (Clarke et al., 2014). Individualising the high-intensity running threshold, assessed via a linear physiological test, of female team-sport athletes may allow for customised training prescription. However, individualisation requires a time-consuming and expensive laboratory-based $\dot{V}O2max$ test, which can be difficult to implement with a large number of athletes in a team-sport setting. Alternatively, the maximal aerobic speed (MAS) of an athlete is highly-correlated with maximal oxygen uptake (Uger & Boucher, 1980) and reflects running economy (Di Prampero, Atchou, Brückner, & Moia, 1986). Assessment of MAS can occur on a large number of athletes during an incremental field running test (Buchheit, Simpson, & Mendez-Villanueva, 2013). The relationship between MAS and high-intensity running has been assessed in youth male soccer athletes (Buchheit et al., 2013) although, to date, no research exists on individualising the velocity thresholds of female team-sport athletes using MAS testing results. For female team-sport athletes who cannot complete individualised physiological or field testing, a threshold of 3.5 $m \cdot s^{-1}$ could be used as guide for high-intensity running, although differences between playing position and standard are not accounted for with this fixed threshold.

The development and implementation of female-specific thresholds, according to playing standard and position, should be investigated. Although thresholds have been developed for female athletes competing in field-based sports (Clarke et al., 2014; Dwyer & Gabbett, 2012), there are no thresholds specifically for court-based sports. Netball, for example, is a court-based team-sport played indoors by elite female athletes. Due to the lack of research on female court-based sports, there is limited information on how to quantify velocity and acceleration thresholds for netball athletes.

3.9 Alternate Approaches to Classify Athlete Activity

Data mining is a research area that aims to discover regularity from within large datasets and yield insights that are not possible using conventional statistics (Chen, Han, & Yu, 1996). Large databases, such as the external load obtained from tracking technologies, can therefore be investigated. Knowledge may be extracted through data mining techniques including classification, where data are sorted into predefined classes based on some common features (Chen et al., 1996). These methods are alternative approaches to the individualisation of team-sport athlete external load. For example, the latent properties of external load from a single athlete can be found using data mining approaches. Velocity or acceleration thresholds are therefore derived directly from the sampled data and can be examined across age, sex, playing standard or position.

Relationships between latent properties in data that may impact athletic performance can be uncovered using data mining (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013b). Machine learning, a data mining technique, has been used to discover the physiological capacities required to medal in sprint cycling (Ofoghi, Zeleznikow, MacMahon, & Dwyer, 2010). A recent review (Ofoghi et al., 2013b) highlighted the lack of a contemporary framework for analysing the match performance data of elite athletes. For example, a traditional statistical analysis on the performance of a team-sport athlete during passing chains may consider a direct relationship with a dependent variable. However, this type of analysis ignores the context of data collection (Ofoghi et al., 2013b). Using data mining techniques, the hidden features that may impact upon passing quality could be examined, going beyond a superficial analysis (Ofoghi et al., 2013b).

An alternative approach is mediation analysis, a statistical technique that examines the relationship between the dependent variable and independent variables to identify plus explain process. Mediation analysis has been applied in elite Australian Football to examine inter-relationships between athlete capacity, match intensity and performance (Mooney et al., 2011). Playing position and experience influence the relationship between an athlete’s capacity, match activity profile and possession output (Mooney et al., 2011). Linear techniques including discriminant analysis (Castellano, Casamichana, & Lago, 2012) and generalised linear modelling have also been used to examine team-sport performance. However, linear techniques may not be an optimum method to analyse the match performance of dynamic and chaotic team-sports.

In contrast, non-linear data mining techniques are not constrained to a single linear variable. Decision trees, a non-linear technique, have been used to explain match outcome in Australian football (Robertson, Back, & Bartlett, 2016), classify team-sport activities from a wearable sensor (Wundersitz et al., 2015b) and explore the attacker and defender interaction during invasion sports (Morgan, Williams, & Barnes, 2013). Decision trees involve the repeated partitioning of data, based on input fields that create branches which can be further split to differentiate the dependent variable. Decision trees can handle missing data and provide an intuitive analysis of a dataset (Morgan et al., 2013). Unlike clustering, decision tree induction is not dependent on the selection of a prior distribution.

Clustering is a data mining technique that could be used to find unknown patterns in large datasets by classification, whereby data is grouped based on similarity (Chen et al., 1996). A large dataset can be meaningfully divided into smaller components or categories using clustering (Punj & Stewart, 1983). These categories may be mutually exclusive (Fayyad et al., 1996). Categories can also be sorted in a hierarchical or overlapping manner. Gaussian mixture models, a cluster method that contains a prior belief about group assignment, have been used to classify shot making in tennis (Wei, Lucey, Morgan, & Sridharan, 2013). These clustering methods represent sub-populations within a dataset and express the uncertainity about cluster assignment. The k-means clustering algorithm divides a dataset into a user-specified number of k clusters (Wu et al., 2008). The k-means algorithm starts with k centroids, selected at random. Each data point within the wider dataset is assigned to its nearest centroid, based on similarity. The centroids are updated each time a data point is assigned (Wu et al., 2008). The centroid mean is then calculated from the data points allocated to that cluster (Wu et al., 2008). The size of the dataset determines the number of repetitions required for the k-means algorithm to reach completion (Wu et al., 2008). Clustering, via the k-means algorithm, could be used in a variety of sport settings, including grouping the external load of an athlete.

Complex statistical or data mining techniques, including clustering, may uncover unknown patterns or counter prior beliefs. These approaches could be used to guide the development of athlete velocity and acceleration thresholds. Self-organising maps (SOM) and clustering have been utilised in elite rugby union to uncover playing styles related to team success (Croft, Lamb, & Middlemas, 2015). The coordination patterns during three different basketball shots from varying distances have also been classified using SOM (Lamb, Bartlett, & Robins, 2010). The lowest variability was recorded in the three-point and hook shots. The SOM displayed a movement output that differed unexpectedly from traditional analysis, including visual inspection and time series data (Lamb et al., 2010). A movement analyst with experience and prior knowledge or bias may have been distracted by other information compared to a SOM, that has a more objective methodology (Lamb et al., 2010). These approaches could also be used to group athlete velocity data, without the requirement of a human input threshold based on a physiologically defined or arbitrary value. These groups could be formed irrespective of an athlete's age, sex, position or playing standard. Patterns within athlete movement, including velocities and accelerations performed, could be derived by applying clustering techniques to external load data.

The accelerometer derived PlayerLoad™ data of elite female netball athletes was grouped by k-means clustering (Young et al., 2016). Optimal clustering was the greatest Euclidean distance obtained from two to five clusters (Young et al., 2016). The seven netball playing positions were divided into two groups according to playing intensity and relative time spent in a low-intensity zone (Young et al., 2016). The PlayerLoad™ for the goal based positions was lower than the attacking and wing positions, likely due to the time spent performing low intensity activity (Young et al., 2016). This study was the first to use data mining techniques, including k-means clustering, to examine athlete load data. However, only accelerometer data was investigated and not the position of an athlete, from GPS or LPS. Capturing the position of an athlete allows for the calculation of displacement, velocity and acceleration. With the large volume of data obtained from athlete tracking systems, data mining represents an technique to gain further insight into athlete activity profiles. Consequently, athlete external load could be analysed without the requirement of an arbitrary or software-implemented threshold.

3.10 Conclusion

Athlete position, velocity and acceleration can be measured during matches or training via optical tracking, GPS and LPS. The analysis of distance, velocity and acceleration over a specified time epoch is termed athlete activity profile. It is difficult to compare literature on field-based sports due to inconsistencies in velocity and acceleration thresholds, even within a single sport. Velocity and acceleration thresholds have been determined from physiological and physical capacity tests. Limited research also exists on female team-sport athletes and how to classify their velocity plus acceleration. Alternatively, data mining can derive patterns from large datasets. With the large volume of data obtained from athlete tracking systems and advancements in classifying movement patterns during skill or endurance performance, data mining is a technique to gain further insight into athlete activity profiles. Consequently, athlete external load could be analysed without velocity or acceleration thresholds. Future work should focus on using data mining techniques to analyse the movement performed by team-sport athletes, particularly elite females and those participating in court-based sports.

AIMS OF THE THESIS

The aim of this thesis was to measure the movement sequences of elite and junior elite female netball athletes during competitive matches using an accurate tracking system. Specifically:

- To assess the indoor accuracy of distance, mean velocity and angular velocity of the Wireless ad Hoc System for Positioning (WASP) during movements, common to court-based team-sports, compared to a criteron (Study One).

- To develop a method, using data mining techniques, to uncover the combination of velocity, acceleration and angular velocity movement sequences performed during a netball match (Study Two).

- To discover the frequently recurring movement sequences of elite female netball athletes, according to individual playing position (Study Three).

- To compare the movement sequences of junior-elite female netball athletes, according to playing postion, with elite athletes and assess the similarities between positions of differing playing standards (Study Four).

CHAPTER 4. STUDY 1 – THE ACCURACY OF A RADIO-FREQUENCY TRACKING SYSTEM FOR INDOOR SPORTS

4.1 Introduction

Accurately measuring the movement of team-sport athletes during training and matches is important for the design of specific conditioning activities and training load management. Athlete movement can be collected via global positioning systems or GPS (Aughey, 2011a), semi-automated optical tracking systems including Prozone® (Di Salvo et al., 2006) and local positioning systems (LPS). These technologies estimate an athlete's position with respect to the coordinates of a playing area, allowing for the calculation of displacement over a specified time epoch (Aughey, 2011a). The examination of athlete movement as quantified by the time spent or distance covered at particular velocities, termed activity profile, can then be calculated. To date, the angle of attack or angular velocities performed by team-sport athletes during matches have not been examined. This is likely due to the inability of current athlete tracking systems to accurately detect short-duration, non-linear movement.

The analysis of athlete activity profile requires an accurate and precise tracking system. Tracking systems must be able to quantify small changes of practical importance within- and between- athlete match activity profile (Jennings, Cormack, Coutts, Boyd, & Aughey, 2010b). The accuracy of GPS has been quantified for team sport use over linear and non-linear courses at a range of velocities (Coutts & Duffield, 2010; Jennings et al., 2010a; Varley et al., 2012). During linear sprinting over a 10 m course, 1 Hz GPS units recorded a coefficient of variation (CV) of 77.2% for measuring total distance covered (Jennings et al., 2010a). During short high-intensity movements representative of court-based sports, GPS can underestimate distance covered, mean and peak speed by up to 30% (Duffield et al., 2010). The inability of GPS to accurately quantify such movements has severe implications for capturing external load during court-based sports. Elite court-based team-sports, such as netball, are contested indoors where GPS is inoperable due to no satellite reception.

An alternate athlete tracking technology for indoor sports is local positioning systems (LPS). Anchor nodes are dispersed around the playing court, with the distance between each anchor node and calibration point measured. Radio-frequency (RF) is then used to transmit the range between LPS mobile nodes worn by athletes and anchor nodes. The accuracy of an LPS has been quantified during soccer-specific (Frencken et al., 2010) and change of direction (Stevens et al., 2014) courses. Only two changes of direction, 90º and 180º turns, were investigated (Stevens et al., 2014), limiting the ecological validity of these studies. Frequent, varying changes of direction should be included when validating a LPS to allow each mobile node to sight different anchor nodes. The LPS mobile nodes used in the aforementioned validation studies (Frencken et al., 2010; Stevens et al., 2014) were located on each participant's shoulders and are therefore impractical for use in elite competition. A different LPS comprising small mobile nodes, worn between an athlete's shoulder blades, is the Wireless ad hoc System for Positioning or WASP (Hedley et al., 2010). The WASP has a relative position error of 18 and 28 cm for outdoor and indoor use, respectively (Sathyan et al., 2012). Indoors, WASP has a mean total distance error of 2.2% in linear running whilst during non-linear movement, a mean error of 2.7% was recorded (Sathyan et al., 2012). The non-linear course used is a test designed to benchmark Australian Football athletes, who are field-based team-sport athletes. Distance and velocity measures from WASP have not been examined during a variety of non-linear movements that are representative of court-based team-sports, including netball. To date, no study has examined measures of angular velocity from an athlete tracking system, including WASP. The accuracy of WASP has also not been examined against a high-resolution criterion measure, such as Vicon (Richards, 1999). Therefore, the aim of this study was to quantify the accuracy of

WASP measures, particularly changes in angular velocity, compared with Vicon during movements that are representative of court-based team-sports.

4.2 Methods

Two International level female netball athletes, a goaler (age; 28 years, height; 183 cm and mass; 70 kg) and mid-courter (age; 22 years, height; 180 cm and mass; 72 kg), provided written informed consent to participate. The study was approved by the University Human Research Ethics Committee. Participants completed a total of 74 trials at two different intensities, sprinting (n = 44) and walking (n = 30). Five movement drills that replicated netball match-play movement were examined (Figure 4-1). Drill one involved a straight 5 m movement then a 90º turn before another straight 5 m; drill two was the same length as drill one yet consisted of a 45º turn; drill three comprised a straight 5 m movement, 180º turn and straight 5 m movement. Drill four consisted of a straight 5 m, 90º turn, straight 5 m movement, 45º turn and a final 2.5 m movement. Drill five comprised a straight 5m, 180º turn, straight 2.5 m movement, 90º turn, straight 2.5 m movement, 45º turn and a final 2.5 m movement. Participants completed a standardised netball warm-up prior to testing. The warm-up included linear and non-linear movement at various speeds plus dynamic stretching of lower body musculature. At least three trials of each movement drill were practiced prior to testing. Drills were performed on a fully sprung indoor netball court. Before commencing each trial, participants started with one foot on and both shoulders behind a start line. The same investigator gave a starting signal and participants were instructed to either “walk” or “sprint.” The speed of both movement intensities was self-selected however participants were encouraged to be consistent in their movements across all drills and trials. Participants were also instructed to sprint at 100% intensity. A three minute rest period was provided between each trial.

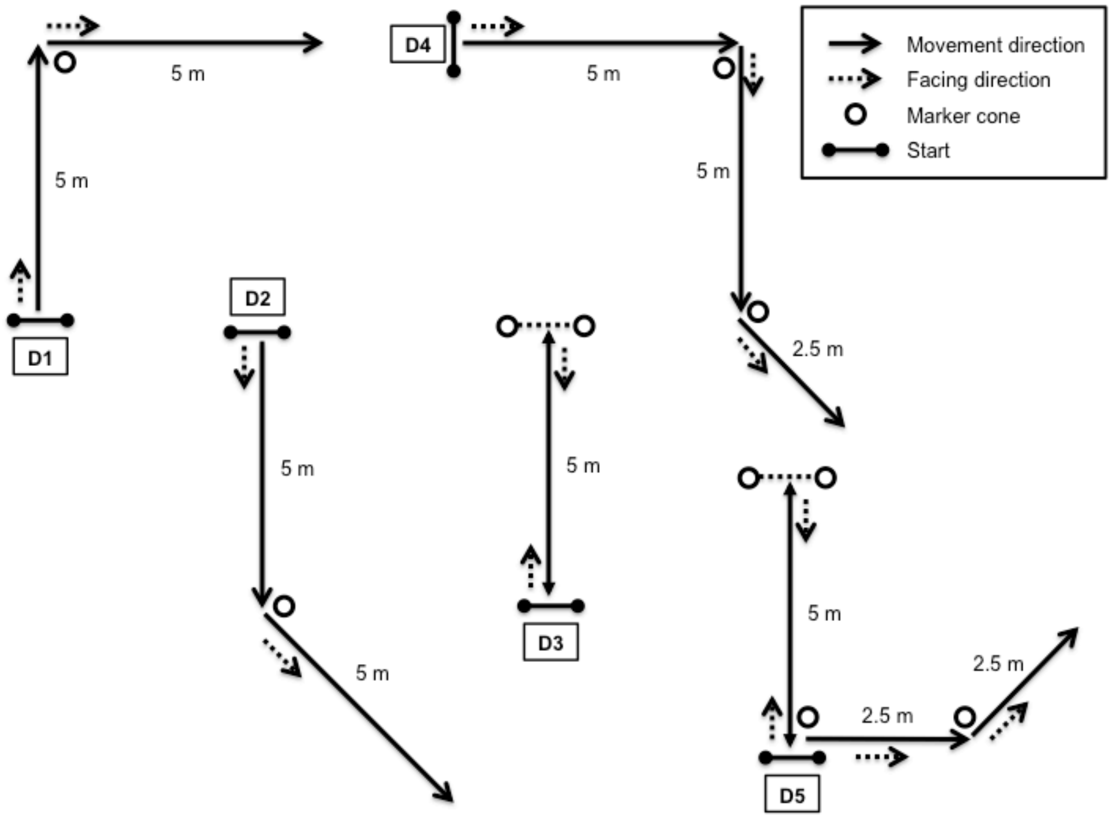

Figure 4-1. A schematic representation of netball-specific movements divided into five drills: D1 = 90º turn, D2 = 45º turn, D3 = 180º turn, D4 = 90º turn followed by 45º turn, D5 = 180º turn, 90º turn followed by 45º turn.

During each drill, LPS data was collected by twelve WASP (Australian Institute of Sport, Canberra, Australia; Commonwealth Scientific and Industrial Research Organisation, Sydney, Australia) anchor nodes that were fixed around the testing space (see Figure 4-2). The height of each anchor node and their distance to the nearest line marking of the calibrated netball court is displayed in Table 4-1.

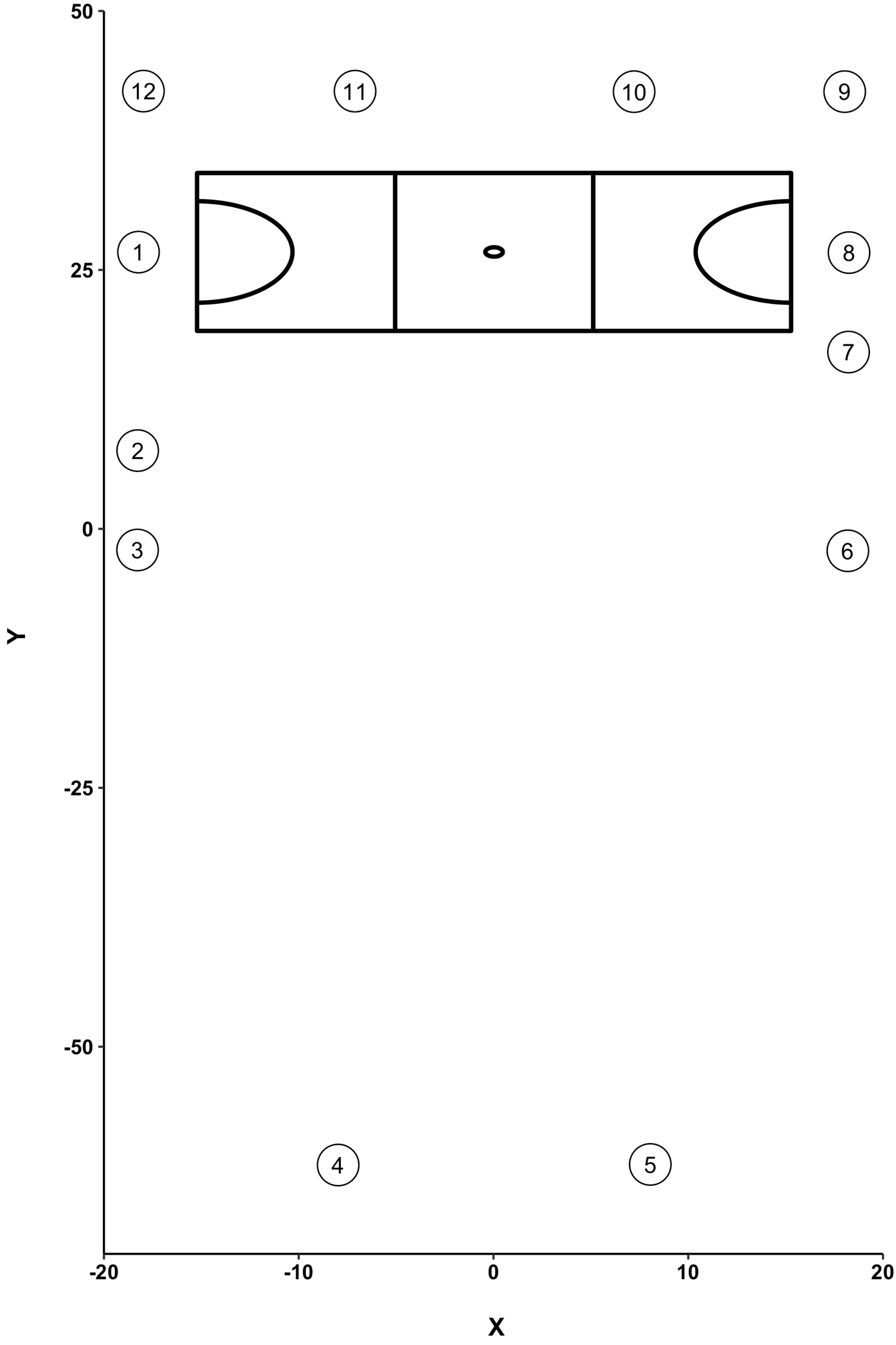

Figure 4-2. The location of each WASP anchor node, open numbered circles denote anchor number, as calibrated within an indoor stadium. Width of the indoor stadium is given by X (m; metres) and length given by Y (m; metres).

Anchor Station	X-axis Distance (m)	Y-axis Distance (m)	Height (m)	Distance to nearest line marking (m)
1	-18.2	26.7	4.0	3.0
2	-18.3	7.6	3.6	11.9
3	-18.3	-2.0	3.6	21.3
4	-8.0	-61.4	2.8	80.5
5	8.1	-61.4	2.8	80.5
6	18.2	-2.1	3.6	21.4
7	18.2	17.1	4.3	3.6
8	18.3	26.7	4.2	3.0
9	18.0	42.2	4.4	8.3
10	7.2	42.2	4.4	7.9
11	-7.1	42.3	4.4	7.9
12	-18.0	42.3	4.2	8.4

Table 4-1. Location and height (m; metres) of each WASP anchor node, relative to a survey point and the nearest line marking of a calibrated netball court within an indoor netball stadium. The width of the indoor stadium is given by the X axis (m; metres) and length is given by the Y axis (m; metres).

Each participant wore a lightweight (~ 100 g) WASP mobile node, measuring 90 x 50 x 25 mm, positioned between the shoulder blades and housed in a custom-built crop-top. The range between each WASP mobile and anchor node is updated at 10 Hz. Using customised software (WheresBruce, Australian Institute of Sport, Canberra, Australia), the location of each mobile node is obtained via multi-lateration and a tracking filter is applied, resulting in a 100 Hz file with positional (x, y) data (Hedley et al., 2011).

A 22 camera Vicon motion-analysis system (Vicon Nexus, Oxford Metrics, United Kingdom), capturing at 200 Hz, was the criterion measure. A reflective marker of 14 mm in diameter was mounted on the mobile node's centre of mass to obtain three-dimensional (3D) position. Markers were also placed on each participant's left wrist, sternum, clavicle, C7, T10 plus the left and right acromion process to obtain trunk kinematics (Dempsey et al., 2007). The capture volume was 7 x 12.5 m and all testing was performed within a third of an indoor netball court. Vicon was calibrated preceding the testing session and image error (RMS in camera pixels) was below 0.20 for all Vicon cameras.

Vicon data was time aligned with WASP to match the duration of each drill. The participant's stationary pose behind the starting line was used to determine the commencement of each drill and sync point between systems. The WASP data was trimmed to reflect the recorded Vicon drill length. Prior to statistical analysis, Vicon signals (*x-y* direction) were filtered using a low-pass, fourth-order 6 Hz Butterworth filter, determined from a residual analysis (Winter, 2009). Positional (X and Y coordinate) data from WASP and Vicon were differentiated to obtain velocity (Stevens et al., 2014). Angular velocity, the rate of change of angular displacement, was obtained from angular displacement. All data were log-transformed to reduce bias due to non-uniformity of error (Varley et al., 2012). Validity was calculated by the standard error of the estimate and expressed as a standard deviation (± 90% confidence limits, CL) of the percentage difference between criterion (Vicon) total distance, mean and peak velocity and angular velocity for all sprinting drills and all walking drills. The process was then repeated for each individual movement drill, split by sprinting and walking. Bias was reported as the percentage difference between criterion and WASP measures. A Pearson product-moment correlation was also calculated between criterion and WASP. All statistical analysis was performed using the R statistical environment (Team, 2013).

4.3 Results

The Vicon and WASP mean angular velocities were very strongly correlated during walking and sprinting, across all movement drills (Table 4-2). Very strong correlations were also associated with walking and sprinting movement for WASP measurement of peak angular velocity. The CV was < 12% for mean and peak angular velocity during walking drills (Table 4-2). The CV was < 3% for mean and peak angular velocity during sprinting drills (Table 4-2).

The WASP accuracy for measuring total distance across all drills was greater during walking movement compared to sprinting (Table 4-2). Similarly, WASP was more accurate during walking compared to sprinting when measuring mean velocity across all movement drills (Table 4-2). In contrast, the CV for walking was higher compared to sprinting for measuring peak velocity (Table 4-2). However, WASP bias was higher during all walking movement drills compared to sprinting. Total distance and mean velocity was underestimated by WASP during sprinting drills. In contrast, total distance, mean and peak velocity was overestimated by WASP during all walking drills (Table 4-2).

The Vicon and WASP total distances were strongly correlated during walking and sprinting across all movement drills (Table 4-2). Weaker correlations were associated with walking and sprinting movement for WASP measurement of peak velocity. Whilst Vicon and WASP were highly correlated for measuring mean velocity during sprinting, walking was associated with a weaker correlation (Table 4-2).

The CV was < 5% for measuring total distance during all drills, for sprinting and walking, with the exception of drill one (Table 4-3). Bias was higher (14.4% to 18.63%) during drills three, four and five (Table 4-3). The total distance during sprinting in drill one was underestimated by WASP yet overestimated during drill two.

	WASP (Mean ± SD)	Vicon (Mean ± SD)	CV as % (± 90% CL)	Bias as % (± 90% CL)	Pearson correlation (± 90% CL)
Total Distance (m)					
Walking	13.9 ± 4.1	12.5 ± 3.4	4.6 ± 1.3	11.8 ± 1.8	0.99 ± 0.01
Sprinting	11.4 ± 3.2	11.5 ± 2.9	6.7 ± 1.2	-1.0 ± 1.8	0.96 ± 0.02
Mean Velocity ($m \cdot s^{-1}$)					
Walking	1.5 ± 0.1	1.4 ± 0.1	4.8 ± 1.3	11.8 ± 1.8	0.48 ± 0.25
Sprinting	3.3 ± 0.4	3.3 ± 0.4	6.5 ± 1.2	-0.5 ± 1.7	0.83 ± 0.08
Peak Velocity ($m \cdot s^{-1}$)					
Walking	2.8 ± 0.4	1.8 ± 0.2	12.3 ± 1.3	60.7 ± 9.1	-0.21 ± 0.30
Sprinting	5.1 ± 0.5	5.0 ± 0.6	11.7 ± 1.2	2.3 ± 3.2	0.31 ± 0.23
Mean Angular Velocity ($deg \cdot s^{-1}$)					
Walking	25.4 ± 6.5	29.3 ± 5.9	9.2 ± 1.3	18.2 ± 3.8	0.94 ± 0.04
Sprinting	80.5 ± 27.1	78.7 ± 28.8	2.8 ± 1.2	-3.2 ± 1.3	0.99 ± 0.01
Peak Angular Velocity ($deg \cdot s^{-1}$)					
Walking	110.3 ± 33.3	115.0 ± 34.5	11.3 ± 1.3	4.4 ± 3.7	0.94 ± 0.04
Sprinting	133.3 ± 45.3	131.1 ± 46.6	2.6 ± 1.2	-2.3 ± 1.0	0.99 ± 0.01

Table 4-2. Comparison of WASP data with criterion (Vicon) across sprinting (n = 44) and walking (n = 30) intensities, irrespective of movement drill. Data are expressed as a coefficient of variation (CV), percent bias and a correlation statistic.

	Walking		Sprinting		Walking	Sprinting	Walking	Sprinting
	WASP (Mean ± SD)	Vicon (Mean ± SD)	WASP (Mean ± SD)	Vicon (Mean ± SD)	CV as % (± 90% CL)	CV as % (± 90% CL)	Bias as % (± 90% CL)	Bias as % (± 90% CL)
Total Distance (m)								
Drill One	11.1 ± 0.9	10.5 ± 0.3	9.4 ± 0.6	9.9 ± 0.5	1.7 ± 2.2	5.2 ± 1.8	5.2 ± 5.9	-4.9 ± 4.4
Drill Two	8.8 ± 0.4	8.3 ± 0.2	8.3 ± 0.6	8.1 ± 0.1	2.9 ± 2.8	0.5 ± 1.9	6.4 ± 4.6	3.0 ± 5.5
Drill Three	12.7 ± 0.9	10.9 ± 0.5	10.8 ± 1.1	10.9 ± 0.5	3.9 ± 2.2	2.2 ± 1.2	18.6 ± 6.2	-1.0 ± 4.1
Drill Four	13.0 ± 1.2	11.6 ± 0.7	10.3 ± 0.7	10.6 ± 0.2	1.2 ± 1.7	2.1 ± 1.6	12.4 ± 2.3	2.9 ± 4.2
Drill Five	20.1 ± 0.7	17.8 ± 0.6	16.8 ± 1.2	16.4 ± 0.3	1.9 ± 1.7	1.5 ± 1.6	14.4 ± 1.4	1.9 ± 3.7
Mean Velocity ($m \cdot s^{-1}$)								
Drill One	1.5 ± 0.1	1.4 ± 0.01	3.3 ± 0.3	3.5 ± 0.2	3.4 ± 2.2	3.9 ± 1.8	5.3 ± 6.0	-4.6 ± 4.4
Drill Two	1.6 ± 0.0	1.5 ± 0.0	3.9 ± 0.2	3.9 ± 0.2	2.7 ± 2.8	4.7 ± 1.8	6.6 ± 4.6	2.5 ± 4.9
Drill Three	1.5 ± 0.1	1.3 ± 0.0	2.9 ± 0.1	3.0 ± 0.3	2.1 ± 2.8	7.6 ± 1.6	16.8 ± 6.9	-0.7 ± 4.1
Drill Four	1.5 ± 0.1	1.4 ± 0.1	3.2 ± 0.3	3.2 ± 0.1	3.3 ± 1.7	3.4 ± 1.6	12.6 ± 2.3	-2.1 ± 3.9
Drill Five	1.6 ± 0.0	1.4 ± 0.0	3.0 ± 0.2	2.9 ± 0.1	1.8 ± 1.7	3.6 ± 1.6	15.5 ± 1.6	2.2 ± 3.7
Peak Velocity ($m \cdot s^{-1}$)								
Drill One	3.1 ± 0.5	1.8 ± 0.1	4.9 ± 0.6	5.3 ± 0.4	3.8 ± 2.2	9.8 ± 1.8	106.1 ± 29.5	-7.8 ± 8.9
Drill Two	2.4 ± 0.2	1.9 ± 0.1	5.6 ± 0.3	5.6 ± 0.3	3.4 ± 2.9	5.2 ± 1.9	27.4 ± 9.7	0.6 ± 7.8
Drill Three	2.4 ± 0.1	1.7 ± 0.1	4.9 ± 0.4	4.4 ± 0.3	4.9 ± 2.9	6.6 ± 1.6	52.2 ± 12.3	11.8 ± 5.9
Drill Four	2.7 ± 0.4	1.8 ± 0.2	4.8 ± 0.4	4.8 ± 0.8	10.3 ± 2.9	16.2 ± 1.6	71.5 ± 21.9	1.1 ± 9.9
Drill Five	2.7 ± 0.2	1.9 ± 0.4	5.3 ± 0.5	5.1 ± 0.3	20.3 ± 1.8	2.9 ± 1.6	52.6 ± 20.3	2.9 ± 2.5

Table 4-3. Comparison of WASP data with criterion (Vicon) across sprinting (n = 44) and walking (n = 30) intensities, for each movement drill. Data are expressed as a coefficient of variation (CV) and percent bias.

The CV was < 4% for measuring mean velocity during all walking drills (Table 4-3). During all sprinting drills, the CV was < 10%. The mean velocity recorded by WASP was overestimated for all walking drills yet underestimated during sprinting, with the exception of drills two and five (Table 4-3). During drill one, two and three, the CV for WASP measurement of peak velocity was < 10% for sprinting and walking movement. However, the CV increased for the remaining drills with the exception of sprinting during drill five (Table 4-3). During walking, WASP overestimated peak velocity for all movement drills. Peak velocity was overestimated by WASP during all sprinting drills, with the exception of drill one.

4.4 Discussion

This study investigated the accuracy of angular velocities obtained from an athlete tracking system against 3D motion analysis during short, non-linear movements performed by elite court-based team-sport athletes. The CV for mean and peak angular velocity during sprinting movements was < 3% across all movement drills, demonstrating the acceptable accuracy for this measure from WASP. During walking movements, the CV for mean and peak angular velocity was < 11.3%. The discrepancy in CV between sprinting and walking angular velocity may be partly due to variation in the geometric dilution of precision, a measure of position accuracy deviation due to geometry of the anchor and mobile nodes (Zhu, 1992). All movement drills commenced and finished at the edge of a netball court, resulting in a lower geometric dilution of precision. Since mobile WASP nodes were located between the scapulae of each participant, the anchor nodes in front of the participant were blocked by the body. When walking, this body blockage is experienced for a longer time duration due to the slower velocity delayed in sighting multiple anchor nodes. This is confirmed by the substantially higher bias for walking drills when compared with sprinting (Table 4-3). Other studies (Frencken et al., 2010; Ogris et al., 2012; Stevens et al., 2014) on LPS accuracy conduct drills in the middle of a court or soccer pitch, allowing for mobile nodes to enjoy a better geometry with anchor nodes. Whilst this research design could have been utilised in the present study, indoor court-based sports are typically contested in stadia with playing areas enclosed by metal walls.

In netball, athletes are confined to playing areas according to their position (The-All-Australia-Netball-Association, 2012). Athletes may also need to throw the ball back into play from the court sideline (The-All-Australia-Netball-Association, 2012). Court-based team-sport athletes are therefore not always in the middle of a playing area, where the geometry of an LPS is increased. To ensure a robust test of the WASP for use in court-based team-sports, drills were designed to commence plus finish at the edge of the court. Whilst this may influence the CV and bias reported, the robust methodology employed allows researchers and practitioners to understand the error of WASP during a "worst-case" situation.

To date, an athlete's angle of attack has not been quantified during training and matches, likely due to limitations in the accuracy of tracking technologies for this type of analysis. Knowledge of an athlete's angular velocities performed during a match may assist coaches and practitioners in designing training drills to target specific angles of attack. In combination with an athlete's position relative to the playing area and their team-mates, angular velocity data could be used for tactical analysis purposes such as understanding the movements performed in the lead up to a shot for goal or intercept.

The accuracy of WASP for quantifying distance covered during short, non-linear drills was acceptable. During all walking drills, the CV was less than 4% for measuring distance travelled. This is similar, at the lower range, to GPS estimates (CV, 3.5 to 17.8%) for measuring distance covered during tennis specific drills in a confined space (Duffield et al., 2010) and similar to that of other RF based LPS (Frencken et al., 2010; Ogris et al., 2012). Research on quantifying the accuracy of LPS has typically been conducted with linear trials (Frencken et al., 2010; Sathyan et al., 2012) or outdoor field-based sport-specific movements performed over distances > 10 m (Frencken et al., 2010; Sathyan et al., 2012). Relative estimations of distance and pre-defined courses plus timing gates have been used as the criterion measure (Frencken et al., 2010; Sathyan et al., 2012). These methodologies cannot quantify the exact course undertaken by each participant during trials, potentially understimating distance covered and therefore are severely limited as a criterion measure during validation trials.

The accuracy of a LPS for use in field-based team-sports has been assessed with 3D motion analysis capture (Ogris et al., 2012; Stevens et al., 2014). The study in this thesis contains a slightly higher CV for total distance covered when compared to other LPS accuracy research (Ogris et al., 2012; Stevens et al., 2014). This may be due to the shorter length plus variation in turning angles of the non-linear courses employed here. One study assessed the distance accuracy of an LPS over three soccer-specific courses, 26.5 m in length with two changes of direction, compared to a 3D motion analysis system (Ogris et al., 2012). The outdoor accuracy of a LPS was quantified over a 25 m course with three changes of direction (Frencken et al., 2010). The indoor LPS accuracy was quantified over eight soccer-specific courses with only 90° and 180° single turns (Stevens et al., 2014), yet this design is not representative of the many changes of direction performed in elite soccer (Faude et al., 2012). In contrast, the present study employed multiple changes of direction including 45°, 90°, 180° plus combined turns, over a course < 15 m. Drill four and five, in particular, are complex movement patterns comprising up to three, short-duration changes in direction over small distances. With the exception of the present study, no athlete tracking technology has been robustly validated against a high-resolution criterion during high-intensity, short-duration movement. The results of the present study therefore cannot be directly compared with other LPS accuracy research. Court-based team-sports are also contested in confined spaces, where tracking systems considered acceptable for use in field-based sports cannot accurately quantify short high-intensity movement (Duffield et al., 2010).

Only amateur (Ogris et al., 2012; Stevens et al., 2014) and moderately trained (Frencken et al., 2010) individuals have participated in research on the accuracy of LPS. In comparison, the present study had elite athletes participating in all drills. The present study consequently has strong external validity as the variety of velocities and angular velocities performed are representative of elite court-based athletes. The athletes who participated in the present study are world-class athletes who represent their country during international test matches. These athletes are consequently more co-ordinated and skilled at performing frequent changes of direction over short-durations when compared to amateur individuals. To ensure ecological validity, since elite athletes likely have a higher peak velocity than untrained individuals, the accuracy of an LPS for tracking athletes should be assessed with elite athletes as participants.

The bias observed in the WASP during trials may be due to RF intereference from the metal-clad indoor venue where testing was conducted. At the elite level, court-based team-sports including basketball, handball, volleyball and netball are held indoors. It is therefore important to measure the accuracy of WASP in metal-clad indoor venues where athlete tracking of court-based sports will occur. Two LPS validation studies (Frencken et al., 2010; Ogris et al., 2012) were conducted on an outdoor soccer pitch, limiting any RF intereference due to multipath from overhead steel structures. An air dome has also been utilised as a testing space for assessing the accuracy of a LPS (Stevens et al., 2014), which may limit RF interference from steel infrastructure. Bias may be introduced to LPS when used indoors due to the strong multipath and RF signal bounce from metal cladding in these venues (Sathyan et al., 2012). When used indoors, the WASP signal contains the direct plus reflected signal from concrete and steel materials. In agreement with the results presented, WASP has a higher relative positional error, during linear and non-linear movements when used indoors compared to outdoor venues, likely due to multipath interference (Sathyan et al., 2012).

Based on results of the current study, researchers should therefore be cautious with low speed WASP data than movement at high speeds. The positioning of the WASP anchor nodes surrounding the court may influence the calculation of athlete position and subsequent displacement plus velocity. The anchor node positioning in the present study was suggested by a developer of the LPS, with nodes mounted as high as possible on the walls of the court. Optimum positioning of the acnhor nodes may improve WASP accuracy (Hedley et al., 2010). The close proximity of a court edge to the walls of a stadium, where anchor nodes are required to be mounted, may restrict the accuracy of LPS. If anchor nodes are located too close to the edge of a court, the mobile nodes may be undetected. It is unknown if displacement and velocity outputs would be altered if these nodes were moved. Future LPS research for indoor sport use should examine the influence of a change in anchor positioning on the calculation of athlete position, displacement plus velocity. Future research on validating the position of athlete tracking systems over time should also use a method that takes into account time dependent data, such time series analysis. Using Pearson correlations allows identification of two events that occur simultaneously, yet does not consider time dependent data.

4.5 Conclusion

Angular velocity can be accurately measured by WASP during short, non-linear movements indoors. Researchers and practitioners can therefore use angular velocity measures from WASP to analyse team-sport athlete angle of attack during training and matches, a measure that until now has not been examined. This may have application for designing specific coaching and conditioning drills. The WASP provides sufficient indoor accuracy to quantify the total distance and velocities performed by elite athletes over short, non-linear courses. A higher CV of WASP compared to other LPS research during sprinting and walking movements is likely due to the shorter course length and enhanced criterion, a 22 camera Vicon motion analysis system. The increased bias for walking mean and peak velocities, compared with sprinting, may be due to the multipath RF interference from steel cladding, a feature of indoor sports stadia. The WASP accuracy may be increased when court-based team-sport athletes are in the centre of the playing area, as opposed to the sidelines, due to less body blockage and a higher geometric precision. Researchers and practitioners may use WASP to quantify the external load of athletes indoors. The WASP has potential application for collecting athlete movement during elite court-based team-sports, including netball, basketball, volleyball and handball. Caution should be used when analysing low speed data from WASP. To enhance geometric precision, nodes should be placed high and as far back from the edges of a court as stadia infrastructure will allow.

CHAPTER 5. STUDY 2 – A MOVEMENT SEQUENCING ANALYSIS OF TEAM-SPORT ATHLETE MATCH ACTIVITY PROFILE

5.1 Introduction

Netball is a predominantly female team sport with a large participation base within Commonwealth countries (Steele & Chad, 1991a). Matches consist of 15 minute quarters and are contested on a 30.5 m by 15.25 m court divided into equal thirds. Players are assigned one of seven positions which restrict movement to specific on-court areas (Woolford & Angove, 1992). The substitution of players is only permitted during quarter and half-time breaks or if an injury time-out is called. The objective of the game is to score a goal through a ring that is 3.05 m above the ground. Netball athletes are not permitted to move more than one step with the ball and when in possession, must pass to a teammate within three seconds.

Quantification of athlete physical movement, or activity profile, during matches is critical in understanding performance. Investigation into athlete match activity profiles can assist with sport-specific preparation and conditioning (Di Salvo et al., 2007; Mendez-Villanueva, Buchheit, Simpson, & Bourdon, 2013). Examination of netball match-play reveals a combination of short, high intensity movement interspersed with periods of low intensity activity, including walking and jogging (Steele & Chad, 1991a). Early studies on netball activity profile investigated sub-elite athletes (Davidson & Trewartha, 2008; Loughran & O'Donoghue, 1999; Steele & Chad, 1991a; Steele & Chad, 1991b) and were conducted before rule changes to the current length of a match, currently 15 minute quarters (Otago, 1983). Positions were either grouped (Steele & Chad, 1991a) into defender, midcourter or goaler, or combined entirely (Davidson & Trewartha, 2008) in the analysis. Only two studies (Fox et al., 2013; Otago, 1983) have examined elite netball match activity profile according to individual playing position, using video analysis.

Video analysis is commonly utilised in netball (Davidson & Trewartha, 2008; Fox et al., 2013; Otago, 1983) however, estimating short, high-intensity movement using inferences from visible movement types is error-prone. Micro-technology, including accelerometers (Boyd et al., 2011) and global positioning systems or GPS (Jennings et al., 2010a), allow quantification of athlete activity profiles according to physical capacity (Buchheit et al., 2010a), chronological age (Mendez-Villanueva et al., 2013), playing standard (Jennings et al., 2012b) and position (Mendez-Villanueva et al., 2013). Accelerometer load, as a measure of activity profile, can differentiate between netball playing standard at the sub-elite level (Cormack, Smith, Mooney, Young, & O'Brien, 2013) but remains to be investigated in an elite cohort. The validity and reliability of GPS to measure short high-intensity movements in confined spaces (Duffield et al., 2010) is likely insufficient for netball use (Duffield et al., 2010). Elite netball matches also take place indoors, where GPS is rendered inoperable. The lack of research on netball match activity profile in contemporary athletes, according to position and playing standard, may be attributed to the types of technologies previously available for this analysis.

Recognising the limitations of GPS and video-analysis, radio-frequency (RF) tracking has been developed to monitor athlete activity both indoors and outdoors. The validity and reliability of the method considered, the Wireless ad-hoc System for Positioning or WASP (Hedley et al., 2010), has been established indoors (Sathyan et al., 2012). At present, RF technology is yet to be deployed in competitive netball matches to quantify match activity profile.

Athlete activity profile is typically analysed using movement thresholds, including velocity bands (Aughey, 2010; Gabbett, Jenkins, & Abernethy, 2012) or arbitrary classifications (Fox et al., 2013). However, comparison between studies is difficult due to the multitude of inconsistent analysis techniques and movement definitions employed (Carling, 2013). Physical output expressed per minute of game time (Varley & Aughey, 2013) or as a function of physiological capacity (Lovell & Abt, 2012) requires pre-determined parameters to be fitted to data. Using pre-defined thresholds to compare across and between groups is problematic given athlete mass (Gabbett, 2002), playing standard (Jennings et al., 2012b), position (Macutkiewicz & Sunderland, 2011) and chronological age (Gastin, Fahrner, Meyer, Robinson, & Cook, 2013) may influence physical output.

Data mining is a problem-solving methodology that sources a logical or mathematical description of patterns and regularities in a data set (Fayyad et al., 1996). Whilst data mining techniques can determine the tactical patterns of play during elite volleyball matches (Jäger & Schöllhorn, 2007), determine weight transfer during the golf swing (Ball & Best, 2007) and examine basketball match score outcome (Sampaio & Janeira, 2003), the analysis of athlete match activity profile, using data mining techniques, remains to be explored.

Clustering mines data according to similarity/ dissimilarity and groups items regarding these criteria. Cluster analysis discriminated between high and low inter-personal coordination between soccer players (Morgan & Williams, 2012). Utilised in analysing the performance qualities of elite track cycling athletes to ascertain riders best suited to the omnium event (Ofoghi et al., 2013a), clustering may assist with informing athlete selection, training and strategic planning. Clustering, via self-organising maps (SOM), can provide an objective method to explain movement patterning during basketball shooting (Lamb et al., 2010). However, applying a clustering approach to athlete match activity profile, remains to be explored. The aim of this study was to develop a movement sequencing technique that exploits the emergent movement characteristics of team-sport athletes. Specifically, to discover the most frequently recurring sequences and create insight into the temporal sequence of movement elements that are representative of netball athlete match activity profile.

5.2 Methods

Activity profiles were collected from six female elite-junior netball athletes via RF tracking (Hedley et al., 2010) during a competitive international match. All seven netball playing positions were represented, with one athlete playing in the WA and C position. The clustering model was first implemented on five athletes, chosen at random, before the developed clustering model was run on the sixth athete's data. Only the first quarter was analysed, as the focus of this study was to develop the technique rather than implement across an entire match. The sampling rate of the RF system is 100 Hz. Raw athlete position data were downloaded post-match via custom-built software (WhereIsBruce?, Australian Institute of Sport, Canberra, ACT, Australia) and exported into the R environment (R: A language and environment for statistical computing, Vienna, Austria). The elemental movement characteristics for each individual athlete over the first quarter (15 minutes in duration) were calculated in the following equations from 1 to 4, respectively. Velocity for each player were derived from the position data:

$$V_i = \frac{\sqrt{\Delta x^2 + \Delta y^2}}{\Delta t}$$

Acceleration was derived from velocity:

$$A_i = \frac{V_i - V_{i-1}}{\Delta t}$$

The angular displacement (θ_i) was calculated from the dot product of consecutive movement vectors, $\boldsymbol{a}$ and $\boldsymbol{b}$:

$$\theta_i = \cos^{-1}\left[\frac{\boldsymbol{a} \cdot \boldsymbol{b}}{||\boldsymbol{a}|| \cdot ||\boldsymbol{b}||}\right]$$

Next, angular velocity (rate of change in angular displacement) was calculated as follows:

$$\omega_i = \frac{\theta_i - \theta_{i-1}}{\Delta t}$$

In each case, (for Equations 1, 2 and 4), t was equal to a time epoch that was varied between separate experimental trials where t = 0.5, 0.75, 1.0, 1.25 and 1.50 seconds respectively. The observations for each of these movement characteristics were classified into groups of arbitrary n-size using a one-dimensional k-means clustering algorithm (Wang & Song, 2011). Four velocity clusters (notionally Walk, Jog, Run, Sprint), three acceleration clusters (Accelerate, Neutral, Decelerate) and four angular velocity clusters (U-Turn, 90° turn, 45° turn, and Straight) were declared. Figure 5-1 illustrates the bandwidths represented by each cluster described above. Figure 5-2 illustrates the relative frequency of each representation in movement classification.

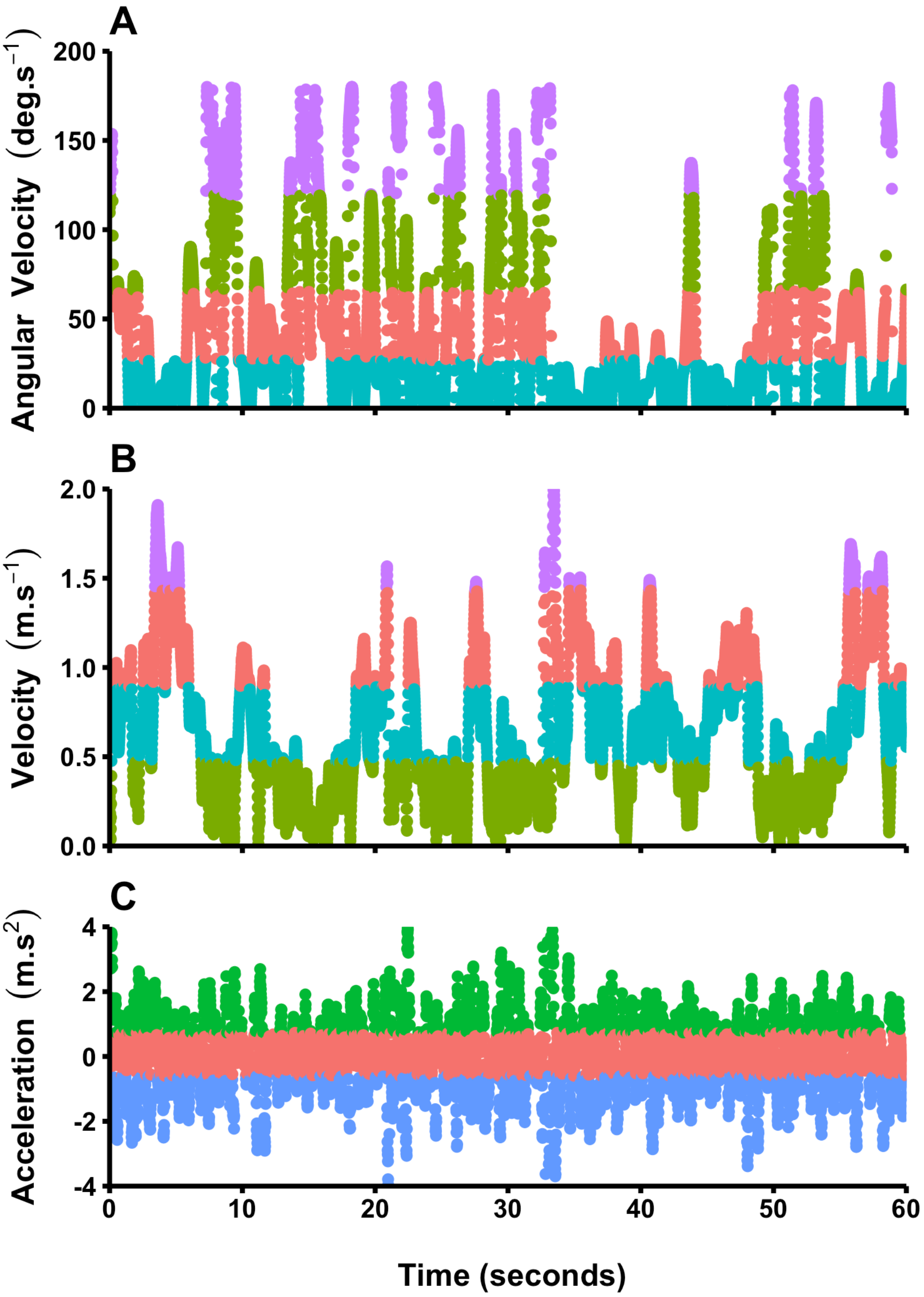

Figure 5-1. Classification bands representing movement clusters with exemplar data for A) Angular Velocity, B) Velocity, and C) Acceleration. The distribution of raw data points within each cluster is presented. Figure 5-1A: purple; U-Turn, green; 90° turn, salmon; 45° turn and aqua; straight. Figure 5-1B: purple; sprint, salmon; run; aqua; jog and green; walk. Figure 5-1C; green; accelerate, salmon; neutral and blue; decelerate.

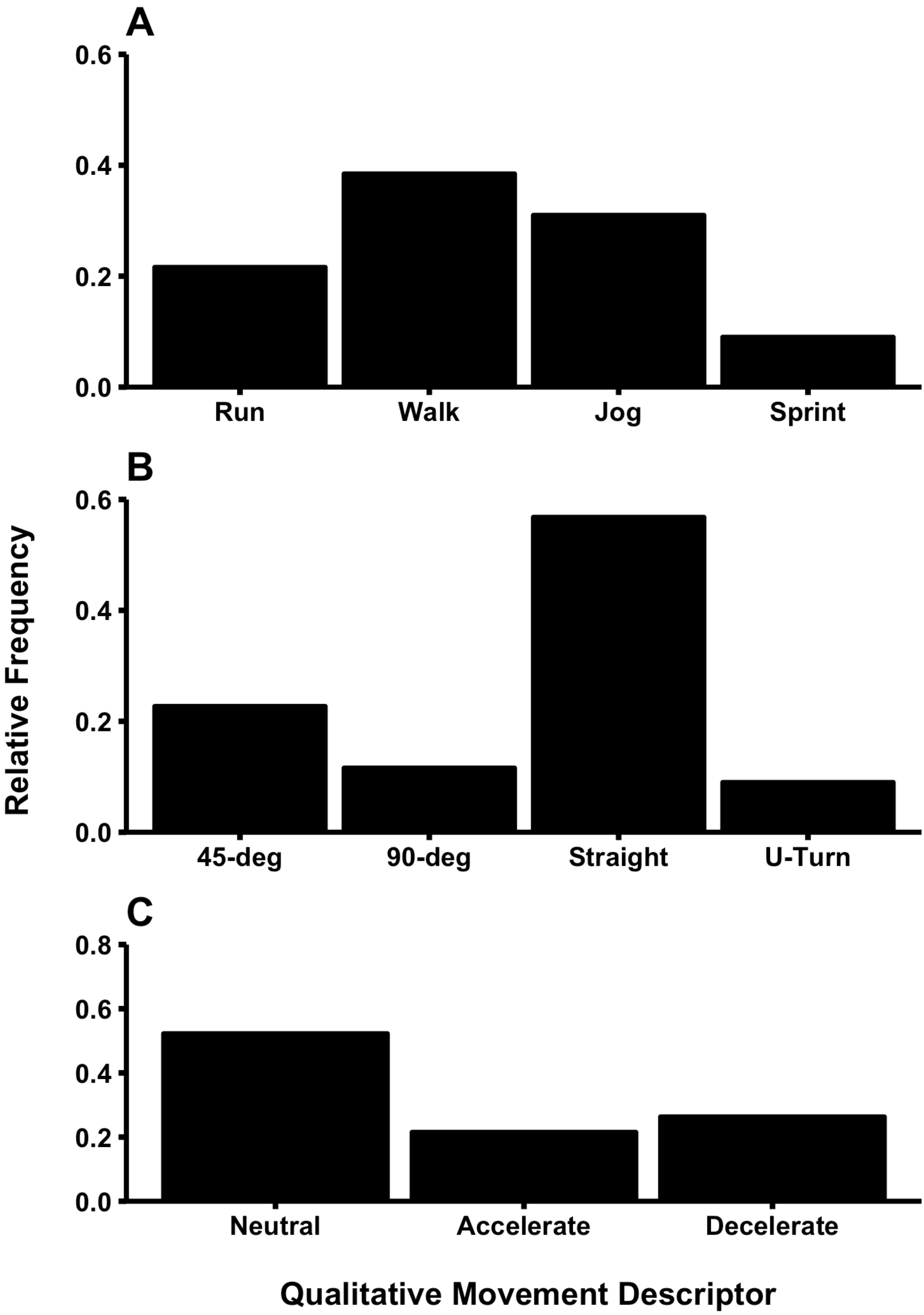

Figure 5-2. Relative frequency of clustered observations for A) Velocity, B) Acceleration and C) Angular Velocity.

This approach produced 48 permutations (4 x 4 x 3), each of which was described as a unique combination of velocity, acceleration and angular velocity. A permuted identification code (upper and lower case alphabet letters) was assigned to each unique combination of velocity, acceleration and angular velocity. Table 5-1 lists the specific alphabetic character assigned to each permutation of velocity, acceleration and angular velocity. These assignments are referred to as movement subunits. A frequency distribution of these movement subunits is displayed in Figure 5-3.

Character	Movement Subunit	Character	Movement Subunit
a	Run Neutral 45°	m	Run Neutral 90°
A	Run Decelerate Straight	M	Run Decelerate U-Turn
b	Run Accelerate 45°	n	Run Accelerate 90°
B	Walk Neutral Straight	N	Walk Neutral U-Turn
c	Run Decelerate 45°	o	Run Decelerate 90°
C	Walk Accelerate Straight	O	Walk Accelerate U-Turn
d	Walk Neutral 45°	p	Walk Neutral 90°
D	Walk Decelerate Straight	P	Walk Decelerate U-Turn
e	Walk Accelerate 45°	q	Walk Accelerate 90°
E	Jog Neutral Straight	Q	Jog Neutral U-Turn
f	Walk Decelerate 45°	r	Walk Decelerate 90°
F	Jog Accelerate Straight	R	Jog Accelerate U-Turn
g	Jog Neutral 45°	s	Jog Neutral 90°
G	Jog Decelerate Straight	S	Jog Decelerate U-Turn
h	Jog Accelerate 45°	t	Jog Accelerate 90°
H	Sprint Neutral Straight	T	Sprint Neutral U-Turn
i	Jog Decelerate 45°	u	Jog Decelerate 90°
I	Sprint Accelerate Straight	U	Sprint Accelerate U-Turn
j	Sprint Neutral 45°	V	Sprint Decelerate U-Turn
J	Sprint Decelerate Straight	w	Sprint Accelerate 90°
k	Sprint Accelerate 45°	x	Sprint Decelerate 90°
K	Run Neutral U-Turn	y	Run Neutral Straight
l	Sprint Decelerate 45°	z	Run Accelerate Straight
L	Run Accelerate U-Turn		

Table 5-1. Alphabetical characters for permuted movement subunits.

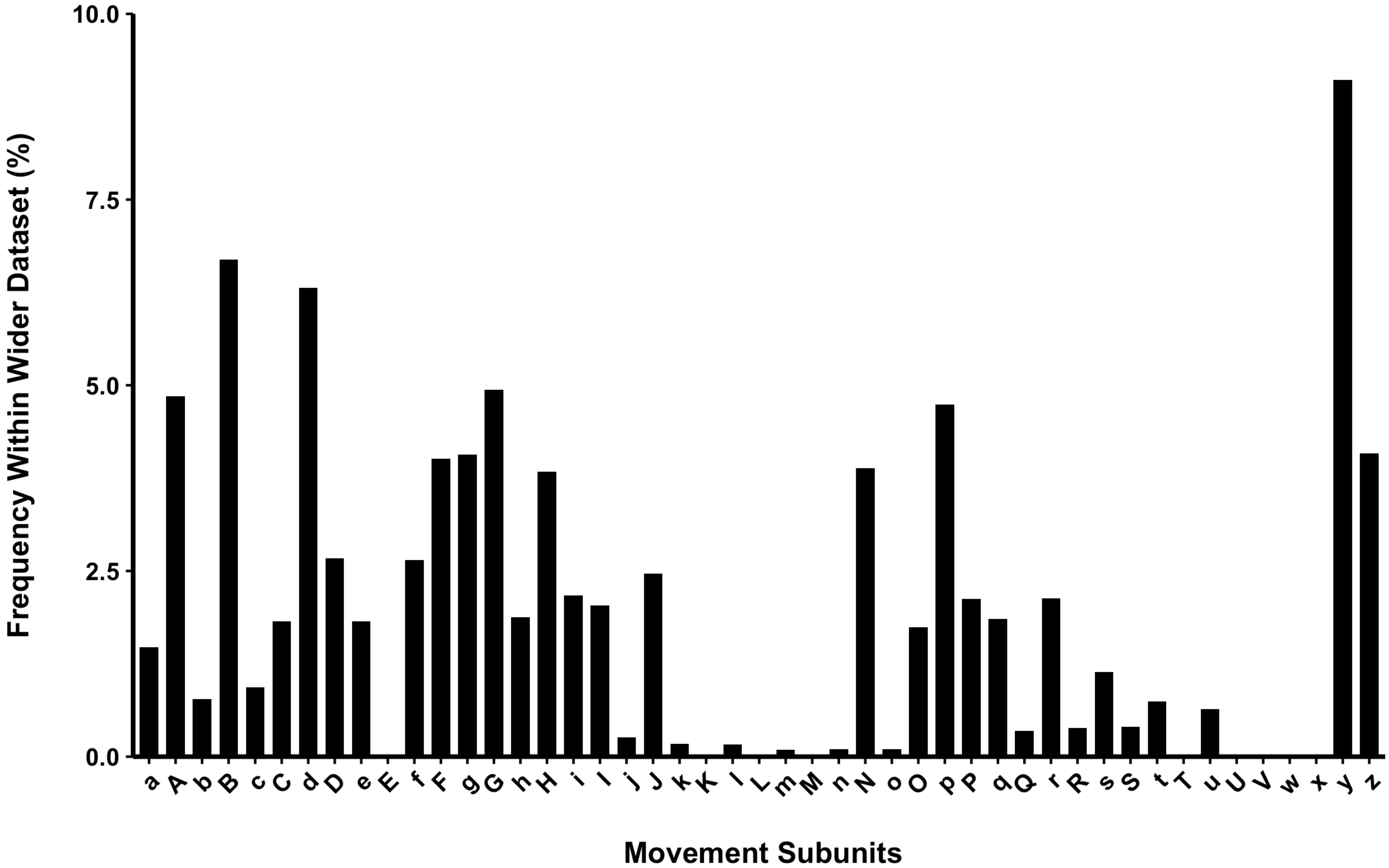

Figure 5-3. Frequency distribution of movement subunits.

The characteristics of any continuous movement are then represented by a temporal sequence of movement subunits. Any sequence of movement subunits is further described as a discrete movement sequence. Any movement sequence is declared different from other movement sequences where the athlete does not move for the duration, equal to the time epoch *t*. In practice it is difficult to identify moments where athletes are motionless in competition, so a movement threshold of 0.5 $m \cdot s^{-1}$ was applied to differentiate movement sequences. Additionally, any movement sequence must exceed the movement threshold for at least 1 second (note that this will occur by default where $t \geq 1.0$ seconds).

Any period of player movement is now described as a set of movement sequences, where each subunit is characterised by an alphabetic character. Movement sequences were therefore represented by character strings of k length, where k is the number of composite subunits. It is also possible to quantify the similarity of movement sequences by comparing character strings using the Levenshtein distance (Levenshtein, 1966), which is a function of the minimum number of single-character edits (including insertions, deletions or substitutions) required to change one sequence into another.

5.3 Results

The means of each of the four velocity clusters, for combined epochs, were 1.1 $m \cdot s^{-1}$, 0.7 $m \cdot s^{-1}$, 0.3 $m \cdot s^{-1}$ and 1.8 $m \cdot s^{-1}$, notionally referred to as running, jogging, walking and sprinting respectively. It is important to note that these labels are arbitrary, and in practice it might be better to simply refer to them in such a manner as slow, slow-moderate, moderate, and fast. The means of the three acceleration clusters were 1.4 $m \cdot s^{-2}$, 0.1 $m \cdot s^{-2}$ and -1.3 $m \cdot s^{-2}$. These values are more clearly defined as accelerating, neutral, and decelerating. The means of the three angular velocity clusters were 149.7 $deg \cdot s^{-1}$, 11.2 $deg \cdot s^{-1}$, 42.7 $deg \cdot s^{-1}$ and 88.9 $deg \cdot s^{-1}$.

Movement sequences were generated using strings of character values. A cluster analysis was conducted using the Ward method (Ward Jr, 1963). All movement strings in the present dataset are therefore grouped proximally according to the Levenshtein distance. A sequence analysis, using hierarchical clustering, revealed the most common clusters. Using this method, 18 clusters were identified and an algorithm to find the longest common substring or LCS (Kuo & Cross, 1989) was utilised to find the longest string that is a substring of two or more strings, within each cluster. The two most common clusters include EEEEE and FEEEE, only one permuted subunit apart. Each cluster was iterated through to find the longest common substring, for each time epoch. The support value for each movement sequence was measured as the percentage of all movements represented by each example. These values were calculated for each of the epoch size. This data is presented in Table 5-2.

Cluster Number	0.5 s		0.75 s		1 s		1.25 s		1.5 s	
	String	%	String	%	String	%	String	%	String	%
1	AzAy	2	zIycAy	1	yyA	11	IJJIJ	5	IIJJIJ	10
2	FJzyHAE	1	yyyy	19	yyy	28	IHHHJ	10	HHH	40
3	EEE	25	yy	50	HHJ	17	HHHJ	19	IJJ	40
4	EEE	25	yIJ	8	IJJIJy	2	HHHHH	14		
5	Yyy	30	IJIJ	3	yyyyyyy	4	IJIJJJ	5		
6	yyIJy	1	yyyyyy	6	JHH	9				
7	hzlycAy	1	HJHH	3	IHHHJ	4				
8	IIJ	3	HHH	15	zAyy	4				
9	ggEE	2	zHA	3	HHA	11				
10	yyyJ	1	E	28	HHHH	11				
11	yyy	30	A	61	IJy	2				
12	EEE	25	zIHHHIIHHJ	1	HAyy	2				
13	zIHHH	1	HAyyy	1	IJIJJJ	2				
14	zIHHHIIHHJg	1	AyyyyyA	1						
15	zyyyyyyyyG	1								
16	aHHHHAz	1								
17	yyyyHHyHH	1								
18	AEEE	3								

Table 5-2. The most frequently reoccurring movements, per cluster, as a function of epoch stamp and support.

5.4 Discussion

This study contributes to the problem of robust athlete activity-profiling that is independent of age, gender, sport-related constraints, and other features of physical capacity. The development of this movement sequencing technique may create insight into the temporal sequence of movement elements in sport. Traditional analyses focus on quantifying athlete movement as a function of arbitrary or commercially developed thresholds.

Using a one-dimensional *k*-means clustering algorithm, four velocity clusters, three acceleration clusters and four angular velocity clusters were identified. By permuting elemental features of movement and characterising continuous athlete movement in the form of strings, the LCS sequence analysis approach revealed discrete and recurring combinations of athletic movement, representative of athlete activity typical in netball. In the 0.5 s epoch, running at a straight or 45° angle with neutral and acceleration components was a common feature for cluster 1. In contrast, the 1.5 s epoch showed sprinting and accelerating in a straight direction immediately followed by a sprint with deceleration was a common feature for cluster 1.

Obtaining the most frequently recurring movements of an athlete or a number of athletes grouped according to position or playing standard, may have application for coaching and conditioning purposes. Knowledge of the movements performed, angle of attack and acceleration qualities may assist with planning sport-specific training and conditioning practices. Sprinting, accelerating and decelerating components were a common feature across a 1.5 s epoch for the athlete tested. This data may be used to target specific training qualities within a program. Further analysis could focus on movements performed before a successful or unsuccessful attempt at goal, which may assist with tactical planning. A movement sequencing analysis of athletes according to chronological age, playing standard and position should be investigated in future analyses.

Eighteen clusters were obtained over a 0.5 s epoch in comparison to three clusters over a 1.5 s movement threshold, highlighting the importance of under-fitting versus over-fitting a model. The number of clusters to trim, or focus on, within a dendrogram is an important consideration when analysing athlete movement. For the purpose of this investigation (and the sport examined), clusters were trimmed at 25. Further investigation into epoch and trimming selection, dependent upon the sport considered, is warranted.

5.5 Conclusion

A movement sequencing technique was developed to analyse athlete activity profile. Using a one-dimensional *k*-means clustering algorithm, four velocity clusters, three acceleration clusters and four angular velocity clusters were identified. The LCS sequence analysis approach revealed discrete and recurring combinations of athletic movement, representative of athlete activity typical in netball. Eighteen clusters were obtained over a 0.5 s epoch, in contrast to three clusters over 1.5 s, highlighting the importance of under-fitting versus over-fitting a model. The three clusters over 1.5 s reveal a combination of sprinting, acceleration and deceleration qualities in a straight direction. Examining athlete activity profile using this movement sequencing technique, in contrast to traditional analyses, may assist with position specific training and conditioning practices.

CHAPTER 6. STUDY 3 – DISCOVERING FREQUENTLY RECURRING MOVEMENT SEQUENCES IN TEAM-SPORT ATHLETE SPATIOTEMPORAL DATA

6.1 Introduction

Profiling the external load of team-sport athletes during matches is useful information for training design and load management (Carling et al., 2008). External load is captured by tracking systems, including global positioning systems (GPS), that estimate an athlete's position with respect to the coordinates of a playing area and allow for the calculation of displacement over a specified time epoch (Aughey, 2011a). Once the trajectory data of an athlete's position is captured, the resulting velocities and accelerations can be calculated. The match activity profile of field-based team-sport athletes has been documented (Aughey, 2011a) however, limited research exists on the external load of athletes participating in court-based sports. This is likely due to elite level matches being played indoors, where GPS is inoperable. The recent development of radio-frequency (RF) based athlete tracking systems (Sathyan et al., 2012) may allow for external load to be captured during elite court-based team-sports.

Athlete external load is typically presented according to the distribution of time spent or distance covered in dissimilar velocity and acceleration bands (Jennings et al., 2012a; Varley et al., 2013b). These predetermined thresholds are established according to the manufacturer of the tracking technology, a body of research (Varley et al., 2013b) or as a function of a physiological capacity (Lovell & Abt, 2012). In female team-sport athletes, up to a 30% difference in match high-speed running was recorded between industry (5 $m \cdot s^{-1}$) and physiological capacity based velocity thresholds (Clarke et al., 2014). Although expressing external load relative to a physiological threshold can identify athletes who are working at or near capacity, it is currently unclear which physiological tests are best representative or related to the intermittent nature of team sport (Carling, 2013). There is also limited research on the relationship between such physiological tests and the movement of athletes during court-based team-sports, including netball.

A popular sport in Commonwealth countries, netball matches are contested over 15 minutes quarters between two teams of seven players. Each of the seven players has a unique positional role that restricts their movement to specific regions of the court. Research on the match movement output of netballers, according to playing position, is largely confined to estimates from video analysis (Fox et al., 2013) or examined in a sub-elite cohort (Cormack et al., 2014). Recently, the load of elite netball athletes was examined during training and matches according to playing position (Young et al., 2016). Although athlete displacement and velocity was not measured, the accelerometer derived player load from each playing position was clustered into groups using a data mining technique (Young et al., 2016).

Data mining is a branch of computer science that sources a logical or mathematical description of patterns and regularities in a data set (Fayyad et al., 1996). Data mining methods can extract previously unknown information from raw data and have useful application in elite sport, including the modeling and extraction of athlete performance patterns (Ofoghi et al., 2013b). Clustering is a data mining method that detects and organises data into a number of groups. The data within each of these groups or cluster are similar to one another, based on some criteria, and dissimilar to data within other groups (Ofoghi et al., 2013b). In sport, clustering has been utilised to assess the tactical patterns of play during elite volleyball matches (Jäger & Schöllhorn, 2007) and classify movement patterns performed during different basketball shots (Lamb et al., 2010). Deemed an semi-supervised data mining technique, clustering has been used to extract movement activity data, including the position, velocity and acceleration of different body parts, from wearable sensors (Ghasemzadeh et al., 2010). Each movement variable was represented by a sequence of characters, with a metric used to find the difference between two character strings (Ghasemzadeh et al., 2010).

Together, the data mining techniques of clustering and string matching present an opportunity to ascertain the movements performed by team-sport athletes, without the requirement of arbitrary or physiologically defined thresholds. Using data mining techniques, the sequences of velocity, acceleration and angular velocity performed by a junior-elite female netball athlete were examined in Chapter Five. Spatiotemporal data, or the real-time position of an athlete relative to a playing area, was collected by a local positioning system (LPS). Four velocity, three acceleration and four angular velocity clusters were obtained by *k*-means clustering, an unsupervised data mining approach that assigns data points to a cluster based on the closest centroid. Each combination of continuous velocity, acceleration and angular velocity movement was assigned a character, with athlete movement represented by strings of characters or sequences. Eighteen movement sequences were obtained and running in a straight or 45° direction with neutral acceleration was a common feature. However, spatiotemporal data was only collected during a quarter of netball and there was no investigation into the differences or similarities in movement sequences performed by the remaining six netball playing positions. Further, only a junior-elite athlete participated and not elite, international level athletes. Therefore, the aim of this chapter was to further develop this methodology to uncover the movement sequences performed by court-based team-sport athletes, according to playing position and independent of industry based, commercially developed or physiologically defined thresholds.

6.2 Methods

The activity profile of 12 elite, international level female netball athletes (age 24.8 ± 2.7 years; height 179.5 ± 6.9 cm, mean ± Standard Deviation (SD), at commencement of study) was collected during four competitive national-level matches. These competitive matches between international level athletes were contested at the Australian Institute of Sport (AIS) in Canberra and formed part of the selection process for the 2016 Commonwealth Games. The elite level athletes who participated in this study represent their country in a limited number of international netball matches that are held annually. Therefore, only a small number of matches were sampled.

The number of individual athletes sampled per netball playing position was five for the centre (C), three for wing defence (WD), five for wing attack (WA), three for goal attack (GA), two for goal defence (GD), three for goal shooter (GS) and two for goal keeper (GK). All participants provided written informed consent. The study was approved by the University Human Research Ethics Committee (HRE14-068) and conformed to the Declaration of Helsinki.

Spatiotemporal data was collected via a RF tracking system, specifically, the Wireless ad hoc System for Positioning (WASP). Indoors, WASP has a relative positional accuracy of 28 cm and a mean distance error of 2.7% (Sathyan et al., 2012). When compared to Vicon, the WASP coefficient of variation (CV) is $< 6\%$ for measuring distance covered during five short (< 15 m) non-linear courses performed indoors by elite netball athletes (see Chapter Four). Over these five separate non-linear courses, the CV for WASP derived mean velocity is $< 8\%$. For mean angular velocity, the CV is $< 3\%$ and for acceleration, the CV ranges from 2.3% to 18.5%.

Each participant wore a WASP mobile node, measuring 90 x 50 x 25 mm, positioned between the shoulder blades. The range between each mobile and the twelve anchor nodes surrounding the netball court was computed at an update rate of 10 Hz and calculated into a 100 Hz file via customised software (WheresBruce, Australian Institute of Sport, Canberra, Australia). This process involves resampling the RF signal via a Kalman filter as described in Sathyan et al., (2012) and is very similar process to the RF tracking system used by Stevens et al., (2014). Further details of the Kalman filter and positioning algorithm used can be found elsewhere (Hedley et al., 2011). Each athlete's positional data (X and Y coordinates) was exported into the R statistical software (R: A language and environment for statistical computing, Vienna, Austria) for further analysis.

Velocity was calculated from each athlete's positional data and acceleration derived from velocity, as per Chapter Five. Angular displacement was calculated via the dot product of consecutive movement vectors. Angular velocity, the rate of change of angular displacement, was obtained from angular displacement. Individual velocity, acceleration and angular velocity movements were clustered using a one-dimensional *k*-means clustering algorithm (Wang & Song, 2011) seeded with 4, 3 and 4 clusters, respectively. The cluster analysis simply assigns a data point to the nearest centroid and doesn't assert statistical difference, therefore, no statistical analysis was performed on these clusters. A qualitative label was assigned to each cluster, which may not align precisely with the mean values but are intended to represent arbitrary descriptors rather than specific quantities. From these clusters, each unique combination of velocity, acceleration and angular velocity movement, termed movement subunits, was assigned an identification code consisting of an upper or lower case alphabetic letter. In short, athlete movement during a match was represented by continuous movement subunits.

To isolate discrete athlete movement sequences, any period during which the athlete moved at a rate lower than $0.5\ m \cdot s^{-1}$ was judged to be moments of inactivity and thus delineated continuous movement subunits to form sequences. The similarity between each movement sequence was quantified using the Levenshtein distance implementation in the R *stringdist* package (Van der Loo, 2014). The Levenshtein distance represents the minimum number of movement subunits required to change, including insertions, deletions or substitutions, one movement sequence into another. Similar movement sequences were then grouped into 25 clusters using a hierarchical cluster analysis (Ward Jr, 1963).

The longest common subsequence (LCS) algorithm, using the R *qualV* package (Jachner, Van den Boogaart, & Petzoldt, 2007), was used to discover the most common athlete movement sequence within each of the 25 clusters. A key feature of the LCS algorithm is to discover all of the common elements or movement subunits, within movement sequences whilst retaining the sequential order. Therefore, the LCS or frequently recurring patterns of athlete movement performed across matches could be located.

To uncover the frequently recurring movement sequences performed by individual playing position, a frequency distribution was conducted using two methods. The relative frequency of individual movement subunits was compiled for each playing position. The relative frequency of the LCS-derived movement sequences for each playing position was also calculated. These distributions can be considered a movement signature for each netball playing position. Further, the Minkowski distance implemented in the R *HistogramTools* package (Stokely, 2014), was used to quantify the distance between playing positions using the LCS results. Briefly, the Minkowski distance was calculated by obtaining the relative percentage contribution of each LCS movement to the wider dataset, for each playing position. A matrix was then constructed, with the similarity between each playing position calculated via the Minkowski distance. A network graph was used to display this similarity between playing positions.

6.3 Results

The centroids of the four velocity clusters were 0.6 $m \cdot s^{-1}$, 1.4 $m \cdot s^{-1}$, 2.5 $m \cdot s^{-1}$ and 3.9 $m \cdot s^{-1}$ respectively. The centroids of the four angular velocity clusters were 13.5 $deg \cdot s^{-1}$, 49.9 $deg \cdot s^{-1}$, 98.9 $deg \cdot s^{-1}$ and 153.6 $deg \cdot s^{-1}$, respectively. Centroids of the three acceleration clusters were -6.8 $m \cdot s^{-2}$, 0.0 $m \cdot s^{-2}$ and 6.9 $m \cdot s^{-2}$, respectively. The within cluster variation, as the sum of Euclidean distance between the data points and each centroid, was 90.2% for velocity, 71.9% for acceleration and 94.7% for angular clusters. The distribution of data points within each velocity, angular velocity and acceleration cluster and the relative frequency of these clusters to the total dataset is demonstrated in Figure 6-1a, b and c, respectively. Qualitative labels were assigned to each cluster, which may not align precisely with the mean values but are intended to represent arbitrary descriptors rather than specific quantities.

The most prevalent movement features of netball match activity were walking with straight movement and neutral acceleration. Neutral acceleration refers to acceleration data assigned to the cluster with a centroid of 0.0 $m \cdot s^{-2}$, which is the mean of all the data points within this cluster. These data points are not necessarily accelerations of 0.0 $m \cdot s^{-2}$. Each movement subunit, the qualitative descriptor comprising the relevant combination of velocity, acceleration and angular velocity and their relative frequency to the wider dataset is presented in Table 6-1.

The 10 most frequently recurring movement sequences and the relative contribution to the wider dataset, according to playing position, is presented in Figure 6-2. These substrings are the longest string within each of the 25 clusters. For example, in 1 of the 25 clusters, “KK” was the LCS within that cluster. In a separate cluster, “NNNNN” was the LCS within that cluster. The difference between “Q” and “QQ”, for example, is that they are one movement subunit apart and were located separately within the 25 clusters. A matrix of the frequently recurring movements across individual playing positions is displayed in Table 6-2. The relative proximity of playing position is visualised in Figure 6-3. The GD, GA and WA are the most closely related netball playing positions. The largest Minkowski distance (19.64) was between the GS and GD. The Minkowski distance between the GS and C was 19.20.

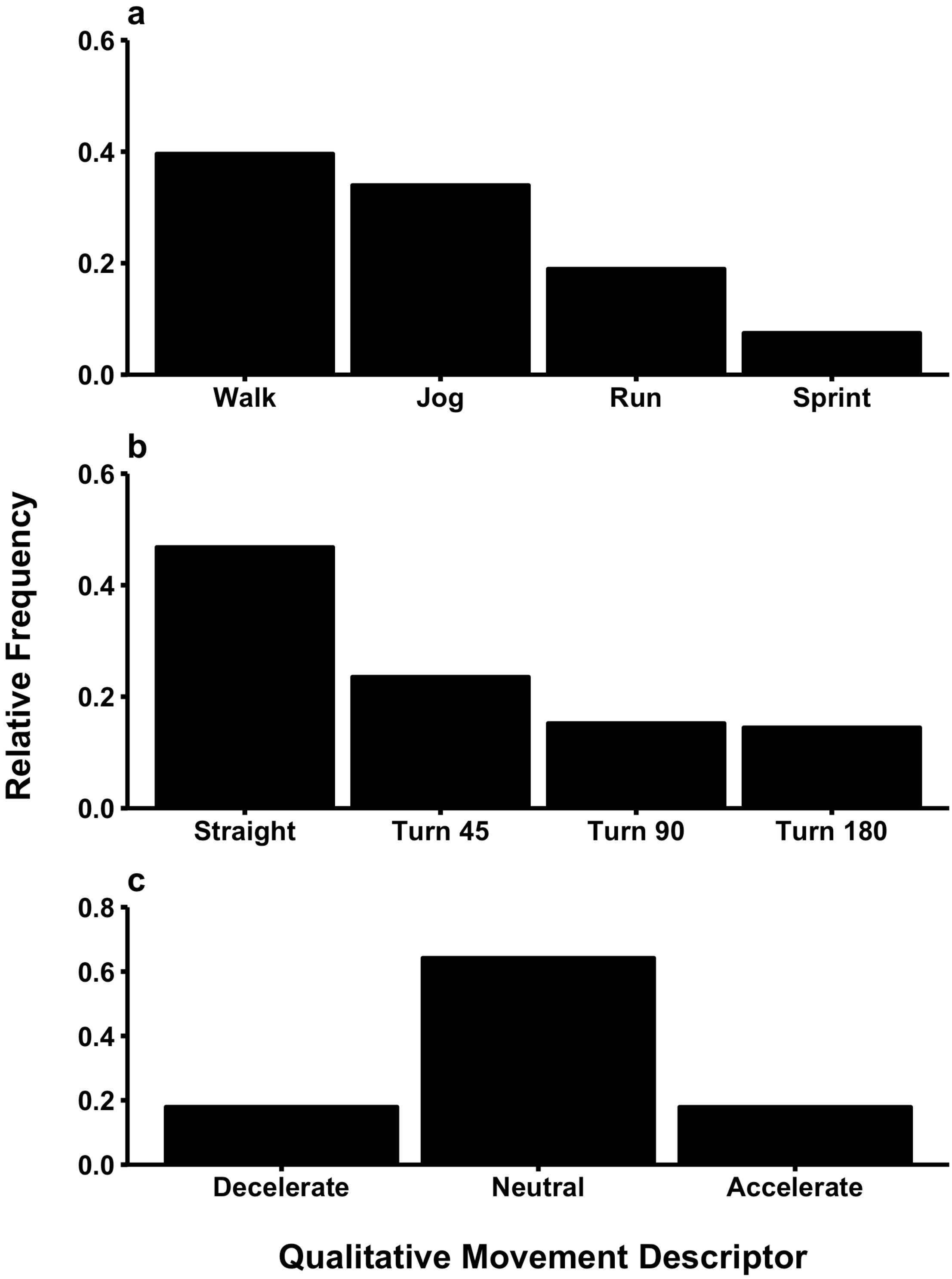

Figure 6-1. The relative frequency of clustered observations for a) velocity, b) angular velocity and c) acceleration movement features.

Movement Subunit	Percentage Contribution	Qualitative Descriptor
a	6.1	Walk Neutral Turn 90
A	1.6	Walk Accelerate Turn 180
b	1.4	Walk Decelerate Turn 90
B	0.2	Run Neutral Turn 180
c	1.3	Walk Accelerate Turn 90
C	0.3	Run Decelerate Turn 180
d	0.7	Run Neutral Turn 90
D	0.3	Run Accelerate Turn 180
e	0.4	Run Decelerate Turn 90
E	1.7	Jog Neutral Turn 180
f	0.5	Run Accelerate Turn 90
F	1.0	Jog Decelerate Turn 180
g	2.5	Jog Neutral Turn 90
G	1.0	Jog Accelerate Turn 180
h	1.0	Jog Decelerate Turn 90
H	0.0	Sprint Neutral Turn 180
i	1.1	Jog Accelerate Turn 90
I	0.0	Sprint Decelerate Turn 180
j	0.1	Sprint Neutral Turn 90
J	0.0	Sprint Accelerate Turn 180
k	0.1	Sprint Decelerate Turn 90
K	8.7	Walk Neutral Straight
l	0.1	Sprint Accelerate Turn 90
L	1.5	Walk Decelerate Straight
m	6.8	Walk Neutral Turn 45
M	1.3	Walk Accelerate Straight
n	1.3	Walk Decelerate Turn 45
N	7.3	Run Neutral Straight
o	1.2	Walk Accelerate Turn 45
O	2.4	Run Decelerate Straight
p	2.4	Run Neutral Turn 45
P	2.5	Run Accelerate Straight
q	1.0	Run Decelerate Turn 45
Q	12.1	Jog Neutral Straight
r	1.1	Run Accelerate Turn 45
R	2.7	Jog Decelerate Straight
s	5.1	Jog Neutral Turn 45
S	2.6	Jog Accelerate Straight
t	1.6	Jog Decelerate Turn 45
T	3.1	Sprint Neutral Straight
u	1.6	Jog Accelerate Turn 45
U	1.3	Sprint Decelerate Straight
v	0.7	Sprint Neutral Turn 45
V	1.4	Sprint Accelerate Straight
w	0.3	Sprint Decelerate Turn 45
x	0.4	Sprint Accelerate Turn 45
y	6.7	Walk Neutral Turn 180
z	1.7	Walk Decelerate Turn 180

Table 6-1. Movement subunits, their percentage contribution to the wider dataset and qualitative descriptor.

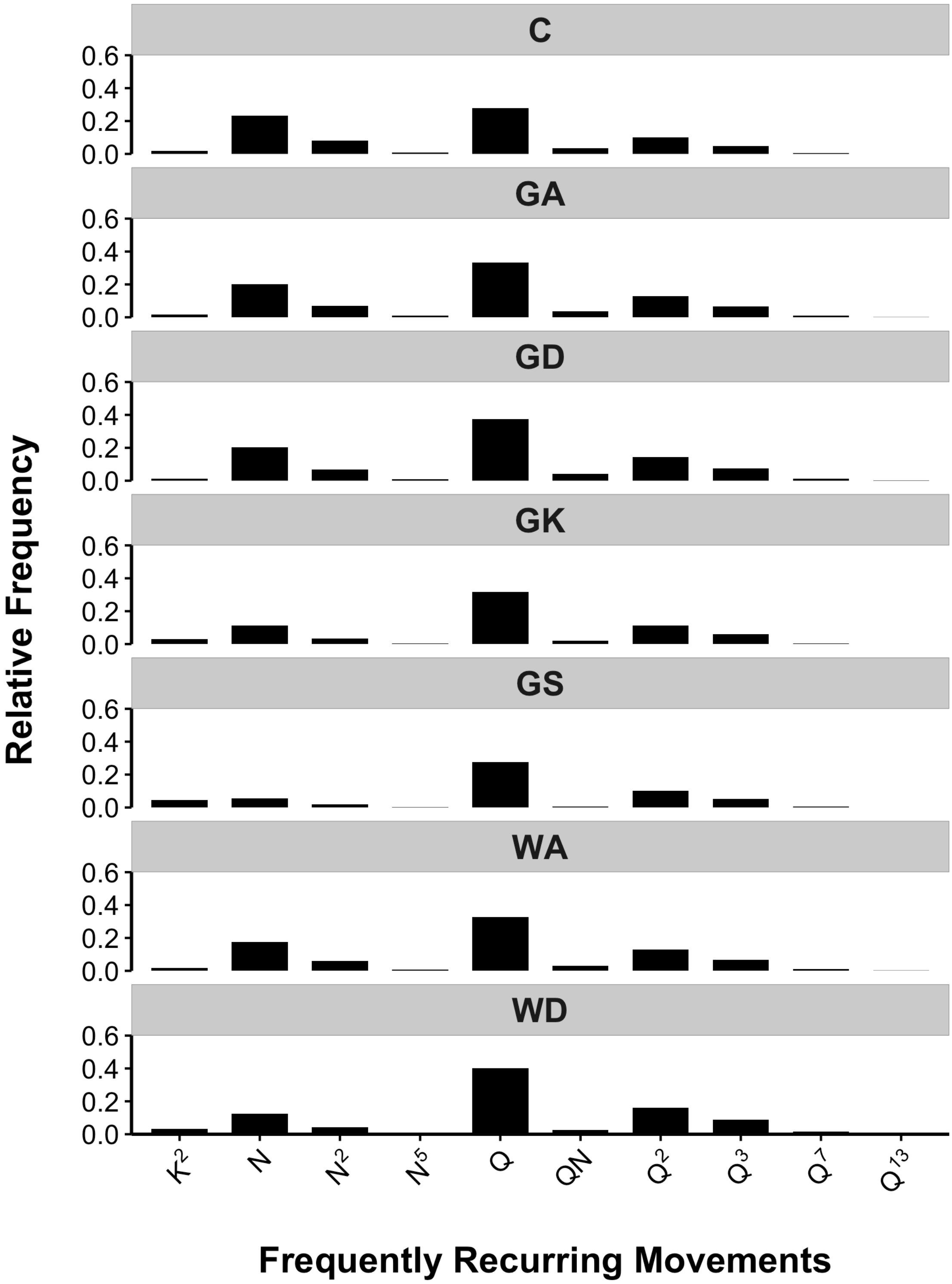

Figure 6-2. The relative contribution of frequently recurring LCS sequences by netball playing position including centre (C), goal attack (GA), goal defence (GD), goal keeper (GK), goal shooter (GS), wing attack (WA) and wing defence (WD). The number of iterations of each movement subunit are represented by b^N, for example K^2 refers to KK and N^5 refers to NNNNN.

	C	GA	GD	GK	GS	WA	WD
C	0.0	7.24	11.37	13.87	19.20	8.42	18.55
GA		0.0	4.55	10.19	17.23	2.58	11.60
GD			0.0	12.18	19.64	5.70	9.37
GK				0.0	7.52	7.71	10.52
GS					0.0	14.78	16.56
WA						0.0	10.30
WD							0.0

Table 6-2. The Minkowski distances for movement sequence distributions between netball playing positions including centre (C), goal attack (GA), goal defence (GD), goal keeper (GK), goal shooter (GS), wing attack (WA) and wing defence (WD).

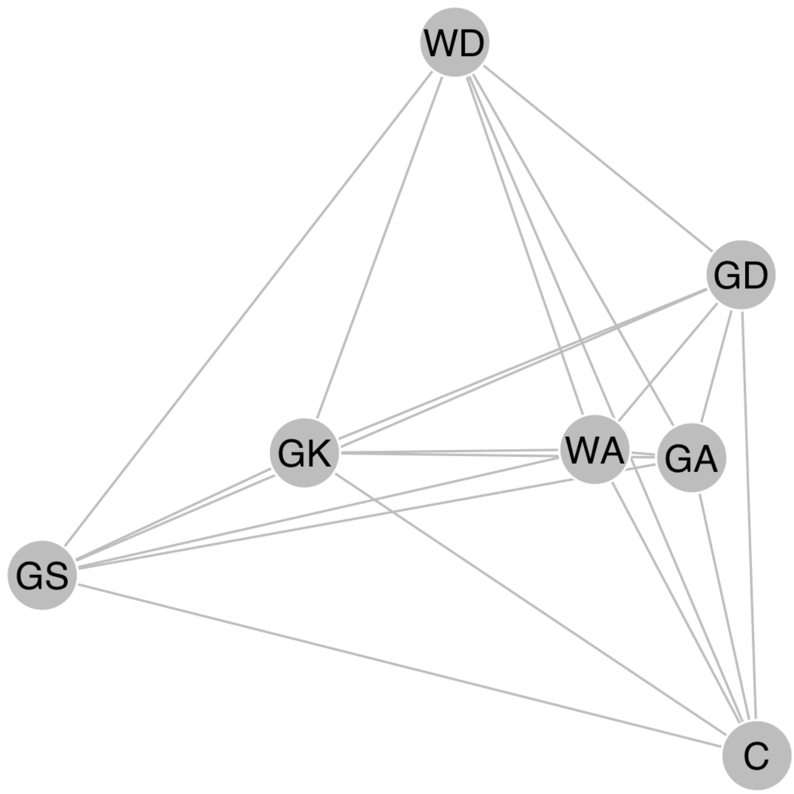

Figure 6-3. A network analysis of movement sequence similarity between netball playing position, including goal shooter (GS), goal keeper (GK), goal attack (GA), goal defence (GD), centre (C), wing attack (WA) and wing defence (WD).

6.4 Discussion

The purpose of this chapter was to describe a new analysis technique of team-sport athlete movement data. The combinations of movement performed by team sport athletes, collected via radio-frequency (RF) athlete tracking data, were quantified by a technique that assessed for similarity or dissimilarity between playing positions. Ten frequently recurring movement sequences, across all netball playing positions and matches, were discovered (Figure 6-2). Only the WA, GA and GD playing positions are closely related (Figure 6-3). Traditional analysis of team sport athlete external load quantifies movement as a function of commercially developed or industry used thresholds, binning velocities or accelerations into descriptive categories. This approach as it does not account for variations in gender, age, position or sport. To address this problem, the present technique examines the combinations of movement performed that can then be used to underpin traditional analysis of external load, irrespective of velocity or acceleration thresholds.

Four velocity, three acceleration and four angular velocity clusters were identified via one-dimensional *k*-means clustering. The centroids of the velocity clusters, notionally referred to as "walking", "jogging", "running" and "sprinting", are lower than the thresholds used to report the external load of female team sport athletes during matches. For example, high speed running performed during field hockey matches was considered as any movement over 4.19 $m \cdot s^{-1}$ (Macutkiewicz & Sunderland, 2011). The amount of high-speed running completed by female rugby athletes was also underestimated when analysed according to an industry based (5 $m \cdot s^{-1}$) compared with a physiologically determined (3.5 $m \cdot s^{-1}$) threshold (Clarke et al., 2014). In the present chapter, the centroid of the "sprinting" cluster was 3.9 $m \cdot s^{-1}$. However, there is no intended comparison between the movement clusters described here and industry standard thresholds. In practice, it is still difficult to compare movement thresholds derived from methods in the current study with other threshold benchmarks, because the number of clusters derived from the raw data are arbitrary. Reducing the number of initial velocity clusters would likely result in different cluster means. By establishing a standardised approach to the initial clustering stage, it would be possible to make internally consistent estimates of time in self-calibrating movement intensity zones. Therefore, rather than prescribing workload bins, the thresholds are learned directly from the data. It is important to note that these self-calibrating movement intensity zones are based on external load measures only and do not provide information relative to an athlete's internal physiological capacity. The proposed methodology is therefore appropriate for a court-based team sport, such as netball, due to the unique court space restrictions, differing roles and anthropometric characteristics of netball playing positions (Steele & Chad, 1991a). The methodology presented could also be applied to field-based team-sports including soccer, rugby and Australian football although future application, including generalisation to all elite female netball athletes, would require testing on a larger dataset.

The network analysis highlights that the WA, GA and GD positions are the most closely related netball positions. The GS role is characterised by movement combinations that are highly dissimilar to all the other positions. However, the most dissimilar pairwise comparison is between the GS and GD positions, an interesting finding given both playing positions are goal based roles. In a recent study on elite netball athlete load, the GD position was grouped with the GS and GK based on the proportion of match time spent performing low intensity activity (Young et al., 2016). The athletes in the present study comprise the national representative team, which may indicate the unique playing style of the GD position in this cohort compared with those from a lower-level competition.

Differences in the accelerometer load of netball playing positions have been investigated across state representative and recreational playing levels (Cormack et al., 2014). Higher standard (state league level) athletes performed a greater proportion of accelerometer load in the vertical plane compared to their lower (recreation) level counterparts (Cormack et al., 2014). When comparing positions, only centre court athletes had a greater load than shooters and there were no clear differences between centres and defenders nor between shooters and defenders (Cormack et al., 2014). In the present study, the seven netball playing positions were studied at an individual level via the combination of velocity, acceleration and angular velocity movements performed by elite level athletes. It is difficult to compare these studies in netball, given the discrepancies in methodology and tracking systems utilised. Rather than simply reporting time spent in different intensity zones, this chapter presents the relative frequency of recurring movement sequences as a characteristic signature that differentiates athlete movement by playing role.

Potential applications of this methodology may include a more granular evaluation of the movement output for each role than can be learned by using speed thresholds alone. This approach may be used to evaluate the developmental progress of young athletes as they build the physical attributes required to compete at more senior levels. The presented methodology may also reduce the need for the traditional collection, analysis and reporting of team-sport athlete external load in arbitrary or ill-defined movement categories. Rather than structuring training programs around time or distance spent in these categories, practitioners and scientists can focus on training the specific movement patterns frequently performed by athletes in each playing position. For example, practitioners could dedicate physical training time to prepare athletes for the most important or frequently recurring patterns performed according to their playing position. Further, athletes who are required to play across multiple roles or positions can prepare physically by ensuring the most frequently recurring movement patterns for these positions are incorporated into training. Alternatively, athletes could be examined on an individual case basis according to the movement sequences they perform during a match and the number or variety of movements performed during training.

Research conducted in elite female netball has been limited to only three matches (Davidson & Trewartha, 2008; Fox et al., 2013). Future work should incorporate more matches to calculate test-retest reliability and examine the repeatability or match-to-match variability of role proximity results in netball. Analysis on the change of movement sequences performed over the duration of a match may ascertain if movements are a function of game style or an individual athlete playing within that position. Although netball was the sport analysed, the methodology presented can be extended to discover the frequently recurring movements within other team-sports. Utilising the Minkowski distance metric, the discovered movement features and distributions by playing role may uncover new relationships between the different playing positions in team-sports. The proposed methodology may assist coaches with tactical planning, through understanding the movement sequences performed by team-sport athletes during specific match activities, for example, the movements performed in the lead up to a shot for goal. Team-sport athletes could use also information derived from the presented methodology for performance analysis purposes, including quantitative spatiotemporal data on their angle of attack during set plays as opposed to traditional inferences from video analysis.

6.5 Conclusion

The sequences of velocity, acceleration and angular velocity movement performed by team sport athletes during matches was discovered by a novel data mining technique. The combinations of these movement sequences were utilised to measure the strength of relationship between the netball playing positions. Using a one-dimensional *k*-means clustering algorithm, four velocity, three acceleration and four angular velocity clusters were obtained from netball athlete positional data. A total of 10 frequently recurring combinations of movement were discovered. To examine the relationship between netball playing positions, the percentage contribution of each frequently recurring movement pattern within the wider dataset was calculated. Based on the combination of velocity, acceleration and angular velocity movements performed, it was discovered that only the WA, GA and GD playing positions are closely related. The GD and GS are the least similar netball playing positions. Future research should examine if these differences are a function of a global position or instead, each individual athlete who plays within that position. Analysis should also be extended to analyse the relationship between each playing position across playing standards, for example, a junior-elite level GA compared to an elite GA.

CHAPTER 7. STUDY 4 –THE MOVEMENT SEQUENCES PERFORMED BY ELITE AND JUNIOR-ELITE FEMALE NETBALL ATHLETES DURING MATCHES

7.1 Introduction

Netball is a court-based team-sport popular in Commonwealth countries. A description of netball and the relevant playing positions is located in Chapter 2.2. At the elite level, netball competition includes major international tournaments such as the Commonwealth Games and Netball World Cup. In Australia, junior elite pathways including representative 21 and under (21/U) squads that prepare athletes for competing at the elite level. The extent to which the activity profiles at the junior elite level prepare athletes to make a successful transition to elite competition is currently unknown.

Quantifying the activity profile of team-sport athletes during matches is useful information for the design of position or playing standard specific training (Carling et al., 2008). The position of athlete during a match can be captured by tracking systems and then analysed according to time spent or distance covered in pre-described movement categories. Elite and junior elite level netball matches are held indoors, where global positioning systems (GPS) are inoperable due to no satellite reception. The development of radio-frequency (RF) based tracking systems (Hedley et al., 2010) allows for athletes to be monitored during court-based team-sports, such as netball.

The physical load of netball athletes, according to playing position, have recently been examined at a domestic (Young et al., 2016) and sub-elite level (Cormack et al., 2014). Goal based playing positions had the lowest playing load, an accelerometer derived movement variable, across matches (Cormack et al., 2014; Young et al., 2016). At the domestic level, the load characteristics of the wing and attacking positions were similar when grouped via *k*-means clustering (Young et al., 2016). Differences in player load between the seven netball positions are 97% *likely* higher at the sub-elite level when compared to recreational level athletes (Cormack et al., 2014). The physical output of junior elite athletes and potential differences between the seven playing positions is yet to be examined. Whilst accelerometer derived load measures the frequency and magnitude of body movement in three dimensions (Boyd et al., 2013), no data is collected on the location of an athlete relative to the coordinates of a playing area, such as a netball court. Displacement and the resulting speed plus acceleration of the athlete over time is therefore unable to be calculated.

The displacement and speed of field-based team-sport athletes competing at differing playing standards, including the junior level, and positions is well documented (Gabbett, 2002; McLellan & Lovell, 2013; Mendez-Villanueva et al., 2011). In Chapter Five, the movement sequences of a junior elite female netball athlete were identified. This technique has also been extended to find the movement sequences of elite female netball athletes according to playing position (Chapter Six). Whilst similarities in the movement sequences performed by the WA, GA and GD playing positions were evident, it is currently unknown if these differences extend to the junior elite playing standard. Therefore, the purpose of this chapter was the examine the movement sequences of netball athletes according to playing position and two playing standards, elite and junior elite.

7.2 Methods

The activity profiles of 15 junior-elite level female netball athletes (age 19.3 ± 0.9 years; height 181.9 ± 8.0 cm, mean ± Standard Deviation (SD), at commencement of study) were collected during three competitive matches. The junior-elite level athletes who participated in this study comprise the national 21 and under squad, who represent their country in a limited number of international netball matches held every four years. Therefore, only a small number of matches can be sampled. In conjunction, data from Chapter Six was included as a comparison and to obtain the most frequently recurring movement sequences of netball.

The number of individual junior-elite athletes examined per netball playing position was five for the centre (C), four for wing attack (WA), three for wing defence (WD), two for goal attack (GA), three for goal defence (GD), three for goal shooter (GS) and three for goal keeper (GK). All participants provided written informed consent. The study was approved by the University Human Research Ethics Committee and conformed to the Declaration of Helsinki.

Spatiotemporal data was collected via the Wireless ad hoc System for Positioning (WASP) that is accurate for tracking athlete movement indoors, detailed in Chapter Four. The CV (%) of WASP for measuring total distance and mean velocity, during walking and sprinting movements, is less than 10% (Chapter Four). Each participant wore a WASP mobile node, measuring 90 x 50 x 25 mm, positioned between the shoulder blades. The range between each mobile node and the twelve anchor nodes surrounding the netball court was computed at an update rate of 10 Hz and calculated into a 100 Hz file via customised software (WheresBruce, Australian Institute of Sport, Canberra, Australia). Each athlete's positional data (X and Y coordinates) was exported into the R statistical software (R: A language and environment for statistical computing, Vienna, Austria) for analysis.

A movement sequencing technique, described in Chapter Six, was applied to each athlete's X and Y data. Briefly, velocity was calculated from positional data and acceleration derived from velocity. Angular displacement was calculated via the dot product of consecutive movement vectors. Angular velocity, the rate of change of angular displacement, was obtained from angular displacement. Individual velocity, acceleration and angular velocity movements were clustered using a one-dimensional *k*-means clustering algorithm (Wang & Song, 2011) seeded with 4, 3 and 4 clusters, respectively. A qualitative label was assigned to each cluster and from these clusters each unique combination of velocity, acceleration and angular velocity movement, termed movement subunits, was assigned an identification code consisting of an upper or lower case alphabetic letter. Continous athlete movement subnits were isolated with by moments of inactivity, judged to be movement lower than 0.5 $m \cdot s^{-1}$, to form movement sequences. The similarity between each sequence was quantified using the Levenshtein distance implementation in the R *stringdist* package (Van der Loo, 2014). Similar movement sequences were then grouped into 25 clusters using a hierarchical cluster analysis (Ward Jr, 1963). The longest common subsequence (LCS) algorithm, using the R *qualV* package (Jachner et al., 2007), was used to discover the most common athlete movement sequence within each of the 25 clusters.

The relative frequency of individual movement subunits was compiled for each playing position across two playing standards, elite and junior elite. The relative frequency of the LCS-derived movement sequences for each playing position and standard were also calculated. These distributions can be considered a movement signature for each netball playing position. The Minkowski distance implemented in the R *HistogramTools* package (Stokely, 2014), was used to quantify the distance between playing positions of differing standards using the LCS results. A network graph, via the *igraph* package (Csardi & Nepusz, 2006) within R was used to display this similarity between playing positions of differing standards. A network graph was also used to visualise the differences between positions across four matches from the elite athlete dataset.

The pooled dataset contains three athletes who represented their national side and comprised part of the national 21/U squad. Therefore, activity profiles on these three athletes were collected during separate elite and junior elite matches. This data represents a unique case to examine the movement sequences of these athletes across playing standards and matches. The relative frequency of the LCS-derived movement sequences, as a global representation of netball, for each athlete's playing position at elite and junior-elite standards was calculated. A distance matrix was also calculated and network graph constructed for these three individual athletes, according to playing position and standard.

7.3 Results

The centroids of the four velocity clusters were 3.9 $m \cdot s^{-1}$, 0.6 $m \cdot s^{-1}$, 1.4 $m \cdot s^{-1}$ and 2.3 $m \cdot s^{-1}$ respectively. The centroids of the four angular velocity clusters were 99.0 $deg \cdot s^{-1}$, 49.9 $deg \cdot s^{-1}$, 153.7 $deg \cdot s^{-1}$ and 13.6 $deg \cdot s^{-1}$ respectively. Centroids of the three acceleration clusters were 6.7 $m \cdot s^{-2}$, 0.0 $m \cdot s^{-2}$ and -6.7 $m \cdot s^{-2}$ respectively. The within cluster variation, as the sum of Euclidean distance between the data points and each centroid, was 90.4% for velocity, 71.6% for acceleration and 94.7% for angular clusters. The distribution of data points within each velocity, angular velocity and acceleration cluster is demonstrated in Figure 7-1a, b and c, respectively.

The most common movements of netball match activity, comprising elite and junior elite playing standards, were walking with straight movement and neutral acceleration. Each movement subunit, the qualitative descriptor comprising the relevant combination of velocity, acceleration and angular velocity and their relative frequency to the wider dataset is presented in Table 7-1. The 11 most frequently recurring movement sequences of netball match activity, comprising both the elite and junior elite playing standards, and relative contribution of each playing standard to the wider dataset is presented in Figure 7-2.

The relative contribution of each playing standard to the wider dataset is also presented in Figure 7-2. A matrix of the frequently recurring movements per netball playing position and across playing standards is presented in Table 7-2. The relative proximity of these playing positions according to each playing standard is visualised in Figure 7-3. The GS and GK are the most closely related netball positions across playing standards. The largest pairwise comparison across playing standards was the WA, with a Minkowski distance of 12.40 (Table 7-2).

Three athletes comprised both the elite and junior elite playing squads. The relative contribution, by each athlete per playing standard and position, to the wider dataset is presented in Figure 7-4. A matrix for each athlete across playing standard and position is displayed in Table 7-3. In the C position, athlete three performed similar movement sequences at the elite and junior elite level, with a Minkowski distance of 1.56 (Table 7-3). The largest pairwise comparison was between athlete two in C and athlete one in WD, with a Minkowski distance of 17.77 (Table 7-3). The relative proximity of these athletes, per playing position and playing standard, is visualised in Figure 7-5.

A network analysis of movement sequence similarity between playing positions across four elite matches is visualised in Figure 7-6. The WD, GS and GK are consistently the most dissimilar netball playing positions across the elite playing standard. This highlights the ability of the movement sequencing technique to consistently detect differences between the netball playing positions at the highest standard of play.

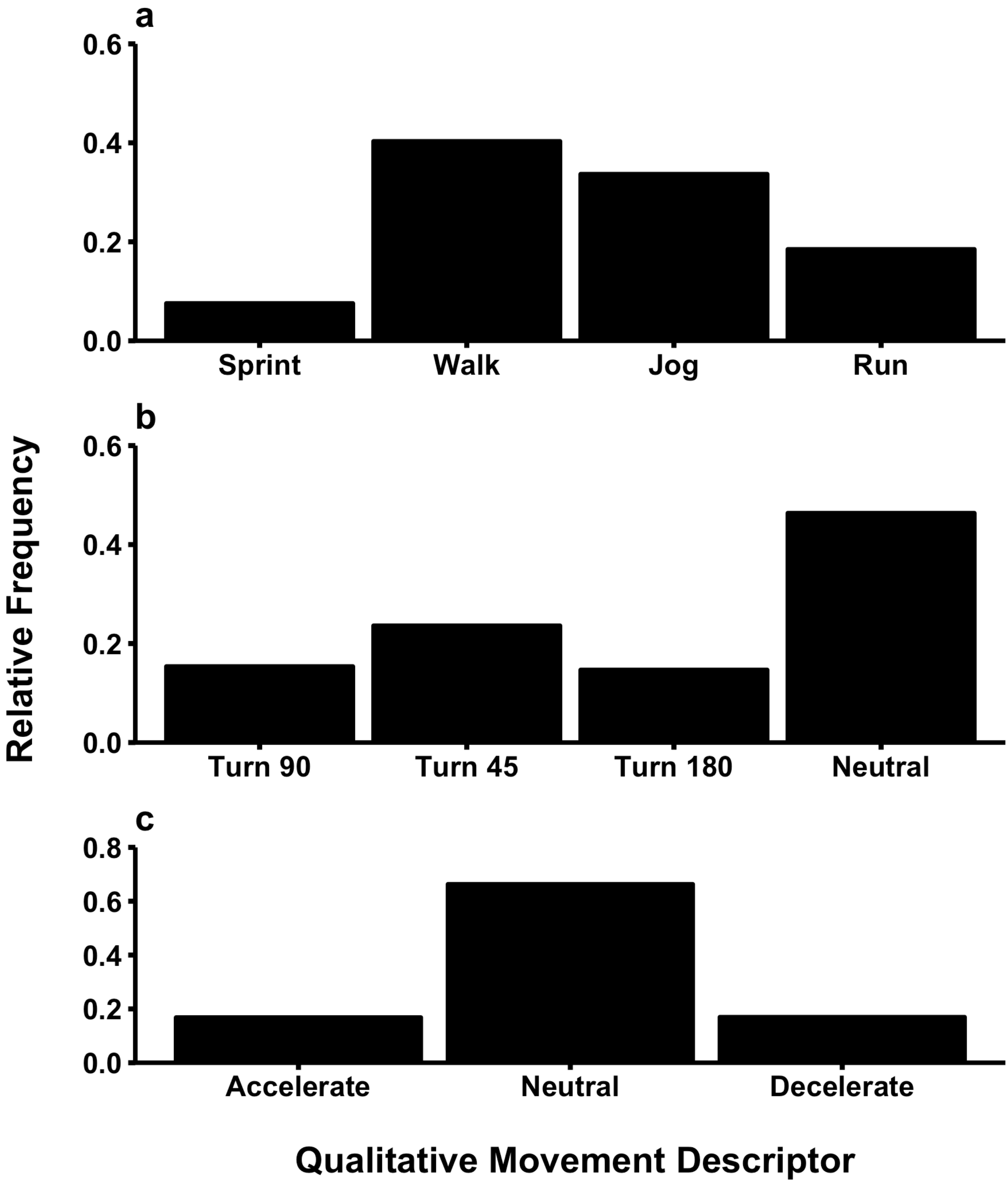

Figure 7-1. The relative frequency of clustered observations for a) velocity, b) angular velocity and c) acceleration movement features across the pooled dataset.

Movement Subunit	Percentage Contribution		Qualitative Descriptor
	Elite	*Junior Elite*	
a	0.1	0.0	Sprint Accelerate Turn 90
A	0.0	0.0	Sprint Decelerate Turn 180
b	0.1	0.1	Sprint Neutral Turn 90
B	1.6	1.5	Walk Accelerate Turn 180
c	0.1	0.0	Sprint Decelerate Turn 90
C	6.5	8.0	Walk Neutral Turn 180
d	1.3	1.1	Walk Accelerate Turn 90
D	1.7	1.7	Walk Decelerate Turn 180
e	5.9	7.3	Walk Neutral Turn 90
E	1.1	0.8	Jog Accelerate Turn 180
f	1.4	1.2	Walk Decelerate Turn 90
F	1.7	1.5	Jog Neutral Turn 180
g	1.2	0.9	Jog Accelerate Turn 90
G	1.0	0.8	Jog Decelerate Turn 180
h	2.6	2.5	Jog Neutral Turn 90
H	0.3	0.2	Run Accelerate Turn 180
i	1.1	0.9	Jog Decelerate Turn 90
I	0.3	0.2	Run Neutral Turn 180
j	0.5	0.4	Run Accelerate Turn 90
J	0.3	0.2	Run Decelerate Turn 180
k	0.7	0.7	Run Neutral Turn 90
K	1.4	1.0	Sprint Accelerate Neutral
l	0.4	0.4	Run Decelerate Turn 90
L	3.2	3.8	Sprint Neutral Neutral
m	0.4	0.3	Sprint Accelerate Turn 45
M	1.3	1.0	Sprint Decelerate Neutral
n	0.7	0.8	Sprint Neutral Turn 45
N	1.3	1.2	Walk Accelerate Neutral
o	0.4	0.3	Sprint Decelerate Turn 45
O	8.3	9.1	Walk Neutral Neutral
p	1.2	1.1	Walk Accelerate Turn 45
P	1.5	1.4	Walk Decelerate Neutral
q	6.6	8.0	Walk Neutral Turn 45
Q	2.7	2.2	Jog Accelerate Neutral
r	1.3	1.2	Walk Decelerate Turn 45
R	12.0	12.8	Jog Neutral Neutral
s	1.7	1.3	Jog Accelerate Turn 45
S	2.7	2.2	Jog Decelerate Neutral
t	5.1	5.4	Jog Neutral Turn 45
T	2.6	1.8	Run Accelerate Neutral
u	1.6	1.2	Jog Decelerate Turn 45
U	7.3	7.4	Run Neutral Neutral
v	1.1	0.8	Run Accelerate Turn 45
V	2.5	1.8	Run Decelerate Neutral
w	2.4	2.7	Run Neutral Turn 45
x	1.0	0.8	Run Decelerate Turn 45
y	0.0	0.0	Sprint Accelerate Turn 180
z	0.0	0.0	Sprint Neutral Turn 180

Table 7-1. The percentage contribution of movement subunits, according to elite and junior elite playing standards, to the wider dataset and qualitative descriptor.

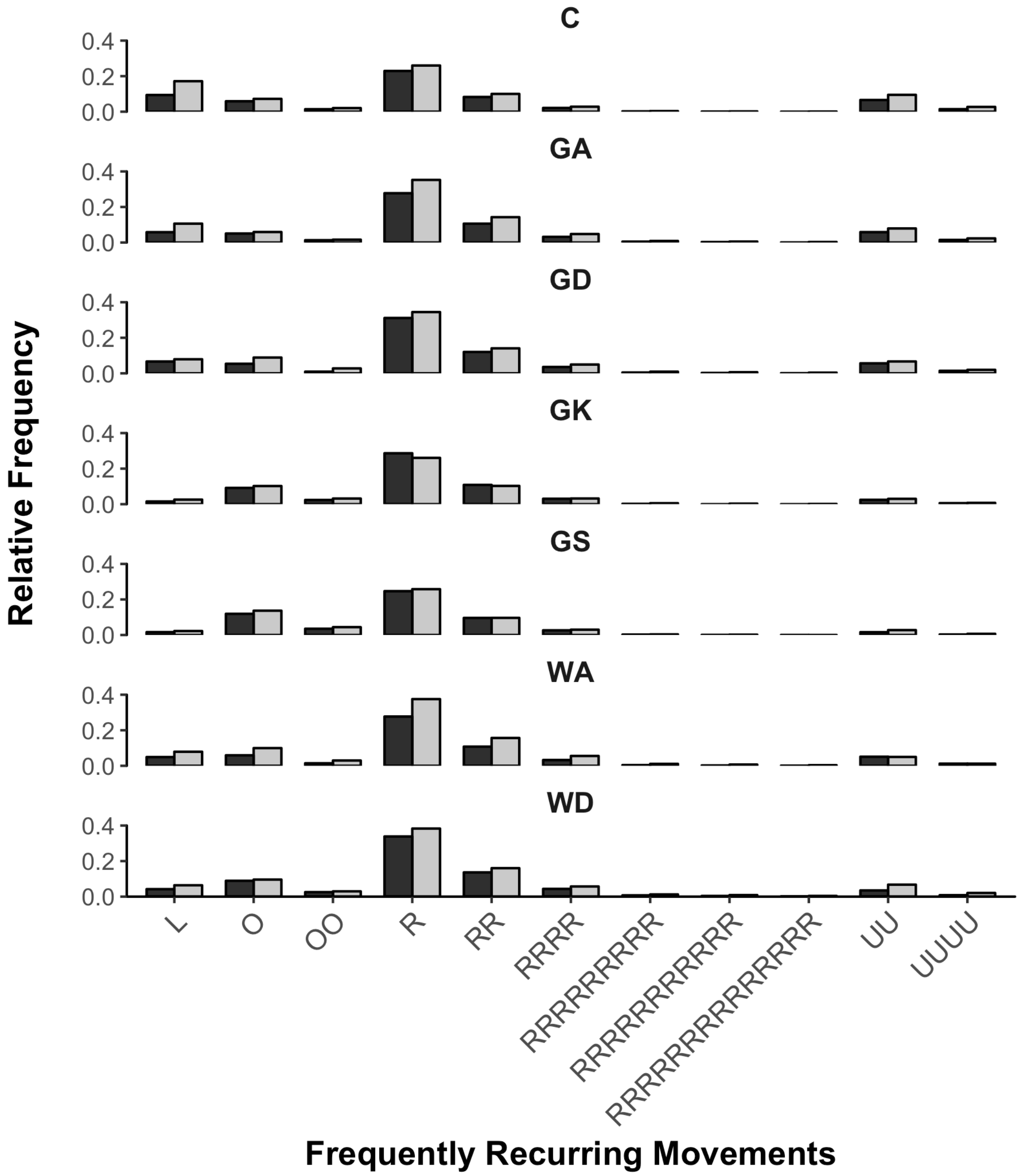

Figure 7-2. The relative contribution of frequently recurring LCS sequences by netball playing position including centre (C), goal attack (GA), goal defence (GD), goal keeper (GK), goal shooter (GS), wing attack (WA) and wing defence (WD). Elite athletes; dark grey bars. Junior elite athletes; light grey bars.

	C_E	C_{JE}	GA_E	GA_{JE}	GD_E	GD_{JE}	GK_E	GK_{JE}	GS_E	GS_{JE}	WA_E	WA_{JE}	WD_E	WD_{JE}
C_E	0.0	9.21	6.62	14.09	9.62	13.75	11.47	9.85	11.54	12.14	7.26	17.44	14.17	18.31
C_{JE}		0.0	12.30	12.44	12.72	13.81	17.60	16.41	18.33	17.88	13.29	17.01	16.96	18.09
GA_E			0.0	10.03	3.83	9.09	7.06	7.24	10.03	10.59	1.49	12.60	8.53	13.10
GA_{JE}				0.0	6.75	4.46	13.62	14.68	17.43	16.82	10.62	6.57	8.69	6.94
GD_E					0.0	6.00	7.85	9.04	11.90	12.02	4.16	9.23	6.05	9.76
GD_{JE}						0.0	10.49	11.60	14.18	13.25	9.09	4.10	5.15	4.67
GK_E							0.0	3.24	5.25	5.93	5.60	12.59	6.75	13.16
GK_{JE}								0.0	3.00	3.79	5.90	14.13	8.87	14.84
GS_E									0.0	2.67	8.72	16.38	11.17	17.21
GS_{JE}										0.0	9.36	15.36	10.70	16.13
WA_E											0.0	12.40	7.79	12.93
WA_{JE}												0.0	6.06	2.66
WD_E													0.0	6.72
WD_{JE}														0.0

Table 7-2. The Minkowski distances for movement sequence distributions between netball playing positions including centre (C), goal attack (GA), goal defence (GD), goal keeper (GK), goal shooter (GS), wing attack (WA) and wing defence (WD) for elite ($_E$) and junior elite ($_{JE}$) playing standards.

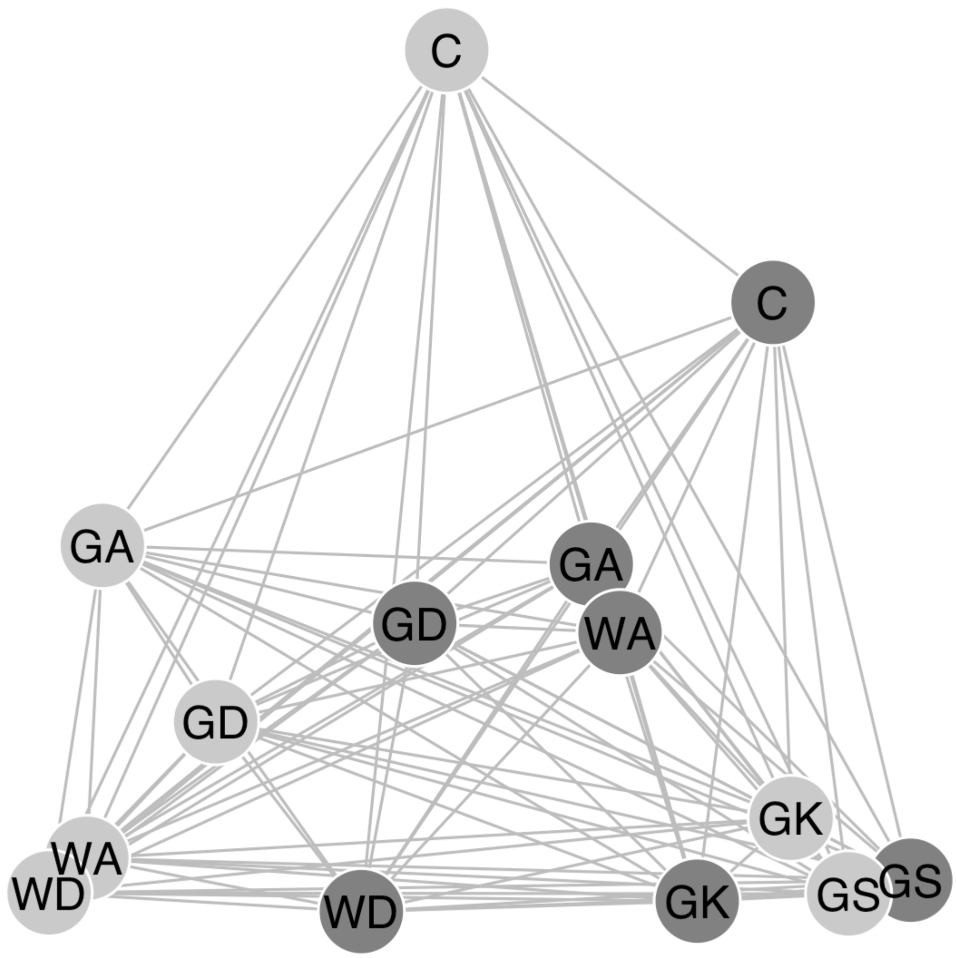

Figure 7-3. A network analysis of movement sequence similarity between netball playing positions, according to playing standard. Elite athletes; dark grey circles. Junior elite athletes; light grey circles.

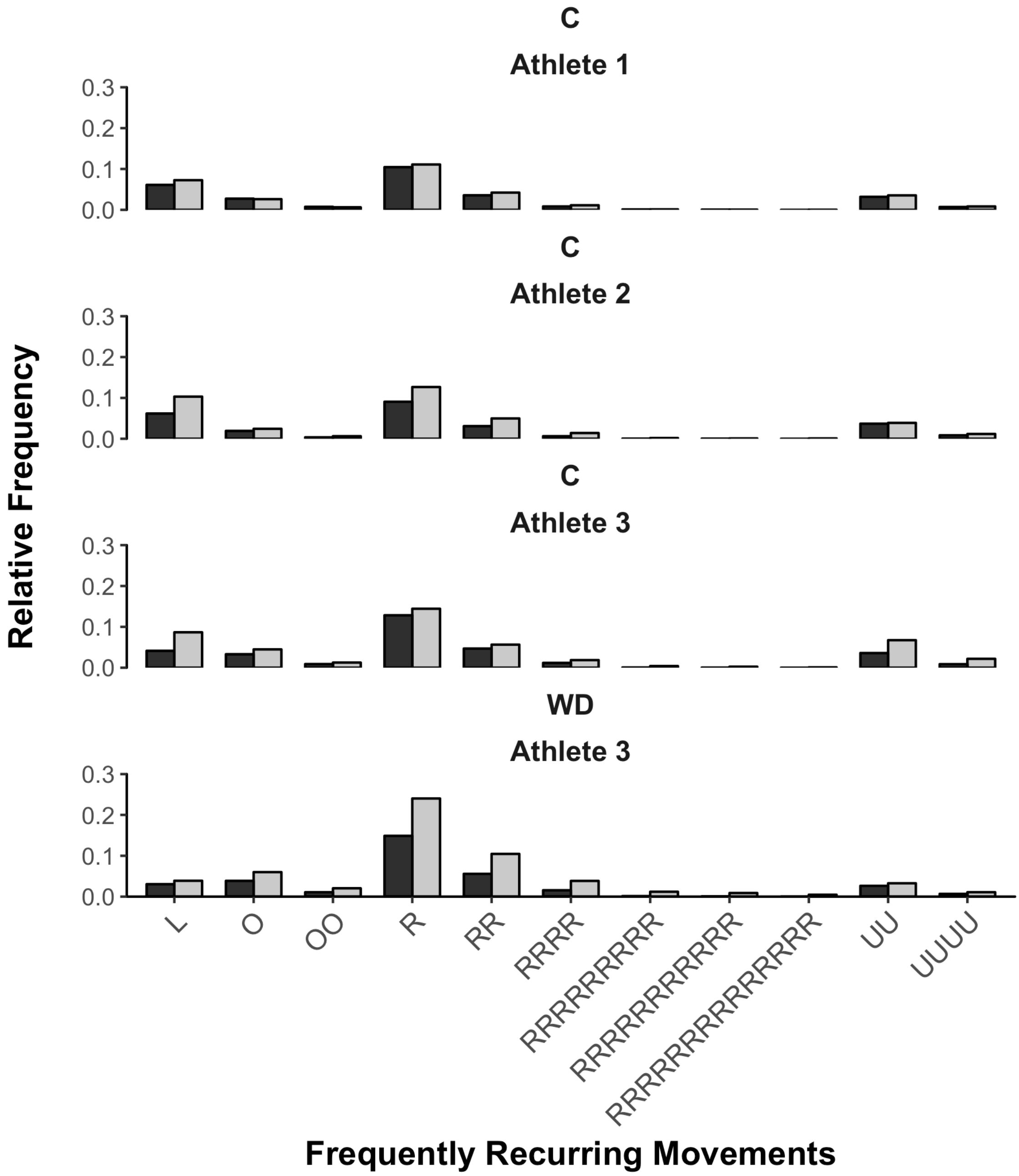

Figure 7-4. The relative contribution of frequently recurring LCS sequences by netball playing position including centre (C) and wing defence (WD) for three athletes across two differing playing standards. Elite level; dark grey bars. Junior elite level; light grey bars.

	$C_{E,1}$	$C_{JE,1}$	$WD_{E,1}$	$WD_{JE,1}$	$C_{E,2}$	$C_{JE,2}$	$C_{E,3}$	$C_{JE,3}$
$C_{E,1}$	0.0	6.13	2.76	13.29	4.85	6.27	3.39	3.67
$C_{JE,1}$		0.0	7.17	12.63	7.84	4.48	6.78	5.62
$WD_{E,1}$			0.0	11.01	7.50	7.88	5.95	6.06
$WD_{JE,1}$				0.0	17.77	14.94	16.15	15.51
$C_{E,2}$					0.0	5.90	1.80	2.72
$C_{JE,2}$						0.0	5.09	3.58
$C_{E,3}$							0.0	1.56
$C_{JE,3}$								0.0

Table 7-3. The Minkowski distances for movement sequence distributions between netball playing positions including centre (C), and wing defence (WD) across elite ($_E$) and junior elite ($_{JE}$) playing standards. Three individual athletes ($_{1, 2, 3}$) who played at both levels were profiled.

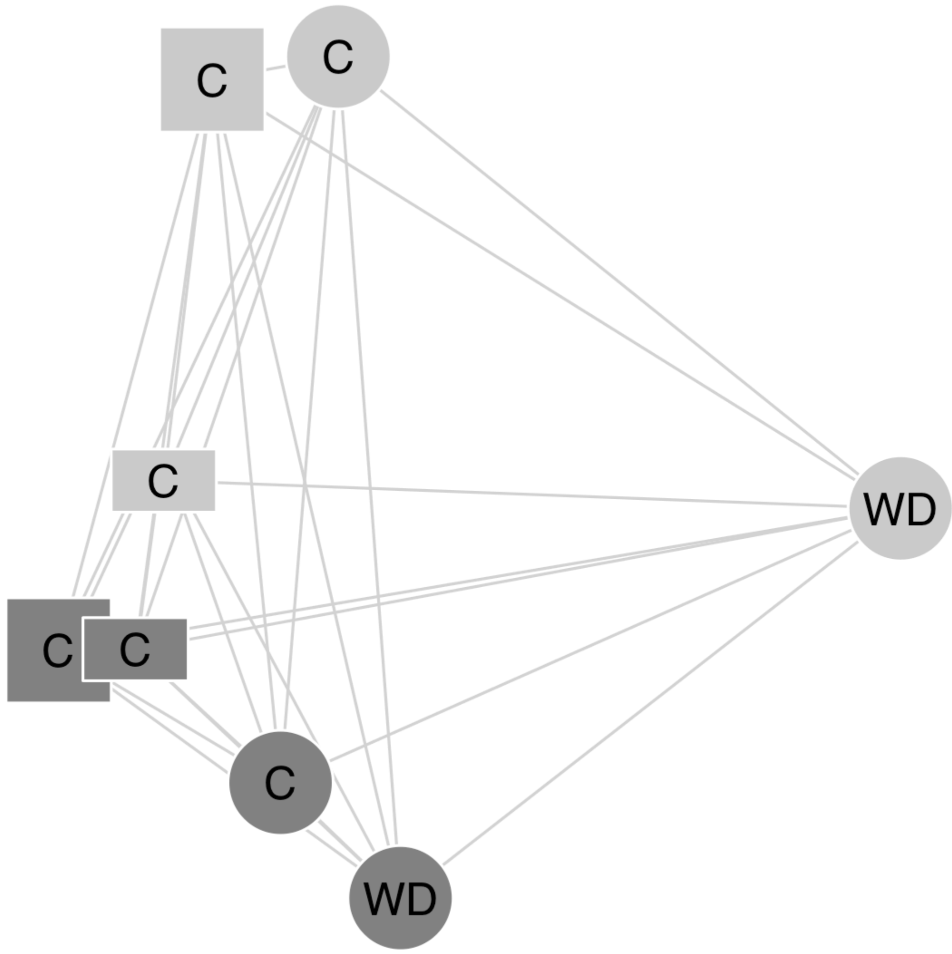

Figure 7-5. A network analysis of movement sequence similarity between playing positions according to elite; dark grey and junior elite standard; light grey. Athlete one; circles. Athlete two; squares and athlete three; rectangles.

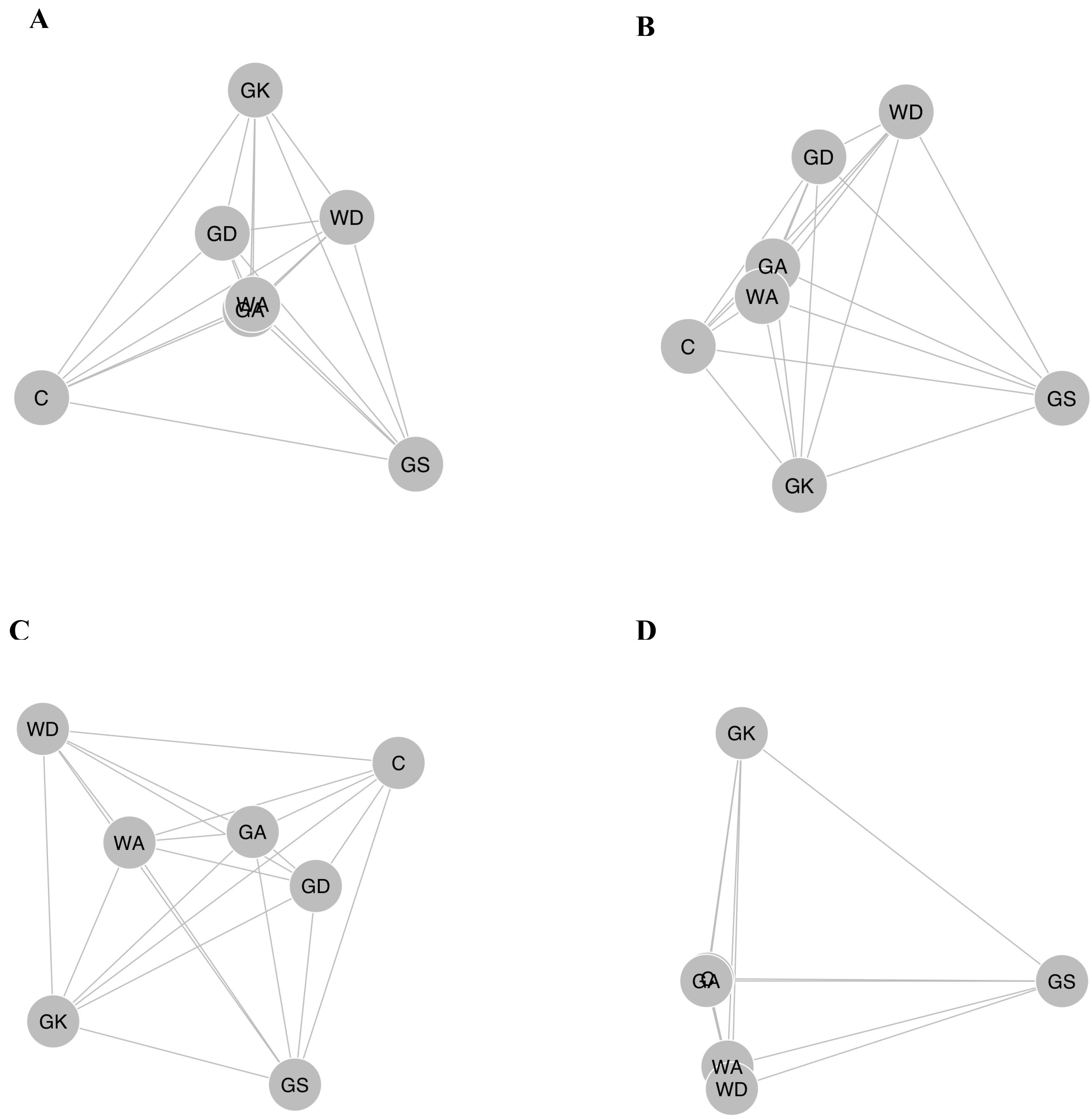

Figure 7-6. A network analysis of movement sequence similarity between playing positions across four elite matches including match one; A, match two; B, match three; C and match four; D.

7.4 Discussion

The purpose of this study was to utilise the analysis technique, developed in Chapter Five and extended in Chapter Six, to examine differences in the movement sequences of team-sport athletes across playing position and standards. The combinations of movement sequences performed by female netball athletes were assessed for similarity between the seven playing positions across two standards, elite and junior-elite. The GS and GK are the most closely related netball positions across playing standards. The largest pairwise positional comparison across playing standards was the WA position, suggesting the attacking roles in netball differ greatly between elite and junior elite playing standards. Eleven frequently recurring movement sequences were discovered. the present technique uncovers and compares the movement sequences performed by playing positions across differing standards, irrespective of traditional analysis using arbitrary speed or acceleration thresholds.

Spatiotemporal data from elite and junior elite female netball athletes was examined to discover the global movement sequences performed. The 11 most frequently recurring movement sequences are detailed in Figure 7-2. Jogging with neutral acceleration and angular velocity was the most frequently performed movement in elite and junior netball. At the junior elite level, walking with neutral acceleration and performing a 180° turn contributed 1.5% more to the wider dataset in comparison to the elite standard (Table 7-2). This may be skill related, potentially suggesting a turnover of the ball or intercept by an athlete, requiring a 180° turn as the direction of play changes. In elite soccer athletes, up to 32% of directional changes were 180° turns, likely due to the transition from attack to defence (Ade, Fitzpatrick, & Bradley, 2016). Profiling the changes in direction performed by team-sport athletes during matches may assist in designing specific conditioning drills to develop individual athlete physical capacities.

The similarities in match external load, between playing positions and across competition standards, has been investigated in field-based team-sports. The high-intensity ($\geq$ 5.5 $m\cdot s^{-1}$) running distance covered by professional soccer athletes was greater for all playing positions, except wide midfielders, in a lower league compared with Championship and Premier League levels (Bradley et al., 2013). More high-intesity running distance was covered when athletes moved down a playing standard, yet this was not apparent for athletes moving up in competition levels (Bradley et al., 2013). Although no data on skill performance was presented, athletes at a higher playing standard likely possess superior technical capabilites. Athletes at a lower standard may therefore utilise more of their physical capacity in an attempt to close down the opposition to regain possession or create position (Bradley et al., 2013). Athletes at higher standards of play may also be selective in their sprint effort distribution, potentially due to a greater match tactical awareness of creating position or filling space. The distribution of sprint efforts, according to a velocity threshold, was not determined in the present study although sprinting with neutral acceleration and neutral angular velocity contributed 3.2% and 3.8% to the total movement subunits for elite and junior elite athletes, respectively (Table 7-1). All other sprinting related activities were less than 1.4% for both playing standards. In elite female hockey, sprinting (activity > 5.3 $m\cdot s^{-1}$) accounted for 1.5% of player match-time (Macutkiewicz & Sunderland, 2011). Similarily, high-intensity running (activity > 5 $m\cdot s^{-1}$) performed by elite soccer athletes accounted for 4.8% of total match time (Krustrup et al., 2005). Irrespective of female team-sports contested on a field or court, the percentage contribution of sprinting movement relative to match duration is low. However, examining only sprinting movement according to a predetermined velocity threshold may underestimate the accelerations performed (Varley & Aughey, 2013). Maximal accelerations are frequently performed during matches from low velocities and may be underestimated via traditional match analysis, as detailed in Chapter Three. In elite soccer, the effort distribution of maximal accelerations is playing position dependent

(Varley et al., 2013a). The movements performed by team-sport athletes during matches should be examined according to playing position.

A movement sequence comparison of netball playing positions, according to elite and junior elite playing standards, is described in Table 7-2. The GS and GK are the most closely related netball positions across playing standards with Minkowski pairwise distances of 2.67 and 3.24, respectively (Table 7-2). When comparing an elite GS with a junior elite GK, the Minkowski distance is 3.00. Similarily, comparison between an elite GK with a junior elite GS results in a Minkowski distances of 5.93. In a study on the accelerometer load of netball athletes during matches, there were no clear differences between shooters and defenders (Cormack et al., 2014). Together, these findings illustrate that the GK and the GS perform similar types of movements at different playing standards during netball matches. Future reseach could examine the accelerometer load of court-based team-sport athletes, including netballers, in combination with positional data from WASP. Examining the movement sequences performed and the global athlete load may allow for an enhanced profiling of training, particularly as movement in the plane, including jumping, can be quantified via accelerometers. Profiling the number of and load associated with jumping effort in court-based team-sports remains to be explored. The combination of accelerometer and positional athlete data may allow practitioners to design training in order to target specific movements performed in matches, including jumping efforts.

The attacking roles in netball differ greatly between elite and junior elite playing standards. The largest pairwise positional comparison across playing standards was the WA with a Minkowski distance of 12.40 (Table 7-2). During international compared to national level competition, the high-speed running by elite field hockey athletes is substantitally increased across all positions except for defenders (Jennings et al., 2012b). The positional differences across playing standards in the present study could likely be due to a greater tactical strategy or athlete physical capacity. In sub-elite male rugby league athletes, physiological capacities including muscular power, agility and speed were substantially greater (24.0% to 40.3%) at a senior compared to junior level (Gabbett, 2002). Similarly, there were large to very large differences in absolute upper-body strength between elite and junior elite male Australian football athletes (Bilsborough et al., 2015). The magnitude of these differences were still large to very large when upper-body strength was expressed relative to each individual athlete's fat-free soft tissue mass (Bilsborough et al., 2015). Although individual physiological capacities were not measured for either playing standard in the present study, junior elite athletes may require specific physical conditioning and resistance training before progressing to the senior level.

Three individual athletes comprised both the elite and junior elite squads presenting a unique opportunity to investigate the movement sequences of these athletes at differing positions across playing standards. The most similar pairwise comparison was between athlete three in the C position, with a Minkowski distance of 1.56 between the elite and junior elite playing standards (Table 7-3). In contrast, athlete one had a Minkowski pairwise distance of 11.01 in the WD position when compared standards. Athlete one and three start in the WD and C positions, respectively, when playing with their domestic teams in the trans-tasman netball league. Together, these results may highlight the differing tactical roles within the same position by the same athlete at different playing standards. The contribution of tactical role to netball playing performance remains to be examined. In junior elite Australian football, match total and high-speed running distance do not predict if athletes are drafted to the senior level (Woods, Joyce, & Robertson, 2016). Instead, contested possession and technical skills were associated with draft outcome (Woods et al., 2016). Drafted players may therefore strategically position themselves to obtain and have an increased use of the ball. Future research should examine contribution of tactical role, including the corresponding change in movement sequences to elite and junior elite netball performance.

7.5 Conclusion

The sequences of velocity, acceleration and angular velocity movement performed by netball athletes during matches was discovered, according to playing position and standard. A total of 11 frequently recurring movement sequences, irrespective of playing position or standard, were uncovered in the sport of netball. To examine the relationship between position and playing standard, the contribution of each frequently recurring movement sequence within the wider dataset was calculated. The GS and GK are the most closely related netball positions across elite and junior elite playing standards. The largest positional difference between playing standards was the WA. Of three athletes who comprised both the elite and junior elite squads, the most similar pairwise comparison across playing standards was between athlete three in the C position. The largest pairwise comparisons were between an elite C and a junior-elite WD. In the dataset examined, differences between positions and within playing standards appear consistent across matches, although future research should investigate the influence of match to match variability on these movement sequences. The movement sequencing technique described may distinguish between netball playing positions and standards, although more matches should be included in future comparisons to consistently detect such differences. Future research should examine the tactical contribution of each position to these movement sequences and explore the relationship between physical capacity and netball external load.

CHAPTER 8: GENERAL DISCUSSION, CONCLUSIONS AND FUTURE DIRECTIONS FOR RESEARCH

8.1 Introduction

This thesis is the starting point in establishing a new methodology to investigate the latent movement sequences of netball. Specifically, this thesis investigated the validity of a local positioning system (LPS) to collect, analyse and create a technique to discover the most frequently recurring latent movement sequences across the seven playing positions within elite and junior-elite female netball. To enable further application of the methodology developed within this thesis, training would be required on a larger data set before testing on a hold-out data set. This would allow estimation of how the presented methodology accurately classifies each of the seven netball playing positions based on their unique movement features. Model training and testing is outside the scope of this thesis, as the aim was to develop a method to derive representative movements of the elite and junior-elite cohorts examined. To assess model accuracy, team-sport athlete spatiotemporal data should also be collected using the LPS validated in this thesis, since the Wireless ad hoc System for Positioning (WASP) is accurate in measuring mean and peak velocity and angular velocity during short non-linear movements.

8.2 Discussion and Future Directions

The activity-profiles of team-sport athletes can be collected via global positioning systems (GPS), accelerometers and video analysis. Video analysis can capture athlete activity (Fox et al., 2013; Gabbett & Mulvey, 2008; Póvoas et al., 2012) although these may be unreliable estimates of movement (Barris & Button, 2008). Whilst accelerometers measure the frequency and magnitude of movement in three dimensions (Boyd et al., 2013), athlete displacement and velocity are unable to be calculated. Limited research exists on the activity profiles of court-based team-sport athletes, likely due to the inability of GPS to accurately quantify short non-linear movement in confined spaces (Duffield et al., 2010). Alternatively, the WASP can accurately measure athlete velocity and angular velocity indoors (see Chapter Four). Practitioners and researchers can therefore use WASP to collect the activity profiles of team-sport athletes indoors.

An important physical component for team-sport athletes is the ability to change direction or angular velocity in response to motion of the ball, opposition or teammates. Understanding the angular velocities performed by team-sport athletes allows for specific physical capacities to be targeted through conditioning drills. Whilst the accuracy of an LPS to detect non-linear movement was investigated during soccer-specific courses (Ogris et al., 2012; Stevens et al., 2014), only a small number of changes in direction were examined. The accurate quantification of short, non-linear movement allows for meaningful changes in activity profile to be detected. The WASP validated in Chapter Four is accurate, compared to Vicon, at measuring total distance, mean and peak velocity and angular velocity during short non-linear movements performed indoors. Although other LPS have been validated against Vicon (Ogris et al., 2012; Stevens et al., 2014), the work completed in this thesis proves that WASP can accurately quantify short, non-linear movement representative of court-based sports (see Chapter Four). Consequently, the WASP could be deployed for measuring athlete activity profiles in court-based sports including tennis, basketball, volleyball, handball and wheelchair rugby. The movement sequences performed in these sports could be examined according to playing role and standard. Using the technique presented in this thesis and positional data from an LPS such as WASP, the distribution of movements performed in training and matches may allow for an enhanced physical output profile rather than aggregated data of distances covered and velocities performed. The movement sequences performed in the lead up to a turnover in basketball, for example, could be examined to profile the tactical behaviours associated with this match event.

Team-sport athlete performance involves collective behaviours between- and within-opposing teams. Tactical behaviour can be calculated by quantifying positional data, relative to a playing area, and inter-player coordination from tracking systems. During small-sided soccer games, the tactical patterns of play have been assessed using GPS (Sampaio & Macas, 2012; Sampaio, Lago, Goncalves, Macas, & Leite, 2013). Limited research exists on the tactical behaviours of court-based team-sport athletes. The WASP could be a useful tool to measure the collective behaviour of court-based team-sport athletes (see Chapter Four). A limitation of Chapter Four is the lack of comparison between WASP and Vicon position estimates. Future research should examine instantaenous position and the respective displacement, velocity and acceleration derivatives from WASP to a high-resolution motion analysis system such as Vicon or computer vision. The intra- and inter-unit reliability of WASP should also be quantified to allow detection of small but important changes in distance, velocity and angular velocity. Changes in team-sport athlete activity-profile can then be detected if the signal is greater than the inherent noise.

Profiling the team-sport athlete activity allows for the design of training to develop specific physical capacities. Traditional activity-profile analysis bins velocities and accelerations into different zones (see Chapter Three). Thresholds values are typically determined arbitrarily (Mohr et al., 2003), from propetiary software (Cunniffe et al., 2009) or other research (Jennings et al., 2012a). The same threshold is often used for the entire playing cohort (Aughey, 2011b; Jennings et al., 2012a; Mooney et al., 2011). In contrast, the methodology developed in Chapter Five quantified team-sport athlete movement without velocity or acceleration thresholds. This approach using data mining techniques, including *k*-means clustering, may add to the traditional analysis of team-sport athlete activity profile. Knowledge of the sequences performed during matches, including concurrent velocity, acceleration and angular velocity movements, may assist in targeting specific training or conditioning qualities. These movement sequences can also be examined according to individual playing position.

The analysis of athlete activity profile, according to playing position, typically involves the time or distance spent in velocity and acceleration zones. Rather than comparing the velocity, acceleration and angular velocities performed by individual playing positions, Chapter Six analysed the similarities between netball playing positions according to the movement sequences performed. The seven netball playing positions are consequently differentiated by a characteristic signature or the frequently recurring movements performed. A more granular examination of athlete movement, according to playing position, can therefore be learned. Practitioners and scientists can subsequently focus on training the specific movement sequences frequently performed by athletes in each playing position. These sequences can also be examined across different playing standards, such as elite and junior-elite levels. Quantifying the movement sequences performed across the athlete pathway in a given sport may have use for conditioning purposes.

Profiling the activity profile across playing standards can assist in preparing team-sport athletes in the transition from lower to higher levels. Understanding the external load of team-sport athletes, according to playing position, across elite and junior-elite levels may allow the targeting of specific physical capacities. Athletes who transition from junior-elite to an elite level of play may therefore be better prepared to withstand the increased match intensity and in turn allow improved on-field performance. Analysis of the differences between team-sport playing standards typically examines distances covered in velocity zones, according to threshold values (McLellan & Lovell, 2013). In Chapter Seven, the movement sequences of elite and junior-elite female netball athletes were collected via WASP, validated in Chapter Four and analysed using the technique developed in Chapter Six. Eleven frequently recurring movement sequences were discovered from elite and junior-elite netball data. Across the two playing levels examined, the GS and GK are the most closely related netball playing positions. The movement sequences performed by the WA position are the most dissimliar comparison across playing standards. For junior-elite WA athletes to play this position at the elite level, specifc physical training may be required to perform specific movement sequences. The differences in activity-profile between elite and junior-elite team-sport athletes is well-documented (Gabbett, 2002; McLellan & Lovell, 2013; Mendez-Villanueva et al., 2011) however the movement sequence technique developed in this thesis could provide coaches and practitioners with specific information on the velocities, accelerations and angular velocities performed, according to playing position, across playing standards. Junior-elite athletes may therefore be better trained to perform the specific movements at an elite level of competition.

Future application of the novel movement sequencing technique developed in this thesis should incorporate more matches to ascertain the test-retest reliability and match-to-match variability of the role proximity results presented in Chapter Six. Advancement of the technique would also require the collection of a large quantity of athlete spatiotemporal data. Since the WASP is the only athlete tracking system currently accurate at measuring peak and mean angular velocity during sprinting and walking non-linear courses (see Chapter Four), spatiotemporal data should be collected using this LPS. For the technique to be applied in team-sports where WASP may not be available, researchers and practitioners are required to validate other tracking technologies, including GPS, for the accurate detection of angular velocity before this variable can be safely used. Future application and development of the movement sequence technique developed here may overcome the subjective determination of athlete movement from manual video-analysis. For example, the movement sequences performed in the lead up to a shot on goal could be learned from athlete spatiotemporal data. The inherent error of human users to accurately classify team-sport athlete activity could consequently be removed.

The interaction between tactical and physical output during team-sport matches is of interest to sport scientists. Local positioning systems, including WASP, provide an athlete's position relative to the playing area and their team members. Although the tactical and physical output of field-based team-sport athletes has been examined (Sampaio et al., 2013), limited research exists on this interaction in court-based athletes. Integrating physical and tactical data may assist in understanding the emergent behavioural interactions at both an individual athlete and team level. By manipulating these variables, adapative behaviour to these environmental conditions can be examined during training and matches.

8.3 Summary

This thesis examined the accuracy of an LPS, specifically the WASP, for measuring elite team-sport athlete movement across short-duration, non-linear courses indoors against a high-resolution criterion system (see Chapter Four). Using this LPS, spatiotemporal data from a junior-elite female netball athlete was analysed using a movement sequencing technique developed in Chapter Five. This technique was furthered and applied to an elite cohort in Chapter Six, to examine the movement sequences performed by elite female netball athletes. These frequently recurring latent movement sequences, according to netball playing position, were then examined at the elite and junior-elite level in Chapter Seven. The novel technique developed in this thesis is an advancement on the traditional analysis of team-sport athlete activity profile. The velocities, accelerations and angular velocities of team-sport athletes can consequently be examined irrespective of pre-determined and arbitrary or physiologically defined thresholds. As this technique is the starting point on the continuum for establishing a new method, future application relies on model training and testing with a much larger dataset. Generalisation to other team-sports would require substantial data to universally validate the method.

8.3 Practical Applications

The practical applications of this thesis are:

1. Researchers and practitioners may use WASP to accurately quantify the non-linear movement of athletes during indoor court-based sports.

2. Spatiotemporal data collected by athlete tracking technologies should be analysed for the movement sequences performed during matches.

3. Junior elite netball athletes may require specific conditioning to perform the different movement patterns of elite netball athletes if advancing to the higher level.

4. The playing positions of netball, at the elite and junior elite level, may have individualised training programs to target the movement position-specific sequences performed.

5. To gain a further understanding of netball athlete movement, more matches should be incorporated to train and test the movement sequencing technique.

8.4 Conclusions

The specific conclusions of this thesis are:

1. The WASP provides sufficient indoor accuracy to quantify the total distance and velocities performed by elite athletes over short, non-linear courses.

2. There is a higher bias during walking compared to sprinting during non-linear courses.

3. At the elite level, the WA, GA and GD are the most closely related netball playing positions as a function of frequently recurring movement sequences performed.

4. Only the GS and GK playing positions are closely related across elite and junior-elite standards of netball play.

5. The movement sequencing technique developed in this thesis can differentiate the netball playing positions although more data is required to train and test this methodology.

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