Institute for Health and Sport

Temporal analysis of physical and skilled performance in professional Australian Rules football

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ABSTRACT

Australian Football requires physical and skilled output from its participants for more than ninety minutes of play. In both research and practice, physical output is typically described using aggregate parameters extracted from wearable technologies. Parameters include volume measures (eg., total distance), work rates (volume expressed relative to time, eg. metreage per minute) and output bands, which bin either accelerations or velocity into a smaller number of thresholds. Similarly, skilled output may be described using coaches' ratings, player rankings and counts of skilled actions, termed involvements. Involvements refer to skilled actions when players are both in possession and not in possession of the ball. These parameters are typically aggregated across pre-set windows, including stints, quarters, and training drills. However, there are periods of altered physical and skilled output within training drills and stints, which are not captured by aggregate parameters. It is also difficult to determine when output meaningfully changes within sessions using these aggregate parameters. Consequently, it is difficult to use aggregate parameters to inform time-based decisions, including substitutions and stint-to-rest, and training drill length prescription. The aim of this thesis therefore was to develop an alternative method to aggregate parameter profiling, which can identify changes—either increases or decreases-- in physical and skilled output within training drills and matches.

Study One quantified the relationship between physical output, skilled output and stint duration in elite Australian football matches. Physical output was quantified using aggregate parameters, extracted from Global Navigation Satellite Local Positioning System devices. Skilled output was quantified using individual player involvements. Random effect models showed negative relationships between duration, high intensity running, and involvements per minute. Metreage per minute had a positive relationship with involvements per minute for most players. Three

conditional inference trees were computed. These models described the impact of factors, including round (ie., game number within a season) and rotation number, and how individuals react to outputs, along with a general set of thresholds for the data. All models demonstrated a weak relationship between physical, skilled output and time. This suggests that wearable technology data and notational analysis feeds could be analysed differently to improve their use in team sports.

Study Two proposed a combined time-series/frequency domain approach to profiling physical and skilled output in team-sport. A binary segmentation change point algorithm was applied to the velocity time-series, collected via wearable technologies of Australian football players during matches. This method overcame the need for pre-set aggregation windows by identifying different segments of physical output through the mean and variability of velocity. Spectral and involvement features were extracted for each segment to describe physical and skilled output respectively. Spectral features were able to describe aspects of output that are not captured using aggregate parameters. For example, spectral kurtosis may describe whether physical output is continuous or intermittent. Between five and seven change points were able to give more insight into physical and skilled output than aggregate parameters, whilst identifying sufficiently different segments of play.

Study Three applied the time-frequency approach of Study Two to match profiling in team-sport. This study demonstrated how a time-frequency approach may identify differences in physical output between matches, that are not apparent from aggregate parameters. Additionally, the time-frequency approach was able to identify changes in physical and skilled output within matches. Alongside the change-point algorithm, *k*-means clustering allowed for segments of movement to be classified through both their time elapsed within a match, and their physical and skilled output. These methods could therefore be used, to increase the specificity of load monitoring and physical activity prescription in team-sports.

Study Four illustrated how a time-series/frequency-domain can be applied to physical output to assess the sequence, specificity and difficulty of team-sport training drills. By condensing velocity data from training drills into a similarity metric relative to match segments, a drill sequence resembling physical output at differing points of a match was generated. This study identified challenge points for each drill, where the mean and variance of velocity within training drills changes. The location and features of challenge points varied substantially by drill. Aggregate work rate parameters may therefore misrepresent the influence of training drill length on physical output. Movement paths were further analysed to explore how players accrue total volume measures such as total distance. These movement paths may reveal differences in physical output between training drills to match outputs, despite similar aggregate parameters.

This thesis demonstrated how a time-frequency analysis of physical and skilled output may increase the sophistication of match and training drill profiling in team-sport. The methods presented in this thesis can identify periods of high physical output late in a match and the movement paths completed by athletes, with differences in physical output between matches. This information may assist practitioners to identify difficult matches (ie., matches with high physical outputs), without relying on typical aggregate parameters. These methods may also increase the specificity of training drill prescription to match outputs. The methods presented may also inform training considerations that are not addressed with aggregate parameters, including training drill sequence and duration.

STUDENT DECLARATIONS:

Doctor of Philosophy by Publication Declaration

"I, David Michael Corbett, declare that the PhD thesis by Publication entitled 'Temporal analysis of physical and skilled output in elite Australian Rules football' is no more than 80,000 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".

"I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures.

Signature: [redacted]

Date: 13/6/2021

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LIST OF PUBLICATIONS & SUBMISSIONS

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Corbett, D. M., Sweeting, A. J., & Robertson, S. (2019). A change point approach to analysing the match activity profiles of team-sport athletes. *Journal of Sports Sciences* 37(14). doi: 10.1080/02640414.2019.1577941

LIST OF ABBREVIATIONS

3D – Three-dimensional

AF – Australian Football

AFL – Australian Football League

AU – Arbitrary Units

CI – Confidence Interval

COD – Change of Direction

FFT – Fast Fourier Transform

GNSS – Global Navigation Satellite System

GPS – Global Positioning System

HR – Heart Rate

HSR – High Speed Running

Hz – Hertz

LPS – Local Positioning System

m.min^{-1} – Metres per minute

m.s^{-1} – Metres per second

m.s^{-2} – Metres per second squared

n – Sample Size

Q – Quartile

RPE – Ratings of Perceived Exertion

RFID – Radiofrequency Identification

r **–** Correlation Coefficient

R^2 – Coefficient of Determination

TS – Time Series

VO_2max – Maximal Oxygen Uptake

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CHAPTER 1 – Introduction

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1.1 Introduction

In team-sport, physical output is typically quantified using aggregate parameters extracted from wearable technologies (Sweeting, Cormack, Morgan, & Aughey, 2017b). Volume parameters, including total distance and PlayerLoad^{TM} (Boyd, Ball, & Aughey, 2013), quantify the total amount of load completed by a player during a training session or a match (Cummins, Orr, O'Connor, & West, 2013). These measures may be further binned into output bands, which quantify volume at different intensities (Sweeting et al., 2017b). Intensity measures, including metreage per minute and maximum velocity, quantify physical output independent of volume. Skilled output may also be described using aggregate parameters. In Australian football, these parameters include Champion Data Player Ratings (McIntosh, Kovalchik, & Robertson, 2018), Coaches Ratings (Sullivan et al., 2014a; Sullivan et al., 2014b) or the total number of skilled actions completed by a player either with or without the ball, as determined through notational analysis (Robertson, Back, & Bartlett, 2016). Both physical and skill output parameters may be aggregated across pre-set windows, including a rotation or on-field stint (Dillon, Kempton, Ryan, Hocking, & Coutts, 2017), quarter (Aughey, 2010) or match (Aughey, 2011). In training, parameters are often aggregated across a training drill or session (Corbett et al., 2018).

Aggregate parameters typically assume physical output is accrued in a linear fashion, and do not account for the intermittent nature of many team-sports (Delaney, Thornton, Duthie, & Dascombe, 2016b). Output bands are also often determined arbitrarily, calculated off physiological test results (Park, Scott, & Lovell, 2018) or based on organisation consensus, and may not reflect the true activity profile of a player (Sweeting et al., 2017b). Further, aggregate parameters moving averages to inform time-related decisions, including stint-to-rest prescription true output of a player. In training, aggregate parameters limit the ability to differentiate physical output between drills (Loader, Montgomery, Williams, Lorenzen, & Kemp, 2012). Aggregate parameters are also unable to identify the relationship between drill length and physical output. This is because aggregate including sprints, to match outputs, is also unknown. or decreases in physical output (Montgomery & Wisbey, 2016). Finally , they can explain total or average physical output, but do not identify how output was accrued (Sweeting, Aughey, Cormack, & Morgan, 2017a). Consequently, a greater understanding of physical and skilled output could be gained, by analysing these factors as a time series.

Time-series analysis may overcome the current need for pre-set aggregation windows. Moving averages have been applied to team-sport velocity time series' to identify differing intensities throughout matches (Varley, Elias, & Aughey, 2012). This method was further developed by identifying peak intensities of three to ten-minute durations, in order to set training benchmarks across football codes (Delaney, Cummins, Thornton, & Duthie, 2018a; Delaney et al., 2016a; Delaney et al., 2015; Delaney, Thornton, Burgess, Dascombe, & Duthie, 2017; Delaney et al., 2016c; Delaney et al., 2018b). Similarly, phase-of-play analysis has been used to examine physical output within short (8 – 40 second) contextual windows (Vella et al., 2021). However, both moving averages and phase-of-play analysis are limited by their use of pre-set aggregation windows. Consequently, it is difficult to use moving averages to inform time-related decisions, including stint-to-rest prescription in team-sport matches. Time series segmentation is a semi-supervised learning technique, which can identify changes in the mean or variance of values in a series (Chen & Gupta, 2011). Although time series segmentation has been used across disciplines, it has not been applied to describe the physical output of team-sport athletes. Utilising this method on a physical output time-series would automatically identify different segments of physical output. Consequently, a breakdown of how output changes across the duration of a training session or match could be attained.

Frequency domain analysis is an alternative to aggregate parameters, which can provide a description of physical and skilled output. Frequency domain analysis is commonly used in engineering and Biomechanics (Wundersitz, Gastin, Robertson, Davey, & Netto, 2015a; Wundersitz et al., 2015b; Wundersitz et al., 2015c). This methodology transforms a signal from the time domain into the frequency domain (Hall & Education, 2007). Subsequently, the shape, magnitude and outliers of the signal are quantified. Consequently, frequency domain analysis may remove the need for output bands (Sweeting et al., 2017b). Furthermore, because it is not time dependent, it would allow for comparisons between match stints and training drills of differing durations (Corbett et al., 2018). This would therefore have potential application across athlete physical output in a team-sport setting and allow for similarities to be examined within competition levels of sport.

Machine learning is an application of artificial intelligence, which may be used to further understand frequency domain features (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). This is because machine learning algorithms can make sense of signals within a data that are not apparent from practitioner insight or linear models (Ofoghi et al., 2013). Utilising machine learning may assist in better understanding physical and skilled output in team-sport (Sweeting et al., 2017a). Supervised learning maps a known output to a series of inputs (Ofoghi et al., 2013). Algorithms, including conditional inference trees and random forests, then learn from these known outputs to classify or predict data points with unknown outputs (Robertson, Gupta, & McIntosh, 2016). These algorithms present a non-linear alternative to prediction and classification problems (Sardá-Espinosa, Subbiah, & Bartz-Beielstein, 2017). As a result, machine learning can account for non-linearity, when examining the relationship between physical output, skilled output and time. Conversely, unsupervised learning approaches, do not distinguish between data inputs and outputs (Ofoghi et al., 2013). Clustering, for example, identifies different groups of data points based on their similarity to one another. Clustering was used to identify different types of training drills in Australian football (Corbett et al., 2018), and to identify player-specific movements in netball (Sweeting et al., 2017a). When used in conjunction with frequency domain features, clustering can minimise the dimensionality of physical and skilled output. Clustering can provide a brief descriptor of physical and skilled output, without relying on a single parameter such as total distance. Consequently, this may assist practitioners to better understand the relationship between physical and skilled output.

Research in team-sport physical and skilled output has typically utilised aggregate parameters. Therefore, match output profiles currently lack specificity. Furthermore, methods to sequence training drills, or evaluate how their characteristics change over time is lacking. The specificity of discrete actions, including sprints, to match outputs, is also unknown. Therefore, the current methods of evaluating physical output are limited. Finally, studies investigating the relationships between physical and skilled output, and time have employed predominantly linear techniques. Therefore, this thesis will examine the relationship between physical and skilled output and time in elite Australian football, using a non-parametric technique. Then, frequency domain analysis will be proposed as an alternative to current aggregate parameters, and time-series analysis as an alternative method to pre-set aggregation windows. This technique will then be compared to current methods of match profiling in a case study, to illustrate a combined time-frequency approach. Finally, applications of time-frequency analysis to evaluate drill sequence, discrete actions and change over time are suggested. Future research may employ these methods in both individual and team-sports.

1.2 Objectives of The Thesis

1.2.1 Objectives

This doctoral investigation presents a more detailed alternative to aggregate parameters, using a time-frequency approach to team-sport output profiling. The primary aim of this thesis is to develop an alternative to aggregate parameter profiling, which is able to identify changes, both increases and decreases, in physical and skilled output within training drills and matches. The secondary aim of this thesis is to demonstrate how a combined time-frequency approach to player profiling, may give greater insight into the physical and skilled output of team-sport athletes in matches. A third objective is to utilise a time-frequency approach to training drill prescription in team-sport.

1.3 Chapter Organisation

Chapter 1 introduces the rationale, aims and objectives of this thesis.

Chapter 2 reviews performance analysis in sport, and current methods used to measure physical and skilled output. It explores match profiling and training drill design. It also reviews time-series, frequency domain and machine learning techniques to analyse physical and skilled output.

Chapter 3 is a cross-sectional study, investigating the relationship between stint duration, physical output and skilled output in elite Australian Rules football. It presents methods which may be utilised in an applied setting, whilst also questioning the efficacy of aggregate parameters to measure physical and skilled output.

Chapter 4 proposes a combined time-series/frequency domain approach to output profiling in team-sport. It identifies potential specifications for a change point algorithm in team-sport, in order to identify changes in output across a match. It also describes physical output using frequency domain features and compares this method with an existing method to measure peak intensity in team-sport matches.

Chapter 5 is a case study, which explores how a time-frequency can be utilised in team-sport match profiling. It demonstrates how a time-frequency approach may reveal insights into physical and skilled output, not available from aggregate parameters. It also demonstrates how the approach may be utilised to better understand changes in physical output within and between matches.

Chapter 6 applied the time-frequency approach presented Chapter 4, to common training design considerations. It demonstrates how a time-frequency approach may be utilised to inform training drill sequence, increase the specificity of training drills and determine training drill length.

Chapter 7 is a general discussion of the preceding chapters. It explores the key themes of this thesis, as well as imitations, practical applications and future research

NB: Chapters 3 and 4 have been published in peer reviewed journals. Chapters 5 and 6 are currently under review.

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CHAPTER 2 – Review of The Literature

2.1 Overview

This review of the literature examines both historical and contemporary performance analysis in team-sport. For the purpose of this thesis, performance analysis refers to the analysis of both skilled and physical output in team-sport matches or training drills. This review will outline how skilled output measurement has evolved from broad analyses of the frequency and success of actions such as goal attempts and passes, into a contemporary suite of metrics, which describe the technical actions completed by individual players and collective movements of teams across the field. Similarly, this review will identify how physical output measurement evolved from notational analysis, with practitioners manually estimating distances completed by players, into methods which directly measure velocity and acceleration. Subsequently, the advantages and disadvantages of different technologies to measure physical output will be examined. Further, common parameters extracted from wearable technologies to describe physical output will be reviewed. Previous applications of parameters extracted from wearable technologies will also be reviewed. Finally, the advantages and disadvantages relevant analytical methods from frequentist statistics, machine learning, time-series analysis and frequency domain analysis will be reviewed.

2.2 Measuring Skilled Output in Team-Sport Athletes

2.2.1 Evolution of Notational Analysis

Performance analysis aims to assist practitioners' decision making, by describing components of human performance (Travassos, Davids, Araújo, & Esteves, 2013). Specifically, notational analysis describes the frequency and success of skilled actions (Bartlett, 2001). In team-sport, notational analysis likely originated in newspaper articles in the 19th Century (Eaves, 2015). When summarising the results of lawn tennis matches, journalists provided statistics such as the total frequency of strokes, as well as the proportion of volleys (Eaves, 2015). Similarly, counts of game events including touch downs, goals from touch downs, fumbles, punts and average length of punts were reported for American gridiron matches (Eaves, 2015). During this period, performance analysis existed as a source of entertainment, and a means to further describe the events of matches. However, the methods used to extract statistics during this period are unknown. Further, the reliance on manual notation, increased the potential for human error.

A systematic approach to performance analysis developed in the 20th Century. Labanotation developed in the early 20th century, to deconstruct the movements of dancers (Guest, 2013). By analysing the direction, duration and body segments involved in movement, Rudolf Laban developed the first objective and systematic methodology to analyse human movement (Barbacci, 2002; Guest, 2013; Loke, Larssen, & Robertson, 2005). A similar methodology was adapted by Reep and Benjamin (1968), who manually sketched passing movements in association football, and categorised actions within each movement in shorthand (Pollard, 2002). The distributions of results from these sketches were analysed to determine passing movements associated with goals (Reep & Benjamin, 1968). Dividing a game into smaller events, including passes or shots, allowed for an objective study of performance in team-sports (Pollard & Reep, 1997). Consequently, this research developed two key paradigms in performance analysis. First, the growth of systematic and methodological data collection. Second, the growth of notational analysis, whereby, team-sport matches can be summarised through a series of smaller match events.

Notational analysis developed further, with the availability of video footage in team-sport matches (James, 2006). Video Footage allows practitioners to view match events multiple times, thus increasing the accuracy of notational analysis. This also means a larger selection of match events can be captured, allowing for a more detailed description of match events. In professional team-sports, commercial providers perform notational analysis for teams. For example, Opta Sports™ performs notational analysis for international sports, including soccer, rugby league and ice hockey. Similarly, providers including Second Spectrum™ and StatSports™ perform notational analysis in the National Basketball Association. A common feature of these providers is the ability to extract a notational analysis time-series. That is, match events are recorded with a time stamp, and presented as a sequence of all on-field actions.

Measuring the count and sequence of all on-field actions is important in AF in order to measure team skill, strategy and success (Robertson, Gupta, & McIntosh, 2016b). Champion Data™ is a notational analysis provider in Australian Football (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015b; Sullivan et al., 2014). Champion Data™ provide a time-series of key actions completed by all athletes during all AFL matches (Robertson et al., 2016b), with a high level of accuracy (Robertson et al., 2016b). Common actions include kicks, tackles and passes. However, despite the notational analysis time-series provided, the majority of research analyses the total frequency of skilled actions across a match. For example, identifying the relationship between match outcome and performance indicators (Robertson, Back, & Bartlett, 2016a), identifying changes in game style between seasons (Woods, Robertson, & Collier, 2017) and assessing individual contributions to team match outcomes (Robertson et al., 2016b). Consequently, it is currently unreported how skilled actions change during a match.

2.2.2 Global Performance Measures

Skilled output refers to the amount of skilled work completed by a team-sport athlete. Given the complex nature of skilled performance (Davids, Glazier, Araújo, & Bartlett, 2003), methods to measure skilled output are less standardised (Corbett et al., 2018a). Across a team, methods may include team-movement based patterns such as dominant regions, player density and congestion (Alexander, Spencer, Mara, & Robertson, 2019; Spencer, Morgan, Zeleznikow, & Robertson, 2016) which aim to quantify how well players' occupy and control space in team-sport matches. However, individual skilled output is often described using aggregate parameters. These parameters are often situation-specific, for example, kicking efficiency (Robertson et al., 2016a). In Australian Football, a common measure of skilled output is Champion Data Player Ratings (Jackson, 2008). This parameter weights skilled actions completed by a player into a continuous value (McIntosh, Kovalchik, & Robertson, 2018). Whilst this parameter correlates with individual (Robertson et al., 2016b) and team success (Robertson et al., 2016b), it does not aim to capture all skilled actions completed by a player. Furthermore, Player Ratings are not available as a time series, and can only provide a global measure of skilled performance for the duration of a match or quarter. Consequently, they are unable to identify changes in skilled output within matches and are most commonly used for between-match comparisons of athletes.

2.2.3 Involvements

In contrast to Player Ratings, skilled involvements describe all on-field skilled output. Consequently, skilled involvements may be used to measure skilled output in Australian football. Skilled involvements refer to the sum total of key actions completed by players during a training session or match. These key actions may be selected by practitioners or coaches, to reflect what they consider to be important for match success. Skilled involvements may be obtained through notational analysis, whereby, key events can be identified. They may also be analysed as a time series. Skilled involvements have been used to explain match outcome

(Robertson et al., 2016a) and to assess the similarity of players on-field skilled output (Jackson, 2016). Future research may utilise skilled involvements as a global measure of player skilled output.

2.3 Measuring Physical Output in Team-Sport

2.3.1 Physiological Analysis

Physiological analysis has become common in many sports (Sweeting, Cormack, Morgan, & Aughey, 2017c). One aim of physiological analysis is to identify the physical capacity of an athlete. This is important, as it gives insight on the peak physical performance achievable by an athlete in a controlled setting (Gomes, Coutts, Viveiros, & Aoki, 2011; Gray & Jenkins, 2010a). In Australian Rules football, this may relate to attributes such as $\dot{V}O_{2MAX}$ (Reilly, Morris, & Whyte, 2009), maximum strength (Gray & Jenkins, 2010b), peak power output (Coutts et al., 2015b) and lactate threshold (Gray & Jenkins, 2010a). However, it is typically not feasible to measure these attributes frequently in the training year (Reilly et al., 2009). This may be due to the cost involved in testing, and the need to manage training loads within a training year (Fry, Morton, & Keast, 1992). Furthermore, there is limited evidence suggesting a relationship between physical capacity, and the outputs of players during matches (Dillon, Kempton, Ryan, Hocking, & Coutts, 2017; Ryan et al., 2018; Ryan, Coutts, Hocking, & Kempton, 2017), with capacity mediating output at most (Mooney et al., 2011). Consequently, physical capacities are typically not used in team-sport performance analysis. Instead, wearable technologies and optical tracking systems which provide a more direct measure of physicphysical output (internal load)

2.3.2 Physical Load and Output in Team-Sport

Physical load refers to the physiological stress placed upon the athlete through training and competition (Rogalski, Dawson, Heasman, & Gabbett, 2013a). From a periodisation perspective, it is useful to measure physical load to ensure athletes' loads are progressed gradually, as not doing so may lead to reduced performance or potential injury (Gabbett, Jenkins, & Abernethy, 2010; Gabbett, 2015; Gabbett, Whyte, Hartwig, Wescombe, & Naughton, 2014). Furthermore, measuring physical load may allow for the comparison of the specificity of training sessions to matches to be evaluated (Corbett et al., 2018a). This is important, as adaptations to training are specific to: energy systems, muscle groups and movement patterns (Coull, Tremblay, & Elliott, 2001; Cronin, McNair, & Marshall, 2001; Tremblay & Proteau, 1998). Consequently, physical load is measured systematically in most professional team-sports (Hartman & Fritz, 1985; Impellizzeri, Rampinini, Coutts, Sassi, & Marcora, 2004; Kelly & Coutts, 2007).

2.3.3 Internal Load Measures

Although not the focus of this review, internal load measures will be discussed in the context of physical output to give futher background (Bartlett, O'Connor, Pitchford, Torres-Ronda, & Robertson, 2017). Internal load measures typically aim to describe an athletes' physiological response, to an external stimulus (Alexiou & Coutts, 2008). Common internal load measures include heart rate (Casamichana & Castellano, 2010; Little & Williams, 2006; Secomb, Sheppard, & Dascombe, 2015), ratings of perceived exertion (Impellizzeri et al., 2004; Moreira et al., 2015; Rogalski, Dawson, Heasman, & Gabbett, 2013b), stress hormone concentrations in blood or saliva (Buchheit et al., 2013b; Gomes et al., 2011) and subjective wellness ratings (Buchheit et al., 2013b). Although internal load contributes to an athletes' total load (Bourdon et al., 2017), these measures are most often used to evaluate an athlete's response to training and loads (Buchheit et al., 2013b). This is in contrast to external load or physical output measures, which describe the objective workload completed by a player (Bourdon et al., 2017).

2.3.4 Observing Physical Output

Notational analysis was an early method of estimating physical output in team-sport matches (Knowles & Brooke, 1974). Several observers would watch a soccer match, and estimate the total distance, peak velocity and distance covered in pre-set velocity bands for a player (Knowles & Brooke, 1974). However, this method had a number of limitations, preventing its systematic adoption in a team-sport environment. Although reliability could be evaluated between raters, it is unknown how their estimates related to the true physical output completed by players. Furthermore, manually estimating physical output becomes increasingly difficult with a larger number of players. Consequently, this method received limited adoption in team-sports. Instead, total duration provided an early proxy for physical output in team-sports. This was later succeeded by wearable technologies and optical tracking systems which provide a more direct measure of physical output (Cummins, Orr, O'Connor, & West, 2013a).

2.3.5 Inertial Sensors

Inertial sensors are wearable devices which can be used to measure the force of a body. In team-sports, tri-axial accelerometers are the most commonly used inertial sensor to measure physical output. Inertial sensors may be included in integrated wearable technologies (see Section 2.3.7) or worn independently. Although triaxial accelerometers are often placed between the scapulae, they can also be attached to any point on the body during training (Buchheit, Gray, & Morin, 2015a; Clarke, Cooper, Hamill, & Clark, 1985; Colby, Dawson, Heasman, Rogalski, &

Gabbett, 2014). Accelerometers measure physical output by calculating acceleration in vertical, forward and lateral planes (Cavagna, Saibene, & Margaria, 1961). Aggregated measures of physical output can be extracted from accelerometers (Boyd, Ball, & Aughey, 2011). Specifically, the sum total of accelerations in all three axes, has been used to describe physical output in team-sport athletes (Boyd et al., 2011; Boyd, Ball, & Aughey, 2013). Accelerations and decelerations have also been used, to give a more sophisticated breakdown of physical output in team-sport matches (Dalen, Jørgen, Gertjan, Havard, & Ulrik, 2016). Triaxial accelerometers are light-weight and inexpensive (Bosch, Marin-Perianu, Havinga, & Marin-Perianu, 2011; Boyd et al., 2013; Cummins et al., 2013a).

Another advantage of accelerometers is the ability to develop sport-specific parameters from their output (Wundersitz et al., 2015b). Specifically, peak impacts have been extracted from accelerometers, to describe the forces associated with contact in team-sports (Wundersitz, Netto, Aisbett, & Gastin, 2013). Additionally, peak accelerations have also been extracted during walking, jogging and running (Wundersitz, Gastin, Richter, Robertson, & Netto, 2014). More specific actions, such as change of direction and jumping have also been identified (Wundersitz et al., 2015c). Accelerometers are primarily limited by their inability to directly measure the velocity or displacement of an athlete (Sweeting, Aughey, Cormack, & Morgan, 2017a). Consequently, whilst they may provide a supplementary understanding of physical output, they should be used alongside location derived measures, such as GPS or optical tracking, to quantify on-field physical output.

2.3.6 Vision-based and Optical Tracking Systems

Manual vision-based tracking systems infer physical output from camera footage (Barris & Button, 2008). In AF, manual vision-based systems typically utilise either broadcast or organizationally collected footage from video cameras (Barris & Button, 2008). Research has estimated distance covered at different velocities from broadcast (Fox, Spittle, Otago, & Saunders, 2013) (Dawson, Hopkinson, Appleby, Stewart, & Roberts, 2004), single camera (Davidson & Trewartha, 2008) and multiple camera set-ups (Klusemann, Pyne, Hopkins, & Drinkwater, 2013; Mohr, Krustrup, & Bangsbo, 2003). Manual vision-based tracking is inexpensive, portable and convenient for athletes, who are not required to physical wear a unit to have position and distance estimates (Carling, Bloomfield, Nelsen, & Reilly, 2008). However, manual vision-based tracking efficacy is limited by footage quality (Carling et al., 2008). Specifically, broadcast footage typically tracks only a small radius surrounding players' in possession of the ball (Sha et al., 2020). Consequently, there may be periods of time where player location cannot be tracked from broadcast footage. Further, it is time consuming to extract physical output parameters using this method. Manual vision-based systems have greater potential for human error than automated tracking systems or wearable technologies (Carling et al., 2008). Although intra and inter-observer reliability has been established for these methods in some sports (Duthie, Pyne, & Hooper, 2003; Fox et al., 2013), there is no established validity in the literature. Consequently, manual vision-based systems should be avoided in favour of semi-automated and automates vision-based systems when measuring physical output.

Semi-automated vision-based systems have overcome many limitations of manual vision-based systems (Carling et al., 2008). These systems place a number of cameras in fixed positions around a field or court (Carling et al., 2008). From this, positional coordinates and thus, kinematic quantities, including velocity and acceleration may be derived (Valter, Adam, Barry, & Marco, 2006). Semi-automated vision based systems have been validated, against timing-gates as a means to measure physical output (Valter et al., 2006). However, the accuracy of semi-automated vision-based systems can vary due to lighting, image quality and changes in camera set up (Valter et al., 2006). Further, there are a number of factors which limit their systematic use in an applied team-sport setting. First, they are an expensive method of measuring physical output (Linke, Link, & Lames, 2020). They are often not portable, require extensive calibration (Barris & Button, 2008) and often have potential for human error (Barris & Button, 2008). Additionally, these systems have only been validated in relatively linear sports with large fields (Linke et al., 2020). In sports, including AF and basketball, which are characterised by contested situations, vision-based systems may struggle to correctly identify players (Sha et al., 2020). Finally, automated systems typically utilise on-field reference lines to track player location (Sweeting, Cormack, & J., 2017b). In sports such as AF, where field-size is variable, vision-based systems would need to be calibrated independently. For these reasons, these systems are typically not used to measure physical output in training (van der Kruk & Reijne, 2018). As a result, semi-automated vision systems are frequently used to measure physical output in team-sport matches, but not training sessions (Barris & Button, 2008). Consequently, they are often not a viable method of consistently measuring physical output in both training drills and matches in many team-sports.

2.3.7 Integrated Wearable Technologies

In team-sports, modern wearable technologies combine gyroscopes, magnetometers and accelerometers with player position relative to a field or location on earth (Cummins et al., 2013a). This is accomplished using a Global Navigation Satellite System (GNSS). Specifically, the distance between a device and satellites in the sky are used to measure players' positions, typically at a rate of 10 to 12 Hz (Larsson, 2003). In indoor environments, where devices cannot communicate with satellites, a local positioning system (LPS) may be used (Sathyan, Shuttleworth, Hedley, & Davids, 2012). In this system, a field or court is surrounded by a series of nodes. Devices then communicate with these nodes, typically using radiofrequency, to detect player position. From this, it is possible to extract a kinematic time series for velocity and acceleration, as well as their angular analogues (Sweeting et al., 2017a). Integrated wearable technologies also typically embed an accelerometer, gyroscope and magnetometer (Cummins et al., 2013a). As a result, they have the same advantages of inertial sensors, whilst also measuring player position.

Integrated wearable technologies are the most commonly used method of capturing physical output in many team-sports, including rugby and AF (Cummins et al., 2013a). They are both relatively inexpensive and require little manual effort. Consequently, GNSS can be used to measure physical output in both training sessions (Bartlett, O'Connor, Pitchford, Torres-Ronda, & Robertson, 2016) and matches (Aughey, 2011). Furthermore, with the growth of Radio Frequency Identification (RFID) integrated wearable technologies measure physical output indoors and outdoors (Sathyan et al., 2012; Serpiello et al., 2018). Their integration of both inertial and locational measurement also gives practitioners a wide range of physical output parameters to utilise. They are also lightweight, minimising the interruption to athletes during training sessions and matches (Coutts & Duffield, 2010a). As a result, they can systematically measure physical output. Consequently, aggregate parameters are often extracted from integrated wearable technologies to describe physical output in team-sport.

2.4 Aggregate Parameters Extracted from Wearable Technologies

2.4.1 Aggregate Parameters

Aggregate parameters extracted from wearable technologies are frequently used to measure physical output in team-sports (Sweeting et al., 2017c). To obtain aggregate parameters, kinematic time series' including velocity and acceleration are derived from positional coordinates (Sweeting et al., 2017a) These time series' are then summarised by a smaller group of parameters (Sweeting et al., 2017b). Aggregate parameters aim to describe the total volume, intensity and composition of physical output in team-sport athletes (Cummins, Orr, O'Connor, & West, 2013b). During matches, these parameters may be aggregated across an on-field stint (Dillon et al., 2017; Orchard, Driscoll, Seward, & Orchard, 2012; Ryan et al., 2017), quarter (Gray, Jenkins, Andrews, Taaffe, & Glover, 2010) or match (Boyd et al., 2013). From a training perspective, these parameters may be aggregated across a training phase (Buchheit et al., 2013a), week (Gabbett & Ullah, 2012), session (Colby et al., 2014; Twist, Waldron, Worsfold, & Gabbett, 2013) or training drill (Corbett et al., 2018b; Loader, Montgomery, Williams, Lorenzen, & Kemp, 2012b). These aggregation periods have frequently been used for injury analysis (Colby et al., 2014; Gabbett et al., 2010; Gabbett & Ullah, 2012), load monitoring (Burgess, 2017; Malone et al., 2015; Nedergaard et al., 2017) and performance analysis (McLaren, Weston, Smith, Cramb, & Portas, 2016; Sullivan et al., 2014; Tee, Lambert, & Coopoo, 2017). However, all of these aggregation windows are pre-set. Consequently, it is difficult to identify how physical output changes over time using these predetermined windows, that are often arbitrarily demarcated into one to ten minute bands (Delaney, Thornton, Burgess, Dascombe, & Duthie, 2017).

2.4.2 Total Distance

Volume parameters summarise the total, accumulated physical output of a player in an aggregation period (Cummins et al., 2013b). Total distance is the most commonly reported volume parameter in team-sport. (Castellano, Casamichana, Calleja-González, San Román, & Ostojic, 2011; Gray et al., 2010; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010c). It is commonly a key component of physical match profiles (Carling & Dupont, 2011; Varley, Gabbett, & Aughey, 2014), and has been used to discriminate between the physical output of players in differing positions (Dawson et al., 2004; McLellan & Lovell, 2013). In training, total distance has also been used to evaluate periodisation (Buchheit et al., 2013a) and changes in volume across a training year (Gabbett, 2015). Total distance has also been used to analyse the characteristics of training drills (Corbett et al., 2018a; Loader, Montgomery, Williams, Lorenzen, & Kemp, 2012a), to aid in training drill prescription. The popularity of total distance is likely due to its ease of interpretation (Cummins et al., 2013a). The main limitation of total distance is its inability to include non-running based components of physical output (Barrett, Midgley, & Lovell, 2014).

2.4.3 Accelerometer Derived Volume

Accelerometer-derived parameters express the instantaneous acceleration of players across three planes in arbitrary units Boyd et al., 2011; Boyd et al., 2013). Depending on the wearable technology provider, slightly different calculations and names may be given to accelerometer derived parameters. For example, BodyLoad™ is a common acclerometer-derived volume parameter in rugby (McLaren et al., 2016; Nedergaard et al., 2017). PlayerLoad™, developed by Catapult Sports, is the most common accelerometer-derived parameter reported in the team-sport literature (Boyd et al., 2013; Gabbett et al., 2014; McInnes, Carlson, Jones, & McKenna, 1995). PlayerLoad™ has been widely used, due to its potential to include non-running components of load into a global volume parameter (Barrett et al., 2014; Barrett et al., 2016; Wik, Luteberget, & Spencer, 2017). These components include jumps, tackles and changes of direction (Barrett et al., 2014; Barrett et al., 2016). Additionally, the reliability of PlayerLoad™

has been confirmed in the literature, with moderate to high test-retest-reliability (Barrett et al., 2014).

PlayerLoad^{TM} has also been used in sports where athletes train and compete both indoors and outdoors. However, there are several limitations with PlayerLoad^{TM} in Australian Football, the team-sport of focus in this thesis. First, AF is predominantly a running based sport. Consequently, PlayerLoad^{TM} is typically collinear with total distance due to the influence of heel strike on accelerometers (Casamichana, Castellano, Calleja-Gonzalez, San Román, & Castagna, 2013). Arguably, there is therefore no need to include it as a measure of physical output in running based sports. Second, the arbitrary units of PlayerLoad^{TM} are not as easily prescribed as total distance in training. This is because PlayerLoad^{TM} measures an abstract quantity, unlike total distance which is directly prescribed by coaches and conditioning staff (Vella et al., 2021). Third, with the mainstream adoption of LPS systems, total distance can also be measured indoors. Additionally, PlayerLoad^{TM} does not directly measure player location or movement paths. As a result, it gives limited context to how players accrue physical output.

2.4.4 Metabolic Power

Metabolic power aims to summarise the energetic demands of physical output (Di Prampero, Botter, & Osgnach, 2015).This is achieved by including the magnitude of accelerations and decelerations, in conjunction with steady-state physical output (Buchheit, Manouvrier, Cassirame, & Morin, 2015b). The popularity of metabolic power is increasing in team-sports including rugby league (Kempton, Sirotic, Rampinini, & Coutts, 2015a), Australian football (Coutts et al., 2015a) and soccer (Osgnach, Poser, Bernardini, Rinaldo, & Di Prampero, 2010).This is likely due to its theoretical potential as a global load aggregate parameter (Delaney et al., 2016a; Delaney et al., 2016c). However, metabolic power has a number of limitations. First, metabolic power does not strongly correlate with a players' energy expenditure in linear and continuous sports (Buchheit et al., 2015b). This is likely because metabolic power calculations are derived from linear running, and thus, have poor agreement with energy expenditure during change of direction movements (Buchheit et al., 2015b). Second, the inclusion of accelerations in a global load measure, is questionable due to the poor validity and reliability of accelerations (further discussed in Section 2.4). As a result, these limitations likely offset the benefits of metabolic power in AF.

2.4.5 Output Bands

Physical output bands aim to describe the physical output completed by players at varying intensities. Specifically, they bin parameters including total distance and acceleration counts, into a smaller number of bands (Sweeting et al., 2017b). These bins are created using static thresholds and have been described using qualitative descriptors. For example in AF, high intensity running, may be defined as all distance covered at speeds > 4.0 $m \cdot s^{-1}$ (Aughey, 2010b). This allows for a more detailed profile of physical output in team-sport matches (Scott, Haigh, & Lovell, 2020; Scott, Norris, & Lovell, 2020). Additionally, using arbitrary bands may allow for a more specific analysis of training drill characteristics (Corbett et al., 2018a; Gabbett, 2015; Gabbett et al., 2014), which may in turn assist with load monitoring and training drill prescription (Farrow, Pyne, & Gabbett, 2008; Gabbett, 2015). However, neither velocity or acceleration bands are standardised in the literature (Park, Scott, & Lovell, 2018). Within and between sports, there are discrepancies in the thresholds set for each band (Sweeting et al., 2017b). For example, both thresholds of 4.0 $m \cdot s^{-1}$ (Sullivan et al., 2014) and 4.17 $m \cdot s^{-1}$ have been used to define high intensity running in AF (Mooney, Cormack, O'brien, Morgan, & McGuigan, 2013; Sweeting et al., 2017b). These inconsistencies are due to the arbitrary selection of physical output bands (Lovell, Scott, & Park, 2019). Consequently, it is difficult to conduct comparisons between and within-sports, using physical output bands. Additionally, because physical output bands are typically applied across a team, they do not account for differences between athletes (Lovell et al., 2019; Park, Scott, & Lovell, 2019). This may decrease the specificity of load monitoring in team-sports (Gabbett, 2015). Consequently, physical output bands may not reflect the true intensity of different players within a team (Gabbett, 2015).

The limitations of physical output bands has led to alternative methods to describe physical output at varying intensities (Lovell et al., 2019; Park et al., 2019).Specifically, there has been a recent interest in setting velocity thresholds to reflect individual differences (Clarke, Anson, & Pyne, 2015). A proposed method of achieving this is utilising results derived from physiological tests. Clarke et al. (2015), utilised $\dot{V}O_{2MAX}$ scores to develop velocity thresholds, in women's Rugby 7's. However, in many team-sports, this would not reflect changes in velocity, which also contribute to load. Additionally, the linear protocols used to set physiological thresholds do not reflect the intermittent nature of many team sports (Sweeting et al., 2017b). Furthermore, physiological tests are infrequently performed, and therefore may not reflect changes in physical capacity within a season (Larsson, 2003). Consequently, velocity bands should be determined using historical data. Murray, Gabbett, and Townshend (2018) utilised players' maximum velocity extracted from GPS devices, to determine individualised velocity bands. However, this method does not describe the distribution of velocity and acceleration data points for each player. Consequently, it is unknown how well this method reflects the true physical output completed by the player.

Data mining methodologies may be utilised as an alternative to velocity bands. Sweeting et al. (2017a) utilised a *k*-means algorithm on instantaneous velocity, acceleration and angular velocity. Subsequently, four, player-specific clusters of physical output for velocity, angular velocity and acceleration were developed. Consequently, this method did not require arbitrarily set thresholds, whilst reflecting physical output at different clusters intensities. Similarly, Park et al. (2018), utilised *k*-means, gaussian mixture models and spectral clustering, to develop three velocity thresholds. These thresholds were qualitatively described as high, very-high and sprinting locomotion (Park et al., 2018). This study differed from (Sweeting et al., 2017a), by accounting for dependency between sequences of velocity data (Park et al., 2018). Together, these studies highlight the efficacy of data mining methods, in summarising the physical output of team-sport athletes. Furthermore, they demonstrate how instantaneous values may be utilised, to give increased insight into team-sport physical output. Therefore, physical output may be best described by utilising both instantaneous values and machine learning. Finally, these studies present an opportunity to examine physical output as a time-series, to account for dependency between data points.

2.4.6 Peak Values

Peak values are intensity parameters, which aim to quantify the highest intensity achieved by a player (Varley, Fairweather, & Aughey, 2012c). In AF, maximum velocity is the most frequently used peak intensity parameter (Cummins et al., 2013a). In other sports, peak acceleration is often used in conjunction with or in place of peak velocity (Delaney, Cummins, Thornton, & Duthie, 2018a). However, peak values are heavily limited by their capture duration. For example, players must only maintain a velocity for < 0.2 s, for it to register as their peak (further discussed in Section 2.4). Consequently, peak values are often inaccurate, due to the small number of data points used (Coutts & Duffield, 2010a). Furthermore, peak values are position dependent, do not identify how frequently players achieve this peak, or how long they maintain it for. Consequently, peak values are limited as an intensity measure in AF. Therefore, work rates are often used to describe intensity in team-sport.

2.4.7 Work Rates

Intensity parameters aim to summarise the difficulty of physical output, independent of duration (Cummins et al., 2013a). In team-sport, this is often described by expressing total volume relative to time (Corbett, Sweeting, & Robertson, 2017; Cummins et al., 2013a). For example, metreage per minute is calculated by dividing total distance by the duration of a session (Coutts & Duffield, 2010a; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010a; Wisbey, Montgomery, Pyne, & Rattray, 2010). Similarly, average acceleration has gained popularity in sports including rugby (Delaney et al., 2018a). Work rates are often used to compare physical output, where session time varies. For example, comparing the loads of different training drills (Corbett et al., 2018b). However, there are several limitations of the work rates used in sport. First, they are linear and therefore calculated using linear statistical techniques. As a result, they do not reflect the intermittent nature of physical output in many team-sports (Delaney et al., 2016a; Delaney et al., 2015; Delaney et al., 2017). Furthermore, they cannot identify non-linear periods of altered physical output within training sessions or matches. Finally, the values of average acceleration and metreage per minute typically fall within a small range. Consequently, these parameters may only be able to identify large differences in physical output.

2.4.8 Moving Averages

Moving averages applied to instantaneous velocity or acceleration, have been proposed as an alternative to existing intensity parameters (Delaney et al., 2018a; Delaney et al., 2016a; Delaney et al., 2015; Delaney et al., 2017). Initially applied to team-sport by Varley et al., (Varley et al., 2012c), this method applies moving averages of varying durations, to the instantaneous velocity and/or acceleration of team-sport athletes (Delaney et al., 2015). This may be applied to physical output during matches, to attain intensity benchmarks for athletes to achieve during training (Delaney et al., 2016c). Moving averages have been used in rugby (Delaney et al., 2016a; Delaney et al., 2015; Reardon, Tobin, Tierney, & Delahunt, 2017; Whitehead et al., 2018a), Gaelic football (Malone, Solan, & Collins, 2017b; Malone, Solan, Hughes, & Collins, 2017c), soccer (Varley, Elias, & Aughey, 2012a) and Australian Rules football (Whitehead, Till, Weaving, & Jones, 2018b). However, moving averages have recently been questioned recently in the literature (Carling, McCall, Harper, & Bradley, 2018). This is because they do not identify the frequency or temporal occurrence of peak intensities (Carling et al., 2018). Furthermore, the ability to translate these parameters into training drills has also been questioned (Carling et al., 2018). Moving averages also cannot examine the impact of match constraints, including substitutions and transient changes in physical output (Carling et al., 2018). Consequently, future research should aim to develop methods which address these issues.

2.5 Validity and Reliability of Wearable Technologies

2.5.1 Validity and Reliability

Validity refers to how well a device or artefact measures what it intends to (Coutts & Duffield, 2010b; Currell & Jeukendrup, 2008; Johnston et al., 2012). Specifically, the construct validity of wearable technologies involves the accuracy of aggregate parameters such as total distance, banded distance and velocity, to the true distance and velocity covered by a player (Coutts & Duffield, 2010b; Frencken, Lemmink, & Delleman, 2010; Gray et al., 2010). On a granular level, validity may refer to the accuracy of positional coordinates relative to a player's true position on a field (Serpiello et al., 2018), and their instantaneous velocity and acceleration (Varley, Fairweather, & Aughey1, 2012b). To assess validity, values extracted from wearable technologies are compared with criterion measures, which may include optical tracking systems (Serpiello et al., 2018) and pre-measured courses (Coutts & Duffield, 2010b). Reliability is the consistency of a measurement tool (Currell & Jeukendrup, 2008). Specifically, the reliability of wearable technologies refers to the similarity of outputs within and between devices (Köklü, Arslan, Alemdaroğlu, & Duffield, 2015; Scott, Scott, & Kelly, 2016). The validity and reliability of both aggregated and instantaneous parameters, is important when analysing the physical output of matches (Aughey, 2011; Gray & Jenkins, 2010a; Mooney et al., 2011), training drills (Gabbett, Jenkins, & Abernethy, 2009; Loader et al., 2012b; Neville, Rowlands, Wixted, & James, 2012) and change over time (Delaney et al., 2017). This is because the extent to which practitioners can utilise technology to inform decisions, is dependent upon the validity and reliability of technology itself.

2.5.2 Validity and Reliability of Aggregate Parameters

The validity and reliability of aggregate parameters extracted from wearable technologies varies (Cummins et al., 2013b). Total distance, extracted from either GPS or LPS devices, has acceptable validity and reliability (Coutts & Duffield, 2010b; Gray et al., 2010; Jennings, Cormack, Coutts, Boyd, & Aughey, 2010b; Scott et al., 2016; Serpiello et al., 2018). However, this validity decreases during change of direction tasks (Serpiello et al., 2018). Furthermore, the validity and reliability of these devices has an inverse relationship at higher velocities (Scott et al., 2016; Varley et al., 2012b). This means aggregate parameters including maximum velocity, and distances covered at high speeds may not accurately reflect the physical output of team-sport athletes (Heidi, André, Jace, Fabio, & Grant, 2019). Furthermore, accelerative parameters, derived from either in-built inertial sensors or from X-Y coordinates, have low validity and reliability (Akenhead, French, Thompson, & Hayes, 2014; Buchheit et al., 2014; Varley et al., 2012b). This has been partially overcome with recent parameters such as average acceleration (Delaney et al., 2018a). Consequently, practitioners should be cautious when using these parameters during training load monitoring, match profiling and drill analysis (Cummins et al., 2013b).

2.5.3 Validity and Reliability of Instantaneous Velocity and Acceleration

There are a limited number of studies examining the validity and reliability of instantaneous velocity and acceleration, extracted from wearable technologies (Luteberget, Spencer, & Gilgien, 2018; Varley et al., 2012b). Varley et al. (2012b), validated the ability of GPS devices to measure constant velocity and acceleration. Furthermore, this study highlighted the increased validity and reliability of new GPS devices (Varley et al., 2012b). However, this study did not validate instantaneous velocity and acceleration in change of direction movements, which also contribute to a players' total physical output (Varley et al., 2012b). Indeed, Luteberget et al. (2018), identified low validity and reliability for LPS devices, in measuring instantaneous velocity in team-sport drills. This demonstrates the dichotomy between the need to maintain validity and reliability in measures taken, and the granularity of how data is analysed. Specifically, analysing wearable technologies on a per-second basis provides a greater understanding of a player's physical output (Varley et al., 2012b; Varley, Jaspers, Helsen, & Malone, 2017). However, doing so may reduce the accuracy of physical output measures (Luteberget et al., 2018).

2.5.4 Filtering

Filtering and post-processing influence the validity and reliability of wearable technologies (Varley et al., 2017). Specifically, high intensity running, and sprint efforts may differ greatly, depending on the filtering technique used (Varley et al., 2017). Thornton et al. (2018) demonstrated substantial differences between aggregate parameters, arising from differing filters. However, this study also demonstrated intra-unit reliability regardless of the filter applied. Consequently, this study suggested filtering techniques may influence validity, but not intra-unit reliability. Thornton concluded that practitioners should have confidence in aggregate parameters, regardless of filter (Thornton et al., 2018). However, this conclusion appears unfounded, due to the unknown validity of aggregate parameters, extracted using different filters. Given the demonstrated intra-unit reliability of devices, but the inability to relate many aggregate parameters with a criterion measure, it is preferable to analyse the raw signal of wearable technologies (Thornton et al., 2018). This would allow for physical output to be analysed in greater depth, without necessarily relating to existing quantities such as sprint count and relying on arbitrary thresholds (Heidi et al., 2019).

2.6 Match Analysis in Team-Sports

2.6.1 Match Profiling

Match profiles summarise the physical and skilled output of team-sport athletes during competition (Sweeting et al., 2017b). These profiles are used to monitor change across a competitive season (Aughey, 2011; Sweeting et al., 2017b) and to plan training (Corbett et al., 2018a; Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010a). Total match outputs have been investigated in soccer (Bradley & Noakes, 2013; Buchheit, Mendez-Villanueva, Simpson, & Bourdon, 2010; Carling, Le Gall, & Dupont, 2012; Dalen et al., 2016), rugby (Clarke, Anson, & Pyne, 2017; Johnston, Gabbett, & Jenkins, 2013; Suárez-Arrones, Portillo, González-Ravé, Muñoz, & Sanchez, 2012), hockey (Jennings, Cormack, Coutts, & Aughey, 2012) and netball (Cormack, Smith, Mooney, Young, & O'Brien, 2014; Davidson & Trewartha, 2008; Fox et al., 2013). Specifically, match profiles have characterised Australian football players, as covering between 10,000 m and 14,000 m in a match (Cummins et al., 2013a; Gray & Jenkins, 2010b; Wisbey et al., 2010). Approximately 30% of this distance is covered at speeds greater than 4 $m{\cdot}s^{-1}$ (Gray & Jenkins, 2010a; Wisbey et al., 2010). Additionally, players complete multiple sprint efforts, changes of directions (Brewer, Dawson, Heasman, Stewart, & Cormack, 2010a; Gray & Jenkins, 2010a; Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015d), tackles and impacts (Wundersitz, Gastin, Robertson, Davey, & Netto, 2015a). Consequently, the total aggregate outputs for entire matches of AF players are well documented.

Positional differences in match profiles have also been investigated in the literature. These differences have been noted in rugby (Austin & Kelly, 2013; Delaney et al., 2015), soccer (Di Salvo, Gregson, Atkinson, Tordoff, & Drust, 2009; Varley & Aughey, 2013), hockey (Macutkiewicz & Sunderland, 2011) and netball (Sweeting et al., 2017a). In Australian football, studies have identified differences in match profiles between key and non-key players (Mooney et al., 2011). Furthermore, nomadic players typically cover greater distance than forwards and backs (Gray & Jenkins, 2010a). Recently, the ability to utilise positional differences in match profiles to inform training design and load monitoring has declined in AF (Barrett et al., 2016). Players are now typically required to cover multiple roles in a team (Scott et al., 2016). Consequently, it is often difficult to accurately categorise players using a single position. Therefore, future research should develop methods to identify similarities in physical output, independent of position. Furthermore, profiling methods should analyse players individually, to best reflect their on-field outputs.

Another aspect of match profiling in Australian football, is the interplay between physical and skilled output (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015c; Sullivan et al., 2014). Specifically, analysing whether changes in physical output are indicative of fatigue (Aughey, 2010a, 2011), or match constraints including pressure and position (Dillon et al., 2017; Ryan et al., 2018). Sullivan et al. (2014) found that physical output had only a minor impact on coaches' perceptions of player performance. Furthermore, physical output had a slight negative relationship with Player Ratings (Sullivan et al., 2014). Similarly, Dillon et al. (2017), identified trivial relationships between physical and skilled output. Conversely, Mooney et al. (2011), identified a relationship between physical capacity and number of disposals, with high intensity running as a mediator. Consequently, the relationship between physical and skilled output in AF is contentious in the literature. The majority of studies examining the interplay between physical and skilled output in AF, have employed parametric statistical approaches. Consequently, they assume a linear relationship between outputs, and independence between parameters. This is problematic, as many commonly used parameters extracted from wearable technologies are co-linear (Casamichana et al., 2013). That is, rather than measuring unique aspects of physical output, they incidentally measure the same aspect. Future research should therefore employ careful parameter selection, to better understand the relationship between physical output, skilled output and time and avoid collinearity, where possible.

2.6.2 Between Match Profiling

In team-sport, between-match profiling has typically examined the consistency of physical and skilled output between matches. In rugby, parameters of high intensity output including high speed running (≥15 km·h^{-1}), very high speed running (>20 km h^{-1}) and PlayerLoad^{TM} vary considerably between matches. Conversely, lower intensity parameters including low speed player load (<7.2 km h^{-1}) and total distance were stable from match-to-match (Kempton, Sirotic, & Coutts, 2014; McLaren et al., 2016). This finding was also consistent with AF, where volume parameters (Coefficient of Variation, CV: %: 5.3–9.2%) were more consistent than intensity parameters (CV %: 13.3–28.6%) (Kempton et al., 2015b). Measures of skilled output were highly variable between matches (CV %: 26.1–60.2 %) (Kempton et al., 2015b). Specifically, number of kicks and handballs for backs (CV %: 43.9 – 63.1%, 53.2 – 78.6 %) and number of handballs for forwards (CV %: 50.9 – 81.1 %) had the highest between-match variability (Kempton et al., 2015b). Conversely, midfielders typically had less variability in kicks, handballs, possessions and player ratings than player in other positions (Kempton et al., 2015b). These findings were also consistent in soccer (Gregson, Drust, Atkinson, & Salvo, 2010). During finals, an even greater increase in high intensity running (> 4.17 m.s^{-1}) was observed (Aughey, 2011). Each of these studies have successfully utilised aggregate parameters, to identify changes in output between matches.

2.6.3 Within-Match Profiling

Within-match profiling aims to examine how output changes across the duration of a match. Changes in match physical output have been identified in soccer (Bradley & Noakes, 2013) and rugby (Lacome, Piscione, Hager, & Carling, 2016). In Australian football, total distance in quarters two to four, declines by up to 10.7%, comparative to quarter one (Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010b). Specifically, a high metreage per minute earlier in a match, is related to reduced physical output later in a match (Coutts et al., 2010b). Although this relationship has been quantified, it has limited applicability to inform decision-making. This is because, each of these studies argue that a reduction in physical output over time is inevitable. None of these studies establish a strong relationship between stint duration and physical output in team-sport matches.

To overcome many of these limitations, studies have utilised stint or rotation length, to identify how physical output changes during a match. Aughey (2010a), identified reductions in high intensity running (HIR, 4.2 to 10.00 $m \cdot s^{-1}$) and maximal accelerations (2.8 to 10.0 $m \cdot s^{-2}$), in second and fourth quarter stints, relative to first and third quarters respectively. Similarly, Dillon et al. (2017) identified trivial-to-moderate reductions (effect size 0.1- 0.69) in relative Champion Data player ratings, relative total and high speed running (>20 $km \cdot h^{-1}$) as a function of duration in Australian football. However, an increased physical output does not necessarily impact skilled performance, in line with other literature (Bauer, Young, Fahrner, & Harvey, 2015). Montgomery and Wisbey (2016), characterised physical output in Australian football, as static in the first 5 minutes of a stint, reducing 3% for every subsequent 2 minutes on field, up to 9 minutes. These studies relate stint length to physical output between matches (Montgomery & Wisbey, 2016). Consequently, it is unknown whether these reductions occur within a match or are the result of match constraints (Dillon et al., 2017; Ryan et al., 2018). Furthermore, all of these studies employed linear techniques to quantify changes in physical output over time. However, linear analysis of physical and skilled output may not adequately model reductions in a team-sport environment. The findings of Aughey (2010a), suggest physical output fluctuates throughout a match. This may be due to contextual factors, including score line and time in possession of the ball (Carling & Dupont, 2011). Consequently, future research should utilise non-linear techniques to model the relationship between physical output and time. This would better account for transient changes in physical output within matches.

Recent literature has examined physical output within phases of play and possession chains. Specifically, total distance and high speed running defined as running at speeds > 25 k/hr^{-1}) has been computed during offensive, defensive and contested possession chains (Rennie, Watsford, Kelly, Spurrs, & Pine, 2018). This method identified greater distance covered when attacking and defending across the length of an Australian football field (Vella et al., 2021). This method provides a novel and interpretable means to analyse physical output in specific match contexts. However, the methodology proposed requires considerable manual coding by experienced practitioners (Vella et al., 2021). Additionally, possession chains are not performed in all training drills. Consequently, this method has limited viability outside of match simulation and small-sided games (Vella et al., 2021). Finally, this methodology has not been validated to identify changes in physical output within matches. Consequently, future research may utilise automatic change-detection methods to players' physical output in training drills and matches. This would reduce manual labour and provide a means to compare training drills and matches.

2.7 Training Analysis in Team-Sports

2.7.1 Training Analysis in Team-Sport

The physical output of training has been investigated extensively in the literature. The majority of these studies have aimed to characterise training across blocks, including preseason (Buchheit et al., 2013a). Additionally, changes in physical output by training or season phase have also been identified (Ritchie, Hopkins, Buchheit, Cordy, & Bartlett, 2016). These changes in physical output have also been related to performance and injury risk (Gabbett et al., 2010; Gabbett & Seibold, 2013; Gabbett & Ullah, 2012; Rogalski et al., 2013a). However, there is limited research examining output characteristics for individual training sessions. Consequently, future analysis should examine how physical and skilled outputs can be utilised for prescriptive purposes.

2.7.2 Analysing Drill Characteristics

Training drills have different characteristics, including different skilled actions, physical volumes and physical intensities (Corbett et al., 2018b). Understanding these characteristics allows practitioners to select drills which achieve their training goals (Corbett et al., 2018b). However, beyond match-derived drills including match simulation and small sided games, there are only a limited number of studies investigating the physical and skilled characteristics of training drills in team-sport. Loader et al. (2012b) utilised hierarchical clustering, to identify different types of training drills in Australian football. Training drills were characterised as game specific conditioning, skill refining with moderate physical intensity and skill refining with a low physical intensity. Similarly, measures of both physical and skilled output have been utilised to identify the characteristics of open and closed training drills (Farrow et al., 2008).

Corbett et al. (2018b) expanded upon this study, by identifying five drill types through physical output and skilled constraints, including pressure, time in possession and disposal number. Additionally, this study characterised training drills, through their specificity to match outputs (Corbett et al., 2018a). All of these studies (Corbett et al., 2018a; Loader et al., 2012a) are limited by their utilisation of work rates which assume physical output accrues gradually throughout a session. Consequently, the true physical output of more intermittent training drills may be over or under-estimated. Furthermore, all of these studies (Corbett et al., 2018a; Loader et al., 2012a) could only assist with training drill selection. Other training considerations, such as training drill sequence, training drill duration and the specificity of movements on a more granular level are not addressed in current drill classification systems (Corbett et al., 2018a; Loader et al., 2012a).

2.7.3 Training Design Frameworks

Training design frameworks provide a theoretical basis for the prescription of technical drills in team-sports (Farrow & Robertson, 2017). Specifically, frameworks can provide considerations for practitioners when designing training drills. A key framework for the prescription of physical activity is 'SPORT' (Grout & Long, 2009, p. 197). Under this framework, practitioners should design training drills which are specific to match outputs, progressively overload athletes, prevent reversibility and maintain variety (Farrow & Robertson, 2017). Indeed, combining conditioning drills with position-relevant tactical actions including kicks, on-field location and energetic profile will likely lead to maximal learning by the athlete (Bradley, Martin Garcia, Ade, & Gomez Diaz, 2019). The 'SPORT' framework is often used in conjunction with the 'FITT' framework (frequency, intensity, time and type), to address both long- and short-term training considerations (Grout & Long, 2009, pp. 188, 197).

Farrow and Robertson (2017) adapted the 'SPORT' framework, to skill acquisition and training design in team-sport. The 'SPORT' framework highlighted the importance of considerations, including specificity and variety, and how they may be monitored and systematically collected in a team-sport environment. Future research should identify how analytical methods can be utilised to address these training considerations. For example, time-series analysis may be utilised to better understand physical intensity. This is because time-series analysis allows for second-by-second analysis (Atchison, Berardi, Best, Stevens, & Linstead, 2017), and can detect changes as they occur. Similarly, clustering methods may be utilised to identify drills with similar physical output but differing movement characteristics, to evaluate variety/tedium.

2.7.4 Specificity & Representative Task Design

Specificity may refer to the extent to which training reflects match outputs (Farrow & Robertson, 2017; Henry, 1968; Proteau, Marteniuk, & Lévesque, 1992). In team-sport, specificity is achieved by prescribing training drills to model outputs similar to matches (Corbett et al., 2018a). However, under a representative task design framework, the greatest training benefit is argued occur when behaviours and constraints are also similar between training sessions and matches (Barris, Davids, & Farrow, 2013; Dicks, Davids, Button, MacMahon, & Farrow, 2009; Farrow & Robertson, 2017; Pinder, Davids, Renshaw, & Araújo, 2011). Recent research has successfully utilised moving averages derived from games to design short conditioning drills (Malone, Roe, Doran, Gabbett, & Collins, 2017a; Malone et al., 2017b). However, it is unknown how skill-based drills may be modified to increase their specificity to match outputs. Consequently, practitioners should identify opportunities to increase the representativeness of training drills to matches. However, the ability to identify these opportunities is largely limited by the aggregate parameters used to assess physical and skilled output. Future research should aim to better characterise physical and skilled output at various points in a match, including discrete actions. This would allow practitioners to more carefully prescribe training drills. Furthermore, methods to increase representativeness beyond drill selection, including training drill sequence, should be investigated.

2.7.5 Challenge Point Framework

The challenge point framework, theorises the relationship between task difficulty and the potential learning benefit of an individual (Guadagnoli & Lee, 2004b). It argues that for every task, there is an optimal challenge point, where an individual is challenged to learn, but not overstimulated (Guadagnoli & Lee, 2004b). The challenge point framework has been utilised conceptually in simple motor tasks (Guadagnoli & Lee, 2004a; Onla-or & Winstein, 2008), education (Guadagnoli, Morin, & Dubrowski, 2012) and rehabilitation (Pesce et al., 2013). In sport, the framework has been utilised in golf to increase learning efficiency (Guadagnoli & Lindquist, 2007). However, there is no literature utilising this framework in a team-sport setting, to inform training drill difficulty from a physical and skilled output perspective. An example of how training drill difficulty may be manipulated, is through training drill duration. A positive relationship has been identified between training drill volume, and players perceived cognitive complexity (Farrow et al., 2008). Consequently, this suggests that drill duration can influence drill difficulty. Future research may therefore apply the challenge point framework to physical output, as a means of examining training drill length. In combination with frequency domain analysis, change point analysis could identify and characterize changes in physical and skilled output over time.

2.8 Frequency Domain Analysis

2.8.1 Frequency Domain Analysis

Frequency domain analysis aims to describe a signal, based on how frequently data points occur at each magnitude (Hall & Education, 2007; Robertson, Caldwell, Hamill, Kamen, & Whittlesey, 2013). For example, frequency domain features have been used to describe how frequently patients move at different linear and angular velocities during rehabilitation (Tedesco, Urru, & O'Flynn, 2017). Consequently, frequency domain analysis describes a series of values independent of time. Each value in a series, and the number times each value occurred, is termed the frequency domain. A Fourier transform is the most common method of converting a series of values into the frequency domain. Although other methods exist, including the Goertzel algorithm, these methods are not commonly used outside of civil and sound engineering (Sysel & Rajmic, 2012). This approach converts a signal into a series of smaller sine waves (Wu et al., 2016). Subsequently, the shape of a signal is then described using features. Frequency domain analysis is commonly used in engineering and Biomechanics, to filter and identify outliers in noisy data (Robertson et al., 2013; Wu et al., 2016). Frequency domain analysis has also been used in finance, to determine option prices (Carr & Madan, 1999). This is because frequency domain analysis can take into account features including volatility (ie., standard deviation) and the shape of distributions (ie., kurosis and skew), which provides a realistic summary of phenomena (Černý, 2006). Similarly, frequency domain features may be useful when summarising physical output in team-sports. This is because frequency domain analysis, in contrast to aggregate parameters, can summarise all data points in a velocity or acceleration time series, without the need to bin data into discrete bands.

2.8.2 Frequency Domain Features

Frequency domain features can be used to describe data points within a time series (Pintelon & Schoukens, 2012). A feature typically extracted is the shape of the signal, and includes measures such as skewness and kurtosis (Bracewell & Bracewell, 1986). Another feature extracted from a signal is central tendency, and includes the centroid, median or mode (Carr & Madan, 1999; Wu et al., 2016). Another feature extracted is noise-based, which describe the signal-to-noise ratio in the frequency domain (Stolt, 1978; Wu et al., 2016). Another type of feature extracted from a time series, is magnitude, and typically includes percentiles to describe the distribution of values in the frequency domain (Bigger Jr et al., 1992; Pintelon & Schoukens, 2012). Because of these features, frequency domain analysis gives a sophisticated description of a series of values, beyond what is captured in standard statistics such as mean and standard deviation (Robertson et al., 2013). The key limitation of frequency domain analysis is interpretability. Whilst aggregate parameters relate to constructs including total distance, frequency domain features are expressed in arbitrary units (Bigger Jr et al., 1992; Ibrahim et al., 2020). Nonetheless, frequency domain features are useful in situations, where the distribution of data needs to be quantified or understood. Therefore, application of frequency domain analysis may be suitable to team-sports whereby skilled and physical data are often non-normally distributed. Consequently, the prevalence of frequency domain analysis is increasing in the literature yet remains to be explored in profiling the physical and skilled output of team-sport data.

2.8.3 Frequency Domain Analysis in Sport

Frequency domain analysis is common in motion analysis. Specifically, it is an integral technique in processing signals from motion capture (Potter et al., 2014; Secomb et al., 2015), dynamometry (de Araujo, Alvares , de Azevedo, da Silva, & Vaz, 2015) and force analysis (Clarke et al., 1985; Fransz, Huurnink, de Boode, Kingma, & van Dieën, 2016). Here, frequency domain analysis is used to develop filters in order to remove noise from measurement equipment. Frequency domain analysis has also been applied to the outputs of wearable technologies, commonly utilised in the motion analysis setting. Wundersitz et al. (2014) extracted frequency domain features from an accelerometer during walking, jogging and running, in order to discriminate between the movement tasks. Similarly, Wundersitz et al. (2015c) extracted frequency domain features from locational, accelerometer and gyroscope outputs to discriminate between common team-sport activities. Furthermore, frequency domain features have been used to characterise concussion (Bishop, Dech, Guzik, & Neary, 2018) and overuse injuries (Oliveira-Junior et al., 2017)from heart rate data. Finally, more recent studies utilising Inertial Measurement Units (IMU's) have been able to classify upper body movements in tennis (McGrath, Neville, Stewart, & Cronin, 2020) and to classify skateboard tricks (Ibrahim et al., 2020). Together, these studies demonstrate that frequency domain analysis presents a useful means to analyse the outputs of wearable technologies. Furthermore, frequency domain analysis may be able to better distinguish between different types of movement (Wundersitz et al., 2015c). Finally, frequency domain analysis is able to describe the shape of a signal and does not require pre-set output bands like aggregate parameter profiling.

2.9 Time Series Analysis

2.9.1 Assumptions of Time Series Analysis

Time series analysis is a branch of statistics, which aims to characterise how data changes over time. A time series is a set of data points, typically sampled at regular intervals (Berndt & Clifford, 1994; Cryer & Chan, 2008). Distinct from time-series forecasting, time series analysis aims to describe values in a series, without drawing an inference to future data points (Atchison et al., 2017). There are several key assumptions which need to be met, to ensure a data set is eligible for time-series analysis (Wiener, 1949). First, there should be an absence of trend. Trend refers to a persistent increase or decrease in the values within a velocity time series (Cryer & Chan, 2008). A trend may misconstrue the characteristics of a time series, when included in analysis. This is because a trend acts as an additional source of variance and distorts the relationships between input and output variables (Cryer & Chan, 2008). Additionally, trends often do not continue indefinitely when forecasting a time-series, and thus, may mislead any time-series forecasts (Tanaka, 2017). There should also be a lack of seasonality (Atchison et al., 2017). That is, values should not be lower or higher in a time-series, purely due to the time it was sampled. Finally, the signal should be stationary, whereby, the mean, variance do not change over time (Cryer & Chan, 2008; Tanaka, 2017). Although some time-series methods have been utilised in sport, predominantly in the form of fixed moving averages (Delaney et al., 2015; Delaney et al., 2017; Delaney et al., 2016c; Delaney et al., 2018b), they have not tested for these time-series assumptions. Consequently, research into physical output using time-series analysis, should ensure each of these assumptions are met, to ascertain the suitability of the analysis technique.

2.9.2 Simple and Exponential Moving Averages

Moving averages are the most common time-series analysis technique (Tanaka, 2017). Broadly, they create subsets of the full time-series, and calculate average values for each subset. Simple moving averages calculate a mean value for n preceding periods. Conversely, exponential moving averages calculate a mean for all values. However, exponential moving averages weight recent values more highly. Consequently, moving averages are primarily used to smooth or filter a time-series. Specifically, moving averages aim to identify whether a change in a time-series is transient, or indicative of a longer-term increase or decrease in the values of a time series. Moving averages were used extensively in the 20th century, in the fields of economics, finance, health care (Tanaka, 2017). In each of these fields, a change in the moving average may indicate a longer-term increase or decrease in values.

Moving averages are the only time-series analysis technique to also be used extensively in sport and have been used as a longitudinal measure of training load (Bourdon et al., 2017; Murray, Gabbett, Townshend, & Blanch, 2017; Williams, West, Cross, & Stokes, 2017). Here, they are used to either complement or replace measures such as training stress balance, to identify shifts in training load, whilst removing noise from the dataset. A major application of moving averages in team sport has been to identify peak intensities of acceleration and metreage per minute. Simple moving averages have been applied to a players' velocity or acceleration time series (Delaney et al., 2016a; Delaney et al., 2015; Delaney, Thornton, Duthie, & Dascombe, 2016b; Delaney et al., 2016c; Delaney et al., 2018b). This information is then used to create intensity benchmarks of varying durations, which players should hypothetically achieve during a training session or drill (Delaney et al., 2015). However, there are several limitations in the use of moving averages to a physical output time series. First, although moving averages can identify a peak intensity, they cannot succinctly summarise how physical output changes across a match. This is because they do not identify the temporal occurrence of peaks, and how these change across the duration of a match (Carling et al., 2018). Further, they only utilise a mean value, and thus cannot capture the variability of a time series (Cryer & Chan, 2008; Tanaka, 2017). In team-sports, this is important, as physical output is often intermittent (Boyd et al., 2013). Finally, moving averages are typically designed to identify real-time changes in a time-series (Tanaka, 2017). Consequently, using moving averages to analyse retrospective data can be confusing and misleading. Specifically, they rely heavily on user interpretation to identify changes in a time-series. These limitations have caused a recent shift in other disciplines, including finance and ecology, to automatic or semi-automatic methods of change detection (Chen & Gupta, 2011).

2.9.3 Time Series Segmentation

Team-sport may utilise time-series segmentation to examine how physical and skilled output change across a training drill or match. Time series segmentation is an analysis technique which divides a time-series into a smaller number of continuous segments (Piotr & Haeran, 2014). Developed in the late 1990's, segmentation algorithms identify a number of change points, based on user specifications. (Taylor, 2000). Hypothesised change type is the first key specification of all segmentation algorithms (Chen & Gupta, 2011; Taylor, 2000). Specifically, users specify whether they wish to identify a change in mean, a change in variance or a change in both A minimum segment length must also be specified. This allows users to specify the sensitivity of the algorithm to short, rapid changes in a time series (Himberg, Korpiaho, Mannila, Tikanmaki, & Toivonen, 2001; Jamali, Jönsson, Eklundh, Ardö, & Seaquist, 2015; Piotr & Haeran, 2014). Finally, users must specify either a penalty value or change point quotient. These specifications allow users to specify the required severity and number of change points. There is no consensus in the literature on which specifications could be used, with most specifications acting as open research questions (Chen & Gupta, 2011). Consequently, the specifications in these algorithms are typically discipline and application perspective.

There are several time-series segmentation algorithms. Binary segmentation is the most common algorithm used (Piotr & Haeran, 2014; Yang & Buenfeld, 2001). Specifically, this algorithm searches through a time series to identify either all change points which fit user specifications, or in the instance of a limited change point quotient, the most severe change points (Killick & Eckley, 2014; Taylor, 2000). Binary segmentation improved upon previous algorithms, including X, Y, Z, due to the ability to recognise multiple change points in a time series (Taylor, 2000). Although other change point algorithms have been proposed, they have yet to be validated in the literature. Furthermore, energy-divisive, arguably the most accurate change point algorithm, requires considerable computing power (James & Matteson, 2013). Thus, it is likely not feasible on a physical output time-series, which contains thousands of data points. Consequently, binary segmentation could be utilised when analysing the physical output of team-sport athletes. Future research should utilise this algorithm, to characterise changes in team-sport data, specifically physical output over time. This would overcome the need to pre-set aggregation windows or use moving averages to summarise output time series.

2.10 Data Mining

2.10.1 Data Mining and Machine Learning in Sport

Data mining is a problem solving methodology which converts raw data into a description of patterns within the data set (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). Specifically, machine learning aims to expose hidden and underlying relationships between variables by training computers to understand how different permutations of variables can influence outcomes. Consequently, machine learning can generate insights which may not be apparent from standard statistical methods including linear regression (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). Machine learning algorithms are often able to better account for contextual factors and variations in values within a data set (Ofoghi et al., 2013). Additionally, basic statistical methods usually assume independence between variables, and that responses increase in a linear fashion (Wasserman, Casey, Champion, & Huey, 2017). In machine learning practitioners expose algorithms to a training data set, in order to allow the algorithm to identify patterns within the data. Subsequently, the performance of an algorithm is then evaluated on a test or holdout data set which has not been seen by the algorithm. This ensures that any insights gleaned from the model are generalizable outside the data set, as opposed to purely being a description of the data set seen by the algorithm (termed overfitting). Machine learning algorithms are often described as either supervised or unsupervised learning. Unsupervised learning is able to describe data sets without dependent and independent variables, and thus, can explore data sets with less structure (Ofoghi et al., 2013). Conversely, supervised learning is used to describe the relationship between independent and dependent variables (Fayyad et al., 1996; Ofoghi et al., 2013). The key limitation of many machine learning algorithms is that they may overfit the data set. Overfitting refers to situations where models accurately describe observed data, but do not generalise to describe phenomena broadly (Ofoghi et al., 2013). This limitation is mitigated by cross validation, whereby, the data set is trained on a subset of the data and "tested" on an unseen subset of the data (Ofoghi et al., 2013). In a field like sport where phenomena is often non-linear, machine learning presents a range of methods and algorithms which may expose patterns in data sets which are not apparent using traditional statistical methods (Ofoghi et al., 2013).

2.10.2 Distance Measures

Distance measures summarise the similarity of two observations across multiple parameters (Maurer, Qi, & Raghavan, 2003; Wang, Zhang, & Feng, 2005). In sport and data science, they are most commonly used to reduce the dimensionality of a data set (Narayanan & Nelson, 2019). Where physical and skilled output is described using a large suite of parameters, distance measures can describe the similarity of two observations with a single value. For example, distance measures have been used to determine similarity between players in Australian football using skilled output parameters (Jackson, 2016). This allowed for players to be described using a continuous value, instead of descriptive player positions (Jackson, 2016; Pers & Kovacic, 2000). However, there is no literature which examines the similarity of training drills to match outputs using similarity measures. Research in this area has only used *z*-scores, which assume normally distributed data and are only capable of describing a single parameter at a time (Corbett et al., 2018b). Consequently, future research may utilise distance measures to examine the similarity of training drills to match outputs across multiple parameters.

Euclidean distance is the most versatile and commonly used distance measure in the literature (Breu, Gil, Kirkpatrick, & Werman, 1995; Maurer et al., 2003; Narayanan & Nelson, 2019). Euclidean distance plots two observations as coordinates on a plane with *n* dimensions (Alfakih, Khandani, & Wolkowicz, 1999). The distance between points is then calculated by calculating the numeric distance between coordinates (Alfakih et al., 1999). Euclidean distance has several advantages over other distance measures. First, it is useful in a range of circumstances, including image processing (Maurer et al., 2003; Wang et al., 2005), language processing (Singha & Das, 2013), locational surveillance (Behrens et al., 2018) and feature-based analysis (Narayanan & Nelson, 2019). This is in contrast to other distance measures, for example cosine similarity, which is specialised to text-based analysis and is not commonly generalised to other types of data (Li & Han, 2013). Second, Euclidean distance is conceptually easier to understand than other distance measures (Prasath et al., 2017). Uniform Manifold Approximation and Projection (McInnes, Healy, & Melville, 2018) and t-Distributed Stochastic Neighbour Embedding (Wattenberg, Viégas, & Johnson, 2016) may best preserve both the global and local structure of a data set. However, they are produced using complex neural networks (Wattenberg et al., 2016), where Euclidean distance can be understood as a generalisation of the Pythagorean theorem. Additionally, these methods likely pose no advantage over Euclidean distance when calculating similarity in a single dimension (as opposed to two or more dimensions, which are uninterpretable by humans but may be used to reduce the dimensionality of a data set for other models (Wattenberg et al., 2016)). Consequently, Euclidean distance provides a robust means to measure the similarity of players' physical and skilled output in team-sport.

2.10.3 Clustering

Clustering is an unsupervised branch of machine learning (Ofoghi et al., 2013). Clustering does not require users to manually select independent or dependent variables (Liao, 2005; Spencer et al., 2016). Instead, it aims to describe how different sets of parameters may group together, to define different data points (Jain, Murty, & Flynn, 1999; Liao, 2005). This is typically achieved by condensing all data points into a single similarity metric, and then allocating them to a centroid identified algorithmically from the data set (Ofoghi et al., 2013). Clustering has been used to identify common movement patterns, captured from wearable tracking, in team-sport (Sweeting et al., 2017a). Additionally, clustering has been used to determine different types of training drills based on their physical and skilled outputs (Corbett et al., 2018b). Clustering has also been used to classify activity types (Corbett et al., 2018b). The key limitation of clustering algorithms, including k-means, is the requirement for practitioners to manually determine the number of clusters Ofoghi et al., 2013). This can be overcome by modelling the relationship between cluster number, and the within-cluster observation error, in order to minimise cluster number without introducing large amounts of noise (Jain, 2010; Jain et al., 1999). These studies demonstrate the ability of clustering to describe outputs of team-sport athletes.

2.10.4 Linear Regression

Linear models are the most common form of regression, both broadly in the literature (Yu & Yao, 2017) and within team-sport (Ofoghi et al., 2013). Linear models describe an independent variable in relation to one or more dependent variables. Linear models assign each dependent variable a coefficient, to quantify the strength it has on the independent variable. Linear models require minimal computing power and are easily interpretable. For this reason, they have been applied to a plethora of problems in team sport. These problems include the relationship between preparation factors on technical and physical output in Australian football (Dillon et al., 2017; Ryan et al., 2018), the relationship between physical output and injury (Colby et al., 2014; Rogalski et al., 2013a) and comparisons of athletes at varying levels of play (Brewer, Dawson, Heasman, Stewart, & Cormack, 2010b). Due to their simplicity and established use in the literature, linear regression is useful as an initial method to explore relationships between dependent and independent variables.

Linear mixed effects models describe a dependent variable as a function of fixed and random effects (Delaney et al., 2016a; Lindstrom & Bates, 1990; Pinheiro, Bates, DebRoy, Sarkar, & Team, 2007). Fixed effects are analogous to independent variables in other linear models (Gałecki & Burzykowski, 2013). That is, they are expected to have an impact of some strength on the dependent variable. Random effects, however, are unique to mixed effects models and have some unknown influence on a dependent variable (Xu, 2003). Common examples of random effects in sport may include game season, gender or participant (Delaney et al., 2016a; Potter et al., 2014; Ryan et al., 2018). Random intercept models are a subset of linear mixed effects models, which give a differing intercept based on random effects (Eyduran et al., 2016). For example, random intercept models have been utilised to give participants different base-line performance values when examining the relationship between emotions and performance in volleyball (Peña & Casals, 2016). Random slope models are less commonly used and alter the strength of each fixed effect based on random effects (Eyduran et al., 2016). For example, the influence of high intensity running on player performance in team-sport could specifically be examined using a random slope model. Linear mixed effects models are advantageous over standard linear models due to their ability to not only explain a large amount of variance but explain the source of the variance (Xu, 2003). This is due to the computation of both conditional and marginal R squared values (Nakagawa & Schielzeth, 2013; Xu, 2003). Marginal R squared describes the amount of variance that can be explained by fixed effects. Conditional R squared describes the amount of variance described by both random and fixed effects (Pinheiro et al., 2007).

2.10.5 Decision Trees

Linear models provide an initial method to explore the relationships between dependent and independent variables. However, linear models are often unable to uncover relationships in data, which has unknown interactions between dependent variables. For example, the relationship between physical output and time in AF has been examined using linear regression (Dillon et al., 2017; Montgomery & Wisbey, 2016). However, linear models assume that physical parameters including total distance and metreage per minute independently impact skilled output and do not account for how these parameters may interact to influence skilled output. In these situations, non-linear regression models may be warranted. Specifically, decision trees summarise how interactions between parameters influence a dependent variable. For this reason, they are becoming increasingly common in the sport literature. Specifically, they have been used to; proactively predict illness from self-report questionnaires , identify performance characteristics of winning outcomes in mixed martial arts (James, Robertson, Haff, Beckman, & Kelly, 2017) and explain match outcome in Australian football (Robertson et al., 2016a) and rugby league (Woods, Sinclair, & Robertson, 2017). The key limitation of decision trees is that they are prone to overfitting (Sardá-Espinosa, Subbiah, & Bartz-Beielstein, 2017). However. This limitation may be mitigated through cross validation (Sardá-Espinosa et al., 2017).

Conditional inference trees are a type of decision tree, which utilise null hypothesis significance testing (NHST) to determine how interactions between parameters influence an independent variable (Sardá-Espinosa et al., 2017). Consequently, they may be advantageous over other forms of decision trees, including recursive partitioned trees, as they are less prone to variable selection bias (Das, Abdel-Aty, & Pande, 2009). Additionally, unlike other tree-based learnings including Bayesian Additive Regression Trees, they require almost no hyperparameter tuning whilst being lightweight and accurate (Sparapani, Logan, McCulloch, & Laud, 2016). Thus, they provide a quick, non-linear way to model relationships with minimal latency between construction and deployment.

2.10.6 Random Forests

A key disadvantage of decision trees is that they are prone to overfitting (Strempel, Nendza, Scheringer, & Hungerbühler, 2013). Random forests attempt to overcome this limitation, by building an ensemble of *n* decision trees to either predict or classify observations (Liaw & Wiener, 2002). Random forests iteratively take subsets of the training data set, compute decision trees and then take either the mean (regression) or mode (classification) to predict or classify an observation (Liaw & Wiener, 2002). In the sport science literature, random forests are most commonly used to maximise holdout set model performance. Specifically, they have been applied to the outputs of wearable technologies to predict energy expenditure (Ellis et al.,

2014) and classify team-sport movements and activities (Wundersitz et al., 2015b). Random forests can also be useful alongside individual decision trees. Whilst decision trees provide a descriptive schematic of how dependent variables interact to influence an independent variable, random forests reduce the chance of overfitting and thus, can more easily be generalised to other data sets (Thornton et al., 2016).

Random forests have many advantages over other regression and classification algorithms (Liu, Wang, Wang, & Li, 2013). First, they are relatively fast and require minimal computational power. Newer algorithms, including gradient boosted trees (Chen & Guestrin, 2016) and categorical feature boosting (Prokhorenkova, Gusev, Vorobev, Dorogush, & Gulin, 2018) often boast higher accuracy than random forests, at the cost of extremely high compute power and long runtimes (Al Daoud, 2019). Consequently, categorical feature boosting and gradient boosting are currently inaccessible to many practitioners. Second, random forests require only a small number of easily interpretable hyperparameters to be tuned (Liaw & Wiener, 2002; Liu et al., 2013). This is in contrast to other classification and regression algorithms, for example support vector machines, which require abstract values including gamma and c parameters to be specified by the user (Liu et al., 2013; Wu et al., 2016). Third, random forests are relatively robust when classifying on both moderately-sized and large data sets (Liaw & Wiener, 2002). This is in contrast to highly accurate deep learning and neural network methodologies, which are only advised with thousands or more observations (Liu et al., 2013; Lu, Chen, Little, & He, 2018; Ofoghi et al., 2013). Finally, random forests are more interpretable than neural networks Liaw & Wiener, 2002). Specifically, random forests uniquely provide variable importance (Liaw & Wiener, 2002). This summarises the strength dependent variables have on an independent variable For these reasons, random forests are a valid method for classification and regression in team-sport.

2.11 Aims of Thesis

The aim of this thesis was to develop a method to quantify change over time in professional Australian Rules football and illustrate the utility of this approach to match profiling and training drill prescription. Specifically:

- To identify how physical and skilled output change as a function of time, in professional Australian Football matches
- To identify and describe segments of physical and skilled output in team-sport matches with an example in Australian Football
- To apply a combined time-series and frequency-domain approach to match profiling in team-sports
- To illustrate how a time-series/ frequency-domain approach can be applied to assess the sequence, specificity and difficulty of team-sport training drills

2.12 References

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CHAPTER 3 – Study 1

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Weak Relationships between Stint Duration, Physical and Skilled Match Performance in Australian Football

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Australian Rules football comprises physical and skilled performance for more than 90 min of play. The cognitive and physiological fatigue experienced by participants during a match may reduce performance. Consequently, the length of time an athlete is on the field before being interchanged (known as a stint), is a key tactic which could maximize the skill and physical output of the Australian Rules athlete. This study developed two methods to quantify the relationship between athlete time on field, skilled and physical output. Professional male athletes ($n = 39$) from a single elite Australian Rules football club participated, with physical output quantified via player tracking systems across 22 competitive matches. Skilled output was calculated as the sum of involvements performed by each athlete, collected from a commercial statistics company. A random intercept and slope model was built to identify how a team and individuals respond to physical outputs and stint lengths. Stint duration (mins), high intensity running (speeds $>14.4\ \text{km}\cdot\text{hr}^{-1}$) per minute, meterage per minute and very high intensity running (speeds $>25\ \text{km}\cdot\text{hr}^{-1}$) per minute had some relationship with skilled involvements. However, none of these relationships were strong, and the direction of influence for each player was varied. Three conditional inference trees were computed to identify the extent to which combinations of physical parameters altered the anticipated skilled output of players. Meterage per minute, player, round number and duration were all related to player involvement. All methods had an average error of 10 to 11 involvements, per player per match. Therefore, other factors aside from physical parameters extracted from wearable technologies may be needed to explain skilled output within Australian Rules football matches.

Keywords: performance analysis, sport statistics, classification tree, team sport, GPS

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INTRODUCTION

Australian Football (AF) involves a high physical and skilled output for more than 90 min of play to maximize team performance (Gray and Jenkins, 2010). Physical and skill output may decline, as a function of time, during AF matches (Coutts et al., 2010). Consequently, a key tactical consideration during AF matches relates to the length of an on-field stint (i.e., the consecutive amount of time spent on ground by a player) for a player, before their physical and/or skilled output is adversely affected (Montgomery and Wisbey, 2016). In elite AF, there is a limitation on the number of player substitutions a team can make within a match. In the 2017 Australian Football League season, this limit was 90 rotations per match. Consequently, it is crucial in AF that stints are not ended (or started) unnecessarily early, or are too short or long in duration.

During an AF match, various athlete performance data is collected. Physical output can be measured via Global Positioning System (GPS) or Radio Frequency Identification (RFID) (Wyld, 2008; Coutts and Duffield, 2010). These devices typically sample at 10 or 15 Hz, allowing for the calculation of total distance (m), distance within velocity bands (i.e., distance covered >14.4 km·h^{-1}), and peak velocity (km·h^{-1}). Match statistics are provided by commercial performance analysis companies (Sullivan et al., 2014b). However, there is less standardization in the measurement of skilled output comparative to physical. Skilled output can be measured by quantifying the number of involvements or actions completed by each player. Involvements may include kicks, handballs and other actions considered important to match success by AF coaching staff. The amount of time each player spends on the field and on the bench is available as a measure of temporal output (Bradley and Noakes, 2013). Potentially due to a combination of cognitive (Tenenbaum and Bar-Eli, 1993) and physiological fatigue (Aughey, 2010), it is unlikely that players can maintain an optimal level of physical and skilled output for an entire match (Thelen and Smith, 1994; Aughey, 2010). In AF, a decrement in physical output has been observed for each quarter completed (Coutts et al., 2010), with a 3% reduction in meterage per minute for every 2 min spent on field during rotations longer than 5 min (Montgomery and Wisbey, 2016). Similarly, the level of skilled involvements for players also likely declines as the duration of a match increases. Recent research has examined how work rate, time on field and situational factors, including the number of stoppages, interact to affect skilled involvement (Sullivan et al., 2014a,b). Although factors influencing the skilled output of players have been identified to date (Sullivan et al., 2014a,b), research assessing how these factors may aid match-day stint/rotation strategies remains to be examined. Measures of skilled, physical and temporal output could be modeled to identify how the skilled output of a team and individual responds to change in temporal and physical output.

For this purpose, generalized linear mixed models present a suitable analysis option, in that they allow for the quantification of independent and dependent variables with repeated measures (Gałecki and Burzykowski, 2013). Random intercept models allow for the quantification of pooled data, whereas random slope modeling outputs differing coefficients and equations for each individual entered into the model (Eyduran et al., 2016). Consequently, the relationship between time, physical and skilled outputs at a team and individual level can be quantified.

Decision trees present an alternative, non-linear option to quantify the relationship between physical, skilled and temporal outputs. Conditional inference trees, for example, incorporate a series of significance tests to create thresholds for each dependent variable (Sardá-Espinosa et al., 2017). These thresholds create branches in the tree, each consisting of differing combinations of dependent variables, which then leads to a prediction of the independent variable. It is possible to nest participants within these trees, thus accounting for how individuals respond to differing combinations of dependent variables. This could allow examination of how physical and temporal parameters interact to influence skilled output.

Utilizing a mixed analysis approach comprised of generalized linear mixed models and conditional inference trees, this study will; (i) identify how athlete skilled output changes as a function of time in an AF match, (ii) determine the extent to which these changes occur at the individual level, and (iii) reveal how different permutations of physical and skilled parameters might correspond to differences in skilled output.

METHODS

Participants

Professional male athletes (n = 39) from an elite Australian Football League (AFL) club provided written informed consent to participate in this study (age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg). All participants completed at least one full match and at least one stint lasting >3 min in the 2016 AF home and away season. Ethical approval was granted by the Victoria University Human Research Ethics Committee.

Data Collection

Skilled output, defined as the sum of events completed by each player, are likely to contribute to team success as an "involvement." This was calculated as the total of involvements completed by each player, aggregated from a timeline supplied by a commercial provider of sports statistics (Champion Data, Melbourne, Australia). Champion Data provide a timeline of key actions time stamped to each player, which can broadly be categories as; (i) disposals, (ii) other offensive actions, and (iii) defensive actions. An Excel spreadsheet was designed to aggregate the number of key involvements completed by each player within each stint. To develop the most meaningful measure of skilled output for the team included in this study, key involvements were chosen in consultation with the coaching group (Appendix 1). The sum of involvements for each player's stint was databased alongside physical data, and saved as a.csv file for analysis.

Data was collected from 14 indoor matches and 7 outdoor matches (n = 21) during the 2016 AFL home and away Season. For all indoor matches, athlete physical output was collected via a Catapult T5 Local Positioning System (LPS) tag (Catapult Sports, Melbourne, Australia). During outdoor matches, all participants wore a Catapult S5 GPS (Jennings et al., 2010) device (Catapult Sports, Melbourne, Australia). Both devices were worn within each player's jumpers in a custom-sewn pouch. All matches were monitored live using proprietary software Openfield (Catapult Openfield v 1.11.2-1.13.1) to ensure an adequate signal quality of >8 packets/second, and that stints were correctly recorded. At the conclusion of each match, files were synchronized to the Catapult Cloud storage system. Data for each stint was then exported into a.csv file for further analysis.

Data Cleaning

This study aimed to provide methods that were generalizable to future data. As a result, several filters were applied to the data to remove outliers (Ofoghi et al., 2013). Only stint maximum velocities in the bottom 98% of the data set (<32.2 km·h^{-1}), durations in the top 95% (>3 min) and involvements in the bottom 98% (<2.2 Involvements/minute) were included in the analysis. These cut-offs were heuristically selected based on perceived practical application of the findings. All parameters were then expressed relative to stint time. Each player was assigned a random ID (1–45), whilst each stint was labeled in the format "Quarter. Stint" (i.e., the first stint of quarter 1 was labeled as 1.1). Round number was labeled from 1 to 23.

Feature Selection

Parameters included in the analyses were selected based on validity, reliability and multicollinearity features. This process was informed via a literature review on common locational parameters (Cummins et al., 2013), a correlation matrix and variance inflation matrix between all parameters. Consequently, meterage per minute (m·min-1), high intensity running (distance >14.4 km·h^{-1}) per minute (m·min^{-1}), very high intensity running (distance >25 km·h^{-1}) per minute (VHIR·min^{-1}), stint time (mins) and involvements per minute (IPM^{-1}) were all selected for inclusion in the study.

Generalized Linear Mixed Models

Generalized linear mixed models were computed in R, using the package *lme4* (R Foundation for Statistical Computing, Vienna, Austria). For all models, player ID, stint and round number were specified as random effects, with the restricted maximal likelihood approach adopted (Gałecki and Burzykowski, 2013). A random intercept model was built to identify how skilled output changes, as a function of the other parameters, across the team. Involvements per and duration were the dependent and independent variables, respectively. Bench time, meterage per minute, high intensity running per minute and very high intensity running per minute were added to the model sequentially, with the Akaike information criteria (AIC) computed after each model to assess variable importance (Akaike, 1981). Preliminary modeling revealed that bench time (the time an athlete spent off the field between stints) had minimal impact upon model performance and it therefore was not included in the final model. Finally, a random slope model was built for each player using the remaining parameters.

Conditional Inference Trees

Three conditional inference trees were constructed using the *party* package in R. This algorithm operates based on a pre-determined level of statistical significance (p < 0.05), and conducts recursive partitioning based on factors most strongly linked with the response variable (Sardá-Espinosa et al., 2017). For the present study, the data were split into an 80% training set and a 20% testing set. Each tree was computed with a 95% confidence interval (CI) under a Bonferroni correction and a minimum terminal node size of 100 instances. The first tree in this study utilized the same parameters as the final generalized linear mixed model. Round and stint number was removed from the second tree, whilst player ID was removed from the final tree. Each tree was cross-validated on the test data set, with model performance represented by the root mean squared error (RMSE) of involvements.

RESULTS

Generalized Linear Mixed Models

Descriptive statistics of each parameter for stints (n = 2493) and matches (n = 21) are shown in **Table 1**. The coefficients for the random intercept model are presented in **Table 2** with a 95% CI. This model had an R^2-value of 0.01, and a conditional R^2 of 0.14 (**Figure 1**).

The coefficients for the random slope model are presented in **Figure 2**. This model had an R^2 of 0.013, and a conditional R^2 of 0.23 (**Figure 1**). The relationship between both duration (for 25/39 players) and high intensity running (for 39/39 players), and involvements per minute was negative. Conversely, MPM experienced a positive relationship with involvements per minute for most players (36/39 players). The relationship between very high intensity running per minute differed considerably depending on the player. Each of these parameters had only a minor relationship with involvements, with the final model having an R^2 of 0.012, and a conditional R^2 of 0.23.

TABLE 1 | Descriptive statistics (mean ± SD) for; Involvements (n), duration (mins), bench time (mins), distance (m), high intensity running (HIR, distance >14.4 km·h^{-1}, m), very high intensity running (VHIR, distance >25 km·h^{-1}, m).

	Stint	Match
Distance (m)	1,816 ± 903	11,608 ± 3, 573
HIR (m)	500 ± 263	3,198 ± 1, 165
VHIR (m)	24 ± 29	154 ± 105
Duration (mins)	13.7 ± 7.0	87.8 ± 27.2
Involvements (n)	3.6 ± 2.6	23.2 ± 9.3
Bench time (mins)	11.6 ± 9.9	74.2 ± 17.2

TABLE 2 | Model 1 and 2: coefficients of fixed effects (95% confidence interval) for Intercept/Involvements per minute (IPM^{-1}), Duration (mins), High intensity running per minute (HIRMPM, m·min^{-1}), meterage per minute (MPM^{-1}, m·min^{-1}) and very high intensity running per minute (VHIRM, m·min^{-1}).

	Estimate (95% CI)	t-Value
MODEL 1		
Intercept (IPM^{-1})	0.108 (0.187, 0.03)	2.695
Duration (mins)	−0.001 (0, −0. 002)	−2.802
HIRMPM (m·min^{-1})	−0.002 (−0.001, −0.003)	−3.746
MPM (m·min^{-1})	0.002 (0.002, 0.001)	4.785
VHIRM (m·min^{-1})	0.003 (0.006, 0)	1.692
MODEL 2		
Intercept (IPM^{-1})	0.142 (0.037, 0.247)	2.648
Stint duration (mins)	−0.002 (−0. 003,0)	−2.572
HIRMPM (m·min^{-1})	0.002 (0.001, 0.003)	3.813
MPM (m·min^{-1})	−0.002 (−0.003, −0.001)	−4.490
VHIRM (m·min^{-1})	0.001 (−0.003, 0.006)	0.684

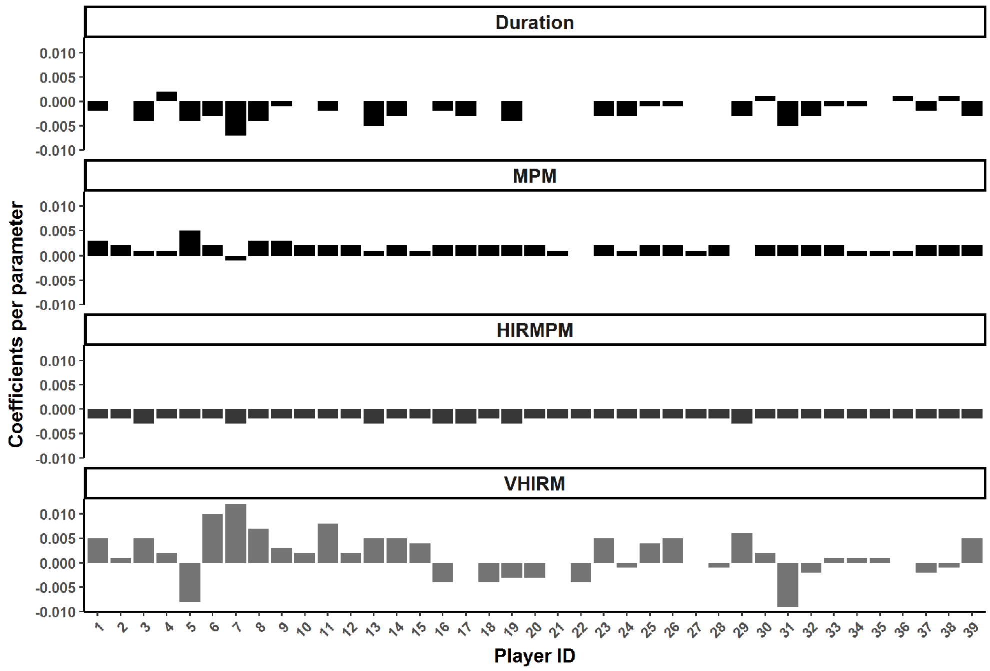

FIGURE 1 | Individual coefficients for Duration (mins), meterage per minute (MPM, m·min^{-1}), high intensity running per minute (HIRMPM, m·min^{-1}), and very high intensity running per minute (VHIRM, m·min^{-1}) in the random slope model.

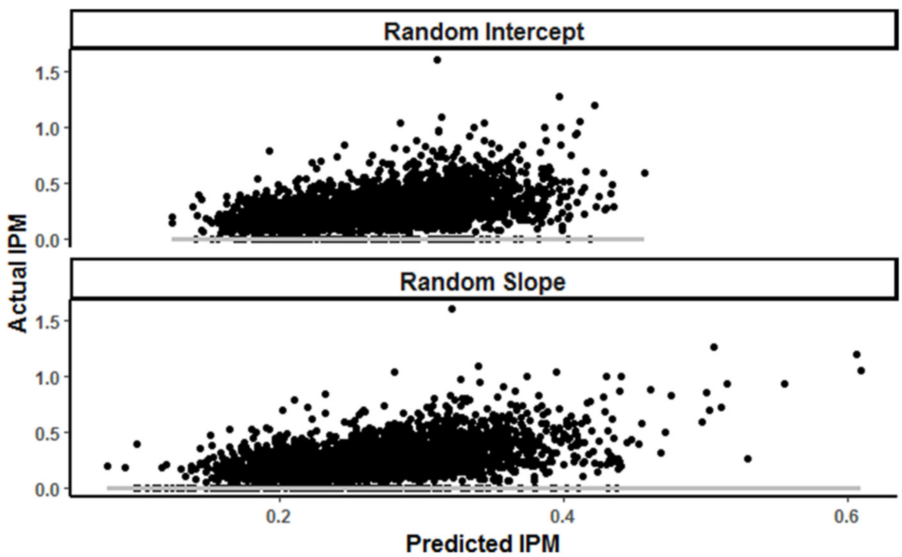

FIGURE 2 | Predicted vs actual involvements per minute (IPM^{-1}) in random intercept and random slope models, with gray reference line at 0 involvements of error.

Conditional Inference Trees

Results from the first conditional inference classification tree revealed Player ID, stint number, duration and round number as the strongest indicators of involvements per minute (**Figure 3**). An RMSE of 0.12 involvements per minute (approximately 10.1 involvements per match) was reported on both the test and training sets. This tree's first partition included player ID, with rotation, duration and Round number forming the second to fourth partitions respectively. The second tree included player, stint duration and stint meterage per minute (**Figure 4**) as the strongest predictors. As per the first conditional inference tree, an RMSE of 0.12 for involvements for minute (10.1 involvements per match) was observed on both the test and train sets. This tree had an initial partition based on Player ID, with subsequent

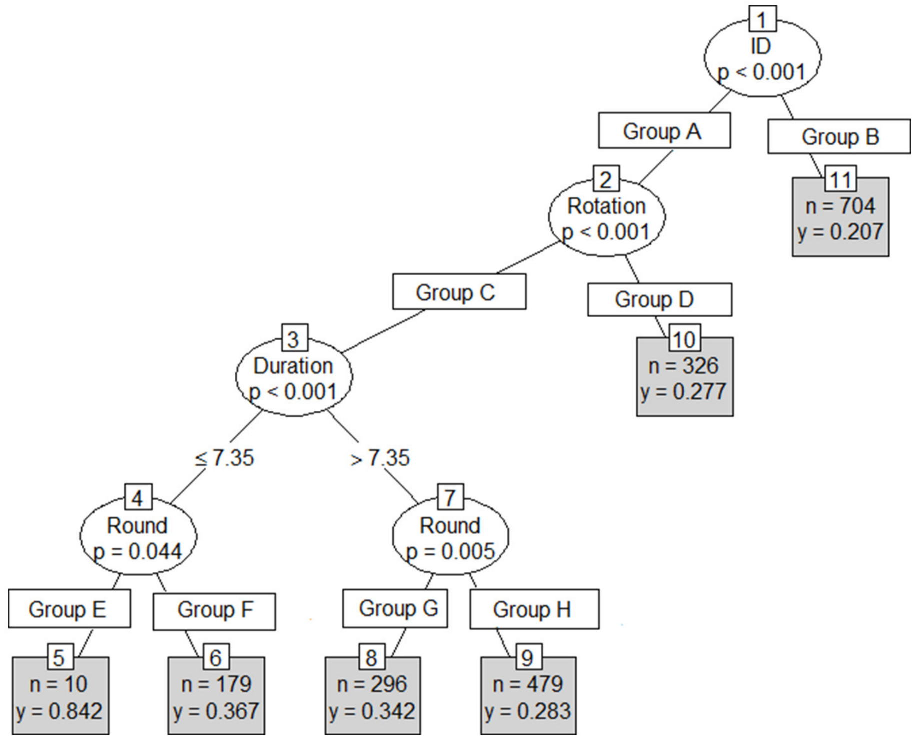

FIGURE 3 | Conditional inference tree with Player ID, Round and Duration (mins) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.
Group A = Player ID (1, 3, 5, 6, 7, 8, 9, 11, 13, 14, 16, 17, 19, 23, 24, 26, 29, 31, 32, 39).
Group B = Player ID (2, 4, 10, 12, 15, 18, 20, 21, 22, 25, 27, 28, 30, 33, 34, 35, 36, 37, 38).
Group C = Rotation (1.1, 1.2, 1.3, 2.2, 2.3, 3.1, 3.2, 3.3, 4.1).
Group D = Rotation (2.1, 4.2, 4.3).
Group E = Round (19).
Group F: Round (1, 3, 4, 6, 7, 8, 9, 12, 13, 15, 16, 17, 18, 20, 21, 22, 23).
Group G = Round (1, 2, 6, 8, 15, 17, 20, 22, 23).
Group H = Round (3, 4, 7, 9, 12, 13, 16, 18, 19, 21).

partitions based on; duration (2nd), an additional division of Player ID (3rd) and finally duration or MPM (4th).The final tree, with ID removed as an input, used only meterage per minute and stint duration to predict involvements per minute (**Figure 5**). An increased RMSE (0.12–0.13 involvements per minute; 11.05 involvements per match) was observed on both sets of data. In this tree, both the first and second partitions were determined using MPM, with duration only forming a partition in instances where MPM exceeded 125.

DISCUSSION

This study developed two methods to quantify the impact of physical outputs, on a team and individual level, on skilled output by elite AF players during matches. The first method comprised two generalized linear mixed models, resulting in broad equations for the team and individual players. Both models had low R^2 and conditional R^2-values, resulting in limited explanatory ability.

The second method, a series of conditional inference trees, identified how different circumstances and combinations of physical parameters may change an athletes' expected skilled output. Whilst partitions in the first tree were dominated by uncontrollable factors, such as round and stint number, the second tree achieved a similar classification accuracy using meterage per minute, player ID and duration. The final tree removed player ID as a parameter to identify a broad set of team rules, which only slightly reduced accuracy (0.13 compared to 0.12 involvements per minute).

The random intercept model broadly showed the strength and direction of influence for each parameter. In the observed team, meterage per minute had a negative relationship with involvements per minute. The only variable to have any positive relationship was high intensity running per minute. Practitioners could use this information as a general "rule of thumb" in match day decision making, whereby, a player who is consistently running at a high meterage per minute for an extended duration, without completing high intensity running, is less likely to reach a maximal skilled output. A limitation of this modeling technique

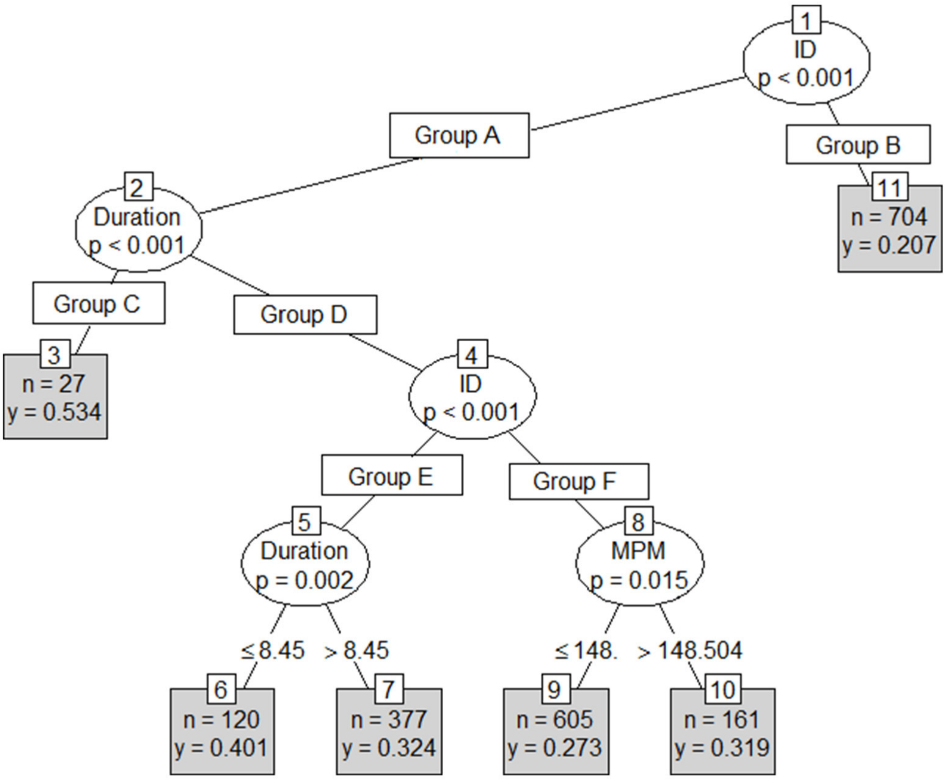

FIGURE 4 | Conditional inference with Player ID, Duration (mins) and meterage per minute (MPM) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.
Group A = Player ID (1, 3, 5-9, 11-17, 19, 23, 24, 26, 29, 31, 32, 39).
Group B = Player ID (2, 4, 10, 12, 15, 18, 20, 21, 22, 25, 27, 28, 30, 33, 34, 35, 36, 37, 38).
Group C = Duration (<5 mins).
Group D = Duration (>5 mins).
Group E = Player ID (3, 5, 6, 7, 8, 13, 29, 32, 39).
Group F = Player ID (1, 9, 11, 14, 16, 17, 19, 23, 24, 26, 31).

is that it does not necessarily apply to all players, and does not identify how players individually respond to different parameters.

The random slope model addresses the above issue by allowing for different coefficients of the physical parameters for each player. This allows for better profiling of each athlete and for the importance of each parameter to better reflect an individual's strengths and weaknesses. In the observed team, for example, each of the parameters had positive and negative relationships with skilled output, depending on the player. However, despite the strengths of this modeling approach there are still limitations. The linear decline of involvements per minute declines in response to the temporal and physical inputs is assumed, when it is unlikely the decline in skilled output would be so gradual. Rather, players likely need time and physical intensity on field before their skilled output reaches an optimal level. Finally, these models suggest some level of independence between the physical and temporal parameters. As a result, they are unable to determine how parameters may interact to affect skilled output.

The first tree in this study used the same parameters entered into the random slope model, to identify how parameters interact to influence skilled output (**Figure 3**). However, the significance testing procedure selected uncontrollable factors, such as round and rotation numbers as the key explainers of skilled output. The first tree provided a schematic of factors that may influence skilled output in AF. However, because none of the factors from this tree are controllable within a match, this tree would likely have limited uptake in an applied setting. The second tree removed round and rotation number and partitioned based on player, stint time and meterage per minute (**Figure 4**). In an applied setting, the schematic created by this tree could be used to identify the conditions that are likely to lead to maximal skilled output for each player. Additionally, it could be used in a real-time monitoring setting, to identify if the current circumstances imposed upon a player are conducive to maximal skilled output.

The final conditional inference tree in this study removed player, in an attempt to generate a broad set of team rules. This could provide a cleaner schematic of influences upon skilled output across a team. Using only meterage per minute and stint time, this model set six major partitions for skilled involvement. This ranged from high physical output, but a mixed skilled output, to a low physical and low skilled output. In this playing

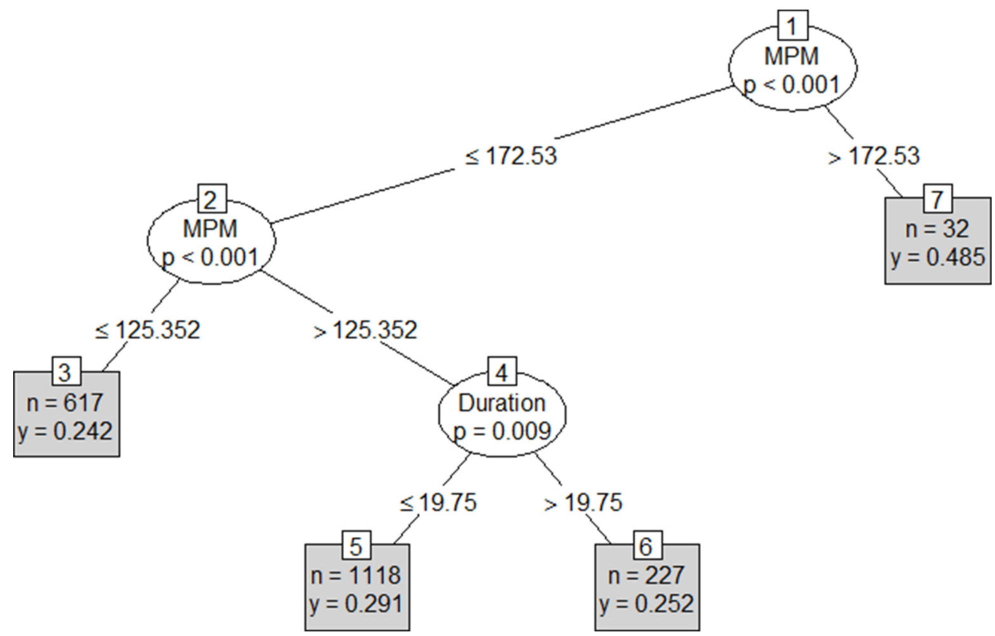

FIGURE 5 | Conditional inference tree including Duration (mins) and meterage per minute (MPM) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.

group, a high intensity (>172 m·min^{-1}), or, a moderate intensity (125–172 m·min^{-1}) and moderate duration (<19.75 min) leads to a higher skilled output. Consequently, match day prescription strategies for the observed team could use this information to limit the stint time of players.

None of the models developed in this study had particularly strong accuracy. The average match duration for a player included in this study was 86 min, resulting in an average error of 0.12 IPM and equating to an average error of approximately 10.1 involvements per match. This is in agreement with other research examining the impact of contextual factors on both physical and skilled output in AF matches. In itself, physical output is influenced by factors, such as the opposition and the location of a match (Ryan et al., 2017). Furthermore, trivial relationships between common locational parameters and Champion Data player ratings as a measure of skilled performance have been noted elsewhere (Dillon et al., 2017). These findings, collectively, highlight the importance of using skilled and technical data alongside locational parameters to inform match day decision-making, as opposed to the latter alone.

There are several factors which may explain the limited relationship between GPS parameters and skilled output in AF matches. Firstly, AF is a dynamic sport, and many circumstantial details are difficult to model. In particular, opposition playing styles and changes in positions (Robertson and Joyce, 2014), may have an impact on both the physical and skilled output of player (Sullivan et al., 2014a). Secondly, the aggregate data utilized in this study is limited in its' ability to identify thresholds for reductions in both physical and skilled output. Other research has examined these outputs across quarters (Bradley and Noakes, 2013), and more recently within stints (Montgomery and Wisbey, 2016). Further work is needed to examine physical and skilled behavior as a time-series, to better describe the outputs competed by players. Finally, this was a methodological study, which aimed to identify trends across a single playing group. For this methodology to be applied to other teams and sports, the modeling approaches would need to be independently run. Therefore, the thresholds created here may not necessarily stand true outside of this playing group.

The models utilized in this study may still aid decision making in elite team sports. They use information that is controllable and readily available during matches, and therefore may assist in situations where objective information is desired to make quick, time-sensitive decisions.

CONCLUSION

This study developed two methods to identify the relationship between physical, skilled and temporal outputs, on an individual and team level. The first method utilized random slope and intercept models to identify factors that may correlate with a decline in skilled output, and what direction their relationship is with skilled output. This could be used to develop a broad equation for the team and individuals, to identify how they would react to differing stint times and physical workloads. The second set of methods utilized conditional inference trees to identify how physical and temporal parameters may interact to influence skilled output. Together, these three models describe; i) the impact of uncontrollable factors, such as round and rotation number, ii) how different individuals react to different outputs and iii) a general set of thresholds for the data entered into the modeling process. These trees can provide a schematic to assist match day prescription in team sports. None of these models held an optimal predictive ability, suggesting that wearable technology data and notational analysis feeds could be analyzed differently to improve their use in team sports.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the National Statement on Ethical Conduct in Human Research, VU Human Research Ethics Committee, with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the VU Human Research Ethics Committee.

AUTHOR CONTRIBUTIONS

Data collection: DC and SR, formulation of the study: DC, AS, and SR, statistical analysis and visualization; DC and AS, first draft; DC, subsequent drafts; DC, AS, and SR, final approval; DC, AS, and SR.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fphys.2017.00820/full#supplementary-material

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

‘Weak Relationships between Stint Duration, Physical and Skilled Match Performance in Australian Football

This chapter is presented in pre-publication format of a recent publication titled:

Corbett, D. M., Sweeting, A. J., & Robertson, S. (2017). Weak relationships between stint duration, physical and skilled match performance in Australian Football. *Frontiers in Physiology, 8*(820). doi:10.3389/fphys.2017.00820

3.1 Abstract

Australian Rules football comprises physical and skilled performance for more than ninety minutes of play. The cognitive and physiological fatigue experienced by participants during a match may reduce performance. Consequently, the length of time an athlete is on the field before being interchanged (known as a stint), is a key tactic which could maximize the skill and physical output of the Australian Rules athlete. This study developed two methods to quantify the relationship between athlete time on field, skilled and physical output. Professional male athletes (n = 39) from a single elite Australian Rules football club participated, with physical output quantified via player tracking systems across 22 competitive matches. Skilled output was calculated as the sum of involvements performed by each athlete, collected from a commercial statistics company. A random intercept and slope model was built to identify how a team and individuals respond to physical outputs and stint lengths. Stint duration (mins), high intensity running (speeds >14.4 km·hr^{-1}) per minute, meterage per minute and very high intensity running (speeds >25 km·hr^{-1}) per minute had some relationship with skilled involvements. However, none of these relationships were strong, and the direction of influence

for each player was varied. Three conditional inference trees were computed to identify the extent to which combinations of physical parameters altered the anticipated skilled output of players. Meterage per minute, player, round number and duration were all related to player involvement. All methods had an average error of 10 to 11 involvements, per player per match. Therefore, other factors aside from physical parameters extracted from wearable technologies may be needed to explain skilled output within Australian Rules football matches.

3.2 Introduction

Australian Football (AF) involves a high physical and skilled output for more than ninety minutes of play to maximize team performance (Gray & Jenkins, 2010). Physical and skill output may decline, as a function of time, during AF matches (Coutts & Duffield, 2010b). Consequently, a key tactical consideration during AF matches relates to the length of an on-field stint (i.e., the consecutive amount of time spent on ground by a player) for a player, before their physical and/or skilled output is adversely affected (Montgomery & Wisbey, 2016). In elite AF, there is a limitation on the number of player substitutions a team can make within a match. In the 2017 Australian Football League season, this limit was 90 rotations per match. Consequently, it is crucial in AF that stints are not ended (or started) unnecessarily early or are too short or long in duration.

During an AF match, various athlete performance data is collected. Physical output can be measured via Global Positioning System (GPS) or Radio Frequency Identification (RFID) (Coutts & Duffield, 2010a; Wyld, 2008). These devices typically sample at 10 or 15 Hz, allowing for the calculation of total distance (m), distance within velocity bands (i.e., distance covered > 14.4 $km \cdot hr^{-1}$), and peak velocity ($km \cdot hr^{-1}$). Match statistics are provided by commercial performance analysis companies (Sullivan et al., 2014b). However, there is less standardization in the measurement of skilled output comparative to physical. Skilled output can be measured by quantifying the number of involvements or actions completed by each player. Involvements may include kicks, handballs and other actions considered important to match success by AF coaching staff. The amount of time each player spends on the field and on the bench is available as a measure of temporal output (Bradley & Noakes, 2013). Potentially due to a combination of cognitive (Tenenbaum & Bar-Eli, 1993) and physiological fatigue (Aughey, 2010), it is unlikely that players can maintain an optimal level of physical and skilled output for an entire match (Aughey, 2010; Thelen & Smith, 1994). In AF, a decrement in physical output has been observed for each quarter completed (Coutts & Duffield, 2010b), with a 3% reduction in meterage per minute for every two minutes spent on field during rotations longer than 5 minutes (Montgomery & Wisbey, 2016). Similarly, the level of skilled involvements for players also likely declines as the duration of a match increases. Recent research has examined how work rate, time on field and situational factors, including the number of stoppages, interact to affect skilled involvement (Sullivan et al., 2014a; Sullivan et al., 2014b). Although factors influencing the skilled output of players have been identified to date (Sullivan et al., 2014a; Sullivan et al., 2014b), research assessing how these factors may aid match-day stint/rotation strategies remains to be examined. Measures of skilled, physical and temporal output could be modelled to identify how the skilled output of a team and individual responds to change in temporal and physical output.

For this purpose, generalized linear mixed models present a suitable analysis option, in that they allow for the quantification of independent and dependent variables with repeated measures (Gałecki & Burzykowski, 2013). Random intercept models allow for the quantification of pooled data, whereas random slope modelling outputs differing coefficients and equations for each individual entered into the model (Eyduran et al., 2016). Consequently, the relationship between time, physical and skilled outputs at a team and individual level can be quantified.

Decision trees present an alternative, non-linear option to quantify the relationship between physical, skilled and temporal outputs. Conditional inference trees, for example, incorporate a series of significance tests to create thresholds for each dependent variable (Sardá-Espinosa, Subbiah, & Bartz-Beielstein, 2017). These thresholds create branches in the tree, each consisting of differing combinations of dependent variables, which then leads to a prediction of the independent variable. It is possible to nest participants within these trees, thus accounting for how individuals respond to differing combinations of dependent variables. This could allow examination of how physical and temporal parameters interact to influence skilled output.

Utilizing a mixed analysis approach comprised of generalized linear mixed models and conditional inference trees, this study will; i) identify how athlete skilled output changes as a function of time in an AF match, ii) determine the extent to which these changes occur at the individual level and iii) reveal how different permutations of physical and skilled parameters might correspond to differences in skilled output.

3.3 Methods

3.3.1 Participants

Professional male athletes (n = 39) from an elite Australian Football League (AFL) club provided written informed consent to participate in this study (age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg). All participants completed at least one full match and at least one stint lasting greater than three minutes in the 2016 AF home and away season. Ethical approval was granted by the Victoria University Human Research Ethics Committee.

3.3.2 Data collection

Skilled output, defined as the sum of events completed by each player, are likely to contribute to team success as an 'involvement'. This was calculated as the total of involvements completed by each player, aggregated from a timeline supplied by a commercial provider of sports statistics (Champion Data, Melbourne, Australia). Champion Data provide a timeline of key actions time stamped to each player, which can broadly be categories as; i) disposals, ii) other offensive actions and iii) defensive actions. An Excel spreadsheet was designed to aggregate the number of key involvements completed by each player within each stint. To develop the most meaningful measure of skilled output for the team included in this study, key involvements were chosen in consultation with the coaching group (Appendix 1). The sum of involvements for each player's stint was databased alongside physical data and saved as a .csv file for analysis.

Data was collected from 14 indoor matches and 7 outdoor matches (n = 21) during the 2016 AFL home and away Season. For all indoor matches, athlete physical output was collected via a Catapult T5 Local Positioning System (LPS) tag (Catapult Sports, Melbourne, Australia). During outdoor matches, all participants wore a Catapult S5 GPS (Jennings, Cormack, Coutts, Boyd, & Aughey, 2010) device (Catapult Sports, Melbourne, Australia). Both devices were worn within each player's jumpers in a custom-sewn pouch. All matches were monitored live using proprietary software Openfield (Catapult Openfield v 1.11.2-1.13.1) to ensure an adequate signal quality of > 8 packets/second, and that stints were correctly recorded. At the conclusion of each match, files were synchronized to the Catapult Cloud storage system. Data for each stint was then exported into a .csv file for further analysis.

3.3.3 Data cleaning

This study aimed to provide methods that were generalizable to future data. As a result, several filters were applied to the data to remove outliers (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). Only stint maximum velocities in the bottom 98% of the data set (<32.2 km·hr^{-1}), durations in the top 95% (>3 minutes) and involvements in the bottom 98% (<2.2

Involvements/minute) were included in the analysis. These cut-offs were heuristically selected based on perceived practical application of the findings. All parameters were then expressed relative to stint time. Each player was assigned a random ID (1-45), whilst each stint was labelled in the format 'Quarter. Stint' (i.e., the first stint of quarter 1 was labelled as 1.1). Round number was labelled from 1-23.

3.3.4 Feature selection

Parameters included in the analyses were selected based on validity, reliability and multicollinearity features. This process was informed via a literature review on common locational parameters (Cummins, Orr, O'Connor, & West, 2013), a correlation matrix and variance inflation matrix between all parameters. Consequently, meterage per minute (m·min-1), high intensity running (distance >14.4 km·hr^{-1}) per minute (m·min^{-1}), very high intensity running (distance >25 km·hr^{-1}) per minute (VHIR·min^{-1}), stint time (mins) and involvements per minute (IPM^{-1}) were all selected for inclusion in the study.

3.3.5 Generalized linear mixed models

Generalized linear mixed models were computed in R, using the package *lme4* (R Foundation for Statistical Computing, Vienna, Austria). For all models, player ID, stint and round number were specified as random effects, with the restricted maximal likelihood approach adopted (Gałecki & Burzykowski, 2013). A random intercept model was built to identify how skilled output changes, as a function of the other parameters, across the team. Involvements per and duration were the dependent and independent variables, respectively. Bench time, meterage per minute, high intensity running per minute and very high intensity running per minute were added to the model sequentially, with the Akaike information criteria (AIC) computed after each model to assess variable importance (Akaike, 1981). Preliminary modelling revealed that bench time (the time an athlete spent off the field between stints) had minimal impact upon model performance and it therefore was not included in the final model. Finally, a random slope model was built for each player using the remaining parameters.

3.3.6 Conditional inference trees

Three conditional inference trees were constructed using the *party* package in R. This algorithm operates based on a pre-determined level of statistical significance ($p<0.05$), and conducts recursive partitioning based on factors most strongly linked with the response variable (Sardá-Espinosa et al., 2017). For the present study, the data were split into an 80% training set and a 20% testing set. Each tree was computed with a 95% confidence interval (CI) under a Bonferroni correction and a minimum terminal node size of 100 instances. The first tree in this study utilized the same parameters as the final generalized linear mixed model. Round and stint number was removed from the second tree, whilst player ID was removed from the final tree. Each tree was cross-validated on the test data set, with model performance represented by the root mean squared error (RMSE) of involvements.

3.4 Results

3.4.1 Generalized linear mixed models

Descriptive statistics of each parameter for stints (n = 2493) and matches (n = 21) are shown in Table 1. The coefficients for the random intercept model are presented in Table 2 with a 95% CI. This model had an R^2 value of 0.01, and a conditional R^2 of 0.14 (Figure 3.1).

Table 3.1-- Descriptive statistics (mean ± SD) for; Involvements (n), duration (mins), bench time (mins), distance (m), high intensity running (HIR, distance >14.4 km·hr-1, m), very high intensity running (VHIR, distance >25 km·hr-1, m)

	Stint	Match
Distance (m)	1816 ± 903	11608 ± 3573
HIR (m)	500 ± 263	3198 ± 1165
VHIR (m)	24 ± 29	154 ± 105
Duration (mins)	13.7 ± 7.0	87.8 ± 27.2
Involvements (n)	3.6 ± 2.6	23.2 ± 9.3
Bench time (mins)	11.6 ± 9.9	74.2 ± 17.2

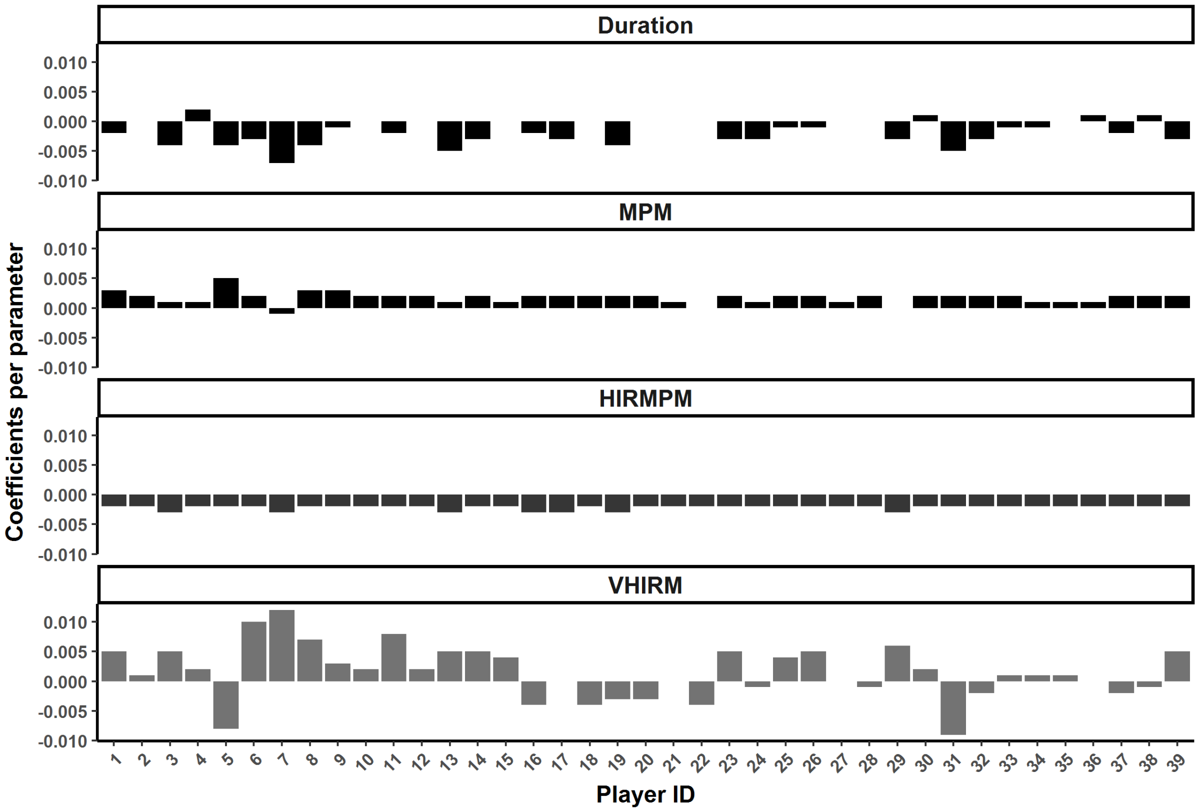

Figure 3.1-- Individual coefficients for Duration (mins), meterage per minute (MPM, m·min−1), high intensity running per minute (HIRMPM, m·min−1), and very high intensity running per minute (VHIRM, m·min−1) in the random slope model.

The coefficients for the random slope model are presented in Figure 3.2. This model had an R^2 of 0.013, and a conditional R^2 of 0.23 (Figure 3.1). The relationship between both duration (for 25/39 players) and high intensity running (for 39/39 players), and involvements per minute was negative. Conversely, MPM experienced a positive relationship with involvements per minute for most players (36/39 players). The relationship between very high intensity running per minute differed considerably depending on the player. Each of these parameters had only a minor relationship with involvements, with the final model having an R^2 of 0.012, and a conditional R^2 of 0.23

Table 3.2-- Model 1 & 2: coefficients of fixed effects (95% confidence interval) for Intercept/Involvements per minute (IPM-1), Duration (mins), High intensity running per minute (HIRMPM, m·min-1), meterage per minute (MPM-1, m·min-1) and very high intensity running per minute (VHIRM, m·min-1)

	Estimate (95% CI)	**t -Value**
Model 1		
Intercept (IPM^{-1})	0.108 (0.187,0.03)	2.695
Duration (mins)	-0.001 (0,-0.002)	-2.802
HIRMPM ($m \cdot min^{-1}$)	-0.002 (-0.001,-0.003)	-3.746
MPM ($m \cdot min^{-1}$)	0.002 (0.002,0.001)	4.785
VHIRM ($m \cdot min^{-1}$)	0.003 (0.006,0)	1.692
Model 2		
Intercept (IPM^{-1})	0.142 (0.037,0.247)	2.648
Stint duration (mins)	-0.002 (-0.003,0)	-2.572
HIRMPM ($m \cdot min^{-1}$)	0.002 (0.001,0.003)	3.813
MPM ($m \cdot min^{-1}$)	-0.002 (-0.003,-0.001)	-4.49
VHIRM ($m \cdot min^{-1}$)	0.001 (-0.003,0.006)	0.684

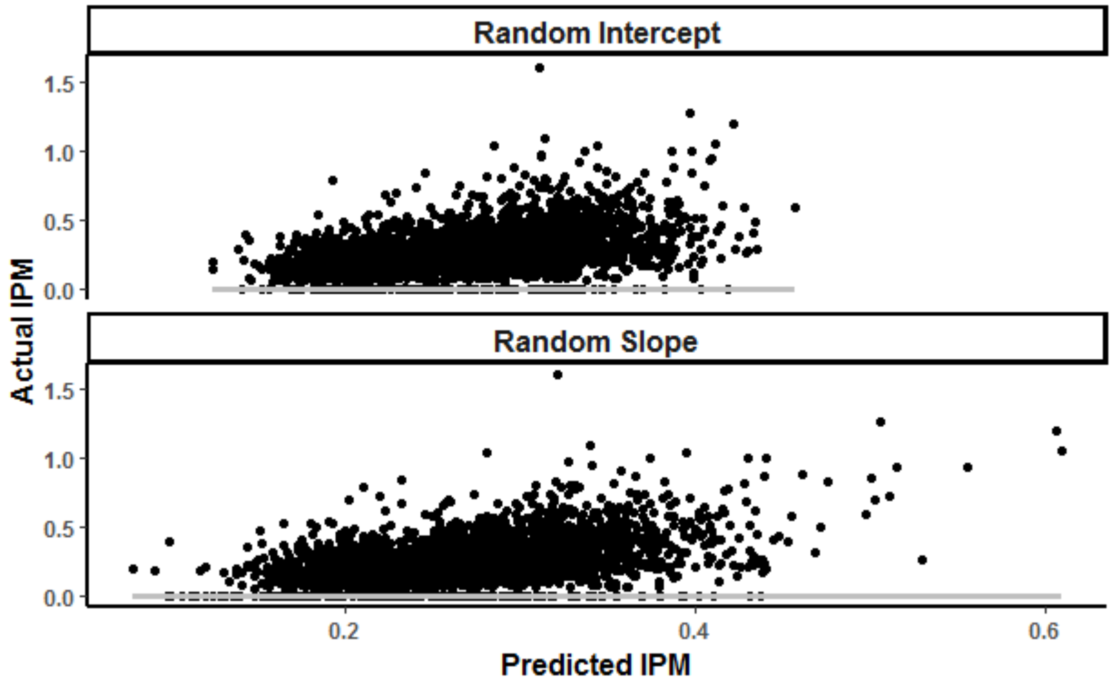

Figure 3.2 -- Predicted vs actual involvements per minute (IPM−1) in random intercept and random slope models, with grey reference line at 0 involvements of error.

3.4.2 Conditional inference trees

Results from the first conditional inference classification tree revealed Player ID, stint number, duration and round number as the strongest indicators of involvements per minute (Figure 3.3). An RMSE of 0.12 involvements per minute (approximately 10.1 involvements per match) was reported on both the test and training sets. This tree's first partition included player ID, with rotation, duration and Round number forming the second to fourth partitions respectively. The second tree included player, stint duration and stint meterage per minute (Figure 3.4) as the strongest predictors. As per the first conditional inference tree, an RMSE of 0.12 for involvements for minute (10.1 involvements per match) was observed on both the test and train sets. This tree had an initial partition based on Player ID, with subsequent partitions based on; duration (2nd), an additional division of Player ID (3rd) and finally duration or MPM (4th).The final tree, with ID removed as an input, used only meterage per minute and stint duration to predict involvements per minute (Figure 3.5). An increased RMSE (0.12 to 0.13 involvements per minute; 11.05 involvements per match) was observed on both sets of data. In this tree, both the first and second partitions were determined using MPM, with duration only forming a partition in instances where MPM exceeded 125.

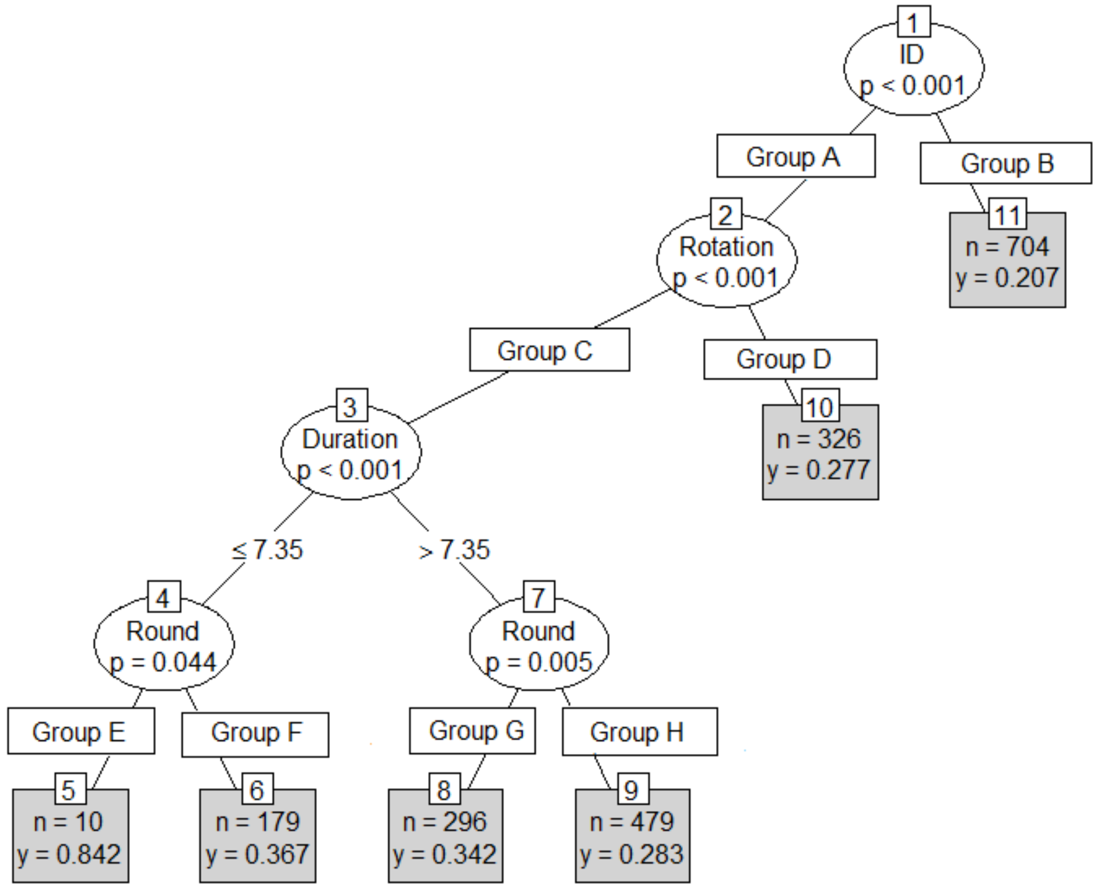

Figure 3.3-- Conditional inference tree with Player ID, Round and Duration (mins) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.

Group A = Player ID (1, 3, 5, 6, 7, 8, 9, 11, 13, 14, 16, 17, 19, 23, 24, 26, 29, 31, 32, 39).

Group B = Player ID (2, 4, 10, 12, 15, 18, 20, 21, 22, 25, 27, 28, 30, 33, 34, 35, 36, 37, 38).

Group C = Rotation (1.1, 1.2, 1.3, 2.2, 2.3, 3.1, 3.2, 3.3, 4.1).

Group D = Rotation (2.1, 4.2, 4.3).

Group E = Round (19).

Group F: Round (1, 3, 4, 6, 7, 8, 9, 12, 13, 15, 16, 17, 18, 20, 21, 22, 23).

Group G = Round (1, 2, 6, 8, 15, 17, 20, 22, 23).

Group H = Round (3, 4, 7, 9, 12, 13, 16, 18, 19, 21).

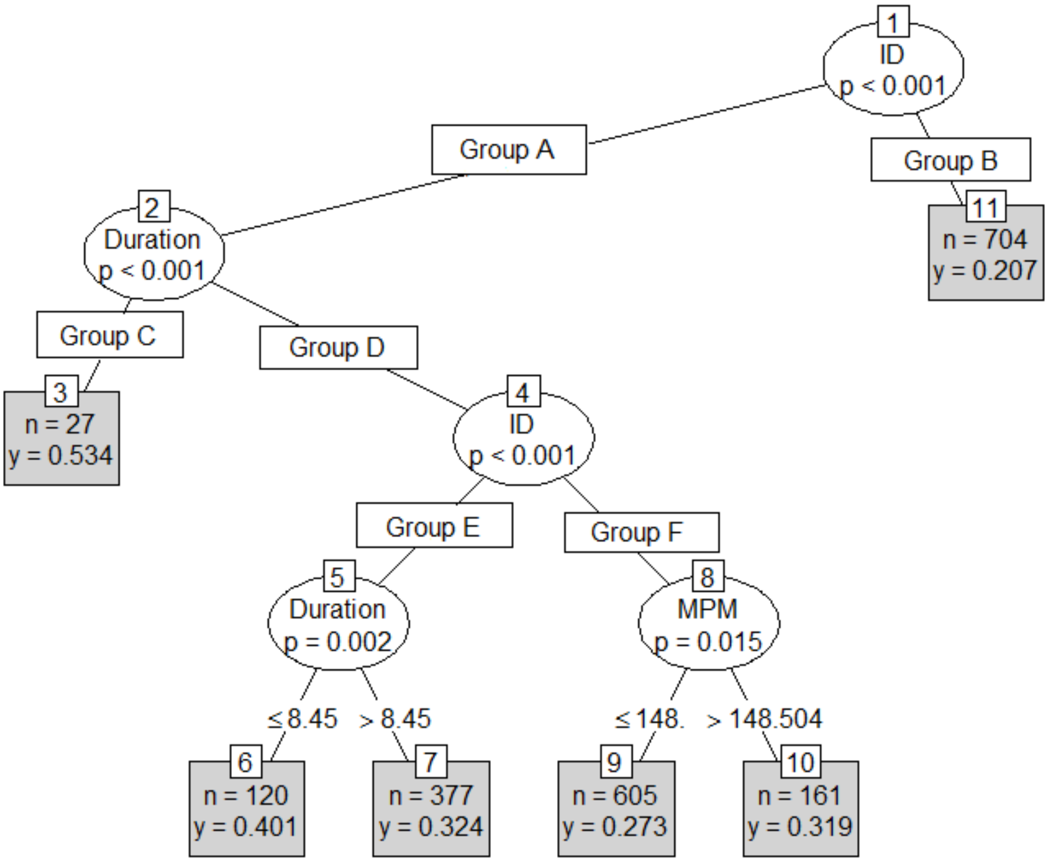

Figure 3.4-- Conditional inference with Player ID, Duration (mins) and meterage per minute (MPM) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.

Group A = Player ID (1, 3, 5-9, 11-17, 19, 23, 24, 26, 29, 31, 32, 39).

Group B = Player ID (2, 4, 10, 12, 15, 18, 20, 21, 22, 25, 27, 28, 30, 33, 34, 35, 36, 37, 38).

Group C = Duration (<5 mins).

Group D = Duration (>5 mins).

Group E = Player ID (3, 5, 6, 7, 8, 13, 29, 32, 39).

Group F = Player ID (1, 9, 11, 14, 16, 17, 19, 23, 24, 26, 31).

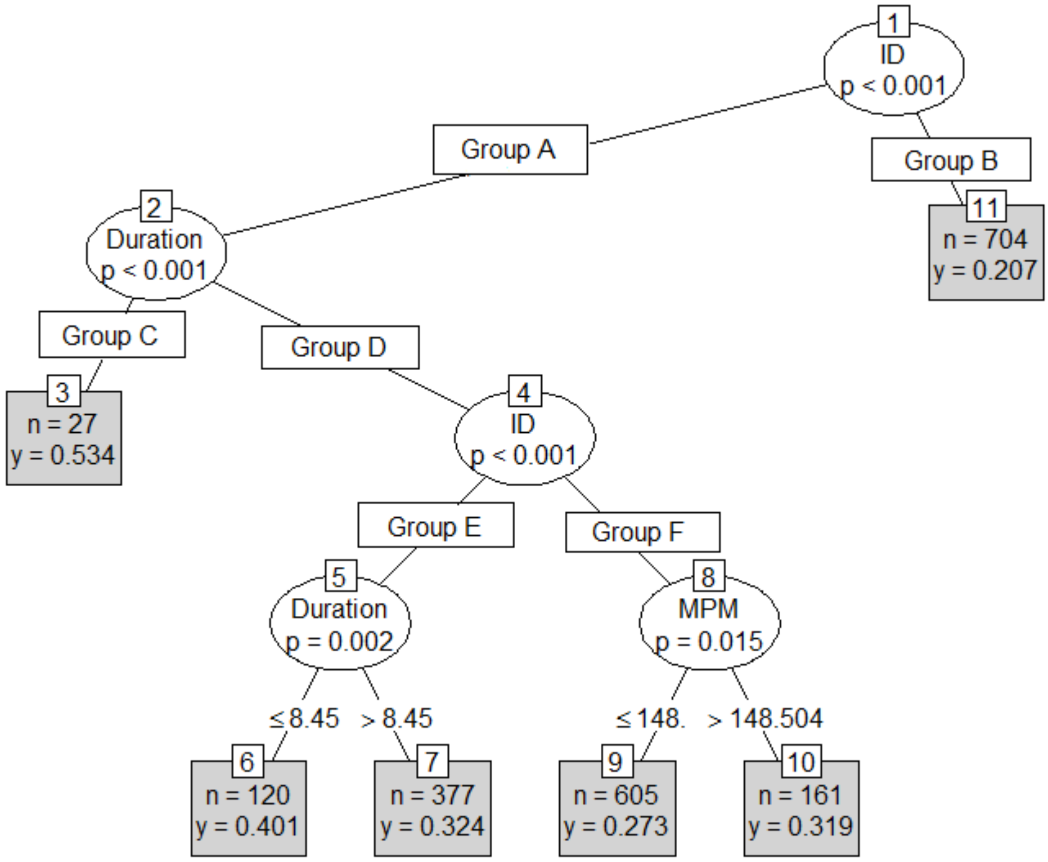

Figure 3.5-- Conditional inference tree including Duration (mins) and meterage per minute (MPM) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.

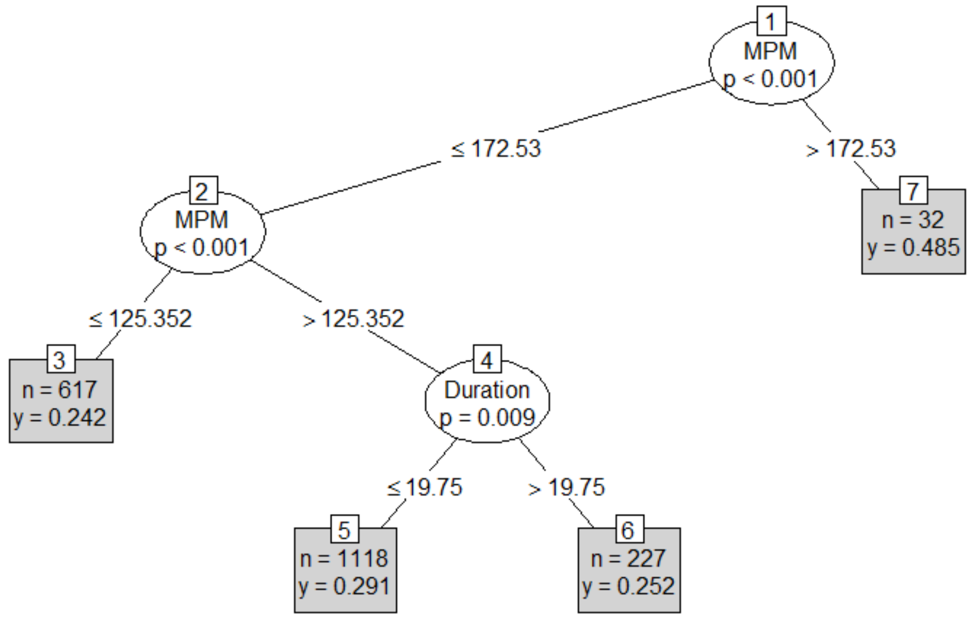

Figure 3.6-- Conditional inference tree including Duration (mins) and meterage per minute (MPM) as independent variables, and involvements per minute (IPM) as the dependent variable where n = the number of cases in each group and y = predicted IPM.

3.5 Discussion

This study developed two methods to quantify the impact of physical outputs, on a team and individual level, on skilled output by elite AF players during matches. The first method comprised two generalized linear mixed models, resulting in broad equations for the team and individual players. Both models had low R^2 and conditional R^2 values, resulting in limited explanatory ability.

The second method, a series of conditional inference trees, identified how different circumstances and combinations of physical parameters may change an athletes expected skilled output. Whilst partitions in the first tree were dominated by uncontrollable factors such as round and stint number, the second tree achieved a similar classification accuracy using meterage per minute, player ID and duration. The final tree removed player ID as a parameter to identify a broad set of team rules, which only slightly reduced accuracy (0.13 compared to 0.12 involvements per minute).

The random intercept model broadly showed the strength and direction of influence for each parameter. In the observed team, meterage per minute had a negative relationship with involvements per minute. The only variable to have any positive relationship was high intensity running per minute. Practitioners could use this information as a general 'rule of thumb' in match day decision making, whereby, a player who is consistently running at a high meterage per minute for an extended duration, without completing high intensity running, is less likely to reach a maximal skilled output. A limitation of this modelling technique is that it does not necessarily apply to all players and does not identify how players individually respond to different parameters.

The random slope model addresses the above issue by allowing for different coefficients of the physical parameters for each player. This allows for better profiling of each athlete and for the importance of each parameter to better reflect an individual's strengths and weaknesses. In the observed team, for example, each of the parameters had positive and negative relationships with skilled output, depending on the player. However, despite the strengths of this modelling approach there are still limitations. The linear decline of involvements per minute declines in response to the temporal and physical inputs is assumed, when it is unlikely the decline in skilled output would be so gradual. Rather, players likely need time and physical intensity on field before their skilled output reaches an optimal level. Finally, these models suggest some level of independence between the physical and temporal parameters. As a result, they are unable to determine how parameters may interact to affect skilled output.

The first tree in this study used the same parameters entered into the random slope model, to identify how parameters interact to influence skilled output (Figure 3.3). However, the significance testing procedure selected uncontrollable factors such as round and rotation numbers as the key explainers of skilled output. The first tree provided a schematic of factors that may influence skilled output in AF. However, because none of the factors from this tree are controllable within a match, this tree would likely have limited uptake in an applied setting. The second tree removed round and rotation number and partitioned based on player, stint time and meterage per minute (Figure 3.4). In an applied setting, the schematic created by this tree could be used to identify the conditions that are likely to lead to maximal skilled output for each player. Additionally, it could be used in a real-time monitoring setting, to identify if the current circumstances imposed upon a player are conducive to maximal skilled output.

The final conditional inference tree in this study removed player, in an attempt to generate a broad set of team rules. This could provide a cleaner schematic of influences upon skilled output across a team. Using only meterage per minute and stint time, this model set six major partitions for skilled involvement. This ranged from high physical output, but a mixed skilled output, to a low physical and low skilled output. In this playing group, a high intensity (>172 $m \cdot min^{-1}$), or a moderate intensity (125-172 $m \cdot min^{-1}$) and moderate duration (<19.75 mins) leads to a higher skilled output. Consequently, match day prescription strategies for the observed team could use this information to limit the stint time of players.

None of the models developed in this study had particularly strong accuracy. The average match duration for a player included in this study was 86 minutes, resulting in an average error of 0.12 IPM and equating to an average error of approximately 10.1 involvements per match. This is in agreement with other research examining the impact of contextual factors on both physical and skilled output in AF matches. In itself, physical output is influenced by factors such as the opposition and the location of a match (Ryan, Coutts, Hocking, & Kempton, 2017). Furthermore, trivial relationships between common locational parameters and Champion Data player ratings as a measure of skilled performance have been noted elsewhere (Dillon, Kempton, Ryan, Hocking, & Coutts, 2017). These findings, collectively, highlight the importance of using skilled and technical data alongside locational parameters to inform match day decision-making, as opposed to the latter alone.

There are several factors which may explain the limited relationship between GPS parameters and skilled output in Australian Football matches. Firstly, AF is a dynamic sport, and many circumstantial details are difficult to model. In particular, opposition playing styles and changes in positions (Robertson & Joyce, 2014), may have an impact on both the physical and skilled output of player (Sullivan et al., 2014a). Secondly, the aggregate data utilized in this study is limited in its' ability to identify thresholds for reductions in both physical and skilled output. Other research has examined these outputs across quarters (Bradley & Noakes, 2013), and more recently within stints (Montgomery & Wisbey, 2016). Further work is needed to examine physical and skilled behaviour as a time-series, to better describe the outputs competed by players. Finally, this was a methodological study, which aimed to identify trends across a single playing group. For this methodology to be applied to other teams and sports, the modelling approaches would need to be independently run. Therefore, the thresholds created here may not necessarily stand true outside of this playing group.

The models utilized in this study may still aid decision making in elite team sports. They use information that is controllable and readily available during matches, and therefore may assist in situations where objective information is desired to make quick, time-sensitive decisions.

3.6 Conclusion

This study developed two methods to identify the relationship between physical, skilled and temporal outputs, on an individual and team level. The first method utilized random slope and intercept models to identify factors that may correlate with a decline in skilled output, and what direction their relationship is with skilled output. This could be used to develop a broad equation for the team and individuals, to identify how they would react to differing stint times and physical workloads. The second set of methods utilized conditional inference trees to identify how physical and temporal parameters may interact to influence skilled output. Together, these three models describe; i) the impact of uncontrollable factors, such as round and rotation number, ii) how different individuals react to different outputs and iii) a general set of thresholds for the data entered into the modelling process. These trees can provide a schematic to assist match day prescription in team sports. None of these models held an optimal predictive ability, suggesting that wearable technology data and notational analysis feeds could be analysed differently to improve their use in team sports.

3.7 Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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CHAPTER 4 – Study 2

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SPORTS PERFORMANCE

A change point approach to analysing the match activity profiles of team-sport athletes

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ABSTRACT
In team-sport, physical and skilled output is often described via aggregate parameters including total distance and number of skilled involvements. However, the degree to which these output change throughout a team-sport match, as a function of time, is relatively unknown. This study aimed to identify and describe segments of physical and skilled output in team-sport matches with an example in Australian Football. The relationship between the number of change points and level of similarity was also quantified. A binary segmentation algorithm was applied to the velocity time series, collected via wearable sensors, of 37 Australian football players (age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg). A change point quotient of between 1 and 15 was used. For these quotients, descriptive statistics, spectral features and a sum of skilled involvements were extracted. Segment similarity for each quotient was evaluated using a random forest model. The strongest classification features in the model were spectral entropy and skewness. Offensive and defensive involvements were the weakest features for classification, suggesting skilled output is dependent on match circumstances. The methodology presented may have application in comparing the specificity of training to matches and designing match rotation strategies.

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Introduction

Physiological and cognitive fatigue typically reduce the ability for team-sport athletes to maintain a maximal output for the duration of competition (Aughey, 2010; Gréhaigne, Godbout, & Bouthier, 2001). Other factors, including game style, positional requirements and opposition tactics, mean that physical and skilled output is dynamic for most team-sport athletes (Woods, Robertson, & Collier, 2017). Understanding the extent to which physical and skilled output change as a function of time may be useful in the prescription of on-field stints relative to time on bench (Corbett, Sweeting, & Robertson, 2017), and designing the workload characteristics of training (Corbett et al., 2017). A sport where many of these applications are pertinent is Australian Football (AF).

In team-sports including AF, physical output is typically described using aggregate parameters extracted from wearable technologies such as global positioning systems (GPS) (Cummins, Orr, O'Connor, & West, 2013). These parameters include global volume measures, such as total distance and PlayerLoad^{TM}, work rate, and velocity bands, which bin total distance into velocity zones (Sweeting, Cormack, Morgan, & Aughey, 2017). These parameters are often aggregated across; an on-field stint (Corbett et al., 2017; Dillon, Kempton, Ryan, Hocking, & Coutts, 2017), quarter (Aughey, 2010) or entire match (Aughey, 2011). Similarly, skilled output is typically quantified using aggregate parameters. In AF these have included global measures of skilled performance, such as Champion Data player rankings (Dillon et al., 2017), coaches ratings (Sullivan et al., 2014) and a count of the total number of skilled actions completed by each player, termed involvements (Corbett et al., 2017).

Aggregating physical and skilled output presents multiple limitations. There are likely periods of altered physical and skilled output that are not captured by aggregate parameters. For instance, there are periods of physical output at a much higher intensity than that of an averaged entire game (Delaney et al., 2015). It is also difficult to determine distinguishable time points where output meaningfully changes (Corbett et al., 2017). By inference it is therefore problematic to use measures of physical and skilled output to inform decisions whereby time is expected to exert an influence.

By analysing physical and skilled output as a time series, a greater understanding of how physical and skilled output change within a match could be developed. However, this presents two challenges. The noise in the signal obtained from wearable technologies contains numerous erroneous data points (Coutts & Duffield, 2010). Physical output in an intermittent sport, for example AF, is likely to be too volatile (Varley, Fairweather, & Aughey, 2012) to identify meaningful changes on a per-second basis. This creates a dichotomy between the interest in identifying changes in physical output over time, and the need to maintain accuracy in measures taken.

Aggregating time-series in smaller windows, has partially overcome the volatility in physical output (Wundersitz et al.,

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2015). In professional AF and rugby league matches, average velocity and acceleration have been calculated for three, five and 10-minute windows (Delaney et al., 2015). A specific representation of the peak physical outputs in both sports, and the length of time these outputs are maintained, was identified. A method of automatically identifying segments within a time series, based on the mean and variance, may expand on this approach. This could allow for the aggregation of physical output over segments of non-uniform size and remove the need to manually select pre-defined time windows. Further, the computation of additional, custom built parameters may allow for a more detailed description of the time series. This could improve the specificity in which match output could be evaluated, and potentially improve training drill design (Corbett et al., 2017).

Time series segmentation or change point analysis, allows for computation of non-uniform segments from a time series. Time series segmentation algorithms are built upon the assumption that within a given time series, there are a number of change points. Thereafter, the behaviour of subsequent data points is inherently different to those before it (Piotr & Haeran, 2014). Users typically apply a penalty value, or specify the number of change points desired (Killick & Eckley, 2014), meaning, in a volatile time series such as team-sport physical output, the algorithm can be limited to a smaller number of aggregation windows (Piotr & Haeran, 2014). The hypothesised maximum number of change points in a velocity time series is unknown. Whilst a higher number of change points provides a more detailed summary of the time series through shorter aggregation windows (Cryer & Chan, 2008) differences between segmental features are likely to decrease.

Frequency domain analysis could be used to summarise players' physical output within segments. Features may include the shape of a signal, including skewness, kurtosis, flatness, entropy, the location of values within a signal, such as percentiles and spectral centroid (Fransz, Huurnink, de Boode, Kingma, & van Dieën, 2016) and customised features to describe the magnitude of values within a signal (Wundersitz et al., 2015). Frequency domain analysis has been applied for the purpose of movement classification (Wundersitz et al., 2015) and anomaly detection (Fransz et al., 2016). To help guide the number of change points selected, data mining classification methods can be used (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). By placing the features of segments extracted from a varying number of maximum change points into a classification algorithm, the trade-off between the uniqueness of segments and a heightened number of change points could be understood.

The first aim of this study was to identify the impact of change point number on the features of segments in Australian footballers' velocity time series. The subsequent aim of this study was to determine a method to identify an optimum number of change points to describe the velocity time series of Australian Rules footballers for general purposes.

Methods

Participants

Professional male athletes players (n = 37, age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg) from an elite AF club provided written informed consent to participate in this study. All players completed at least one full match in the 2017 Home and Away Australian Rules Premiership season. Ethical approval was granted by the University Human Research Ethics Committee (Code HRE17-127).

Data collection

Locational data was collected from 19 rounds comprising; 12 indoor matches and 7 outdoor matches (n = 19) during the 2017 Home and Away Season. For all matches, players were fitted with a 10 Hz Catapult T6 Local Positioning System (LPS) tag (indoor matches), or a 10 Hz Catapult S5 Global Navigation System (GNSS) device (outdoor matches). Both LPS and GNSS devices were worn in custom sewn pouches within players' jerseys. Both LPS and GPS systems have established acceptable validity and reliability in measuring the physical output of team-sport athletes (Coutts & Duffield, 2010; Luteberget, Spencer, & Gilgien, 2018). All matches were monitored live using proprietary software Openfield (Catapult Openfield v 1.11.2–1.13.1) to ensure an adequate signal quality of > eight packets/second and an average horizontal dilution of precision of 0.6–1.5. A comma separated value file of instantaneous data for velocity was cleaned to exclude time on bench, as well as quarter and half-time breaks. This was to allow velocity data for each player in each match to be analysed as a single continuous time series.

Skilled output was quantified via match involvements. An involvement was defined as any singular skilled action completed by a player (Corbett et al., 2017). An involvement could further be categorised as either offensive or defensive (Table A1). Involvements were extracted from a timeline by a commercial sports statistics provider (Champion Data, Melbourne, Australia). This timeline includes each involvement that occurred in a match, along with the corresponding player and timestamp.

Time series analysis

Time series analysis methodologies are built upon the assumptions of stationarity, absence of seasonality and absence of trend (Cryer & Chan, 2008). Stationarity refers to the consistency of mean, variance and autocorrelation over time (Cryer & Chan, 2008). The Dickey-Fuller test for stationarity was applied to all velocity time series' and returned an average test statistic of −19.87, a lag order of 39 and a p-value of <0.01, suggesting the velocity time series was stationary (Tanaka, 2017). Seasonality refers to a time series, where data points periodically fluctuate at fixed intervals (Atchison, Berardi, Best, Stevens, & Linstead, 2017). Due to the uneven length of quarters in AF, the velocity time series' do not violate the assumption of seasonality. The inability of linear approaches in the literature to determine a linear change in physical output as a function of time within matches, demonstrates an absence of trend (Dillon et al., 2017). This suggests that instantaneous velocity files do not violate any of the assumptions for time series analysis and can be analysed without any transformations.

Change points were used to divide each players' velocity time series into a number of smaller segments. Preliminary change point analysis was conducted on each velocity time series. This included an unsupervised power of the pruned extract of time (PELT) change-point analysis, and a "change point for a range of penalties" (CROPS) analysis. CROPS analysis identified the impact of differing penalty values on change point quotient. These algorithms identified 1026 and 82 change points respectively per time series. Consequently, it was deemed necessary to limit the number of change points identified.

For this purpose, 15 trials of a binary segmentation algorithm were run, searching for between two and 16 change points. All change points were calculated in the R changepoint package, with an AIC penalty value of 0.01. Binary segmentation is the most widely used change point algorithm (Killick & Eckley, 2014). It functions by progressively dividing the data set into a series of smaller segments, until additional change points cannot be located (Killick & Eckley, 2014). It is computationally fast and has established validity within the literature (Piotr & Haeran, 2014).

Descriptive statistics

The peak three and five minute moving averages achieved by any player in each Round were calculated for metreage per minute, in line with previous literature (Delaney et al., 2015). Additionally, the peak segment based on metreage per minute, as well as it's corresponding segment number and duration was also obtained. This was done to compare the change point approach introduced in this study, with previously used moving averages to establish peak match intensities.

Pearson's product moment correlation was calculated between on-ground stint end time and change point location for every stint completed by every player. This was done to assess the relationship between on-ground stints and change point location.

Feature extraction

A fast Fourier transform was applied to the velocity time series'. The following frequency domain features were extracted using the seewave package (Sueur, Aubin, & Simonis, 2008) in R; minimum amplitude, spectral centroid, maximum amplitude, spectral entropy, skewness, spectral flatness measure, kurtosis, standard error of mean (SEM) and the frequency precision of the spectrum, 25th percentile (Q_{25}), 75th percentile (Q_{75}) and interquartile range (IQR). An energy feature, designed to reduce multiple inputs from wearable technologies into a single metric (Wundersitz et al., 2015) was also extracted for each segment. Energy has been used to discriminate between different movement tasks, for the purpose of classification. Energy is defined in Equation (1)

Equation (1) – Equation for spectral energy where *ai* are the sum of the squared values for axes *i* (*i* = acceleration & velocity) and p = number of observations per axis (Wundersitz et al., 2015)

$$E = \sum 3_i = 1^{ai}/p \quad (1)$$

To describe skilled output within each segment, two features were extracted from the Champion Data time series for each player in each match. These were; defensive action count and offensive action count.

Segment similarity

For 15 change point trials, a random forest was utilised to classify cases as segment number, using both spectral and involvement features. This was done to quantify the impact of increasing change point quotient (Q), on the similarity of features within each segment. The random forest in this study was created using the randomForest package in R (Liaw, 2002). To identify segment number, 70% of the data was used with the following features: Player Number, 25th percentile (Q_{25}), 75th percentile (Q_{75}), interquartile range, spectral centroid, skewness, kurtosis, spectral flatness measure, spectral entropy, spectral precision, segment duration (seconds) and energy. Each of these methods were then tested on the remaining 30% of the data, with the corresponding classification accuracy and confusion matrix computed. The results of a multidimensional scaling algorithm (MDS) were also utilised to visually demonstrate the impact of Q on segment similarity, based on an average value across all players, for each segment and feature.

Results

Change point locations

An example of the influence of change point quotient (Q), on the location of change points for a single player, is shown in Figure 1. For the purpose of visual comparison, change point quotients of; two (A), five (B), 10 (C) and 15 (D) are shown. This figure depicts the functioning of the binary segmentation algorithm, which progressively identified change points within existing segments. By increasing Q from two to five, additional segments were created within segments at the beginning of the match. As this increased from five to 10, additional segments were created towards the beginning and end of the match. When increased from 10 to 15, additional change points occurred midway through the match.

Change points locations within matches varied considerably between players. The average change point location, measured as on-field seconds lapsed within a match, is depicted in Figure 2. The majority of segments occurred towards the beginning of a match for some players (eg. Player 18), whilst others had a greater number of change points occurring towards the end of a match (eg. Player 12 and Player Seven). The change points for some players were relatively evenly spaced (eg. Player 14 and Player Five), whilst other players had a number of change points occurring in close proximity with one another (eg. Player Nine).

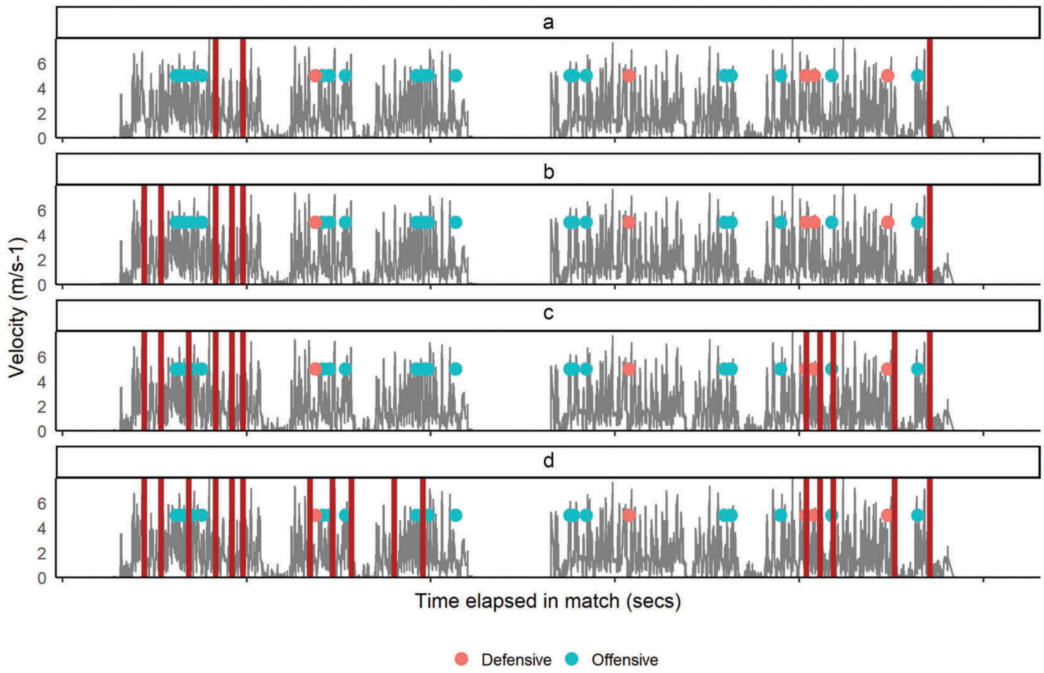

Figure 1. Example of the influence of change point quotient (Q) on the number and location of change points for a single player across a single match. a = Q of 2, b = Q of 5, c = Q of 10, d = Q of 15. Blue and red circles indicate offensive and defensive involvements, respectively. Fixed vertical lines denote change point location.

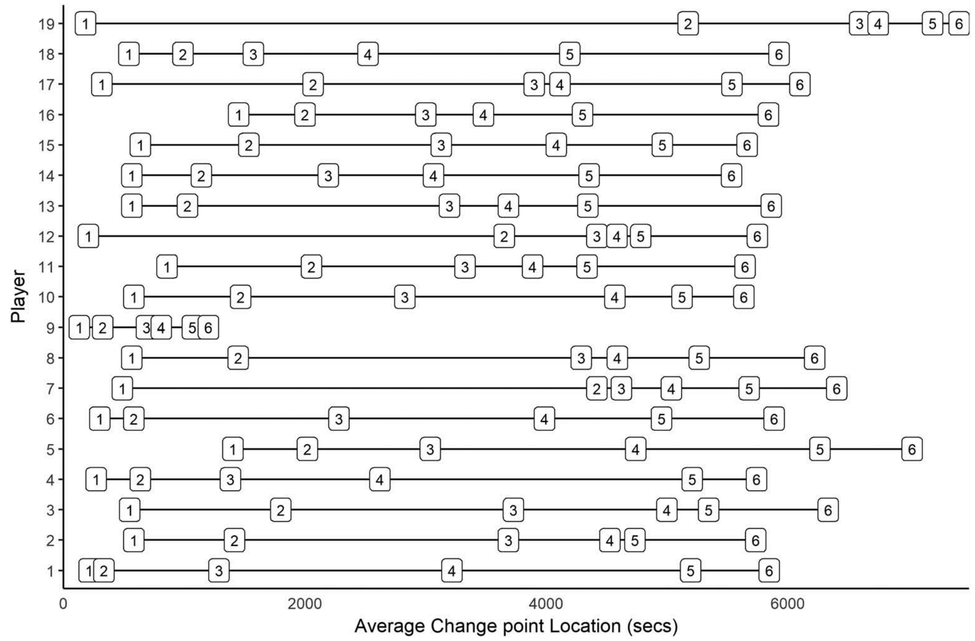

Figure 2. Average change point locations (Q = 5) for all players in the 2017 Home and Away Australian Football Season, shown as elapsed time on ground in seconds.

Descriptive statistics

The peak segment and its corresponding duration and metreage per minute for each Round is depicted in Table 1. This table also depicts the peak 3 and 5-minute moving averages attained by any player for metreage per minute by Round. In some Rounds, the change point method was able to detect segments with a higher intensity than the moving average method (ie., Round 8). In other instances, the change point method was able to detect a similar intensity to the moving average method, maintained for a longer period of time (ie., Round 1). There were several Rounds, where peak intensity was lower than both 3 and 5-minute moving average intensities (eg., Round 15). Peak match intensities occurred at varying time points during the match. Furthermore, there was also only a weak relationship (r= 0.21) between segment location, and stint end time. This suggests physical output is independent of on-ground stints.

Table 1. Peak segment number, peak segment duration, peak segment meterage per minute (MPM), 3-minute and 5-minute moving averages for meterage per minute (MPM) in each Round. 3-minute and 5-minute moving averages are presented as the peak value attained by any player in each Round. Round refers to each match in the 2017 Home and Away Season.

Round	Peak segment (n)	Segment duration (minutes)	Peak segment (MPM)	3-Minute moving average (MPM)	5-Minute moving average (MPM)
1	1	6	193	206	194
2	2	4	212	239	218
3	3	3	197	211	191
5	4	4	211	221	207
6	2	7	208	210	208
7	3	6	197	238	217
8	2	3	213	212	195
9	6	4	192	197	183
10	1	6	194	216	196
12	1	3	204	206	185
13	1	5	199	223	197
14	4	4	201	208	195
15	1	4	176	206	190
16	3	6	178	200	182
17	5	3	195	210	195
18	3	5	201	209	195
19	1	6	182	217	204
20	5	3	174	198	185
21	5	5	191	221	206
22	4	4	201	208	195
23	3	3	207	217	201

Feature extraction

The distribution of values for six of the extracted features, for all players in all matches, in each of the segments (where Q = 5) is shown in Figure 3. The shape of distributions for spectral skewness, defensive action count and offensive action count also appeared similar regardless of segment, with minor discrepancies in values at the lower end of the distribution for each feature. The shape of the spectral energy and spectral flatness distributions appeared considerably different depending on segment.

Segment similarity

The accuracy of the random forest in classifying segments through their features is shown in Figure 4. Where Q = 1, the random forest was able to classify segments correctly 64% of the time. This decreased linearly towards Q = 4/Q = 7, where the model was correctly able to classify segments 27% of the time. After this, there was a steady decline in the ability for the random forest to differentiate between segments through their features, reaching a classification accuracy of 14%, where Q = 15. This is reinforced by Figure 5, which demonstrates an increase in segment similarity as Q increases. For example, a smaller change point quotient (Q = 2) returned three distinct segments based on their feature, whilst a higher quotient (Q = 15), created 16 segments – most of which were closer together. When Q = 5, there were six segments, which were dissimilar to one another.

The confusion matrix for the final model, where Q = 5, is shown in Table 2. This model had a classification accuracy of 26.7% (95% CI; 23.7%–29.9%). Spectral kurtosis (18.1), 75th percentile of velocity (18.1) and spectral flatness (19.3) were the three strongest variables in the random forest as measured through mean decrease in gini coefficient. Offensive action count (6.8), defensive action count (6.8) and Player ID (5.6), were the weakest classifiers in the random forest.

Discussion

This study aimed to identify and describe segments of physical and skilled output in team-sport matches with an example in

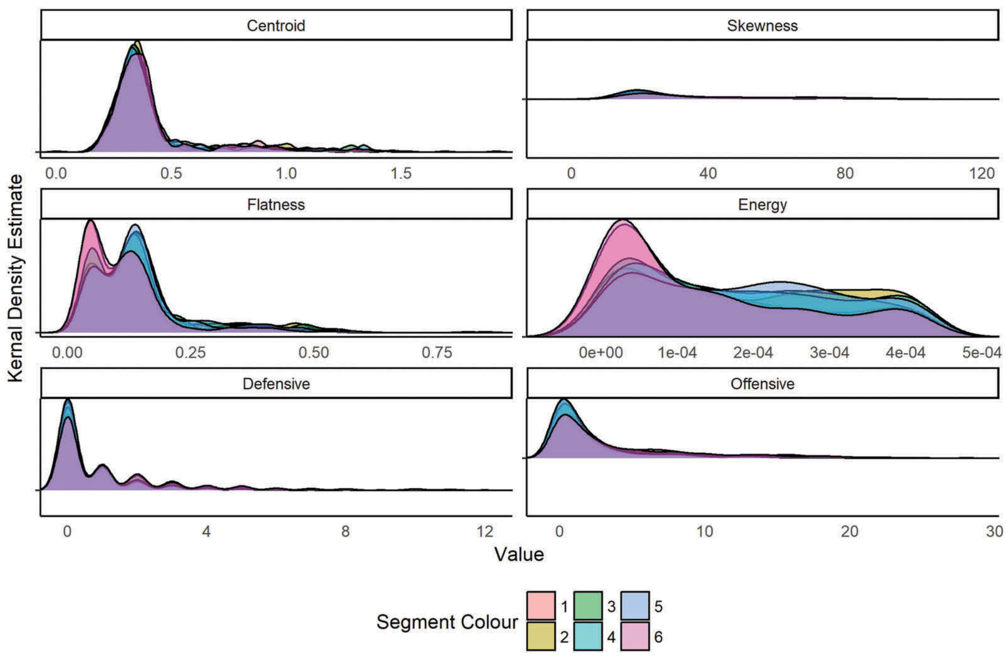

Figure 3. Distribution of values for six of the features, across all segments (where Q = 5), for all players in all matches in the 2017 AFL Home & Away season.

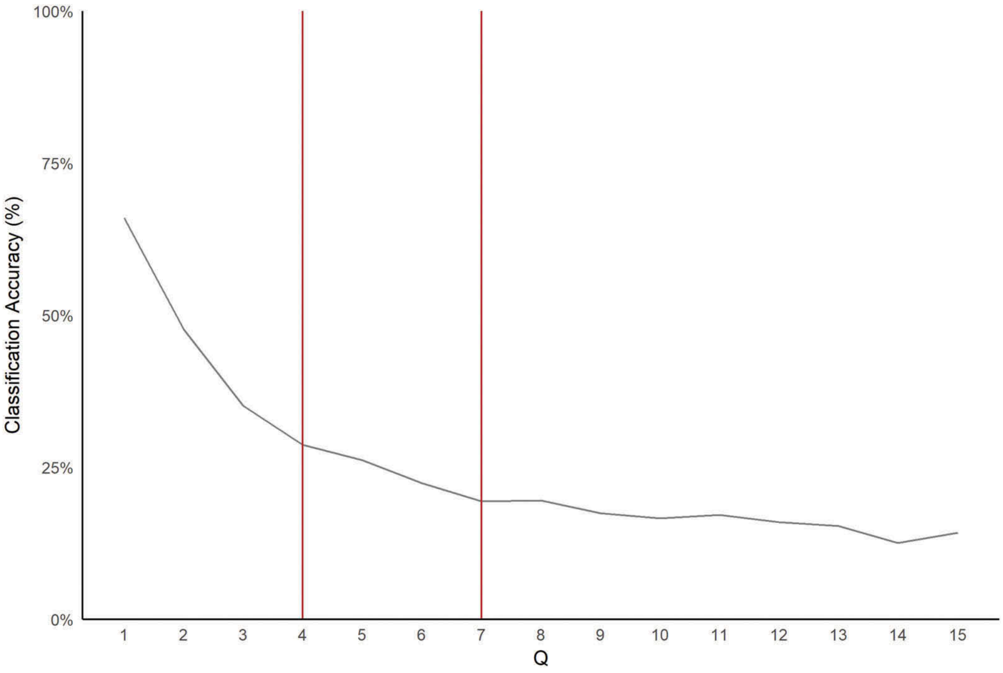

Figure 4. Scree plot, depicting classification accuracy of 15 random forest models, with a change point quotient of between 1 and 15.

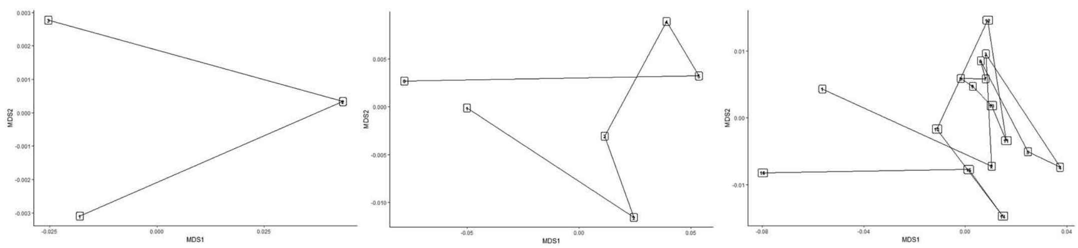

Figure 5. Similarity plots of the average features for each segment, with a change point quotient of 2 (left), 5 (centre) and 15 (right). Values were calculated using the average across all matches and players, for each feature in each segment, reduced to a single set of Cartesian coordinates using multidimensional scaling.

Table 2. Confusion matrix for final random forest (RF) classifications (where Q = 5) – actual cases vs classified cases.

		Predicted class						
		1	2	3	4	5	6	Overall %
Actual Class	**1**	54	25	23	21	20	26	32
	2	15	31	20	23	22	20	24
	3	8	19	28	23	28	9	24
	4	13	23	25	26	19	20	21
	5	12	16	17	16	29	10	29
	6	30	21	19	19	22	45	29

Australian Football. The physical output of team-sport athletes was split into between two and 16 segments and then summarised each of these segments using spectral features and a measure of skilled output. An advantage of this method is the ability to analyse outputs across a match, without having to specify fixed duration windows. By assessing segment similarity using a random forest model and multidimensional scaling, it was determined that between six and eight segments could be used to describe the physical output of team-sports athletes.

Whilst considerable research has utilised aggregated data over periods of equal length, this study utilised a binary segmentation algorithm which split the velocity time series of all players into between two and 16 unequal segments. Each of these segments was categorised by data points with a different mean or variance, compared to the previous or subsequent segment (Piotr & Haeran, 2014). These segments varied in their location and duration between players and had only a small relationship with on-field stint end time. This highlights the importance of analysing velocity data as a time series, as aggregating across quarters or on-field stints may not be sufficient when analysing changes in physical output.

By analysing velocity data across static windows, such as three or five-minute periods, details of potentially high or low periods of physical activity may be lost. Indeed, the change point algorithm often detected higher or similar peak match intensities as moving average windows. There were several instances where the change point algorithm extracted lower peak intensities than the moving average method. This is likely due to the algorithm used, which searched for a change in both mean and variance in velocity. This is in contrast to moving averages which summarise match intensity using only mean velocity or acceleration (Delaney et al., 2015). Additionally, this study was able to identify the time point at which peak match intensities occurred. This may be useful for practitioners wishing to increase the specificity of their training sessions to match demands (Al-Abood, Davids, & Bennett, 2001). For example, peak intensity segments occurred at varying points of the match. Therefore, it may be useful to reach these intensities during training at varying points of the session.

Spectral features were used to summarise the data points for every player's segments in all matches. Ridge plots for all players, were utilised to highlight the difference in distributions of each feature across six different segments. Whilst some features, such as spectral centroid (i.e., mean velocity within each segment) did not appear to change between segments, other parameters such as spectral energy and spectral flatness measure had different distributions depending on the segment. Spectral features are able to describe additional aspects of physical output, not currently captured by parameters such as work rate. These include; whether running was intermittent or more steady state (spectral flatness measure), how intensity was maintained across a segment (Q_{25} and Q_{75}) and how physical output was distributed across a segment (kurtosis and skew). These features may be utilised to give a greater understanding of how physical output is accrued in a segment. Whilst work rates such as metreage per minute are predominantly used in AF, these findings suggest that additional detail could be gained from velocity data by utilising spectral measures of variance.

Skilled output, measured through match involvements, showed no clear differences between segments. Consequently, they were the weakest features in the random forest model for classification. This highlights the dynamic nature of skilled actions in AF. Skilled output can be affected by many factors including the strategy of the opposing team, player roles, team composition and team form (Corbett et al., 2017; Woods et al., 2017).

Multidimensional scaling and similarity plots were used to combine spectral features and explore the similarity of segments for each player for four different change point quotients. These plots were useful in highlighting two phenomena. First, there was a trade-off between the number of change points selected, and the differences in features of each segment. For example, a change point quotient of two generated three distinct change points and a change point quotient of five generated six somewhat different segments. A quotient of 15, however, generated two clearly distinct segments, and 14 segments with relatively similar features. This suggests that increasing the change point quotient past a point is likely to yield a number of similar segments, which provide limited added detail over using a smaller number of change points.

To quantify the increasing similarity of segments as change point quotient increased, a series of random forest models were constructed. Spectral and involvement features were calculated for 15 different change point quotients, and the accuracy of the random forest to identify segment number through these features was calculated. As anticipated, the highest classification accuracy occurred where $Q = 1$. Between $Q = 4$ and $Q = 7$ signified an inflection point in the classification accuracy of the random forest models. In the random forest model, the strongest classification variables were measures of shape and spread, such as spectral flatness, kurtosis and the location of the 75th percentile of velocity. This highlights the ability of a change-point and frequency domain analysis, to describe phenomena which would be lost in aggregate parameters such as metreage per minute (Corbett et al., 2017; Dillon et al., 2017).

The differences between segments when a higher change point quotient is used are likely to be subtle (Piotr & Haeran, 2014). A very low number of change points, on the other hand, may provide a description of the velocity time series, that is no more detailed than aggregating across pre-determined windows such as a quarter or stint. When attempting to investigate changes in physical and skilled output over time, or when attempting to identify periods of high physical output, a single change point may provide a less detailed description of the time series, than aggregating across a pre-set window such as quarter or stint on ground. As a result, a quotient of five was ultimately selected to summarise the most unique periods of physical output for each player. This is because it provides a trade-off between providing increased detail of a time series (as visually inspected through the similarity plots), without generating segments that are unnecessarily similar to one another (as calculated from the random forest model). When examining sequences of physical output, change point quotient may be modified to provide a more granular description of the velocity time series.

There are numerous applications of the change point method to AF matches. Change points could be compared with changes in position, team strategy or on-field stints, to better quantify in-match output. Similarly, this method could be adapted to identify changes in physical and skilled output as a function of time, by identifying change points within on-field stints. To date, the literature has identified only a trivial-small relationship between physical output, skilled output and time (Corbett et al., 2017; Dillon et al., 2017; Ryan, Coutts, Hocking, & Kempton, 2017). However, this could possibly be due to the aggregate parameters utilised in all of these studies. By aggregating features or parameters across different segments, it may be possible to infer patterns, decrements or changes in physical output as a function of time.

The methodologies used in this study have applications in a team-sport training environment. Feature extraction has already been used to classify movements based on accelerometer and GPS inputs (Wundersitz et al., 2015). In the present study, feature extraction was used to provide a more detailed description of physical output than measures such as total distance or distance covered in velocity bands. At present, velocity bands are often heuristically chosen (Sweeting et al., 2017) or individualised by an external physiological factor, such as maximal aerobic sprinting score (Cummins et al., 2013). The features of spread used in this study (eg., Q_{25}, Q_{75}) could be used to develop bands based on how often players reach different velocities. These detailed measures may be useful in evaluating the specificity of training drills to match demands. In rehabilitation, for example, it is common practice for players' to complete a session in which GPS parameters in training resemble that of a match (Kelly & Coutts, 2007). By utilising these features, practitioners would have a greater understanding of whether players have completed a training session with similar match intensity (Delaney et al., 2015).

The methods utilised in this study could also be applied in sports where pacing is a key strategy. In track cycling, for example, the ability of athletes to increase or decrease their velocity at crucial moments in an event is a key strategic consideration. The change point methodology could be applied to the instantaneous velocity of such sports, to dissect opposition strategies, and to evaluate the strategy of a given athlete (Woods et al., 2017). Depending on the application, the change point quotient may be modified.

Conclusion

This study proposed a method to divide the velocity time series into a series of unequal blocks. For this study, a change point quotient of between five and seven was selected, as providing increased insight into the velocity time series, whilst identifying sufficiently different segments of play through their physical and skilled output. Differing change point quotients may be utilised, depending on the purpose of practitioners. These methods could be utilised to increase the sophistication of match profiling in team-sports, and in turn, could allow practitioners to clearly investigate the specificity of their training sessions in meeting match demands.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Table A1. Involvements included in this study.

Involvement category	Reason for usage
Disposals (Boundary Kick Ineffective, Kick In Short, Handball Effective, Handball Ineffective, Kick Effective, Kick In Long, Handball Clanger, Handball, Boundary Kick Long, Ground Kick Ineffective, Kick Long To Advantage, Kick Ineffective, Kick Backwards, Kick Inside 50, Kick Short, Kick Long,	Measure each time the player interacted with the ball
Offensive Actions (Mark Contested, Knock On Effective, Centre Bounce Clearance, Gather, Ball Up Hitout To Advantage, Loose Ball Get, Mark From Opp Kick, Free For, Mark Lead, Inside 50, Mark, Mark Lead, Mark Uncontested, Mark Play On, Handball Received, Shark, Hitouts to Advantage)	Measure every action which the club deems important in contributing to a goal
Defensive Actions (Block, Smother, Smotherer After Disposal, Run Down Tackle Dispossessed, Pressure Credit, Chase, Tackle, 1-on-1 Contest Defender, Spoil Gaining, Spoil Defensive, Hold	Measure each time a player contributed to the team by potentially preventing the oppositions' goal.

“A change point approach to analysing the match activity profiles of team-sport athletes”

This chapter is presented in pre-publication format of a recent publication titled:

Corbett, D. M., Sweeting, A. J., & Robertson, S. (2019). A change point approach to analysing the match activity profiles of team-sport athletes. *Journal of Sports Sciences*. doi: 10.1080/02640414.2019.1577941

4.1 Abstract

In team-sport, physical and skilled output is often described via aggregate parameters including total distance and number of skilled involvements. However, the degree to which these output change throughout a team-sport match, as a function of time, is relatively unknown. This study aimed to identify and describe segments of physical and skilled output in team-sport matches with an example in Australian Football. The relationship between the number of change points and level of similarity was also quantified. A binary segmentation algorithm was applied to the velocity time series, collected via wearable sensors, of 37 Australian football players (age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg). A change point quotient of between 1 and 15 was used. For these quotients, descriptive statistics, spectral features and a sum of skilled involvements were extracted. Segment similarity for each quotient was evaluated using a random forest model. The strongest classification features in the model were spectral entropy and skewness. Offensive and defensive involvements were the weakest features for classification, suggesting skilled output is dependent on match circumstances. The methodology presented may have application in comparing the specificity of training to matches and designing match rotation strategies.

4.2 Introduction

Physiological and cognitive fatigue typically reduce the ability for team-sport athletes to maintain a maximal output for the duration of competition (Aughey, 2010; Gréhaigne, Godbout, & Bouthier, 2001). Other factors, including game style, positional requirements and opposition tactics, mean that physical and skilled output is dynamic for most team-sport athletes (Woods, Robertson, & Collier, 2017). Understanding the extent to which physical and skilled output change as a function of time may be useful in the prescription of on-field stints relative to time on bench (Corbett, Sweeting, & Robertson, 2017), and designing the workload characteristics of training (Corbett et al., 2017). A sport where many of these applications are pertinent is Australian Football (AF).

In team-sports including AF, physical output is typically described using aggregate parameters extracted from wearable technologies such as global positioning systems (GPS) (Cummins, Orr, O'Connor, & West, 2013). These parameters include global volume measures, such as total distance and PlayerLoad^{TM}, work rate, and velocity bands, which bin total distance into velocity zones (Sweeting, Cormack, Morgan, & Aughey, 2017). These parameters are often aggregated across; an on-field stint (Corbett et al., 2017; Dillon, Kempton, Ryan, Hocking, & Coutts, 2017), quarter (Aughey, 2010) or entire match (Aughey, 2011). Similarly, skilled output is typically quantified using aggregate parameters. In AF these have included global measures of skilled performance, such as Champion Data player rankings (Dillon et al., 2017), coaches ratings (Sullivan et al., 2014) and a count of the total number of skilled actions completed by each player, termed involvements (Corbett et al., 2017).

Aggregating physical and skilled output presents multiple limitations. There are likely periods of altered physical and skilled output that are not captured by aggregate parameters. For instance, there are periods of physical output at a much higher intensity than that of an averaged entire game (Delaney et al., 2015). It is also difficult to determine distinguishable time points where output meaningfully changes (Corbett et al., 2017). By inference it is therefore problematic to use measures of physical and skilled output to inform decisions whereby time is expected to exert an influence.

By analysing physical and skilled output as a time series, a greater understanding of how physical and skilled output change within a match could be developed. However, this presents two challenges. The noise in the signal obtained from wearable technologies contains numerous erroneous data points (Coutts & Duffield, 2010). Physical output in an intermittent sport, for example AF, is likely to be too volatile (Varley, Fairweather, & Aughey, 2012) to identify meaningful changes on a per-second basis. This creates a dichotomy between the interest in identifying changes in physical output over time, and the need to maintain accuracy in measures taken.

Aggregating time-series in smaller windows, has partially overcome the volatility in physical output (Wundersitz et al., 2015). In professional AF and rugby league matches, average velocity and acceleration have been calculated for three, five and 10-minute windows (Delaney et al., 2015). A specific representation of the peak physical outputs in both sports, and the length of time these outputs are maintained, was identified. A method of automatically identifying segments within a time series, based on the mean and variance, may expand on this approach. This could allow for the aggregation of physical output over segments of non-uniform size and remove the need to manually select pre-defined time windows. Further, the computation of additional, custom built parameters may allow for a more detailed description of the time series. This could improve the specificity in which match output could be evaluated, and potentially improve training drill design (Corbett et al., 2017).

Time series segmentation or change point analysis, allows for computation of non-uniform segments from a time series. Time series segmentation algorithms are built upon the assumption that within a given time series, there are a number of change points. Thereafter, the behaviour of subsequent data points is inherently different to those before it (Piotr & Haeran, 2014). Users typically apply a penalty value, or specify the number of change points desired (Killick & Eckley, 2014), meaning, in a volatile time series such as team-sport physical output, the algorithm can be limited to a smaller number of aggregation windows (Piotr & Haeran, 2014). The hypothesised maximum number of change points in a velocity time series is unknown. Whilst a higher number of change points provides a more detailed summary of the time series through shorter aggregation windows (Cryer & Chan, 2008) differences between segmental features are likely to decrease.

Frequency domain analysis could be used to summarise players' physical output within segments. Features may include the shape of a signal, including skewness, kurtosis, flatness, entropy, the location of values within a signal, such as percentiles and spectral centroid (Fransz, Huurnink, de Boode, Kingma, & van Dieën, 2016) and customised features to describe the magnitude of values within a signal (Wundersitz et al., 2015). Frequency domain analysis has been applied for the purpose of movement classification (Wundersitz et al., 2015) and anomaly detection (Fransz et al., 2016). To help guide the number of change points selected, data mining classification methods can be used (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). By placing the features of segments extracted from a varying number of maximum change points into a classification algorithm, the trade-off between the uniqueness of segments and a heightened number of change points could be understood.

The first aim of this study was to identify the impact of change point number on the features of segments in Australian footballers' velocity time series. The subsequent aim of this study was to determine a method to identify an optimum number of change points to describe the velocity time series of Australian Rules footballers for general purposes.

4.3 Methods

4.3.1 Participants

Professional male athletes (n = 37, age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg) from an elite AF club provided written informed consent to participate in this study. All players completed at least one full match in the 2017 Home and Away Australian Rules Premiership season. Ethical approval was granted by the University Human Research Ethics Committee (Code HRE17-127).

4.3.2 Data Collection

Locational data was collected from 19 rounds comprising: 12 indoor matches and 7 outdoor matches (n = 19) during the 2017 Home and Away Season. For all matches, players were fitted with a 10 Hz Catapult T6 Local Positioning System (LPS) tag (indoor matches), or a 10 Hz Catapult S5 Global Navigation System (GNSS) device (outdoor matches). Both LPS and GNSS devices were worn in custom sewn pouches within players' jerseys. Both LPS and GPS systems have established acceptable validity and reliability in measuring the physical output of team-sport athletes (Coutts & Duffield, 2010; Luteberget, Spencer, & Gilgien, 2018). All matches were monitored live using proprietary software Openfield (Catapult Openfield v 1.11.2-1.13.1) to ensure an adequate signal quality of > eight packets/second and an average horizontal dilution of precision of 0.6-1.5. A comma separated value file of instantaneous data for velocity was cleaned to exclude time on bench, as well as quarter and half-time breaks. This was to allow velocity data for each player in each match to be analysed as a single continuous time series.

Skilled output was quantified via match involvements. An involvement was defined as any singular skilled action completed by a player (Corbett et al., 2017). An involvement could further be categorised as either offensive or defensive (Appendix A). Involvements were extracted from a timeline by a commercial sports statistics provider (Champion Data, Melbourne, Australia). This timeline includes each involvement that occurred in a match, along with the corresponding player and timestamp.

4.3.3 Time series analysis

Time series analysis methodologies are built upon the assumptions of stationarity, absence of seasonality and absence of trend (Cryer & Chan, 2008). Stationarity refers to the consistency of mean, variance and autocorrelation over time (Cryer & Chan, 2008). The Dickey-Fuller test for stationarity was applied to all velocity time series' and returned an average test statistic of -19.87, a lag order of 39 and a p-value of <0.01, suggesting the velocity time series was stationary (Tanaka, 2017). Seasonality refers to a time series, where data points periodically fluctuate at fixed intervals (Atchison, Berardi, Best, Stevens, & Linstead, 2017). Due to the uneven length of quarters in AF, the velocity time series' do not violate the assumption of seasonality. The inability of linear approaches in the literature to determine a linear change in physical output as a function of time within matches, demonstrates an absence of trend (Dillon et al., 2017). This suggests that instantaneous velocity files do not violate any of the assumptions for time series analysis and can be analysed without any transformations.

Change points were used to divide each players' velocity time series into a number of smaller segments. Preliminary change point analysis was conducted on each velocity time series. This included an unsupervised power of the pruned extract of time (PELT) change-point analysis, and a "change point for a range of penalties" (CROPS) analysis. CROPS analysis identified the impact of differing penalty values on change point quotient. These algorithms identified 1026 and 82 change points respectively per time series. Consequently, it was deemed necessary to limit the number of change points identified.

For this purpose, 15 trials of a binary segmentation algorithm were run, searching for between two and 16 change points. All change points were calculated in the R changepoint package, with an AIC penalty value of 0.01. Binary segmentation is the most widely used change point algorithm (Killick & Eckley, 2014). It functions by progressively dividing the data set into a series of smaller segments, until additional change points cannot be located (Killick & Eckley, 2014). It is computationally fast and has established validity within the literature (Piotr & Haeran, 2014).

4.3.4 Descriptive statistics

The peak three and five minute moving averages achieved by any player in each Round were calculated for metreage per minute, in line with previous literature (Delaney et al., 2015). Additionally, the peak segment based on metreage per minute, as well as it's corresponding segment number and duration was also obtained. This was done to compare the change point approach introduced in this study, with previously used moving averages to establish peak match intensities.

Pearson's product moment correlation was calculated between on-ground stint end time and change point location for every stint completed by every player. This was done to assess the relationship between on-ground stints and change point location.

4.3.5 Feature extraction

A fast Fourier transform was applied to the velocity time series'. The following frequency domain features were extracted using the seewave package (Sueur et al., 2016) in R; minimum amplitude, spectral centroid, maximum amplitude, spectral entropy, skewness, spectral flatness measure, kurtosis, standard error of mean (SEM) and the frequency precision of the spectrum, 25th percentile (Q_{25}), 75th percentile (Q_{75}) and interquartile range (IQR). An energy feature, designed to reduce multiple inputs from wearable technologies into a single metric (Wundersitz et al., 2015) was also extracted for each segment. Energy has been used to discriminate between different movement tasks, for the purpose of classification. Energy is defined in Equation 1.

Equation 1-- Equation for spectral energy where ai are the sum of the squared values for axes i (i = acceleration & velocity) and p = number of observations per axis (Wundersitz et al., 2015)

$$E = \sum^{3}{}_{i} = 1^{ai}/p \qquad (1)$$

To describe skilled output within each segment, two features were extracted from the Champion Data time series for each player in each match. These were; defensive action count and offensive action count.

4.3.6 Segment similarity

For 15 change point trials, a random forest was utilised to classify cases as segment number, using both spectral and involvement features. This was done to quantify the impact of increasing change point quotient (Q), on the similarity of features within each segment. The random forest in this study was created using the randomForest package in R (Liaw, 2015). To identify segment number, 70% of the data was used with the following features: Player Number, 25th percentile (Q_{25}), 75th percentile (Q_{75}), interquartile range, spectral centroid, skewness, kurtosis, spectral flatness measure, spectral entropy, spectral precision, segment duration (seconds) and energy. Each of these methods were then tested on the remaining 30% of the data, with the corresponding classification accuracy and confusion matrix computed. The results of a multidimensional scaling algorithm (MDS) were also utilised to visually demonstrate the impact of Q on segment similarity, based on an average value across all players, for each segment and feature.

4.4 Results

4.4.1 Change point locations

An example of the influence of change point quotient (Q), on the location of change points for a single player, is shown in Figure 4.1. For the purpose of visual comparison, change point quotients of; two (A), five (B), 10 (C) and 15 (D) are shown. This figure depicts the functioning of the binary segmentation algorithm, which progressively identified change points within existing segments. By increasing Q from two to five, additional segments were created within segments at the beginning of the match. As this increased from five to 10, additional segments were created towards the beginning and end of the match. When increased from 10 to 15, additional change points occurred midway through the match.

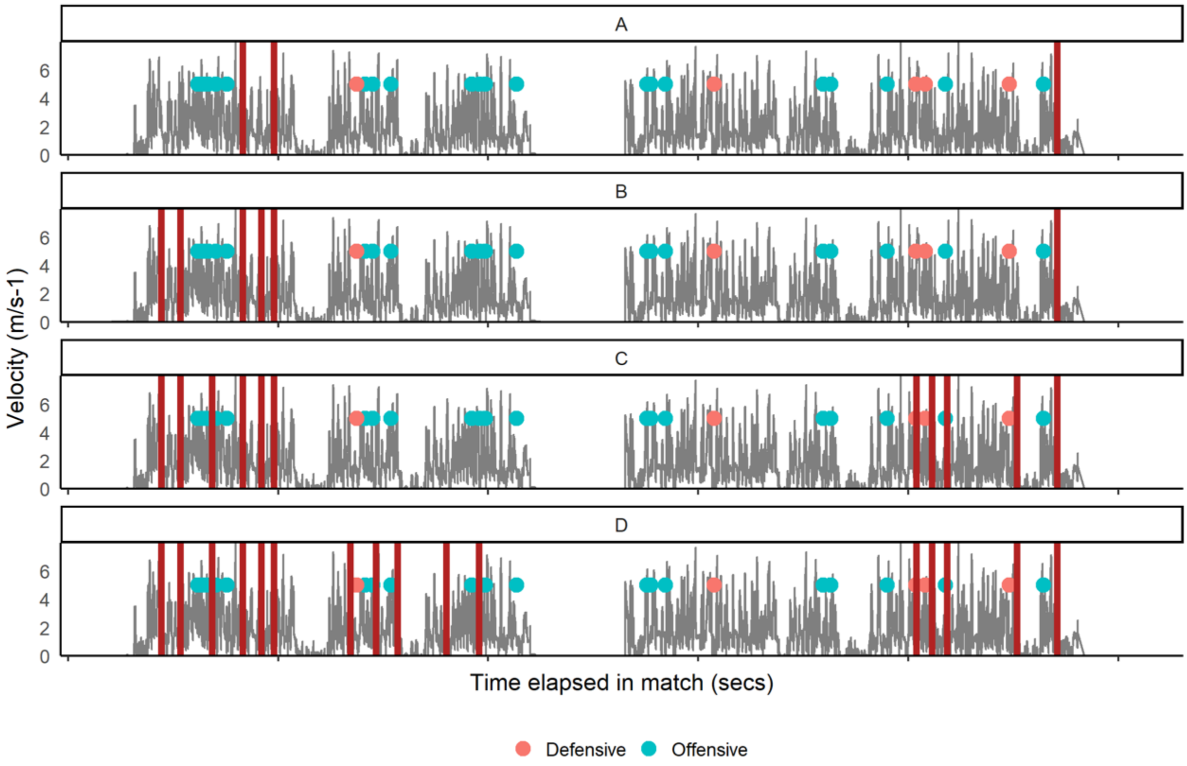

Figure 4.1—Example of the influence of change point quotient (Q) on the number and location of change points for a single player across a single match. A = Q of 2, B = Q of 5, C = Q of 10, D =Q of 15. Blue and red circles indicate offensive and defensive involvements, respectively. Fixed vertical lines denote change point location.

Change points locations within matches varied considerably between players. The average change point location, measured as on-field seconds lapsed within a match, is depicted in Figure 4.2. The majority of segments occurred towards the beginning of a match for some players (eg. Player 18), whilst others had a greater number of change points occurring towards the end of a match (eg. Player 12 and Player Seven). The change points for some players were relatively evenly spaced (eg. Player 14 and Player Five), whilst other players had a number of change points occurring in close proximity with one another (eg. Player Nine).

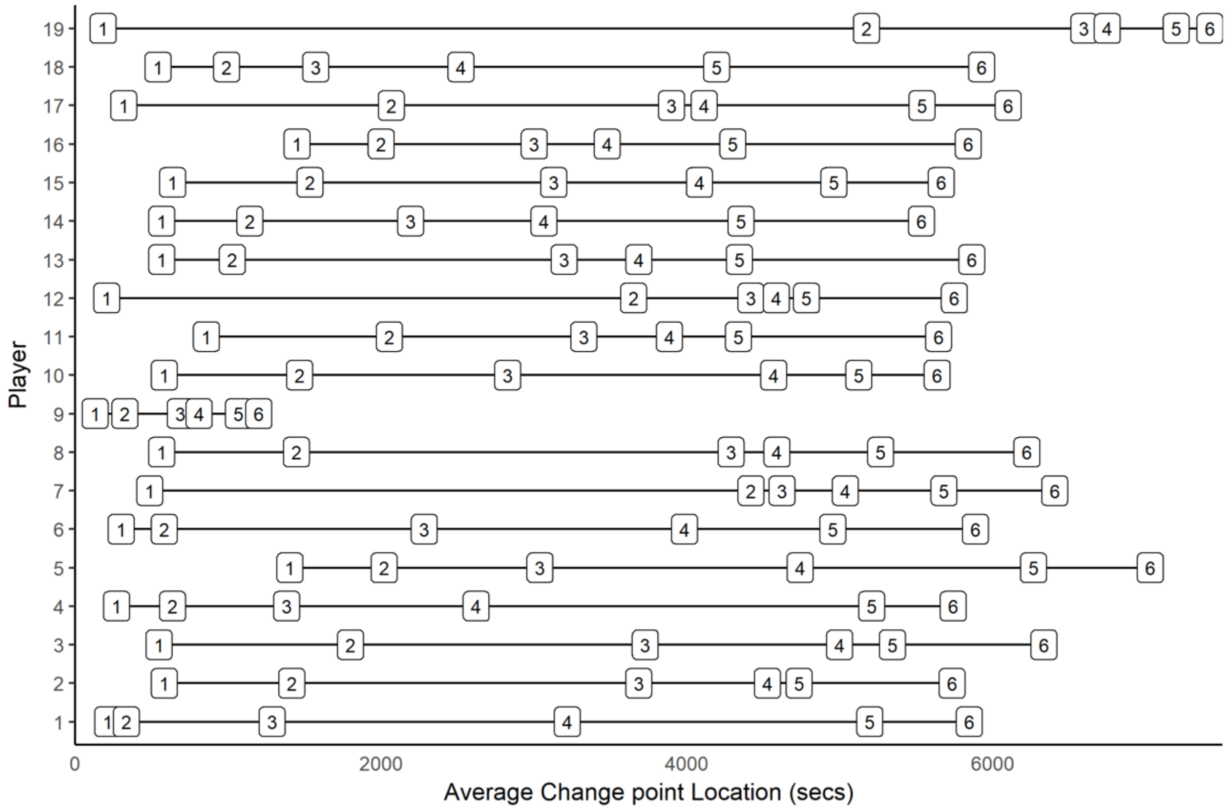

Figure 4.2— Average change point locations (Q = 5) for all players in the 2017 Home and Away Australian Football Season, shown as elapsed time on ground in seconds.

4.4.2 Descriptive statistics

The peak segment and its corresponding duration and metreage per minute for each Round is depicted in Table 4.1. This table also depicts the peak 3 and 5-minute moving averages attained by any player for metreage per minute by Round. In some Rounds, the change point method was able to detect segments with a higher intensity than the moving average method (ie., Round 8). In other instances, the change point method was able to detect a similar intensity to the moving average method, maintained for a longer period of time (ie., Round 1).

There were several Rounds, where peak intensity was lower than both 3 and 5-minute moving average intensities (eg., Round 15). Peak match intensities occurred at varying time points during the match. Furthermore, there was also only a weak relationship (r = 0.21) between segment location, and stint end time. This suggests physical output is independent of on-ground stints.

Table 4.1—Peak segment, peak segment duration, peak segment meterage per minute (MPM), 3-minute and 5-minute moving averages for meterage per minute (MPM) in each round

Round	Peak Segment	Segment duration (minutes)	Peak Segment MPM	3-minute moving average (MPM)	5-minute moving average (MPM)
1	1	6	193	206	194
2	2	4	212	239	218
3	3	3	197	211	191
5	4	4	211	221	207
6	2	7	208	210	208
7	3	6	197	238	217
8	2	3	213	212	195
9	6	4	192	197	183
10	1	6	194	216	196
12	1	3	204	206	185
13	1	5	199	223	197
14	4	4	201	208	195
15	1	4	176	206	190

16	3	6	178	200	182
17	5	3	195	210	195
18	3	5	201	209	195
19	1	6	182	217	204
20	5	3	174	198	185
21	5	5	191	221	206
22	4	4	201	208	195
23	3	3	207	217	201

4.4.3 Feature extraction

The distribution of values for six of the extracted features, for all players in all matches, in each of the segments (where Q = 5) is shown in Figure 4.3. The shape of distributions for spectral skewness, defensive action count and offensive action count also appeared similar regardless of segment, with minor discrepancies in values at the lower end of the distribution for each feature. The shape of the spectral energy and spectral flatness distributions appeared considerably different depending on segment.

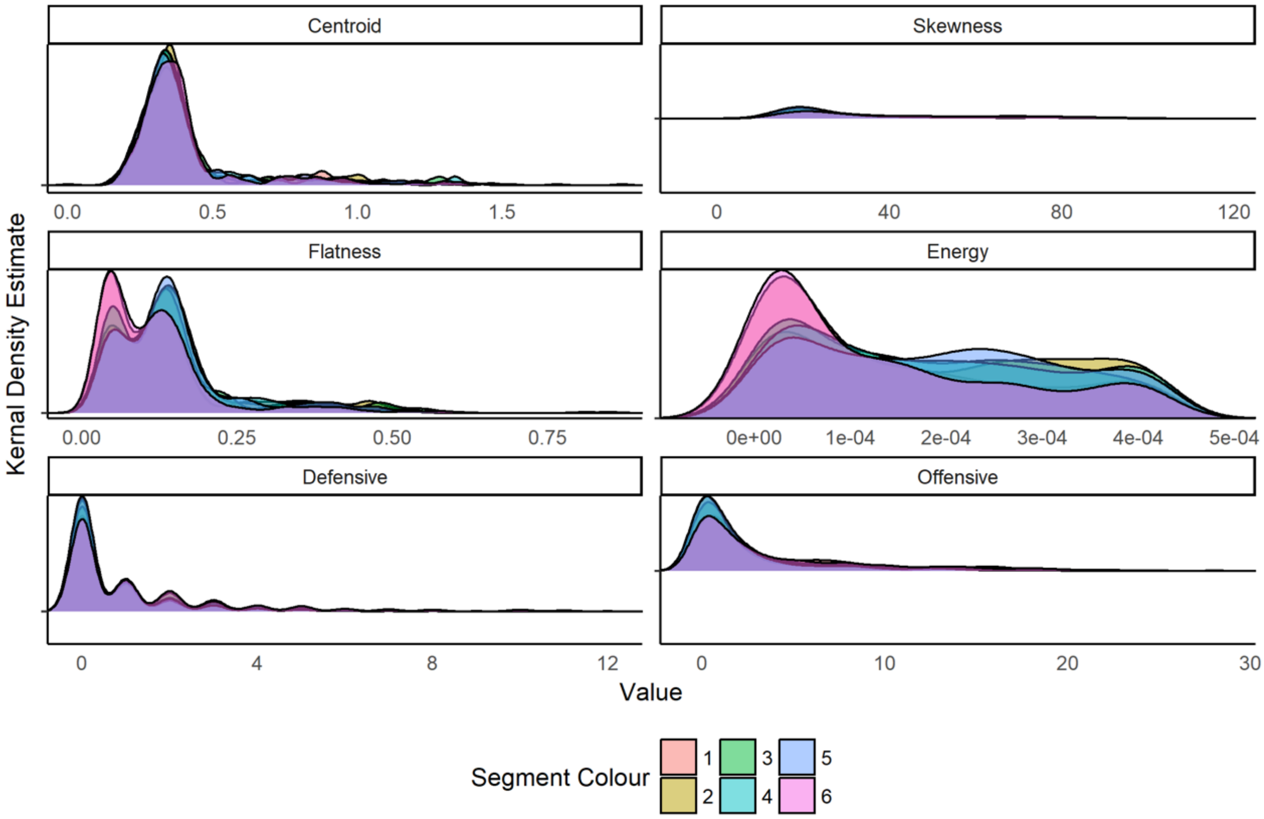

Figure 4.3— Distribution of values for six of the features, across all segments (where Q = 5), for all players in all matches in the 2017 AFL Home & Away season.

4.4.4 Segment similarity

The accuracy of the random forest in classifying segments through their features is shown in Figure 4.4. Where Q = 1, the random forest was able to classify segments correctly 64% of the time. This decreased linearly towards Q = 4/Q = 7, where the model was correctly able to classify segments 27% of the time. After this, there was a steady decline in the ability for the random forest to differentiate between segments through their features, reaching a classification accuracy of 14%, where Q = 15. This is reinforced by Figure 4.5, which demonstrates an increase in segment similarity as Q increases. For example, a smaller change point quotient (Q = 2) returned three distinct segments based on their feature, whilst a higher quotient (Q = 15), created 16 segments—most of which were closer together. When Q = 5, there were six segments, which were dissimilar to one another.

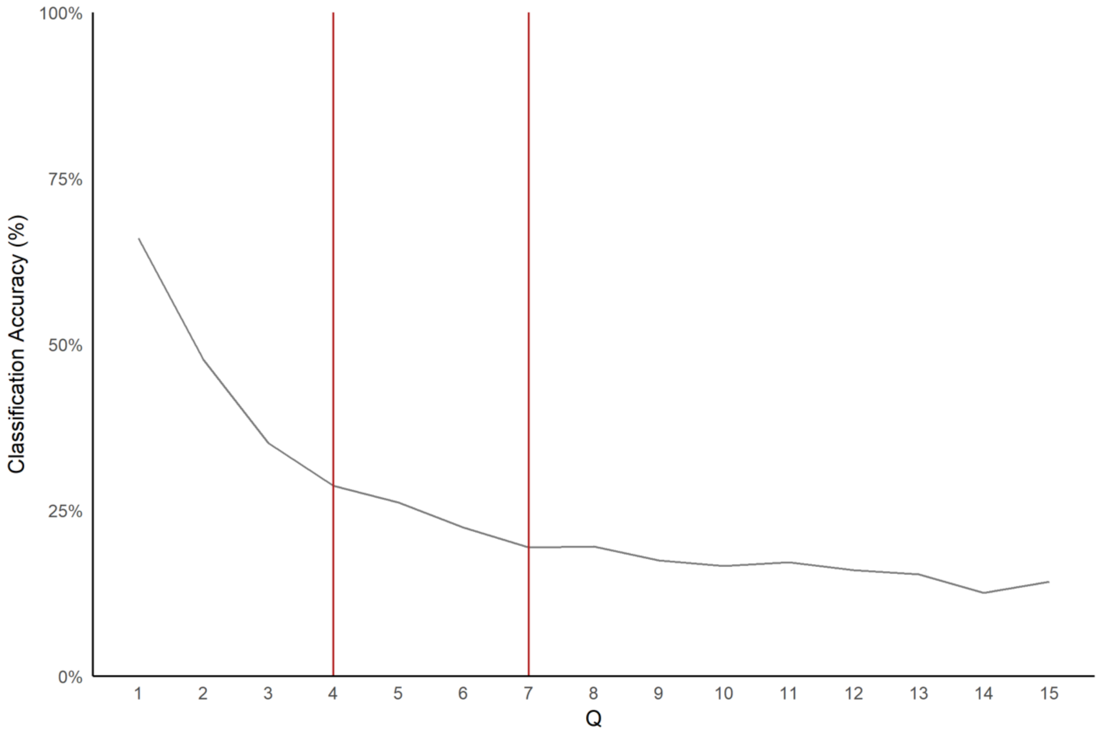

Figure 4.4—Scree plot, depicting classification accuracy of 15 random forest models, with a change point quotient of between 1 and 15.

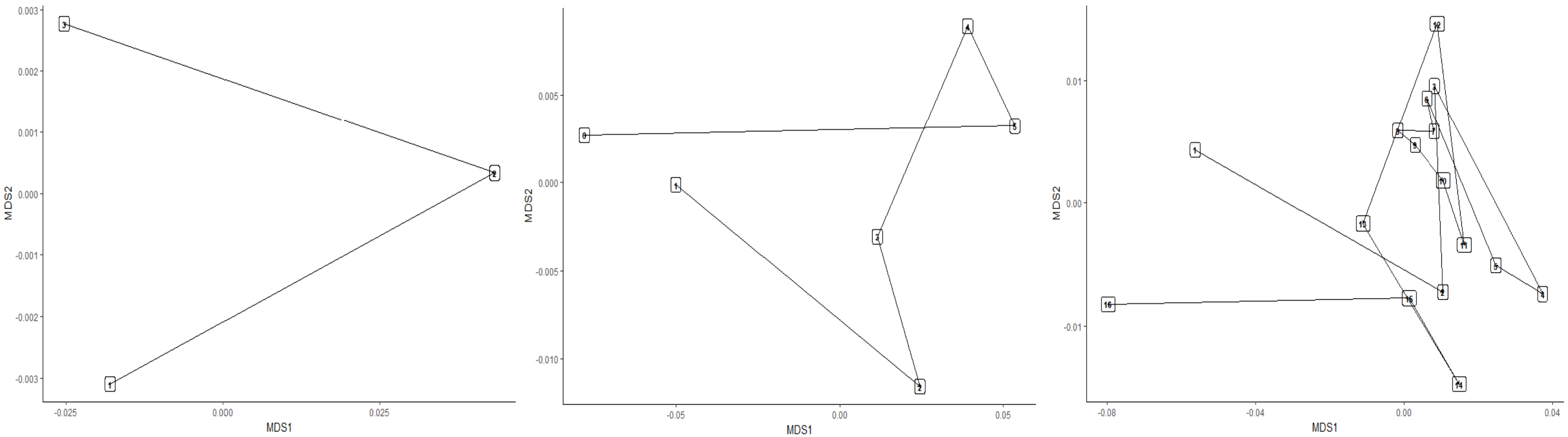

Figure 4.5—Similarity plots of the average features for each segment, with a change point quotient of 2 (left), 5 (centre) and 15 (right). Values were calculated using the average across all matches and players, for each feature in each segment, reduced to a single set of Cartesian coordinates using multidimensional scaling

Table 4.2-- Confusion matrix for final random forest (RF) classifications (where Q = 5)-- actual cases vs classified cases

		Predicted Class						
		1	**2**	**3**	**4**	**5**	**6**	**Overall %**
Actual Class	**1**	54	25	23	21	20	26	32
	2	15	31	20	23	22	20	24
	3	8	19	28	23	28	9	24
	4	13	23	25	26	19	20	21
	5	12	16	17	16	29	10	29
	6	30	21	19	19	22	45	29

4.5 Discussion

This study aimed to identify and describe segments of physical and skilled output in team-sport matches with an example in Australian Football. The physical output of team-sport athletes was split into between two and 16 segments and then summarised each of these segments using spectral features and a measure of skilled output. An advantage of this method is the ability to analyse outputs across a match, without having to specify fixed duration windows. By assessing segment similarity using a random forest model and multidimensional scaling, it was determined that between six and eight segments could be used to describe the physical output of team-sports athletes.

Whilst considerable research has utilised aggregated data over periods of equal length, this study utilised a binary segmentation algorithm which split the velocity time series of all players into between two and 16 unequal segments. Each of these segments was categorised by data points with a different mean or variance, compared to the previous or subsequent segment (Piotr & Haeran, 2014). These segments varied in their location and duration between players and had only a small relationship with on-field stint end time. This highlights the importance of analysing velocity data as a time series, as aggregating across quarters or on-field stints may not be sufficient when analysing changes in physical output.

By analysing velocity data across static windows, such as three or five-minute periods, details of potentially high or low periods of physical activity may be lost. Indeed, the change point algorithm often detected higher or similar peak match intensities as moving average windows. There were several instances where the change point algorithm extracted lower peak intensities than the moving average method. This is likely due to the algorithm used, which searched for a change in both mean and variance in velocity. This is in contrast to moving averages which summarise match intensity using only mean velocity or acceleration (Delaney et al., 2015). Additionally, this study was able to identify the time point at which peak match intensities occurred. This may be useful for practitioners wishing to increase the specificity of their training sessions to match demands (Al-Abood, Davids, & Bennett, 2001). For example, peak intensity segments occurred at varying points of the match. Therefore, it may be useful to reach these intensities during training at varying points of the session,

Spectral features were used to summarise the data points for every player's segments in all matches. Ridge plots for all players, were utilised to highlight the difference in distributions of each feature across six different segments. Whilst some features, such as spectral centroid (i.e., mean velocity within each segment) did not appear to change between segments, other parameters such as spectral energy and spectral flatness measure had different distributions depending on the segment. Spectral features are able to describe additional aspects of physical output, not currently captured by parameters such as work rate. These include; whether running was intermittent or more steady state (spectral flatness measure), how intensity was maintained across a segment (Q_{25} and Q_{75}) and how physical output was distributed across a segment (kurtosis and skew). These features may be utilised to give a greater understanding of how physical output is accrued in a segment. Whilst work rates such as metreage per minute are predominantly used in AF, these findings suggest that additional detail could be gained from velocity data by utilising spectral measures of variance.

Skilled output, measured through match involvements, showed no clear differences between segments. Consequently, they were the weakest features in the random forest model for classification. This highlights the dynamic nature of skilled actions in AF. Skilled output can be affected by many factors including the strategy of the opposing team, player roles, team composition and team form (Corbett et al., 2017; Woods et al., 2017).

Multidimensional scaling and similarity plots were used to combine spectral features and explore the similarity of segments for each player for four different change point quotients. These plots were useful in highlighting two phenomena. First, there was a trade-off between the number of change points selected, and the differences in features of each segment. For example, a change point quotient of two generated three distinct change points and a change point quotient of five generated six somewhat different segments. A quotient of 15, however, generated two clearly distinct segments, and 14 segments with relatively similar features. This suggests that increasing the change point quotient past a point is likely to yield a number of similar segments, which provide limited added detail over using a smaller number of change points.

To quantify the increasing similarity of segments as change point quotient increased, a series of random forest models were constructed. Spectral and involvement features were calculated for 15 different change point quotients, and the accuracy of the random forest to identify segment number through these features was calculated. As anticipated, the highest classification accuracy occurred where Q = 1. Between Q = 4 and Q = 7 signified an inflection point in the classification accuracy of the random forest models. In the random forest model, the strongest classification variables were measures of shape and spread, such as spectral flatness, kurtosis and the location of the 75th percentile of velocity. This highlights the ability of a change-point and frequency domain analysis, to describe phenomena which would be lost in aggregate parameters such as metreage per minute (Corbett et al., 2017; Dillon et al., 2017).

The differences between segments when a higher change point quotient is used are likely to be subtle (Piotr & Haeran, 2014). A very low number of change points, on the other hand, may provide a description of the velocity time series, that is no more detailed than aggregating across pre-determined windows such as a quarter or stint. When attempting to investigate changes in physical and skilled output over time, or when attempting to identify periods of high physical output, a single change point may provide a less detailed description of the time series, than aggregating across a pre-set window such as quarter or stint on ground. As a result, a quotient of five was ultimately selected to summarise the most unique periods of physical output for each player. This is because it provides a trade-off between providing increased detail of a time series (as visually inspected through the similarity plots), without generating segments that are unnecessarily similar to one another (as calculated from the random forest model). When examining sequences of physical output, change point quotient may be modified to provide a more granular description of the velocity time series.

There are numerous applications of the change point method to AF matches. Change points could be compared with changes in position, team strategy or on-field stints, to better quantify in-match output. Similarly, this method could be adapted to identify changes in physical and skilled output as a function of time, by identifying change points within on-field stints. To date, the literature has identified only a trivial-small relationship between physical output, skilled output and time (Corbett et al., 2017; Dillon et al., 2017; Ryan, Coutts, Hocking, & Kempton, 2017). However, this could possibly be due to the aggregate parameters utilised in all of these studies. By aggregating features or parameters across different segments, it may be possible to infer patterns, decrements or changes in physical output as a function of time.

The methodologies used in this study have applications in a team-sport training environment. Feature extraction has already been used to classify movements based on accelerometer and GPS inputs (Wundersitz et al., 2015). In the present study, feature extraction was used to provide a more detailed description of physical output than measures such as total distance or distance covered in velocity bands. At present, velocity bands are often heuristically chosen (Sweeting et al., 2017) or individualised by an external physiological factor, such as maximal aerobic sprinting score (Cummins et al., 2013). The features of spread used in this study (eg., Q_{25}, Q_{75}) could be used to develop bands based on how often players reach different velocities. These detailed measures may be useful in evaluating the specificity of training drills to match demands. In rehabilitation, for example, it is common practice for players' to complete a session in which GPS parameters in training resemble that of a match (Kelly & Coutts, 2007). By utilising these features, practitioners would have a greater understanding of whether players have completed a training session with similar match intensity (Delaney et al., 2015).

The methods utilised in this study could also be applied in sports where pacing is a key strategy. In track cycling, for example, the ability of athletes to increase or decrease their velocity at crucial moments in an event is a key strategic consideration. The change point methodology could be applied to the instantaneous velocity of such sports, to dissect opposition strategies, and to evaluate the strategy of a given athlete (Woods et al., 2017). Depending on the application, the change point quotient may be modified.

4.6 Conclusion

This study proposed a method to divide the velocity time series into a series of unequal blocks. For this study, a change point quotient of between five and seven was selected, as providing increased insight into the velocity time series, whilst identifying sufficiently different segments of play through their physical and skilled output. Differing change point quotients may be utilised, depending on the purpose of practitioners. These methods could be utilised to increase the sophistication of match profiling in team-sports, and in turn, could allow practitioners to clearly investigate the specificity of their training sessions in meeting match demands.

4.7 Acknowledgments

The authors wish to thank the athletes of the Western Bulldogs for their participation in this study.

4.8 Declaration of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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CHAPTER 5 – Study 3

“Profiling individual team-sport athlete physical and skilled output with frequency and time-series domain analysis”

This chapter is presented in pre-publication format of a recent submission to The Journal of Strength and Conditioning Research titled:

Corbett, D. M., Sweeting, A. J., & Robertson, S. Profiling individual team-sport athlete physical and skilled output with frequency and time-series domain analysis

5.1 Abstract

The aim of this study was to apply a combined time-series and frequency-domain approach to match profiling in team-sports. An exemplar player was selected from a professional Australian Rules football club. Physical output was measured using a Catapult S5 GNSS device (outdoor matches) or a Catapult T6 RFID device (indoor matches). Aggregate parameters (total distance; metreage per minute; high intensity running; very high intensity running) were calculated for an exemplar match and as an average across all matches. A binary segmentation algorithm was applied to the player’s velocity time series for each match to identify differentiated segments. Frequency-domain features were extracted across a match and for each segment, to describe physical output. Aggregate offensive actions and defensive actions were extracted to describe skilled output. *K*-means clustering was also used to classify segments through their physical and skilled output. Using aggregate parameters, the exemplar match was similar to historical data. The methods used in this study were able to identify differences between the exemplar match and historical data. These methods were also able to quantify change in physical and skilled output both within and between matches. This study identified differences within and between matches that were not apparent from aggregate parameters. These methods could

therefore be used, to increase the specificity of load monitoring and physical activity prescription in team-sports.

5.2 Introduction

In team-sports, physical and skilled output are typically described using aggregate parameters (Corbett, Sweeting, & Robertson, 2017; Cummins, Orr, O'Connor, & West, 2013). To quantify physical output, parameters such as total distance are used in addition to velocity bands which bin distance covered into an arbitrary number of thresholds (Sweeting, Cormack, & J., 2017). Similarly, skilled output is also often measured using parameters such as player rankings, player ratings and involvements (McIntosh, Kovalchik, & Robertson, 2018). These parameters are typically aggregated across an entire match, quarter, or on-ground stint (Corbett et al., 2017). Currently, aggregate parameters form the basis of within-player match profiling, which describes the total output completed by a player, as well as how output changes both within and between matches (Gray & Jenkins, 2010a).

Velocity bands aim to distinguish between distance covered at low, moderate and high intensities (Sweeting et al., 2017). However, the methods used to determine velocity bands, and thus, what constitutes high intensity, is contentious (Cummins et al., 2013; Sweeting et al., 2017). Even within the same team-sport, velocity bands vary considerably in the literature (Cummins et al., 2013; Sweeting et al., 2017). Standardised velocity bands may also under or over-estimate the intensity of a match for a given player (Cummins et al., 2013). Consequently, there is a dichotomy between ease of interpretation and the sophistication by which velocity bands describe physical output. This has led to a recent interest in promoting the individualisation of velocity bands. Methods used to individualise velocity bands have ranged from; machine learning algorithms applied to the raw velocity output of each player (Sweeting et al., 2017), to using physiological test results such as maximal aerobic sprinting scores as a threshold (Clarke, Anson, & Pyne, 2015; Gabbett, 2015). However, using a score derived from a continuous running protocol may not accurately reflect the non-linear, sporadic nature of team-sport physical output.

By binning total distance into velocity bands, aggregate parameters are limited in their ability to describe the velocities attained by each player (Liu, Hussain, Tan, & Dash, 2002). For example, “Very High Intensity Running” or “Sprinting” is a common velocity band used in Australian football, to describe all distance covered at > 25 km/hr^{-1} (Coutts, Quinn, Hocking, Castagna, & Rampinini, 2010). However, velocities completed by a player may be more heavily concentrated at either end of this band. This limits application from a training prescription perspective, when specifically preparing athletes for the demands of a match. Aggregate parameters also provide limited insight into how distance was accrued. For example, it is possible for continuous running to return the same metreage per minute as a number of high intensity efforts interspersed with stationary periods. Similarly, whilst velocity band efforts describe the number of times a player completes a bout of physical activity in each band, they do not identify the magnitude of duration of each effort (Brewer, Dawson, Heasman, Stewart, & Cormack, 2010).

Aggregated parameters are also limited with respect to their inability to describe changes in physical output over time (Dillon, Kempton, Ryan, Hocking, & Coutts, 2017). In team-sport, there is only a weak relationship between aggregate parameters and time (Corbett et al., 2018; Corbett et al., 2017; Dillon et al., 2017). Furthermore, aggregate parameters are unable to identify key time points where physical output changes for individual athletes (Corbett, Sweeting, & Robertson, 2019). As a result, match profiling currently has limited application for decisions related to time, such as the length of on-field stints relative to time on bench.

The abovementioned limitations have led to a recent interest in alternative methodologies. Corbett et al. (Corbett et al., 2019) proposed a combined time-series segmentation and frequency domain analysis approach to activity profiling for team sport athletes. Using time-series segmentation, the velocity time series of team-sport athletes were divided into four to seven segments of differing lengths per match. Individual match profiles were developed using frequency domain features, which describe the distribution of data points for each player. Additionally, the sophistication of profiling was increased by utilising frequency domain features to identify differences in physical and skilled output as a result of position. By using time-series segmentation to identify commonly recurring movement patterns for each player, changes in physical and skilled output over time could be analysed using frequency-domain features extracted from each segment (Tedesco, Urru, & O'Flynn, 2017).

The aim of this study was to utilise a combined time-series/frequency-domain analysis approach, to within-athlete match profiling in team sports. Specifically, to i) combine frequency domain features derived from positional data with skilled involvement-based features in order to develop individualised match profiles for team-sport athletes; ii) to identify a method to demonstrate how individualised profiles change within matches, iii) to identify a method to identify how individualised profiles change between matches and iv) to compare a combined frequency-domain and time-series approach to match profiling, with standard match profiling using aggregate parameters. It was hypothesized that a combined time-series/frequency-domain approach could integrate physical and skilled output features in match profiling. Further, it was hypothesized that this approach could highlight differences in match outputs which were not apparent from aggregate parameters.

5.3 Methods

5.3.1 Experimental Approach to the Problem

A combined time-series/frequency-domain analysis approach was applied to match profiling in team sports using a case study design. To measure physical output, an exemplar player was fitted with a Catapult T6 Local Positioning System (LPS) tag (indoor matches), or a 10 Hz Catapult S5 Global Navigation System (GNSS) device (outdoor matches) for all matches in the 2017 Home and Away season. Skilled output was quantified using match involvements. Time-series segmentation and frequency domain analysis was utilised to identify changes in physical output within a match. A *k*-means algorithm was then applied to these features, to identify changes between matches. Frequency domain characteristics were compared with aggregate parameters, to highlight differences in match output between the two approaches.

5.3.2 Subjects

A single professional male athlete from an elite Australian Rules football (AFL) club provided written informed consent to participate in this study. This player completed 19 matches in the 2017 Home and Away Australian Rules Premiership season. Ethical approval was granted by the University Human Research Ethics Committee.

5.3.3 Procedures

Locational (GNSS or LPS) data was collected from 12 indoor matches and seven outdoor matches (n = 19) during the 2017 AFL regular season for an exemplar player. Both GNSS and LPS devices have been validated in the literature to measure on-field athlete location (Sathyan, Shuttleworth, Hedley, & Davids, 2012). LPS and GNSS devices were worn in custom sewn pouches within the athletes' jersey. All matches were monitored live using proprietary software Openfield (Catapult Openfield v 1.11.2-1.13.1) to ensure an adequate signal quality of > eight packets/second. Instantaneous data for velocity was exported from Openfield for later analysis.

Involvements were extracted from a timeline by a commercial sports statistics provider (Champion Data, Melbourne, Australia). This timeline includes each involvement that occurred in a match, along with the corresponding player and timestamp. An involvement was defined as any singular skilled action completed by the player (Corbett et al., 2017). An involvement could further be categorised as either offensive or defensive (Appendix A).

For the exemplar player, a single match was selected. This was used to compare the athletes' aggregate parameters in a single match, with their historical data completed across all matches. This match was selected, due to it falling within one standard deviation of the mean for; total distance (m), total duration (minutes), metreage per minute ($m.min^{-1}$), total HIR (distance covered at velocities > 5.0 $m{\cdot}s^{-1}$) and VHIR (distance covered at velocities > 7.5 $m{\cdot}s^{-1}$). One standard deviation was selected, as values within this range are described as typical in the statistical literature (Wasserman, Casey, Champion, & Huey, 2017). Consequently, it was a typical match for the exemplar player, as defined through aggregate parameters.

5.3.4 Statistical analysis

Aggregate parameters were extracted for the exemplar player for each match. These parameters were; total distance (m), total duration (minutes), metreage per minute ($m.min^{-1}$), total HIR (distance covered at velocities > 5.0 $m{\cdot}s^{-1}$) and VHIR (distance covered at velocities > 7.5 $m{\cdot}s^{-1}$). These parameters were extracted as a means of comparing the combined time-series and frequency-domain approach proposed in this study, with match profiling using aggregate parameters. The following statistical features were extracted for each of the five parameters used in this study; minimum, 25th percentile, median, 75th percentile and maximum.

The velocity time-series did not violate any of the assumptions of time-series analysis (stationarity, seasonality and trend) and therefore was deemed suitable for analysis without any further transformation (Corbett et al., 2019). To identify a change in physical output over time, a binary segmentation algorithm was used with a change point quotient (Q) of five. A change point quotient (Q) of five was selected, as between five and eight segments have been shown as able to describe the velocity time-series whilst minimizing the similarity of segments (Corbett et al., 2019). A penalty value of 0.01 was applied, as assessed using the Aikake Information Criterion (AIC). A minimum segment length of five minutes was specified in order to reduce the sensitivity of the algorithm to brief high-intensity efforts.

Frequency-domain features were used to describe the velocity trace of the exemplar player. A fast-Fourier transform was applied to the velocity time-series of the participant. The following frequency domain features were extracted using the *seewave* package in R; minimum amplitude, spectral centroid, maximum amplitude, spectral entropy, skewness, spectral flatness measure, kurtosis, standard error of mean (SEM) and the frequency precision of the spectrum, 25th percentile (Q_{25}), 75th percentile (Q_{75}) and interquartile range (IQR). An energy feature, designed to reduce multiple inputs from wearable technologies into a single metric (Wundersitz et al., 2015) was also extracted for each segment. Energy is defined in Equation 5.1 (Wundersitz et al., 2015). All frequency domain features were extracted for both individual segments, and the participants' entire match.

Equation 5.1-- Equation for spectral energy where ai are the sum of the squared values for axes i (I = acceleration & velocity) and p = number of observations per axis (Wundersitz et al., 2015).

$$E = \sum^{3}_{i} = 1^{ai}/p \qquad (1)$$

To identify frequently recurring movement patterns, a *k*-means clustering algorithm was run using involvement and frequency domain features for the participant. Frequency domain features were selected based on their established ability to describe the following aspects of the velocity signal; central tendency (spectral centroid), range (interquartile range), shape (skewness, kurtosis, spectral flatness measure and spectral entropy), duration (seconds) and shape (spectral energy). The sum of offensive actions, and defensive actions were used as two involvement features to describe the skilled output of athletes. The *k*-means algorithm was run with between one and 30 cluster centres. This was done to minimize both the number of cluster centres and the number of outliers within each cluster. A scree plot of the within cluster sum of squares (WSS) of each trial as a function of *k* was computed. Based on visual inspection of the plot, six cluster centres were selected for use. For each cluster, player movement path charts were generated to provide context for the frequency-domain and involvement-based features utilised in this study. These paths display player position, depicted as X and Y for each time point in the segment, with the location where skilled actions occurred also displayed.

5.4 Results

5.4.1 Aggregate parameter profiling

An example of player profiling using aggregate parameters is depicted in Figure 5.1. The distribution of values attained for each parameter across a season are shown as a box and whisker plot. A black diamond is used to denote the value achieved for each parameter in the exemplar match. For this match, the player was slightly below their median value for duration, HIR distance, metres/minute and total distance. However, they were slightly above median for VHIR distance.

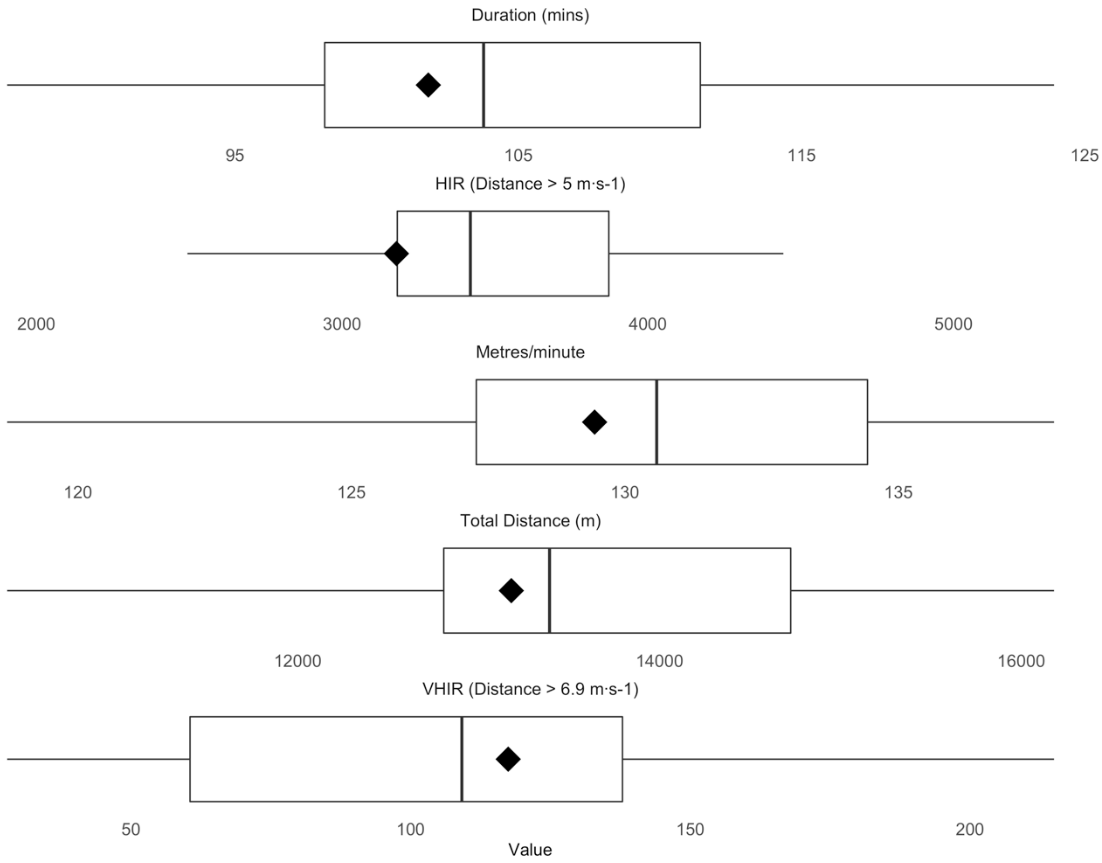

Figure 5.1 – A series of box and whisker plots, depicting how aggregate parameters of physical output may currently be reported in the field. Each plot shows the distribution of values achieved across the season for the exemplar player, for each parameter. The black diamond depicts the value achieved in the exemplar Round.

5.4.2 Frequency domain profiling

The frequency domain profile of the exemplar player is depicted in Figure 5.2. The exemplar match (white) is overlaid upon the total distribution of velocity for the player across the entire season (black). Data points in grey represent an overlap between the exemplar match and the player's historical data. At these data points, the player's historical and exemplar physical output were similar. A greater proportion of data points exist at ~ 2.5 $m \cdot s^{-1}$, and a slightly greater proportion of data points at ~ 5 $m \cdot s^{-1}$. This indicates that the player spent more time at these speeds more frequently than they typically would in a match. There were less data points between ~ 0 and 0.5 $m \cdot s^{-1}$, suggesting the player spent less time stationary than they would in a typical match.

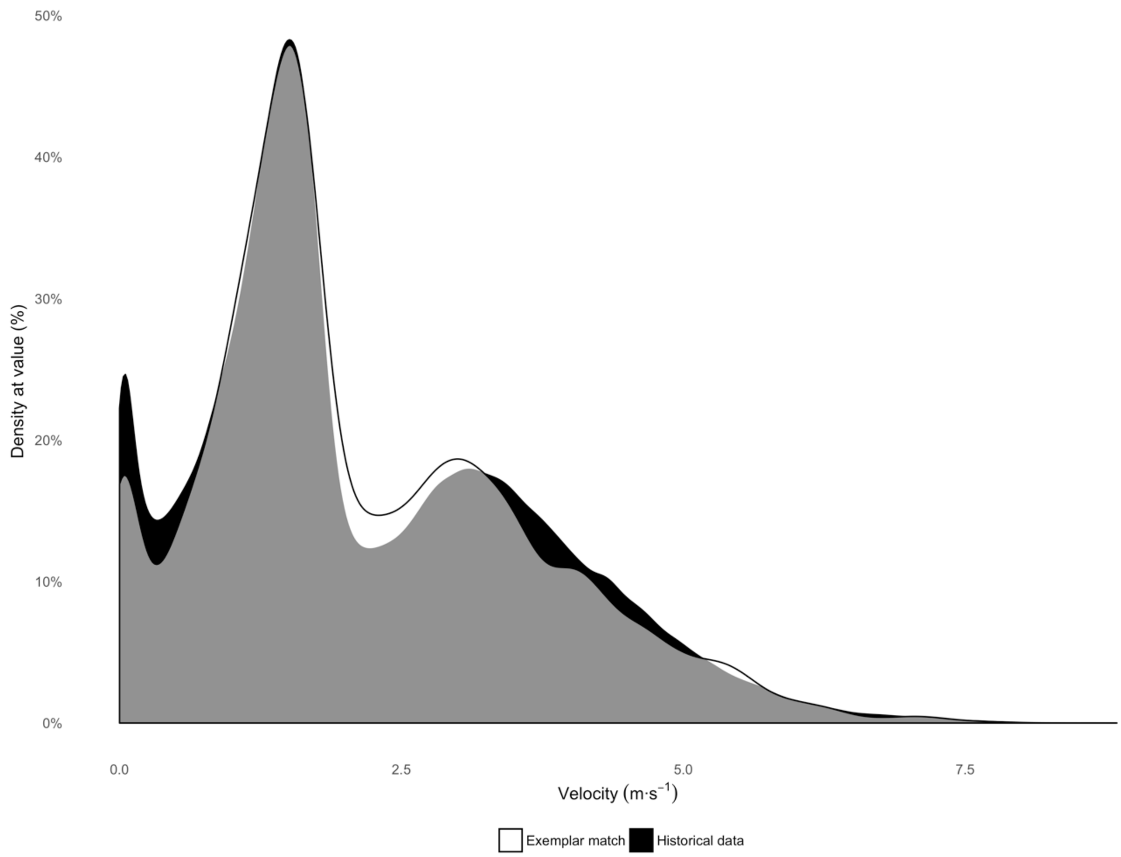

Figure 5.2 – A density plot depicting the frequency of data points recorded at each velocity across an entire match. The black density series is the distribution of velocity values across the entire season. The white density series is the distribution of velocity across the exemplar match. Data points in grey represent overlaps between the values of the exemplar match and values across the entire season.

The frequency domain profile for the player within each segment is shown in Figure 5.3. The first segment of the match had a similar velocity distribution to previous first segments in other matches. Segments Two, Three and Four had less data points > 2.5 m·s^{-1} (-12%, -1% & -16% respectively). Segment Three had more data points > 5.0 m·s^{-1} than previous third segments in other matches (+ 4%).

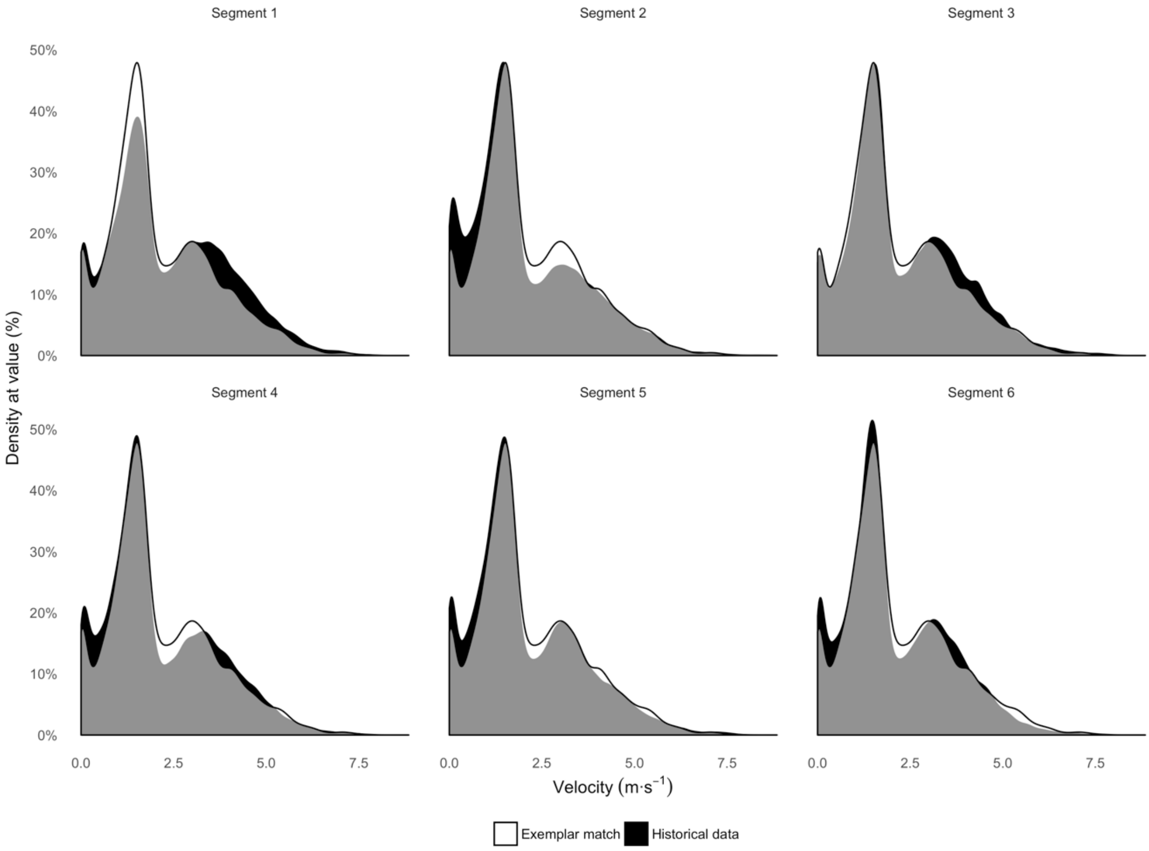

Figure 5.3 – A density plot depicting the frequency of data points recorded at each velocity within each segment. The black density series is the distribution of velocity values across the entire season for each segment. The white density series is the distribution of velocity across the exemplar match for each segment. Data points in grey represent overlaps between the values of the exemplar match and values across the entire season.

5.4.3 k-Means clustering

The results of the *k*-means clustering algorithm are depicted in Table 5.1. Cluster One had a small number of offensive and defensive involvements with moderate values for all frequency-domain features. Cluster Two typically had no defensive actions and a short duration, but all other frequency-domain features were moderate. Cluster Three had a relatively high number of offensive actions and the equal highest number of defensive actions. Cluster Three was also relatively long in duration, had the highest value for kurtosis and a moderate standard deviation. Cluster Four segments typically had no defensive actions and one offensive action. This cluster had a low interquartile range, the lowest standard deviation of any cluster and the lowest kurtosis. Cluster Five segments typically had the highest number of offensive and defensive actions, and the longest duration. They also had the highest standard deviation. Cluster Six segments had a small number of offensive and defensive actions, the lowest interquartile range and a low standard deviation. Six movement paths from Cluster Four are depicted in Figure 5.4. These segments had the shortest duration and included only a small number of skilled actions.

Table 5.1 – cluster centres for each feature used in the *k*-means clustering algorithm.

Cluster number	Standard deviation (SD)	Interquartile range (IQR)	Centroid	Skewness	Kurtosis	Spectral flatness measure	Duration (seconds)	Energy	Defensive actions/minute	Offensive actions/minute
1	0.85	0.41	0.44	39.28	1933.26	0.12	873	0.0001	0.07	0.21
2	0.87	0.55	0.49	30.89	1172.09	0.2	516	0.0001	0.03	0.2
3	0.84	0.28	0.4	57.85	4276.55	0.05	1983	0.0000	0.09	0.18
4	0.83	0.33	0.41	24.81	758.99	0.17	352	0.0001	0.06	0.18
5	0.95	0.58	0.54	73.67	7030.6	0.06	3295	0.0000	0.05	0.16
6	0.86	0.31	0.42	47.78	2877.93	0.06	1300	0.0000	0.07	0.15

The proportion of segments belonging to each cluster is shown in Figure 5.5. In the exemplar match (Round 16), all segments fell into Cluster One, Four or Five. This suggests, that for differing components of the match, the player had a comparatively highly variable velocity accompanied by periods of low defensive involvement. They also likely did not have an extremely high number of offensive and defensive involvements, or periods of lower variability, which define Cluster Two and Six respectively.

Figure 5.4—Six movement paths completed by the exemplar player, located in Cluster 4. Movement paths are drawn as the longitude and latitudes covered by each player for the duration of the segment. Darker portions of the path depict a higher velocity, whilst lighter portions depict a lower velocity. Skilled actions are annotated throughout the path, where HE = Handball Effective, T = Tackle.

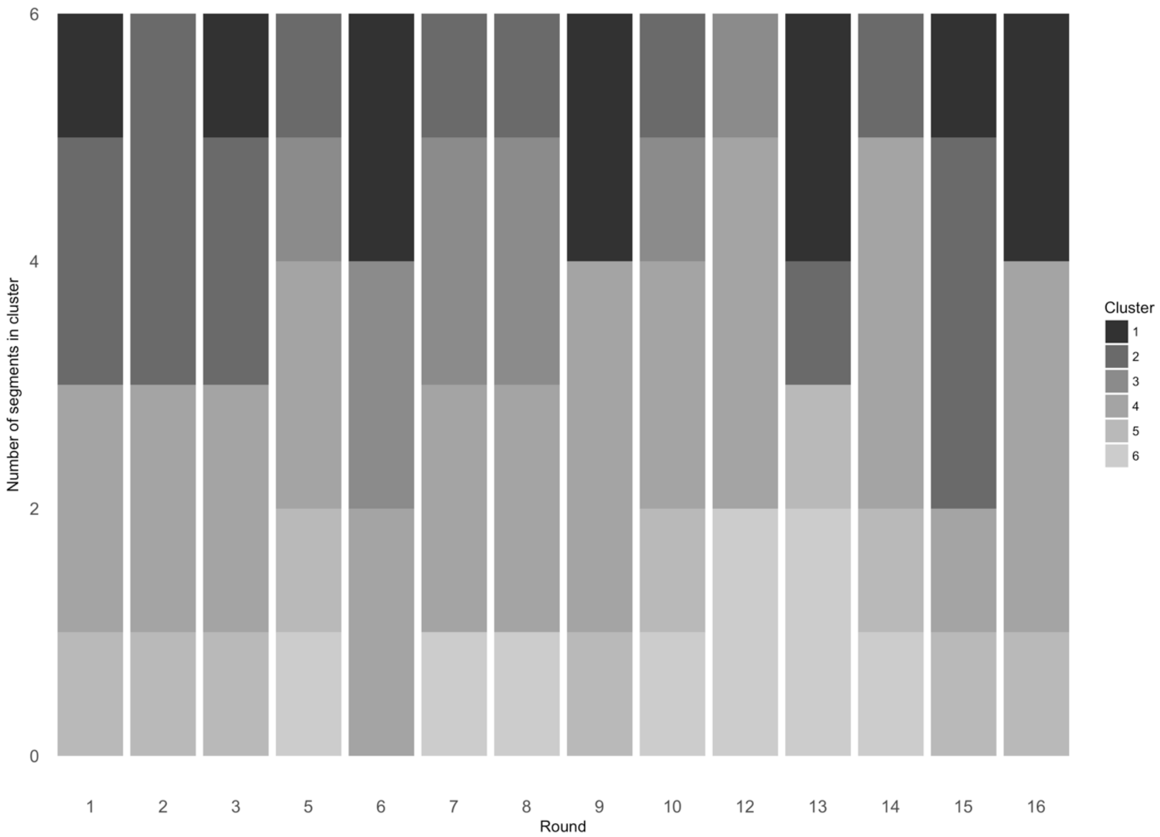

Figure 5.5—Stacked bar chart, indicating the proportion of segments within each cluster for the exemplar player.

5.5 Discussion

The aim of this study was to apply a combined frequency-domain/time-series approach to match profiling in team sports. Unlike profiling undertaken using aggregate parameters, this approach was able to identify changes in physical and skilled output within and between matches. A method was also developed to identify commonly occurring clusters of physical and skilled output within matches These results were visualised as movement paths to provide context to the values attained by the player.

A box and whisker plot compared a single athletes' data in an exemplar match across commonly used aggregate parameters. These parameters suggested that the athletes' physical output in the exemplar match was similar to historical match data. This is in line with literature, which has demonstrated low match-to-match variability (CV: 5.3 – 9.2%) in aggregated measures, such as total distance and meterage per minute (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015). As a result, individual athlete aggregate parameters suggest physical output remained consistent across different matches.

However, the frequency domain plots utilised in this study illustrate that dissimilarity in the player's physical output longitudinally may in fact be present. In the exemplar match, the player spent less time stationary (0 $m \cdot s^{-1}$) and spent a greater amount of time running at speeds between 2.5 $m \cdot s^{-1}$and 5.0 $m \cdot s^{-1}$. Whilst the parameter, high intensity running, suggested that the player completed less volume at higher velocities, the approach used in this study suggests that the match was not necessarily of a lower intensity for the player, comparative to the norm. This reflects the limitations of binning velocity data points into a number of arbitrary bands (Sweeting et al., 2017). By viewing velocity as a continuous variable, match intensity can be described without pre-determining velocity thresholds. As a result, the method in this study was able to identify differences in physical output between matches, which have not been found when using aggregate parameters (Kempton et al., 2015).

The use of a time-series segmentation, to the physical output of team-sport athletes was a novel application presented in this study. The method used in this paper compared a player's physical output of different segments of a match, with segments occurring at similar time points in previous matches. This revealed segments where the player had a higher physical output than they had in previous games. For example, the player had a greater number of data points in their third and fifth segments, at speeds > 5 $m{\cdot}s^{-1}$. Consequently, the exemplar player ran at fast velocities at various segments in the match. This finding expands upon previous research identifying peak intensities across various football codes (Delaney et al., 2015), by identifying intensities at specific time points. Additionally, the methods in this study did not require fixed or pre-set durations, to analyse change over time. As a result, this method can be utilised to identify not only a peak physical intensity, but the duration at which the athlete maintains that intensity for. This may be useful when setting benchmarks of physical output for players to achieve during training (Delaney et al., 2015).

Alongside the change-point algorithm used, *k*-means clustering allowed for segments of movement to be classified through both their time elapsed within a match, and their physical and skilled output. By visualising the results of *k*-means clustering as movement paths, context was given to explain how the player achieved their frequency-domain and involvement-based features. This is able to describe various movement paths such as linear running, running with a change of direction and running whilst completing skilled actions. This gives insight into the non-linear output of a match, where inertial parameters may be inaccurate (Akenhead, French, Thompson, & Hayes, 2014). Practitioners may utilise these movement paths, to develop conditioning drills which best replicate match demands through not only their physical output, but also through their running paths.

Changes in the number of segments belonging to each cluster, can be utilised to identify differences in a player's physical and skilled output between matches. For example, in the exemplar match, the player did not have any Cluster Six segments, which are typified by a low standard deviation of velocity data points, but had a higher number of Cluster Four segments, which had the lowest range and standard deviation. This suggests that the player completed more steady-state running than they would in a typical match. These findings have not previously been discussed in the literature because match profiling strategies aim to describe physical and skilled output as a whole, without identifying the ways in which athletes achieve these outputs (Gray & Jenkins, 2010b). This method allows users to easily identify deviations in the physical and skilled output of athletes between matches without requiring pre-set velocity bands.

This study applied a combined time-series/frequency-domain approach, to match- profiling in team sports. By doing so, it was able to identify differences—both within and between matches—that were not apparent from aggregate parameters. These methods could therefore be used, to increase the specificity of load monitoring and physical activity prescription in team-sports.

5.6 Practical Applications

The match profiling methodology presented in this study, may be practically useful in two ways. First, it allows for more detailed monitoring of the physical and skilled output completed by athletes. The methods presented in this study are able to identify; periods of high physical output late in a match, the movement paths completed by athletes and differences between matches. This may give insight into difficult matches for a player, despite seemingly typical aggregate parameters. Secondly, by clearly outlining the typical physical and skilled output of a player, practitioners are able to increase the specificity of their exercise prescription to match demands (Izquierdo, Häkkinen, Gonzalez-Badillo, Ibanez, & Gorostiaga, 2002; O'Keeffe, Harrison, & Smyth, 2007; Reilly, Morris, & Whyte, 2009). Further research may utilise frequency domain and time-series analysis, to increase the sophistication of between-athlete match profiling.

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CHAPTER 6 – Study 4

‘Methods for prescribing drill sequence, specificity and difficulty in team-sport training using player physical output”

This chapter is presented in pre-publication format of a recent submission to The Journal of Sport Sciences titled:

Corbett, D. M., Sweeting, A. J., & Robertson, S. Methods for prescribing drill sequence, specificity and difficulty in team-sport training using player physical output

6.1 Abstract

Team sport athlete training sessions are typically designed relative to the requirements of competition. However, the design of training, including drill order and length, is often determined heuristically. Further, examining only aggregate parameters, such as average metres per minute during a training drill, provides limited insight into the movement paths performed by athletes. Subsequently, designing drill order, specificity and difficulty is challenging based on current methodology. Therefore, the aim of this study was to describe how a time-series and frequency-domain approach can be applied to assess the order, specificity and difficulty of team-sport training drills. Positional data was collected via wearable technology devices for n = 37 elite Australian football athletes during 19 matches and 30 training sessions, across a season. A method was applied to sequence training drills, based on their specificity to physical output at different stages of a match. The challenge point framework was then adopted to inform training drill duration, based on the mean and variability of athlete velocity. The movement paths performed by athletes were also used to evaluate the similarity of sprinting in training sessions and

matches. Together, these methods could be utilised by practitioners to provide an evidence base for decisions related to training drill prescription.

6.2 Introduction

Team-sport athletes perform training drills on a weekly basis (Corbett et al., 2018). However, excessively long sessions and/ or drills are detrimental, given physiological and cognitive fatigue limit the effectiveness of training (Donovan & Radosevich, 1999). Consequently, it is important to design training drills and subsequently, sessions, that maximise the opportunity for athletes to improve cognitive capacity, including decision making (Passos, Araújo, Davids, & Shuttleworth, 2010), skill and physical performance, including aerobic capacity (Reilly, Morris, & Whyte, 2009). Therefore, the planning and design of training drills and sessions is an important yet often time-consuming responsibility of coaches and high-performance staff.

A key consideration in team-sport training design is drill difficulty (Farrow & Robertson, 2017). Training drill difficulty can be determined by considering the interaction between cognitive effort, physical fitness, skill level and task or environmental constraints (Farrow & Robertson, 2017). Consequently, difficulty may be related to an athlete's ability to maintain physical or skilled output in a drill (Aughey, 2010b; Bradley & Noakes, 2013). The challenge point framework explains the relationship between task difficulty and the learning benefit of athletes (Guadagnoli & Lee, 2004; Guadagnoli & Lindquist, 2007). Used extensively to design motor tasks (Guadagnoli & Bertram, 2014), a challenge point during human movement could constitute the location after which, learning by an athlete begins to diminish. Given the systematic quantitative monitoring of training drills in elite team-sport, this framework could also be applied in the high-performance sport setting (Farrow & Robertson, 2017). A potential application of the challenge point framework is the determination of training drill length, based on athlete physical output. Here, a challenge point framework could be identified using changes in the expected or actual velocity of a team-sport athlete within a training drill. The physical parameters, including changes in total distance or high-speed running, could then be compared pre- and post-challenge point to identify changes in physical output over time. However, this application is yet to be applied to the physical output of a team-sport athlete within and across training drills.

Another key decision in the design of team-sport training is drill order or sequencing (Donovan & Radosevich, 1999). The sequence of training drills performed by athletes within a session influences subsequent physical output (Sánchez et al., 2018). For example, drills placed at the end of training sessions typically have less total distance and high intensity running, than if they were performed towards the beginning (Sánchez et al., 2018). The learning effect gained from each drill is subsequently impacted by drill sequence (Reza, Samaneh Miar Abase, & Masoomeh, 2018). A framework that may be useful to determine drill sequence is representative task design (Pinder, Davids, Renshaw, & Araújo, 2011), whereby drills would ideally be ordered based on the similarity and timing of physical and skilled output to a match. In this setting, representativeness becomes analogous to physical specificity; a term used to describe how closely a training stimulus resembles match outputs on a metabolic and mechanical level (Cronin, McNair, & Marshall, 2001; Reilly et al., 2009; Tremblay & Proteau, 1998). Utilising this approach would allow high-performance staff to further increase the specificity of a training session beyond drill selection.

In team-sports, athlete physical output during training and matches can be quantified via wearable technologies, including global and local positioning systems (Corbett, Sweeting, & Robertson, 2017). Typically, aggregate parameters including total distance covered and meters per minute will be examined within and across training drills. However, examining only aggregate parameters such as total distance is problematic, because they do not describe how physical output changes within a training drill, session or match (Corbett, Sweeting, & Robertson, 2019). Further, the features of smaller physical actions, including sprints, cannot be described using aggregate parameters (Corbett et al., 2019). Recently, the physical output of team-sport athletes has been analysed as a time series, via simple moving averages (Delaney et al., 2015). Although simple moving averages can identify peak physical output, they do not identify how athletes attain this peak (Carling, McCall, Harper, & Bradley, 2018). For example, steady state running and repeat sprint efforts may attain the same physical output using simple moving averages (Carling et al., 2018). Given moving averages do not describe the temporal occurrence of peak physical output and require pre-determined aggregation windows (Carling et al., 2018), they are limited in their ability to identify change in physical output over time. Subsequently, research examining how match physical output can be replicated in training is often limited to match simulation and small-sided game style drills (Carling et al., 2018).

A combined time-frequency approach may overcome many of the limitations associated with simple moving averages. Corbett et al. (2019) proposed a combined time-frequency approach to analysing physical output in team-sports. Using a change point algorithm, differing segments of match physical output were analysed. Each segment's characteristics were then described using frequency domain features (Corbett et al., 2019). Using this approach, drill order or sequence could be determined by identifying the similarity of match features to drills. A challenge point for each training drill could then be identified via examining how frequency domain features change over time. By also visualising athlete trajectories, or plots of athlete positional data over time as represented on a playing surface, the specificity of drill movements to match output could be further evaluated on a more granular level.

The aim of this study was to describe how a time-series and frequency-domain approach can be applied to athlete physical output, to assess the sequence, specificity and difficulty of team-sport training drills. Specifically, to i) develop a drill sequencing system, through the specificity of drills to match outputs ii) identify a method to identify physical challenge points for each drill iii) identify a method to evaluate the specificity of movement paths within training drills, to matches.

6.3 Methods

6.3.1 Participants

Professional male athletes (n = 37, age: 23 ± 4 years, height: 187 ± 8 cm, mass: 86 ± 9 kg) from an elite Australian Football (AF) club provided written informed consent to participate in this study. All players completed at least one full match in the 2017 home and away Australian Rules Premiership season. Ethical approval was granted by the University Human Research Ethics Committee (Code HRE17-127).

6.3.2 Data Collection

Positional data was collected from 12 indoor and 7 outdoor (*n* = 19) matches and 30 outdoor training sessions during the 2017 home and away season. For all indoor matches, participants wore a 10 Hz Local Positioning System (LPS) device (Catapult T6) in a custom sewn pouch within the athlete's playing jumper. During outdoor matches and all training sessions, a 10 Hz Global Navigation System (GNSS) device (Catapult S5) was worn as above or housed in a pocket within a custom designed vest. The LPS and GNSS systems have established acceptable validity and reliability in measuring the physical output of team-sport athletes (Coutts & Duffield, 2010; Luteberget, Spencer, & Gilgien, 2018). All matches and training sessions were monitored live using proprietary software (Catapult Openfield v1.11.2-1.13.1) to ensure an adequate signal quality of > eight packets/second and an average horizontal dilatation of precision between 0.6 to 1.5. A comma separated value file of instantaneous velocity data was exported from Openfield for analysis.

6.3.3 Match analysis

Given instantaneous velocity files do not violate any assumptions of time-series analysis, a change point approach can be used to divide an athlete's velocity trace into a number of smaller segments. Periods of inactivity due to interchanges (matches) and coach instruction (training) were removed to create a continuous velocity time-series for analysis. To identify the different segments of an athlete's instantaneous velocity during matches, via change point analysis, the binary segmentation algorithm was used in the present study. This algorithm and the subsequent methodology are described in Chapter Four. Briefly, binary segmentation is a widely used change point algorithm, which progressively divides a data set into smaller sections until the number of change points is exhausted (Killick & Eckley, 2014).A change point quotient (Q) of five was utilised, as this can best describe the velocity time-series whilst minimising the similarity of segments (Corbett et al., 2019). A penalty value of 0.01 was applied, as assessed using the Aikake Information Criterion (AIC).

Frequency domain features were extracted for each individual segment, of an athlete's trace, using the *seewave* package in R (Sueur et al., 2018). Features included minimum amplitude, spectral centroid, maximum amplitude, spectral entropy, skewness, spectral flatness measure, kurtosis, standard error of mean (SEM) and the frequency precision of the spectrum, 25th percentile (Q_{25}), 75th percentile (Q_{75}) and interquartile range (IQR).

6.3.4 Drill sequencing

Frequency domain features were also extracted for each training drill. To determine the similarity of training drills to segments of athlete physical output during a match, a similarity matrix was calculated. This was achieved by condensing the frequency domain features of drills and match segments for all players, into a single similarity metric. Euclidean distance was chosen, as it is valid and widely reported in the literature (Singh, Yadav, & Rana, 2013). Euclidean distance is the square root of the sum of squared distance between each feature, for each training drill to each match segment. The drill with the lowest mean Euclidean distance across all players was then selected for each match segment. The following constraints were also applied; the drill was not match simulation, the drill had not occurred previously in the session and the drill was not solely conditioning based. The distribution of velocity values for match segments and sequenced drills for an exemplar player were visualised for the purpose of this study.

6.3.5 Drill challenge point analysis

To determine a challenge point for each training drill, a secondary change point analysis was run to identify the largest change in mean and variability of velocity for each training drill, for each athlete. This was done to account for the intermittent nature of training drills in team-sports (Corbett et al., 2018). A change point quotient (Q) of one was selected, given there is a single challenge point before athlete learning and performance begins to diminish (Guadagnoli & Lee, 2004). To identify changes in physical output, frequency-domain features were calculated for the pre-challenge point (Segment 1) and post-challenge point (Segment 2), for each athlete in each training drill. Mean challenge point location and frequency-domain features were then calculated across the wider cohort, for each drill.

6.3.6 Drill movement path analysis

To analyse the specificity of very high intensity movement paths within match simulation drills to match output, each player's 99th percentile (Q_{99}) of velocity was heuristically selected as a threshold (Pintelon & Schoukens, 2012). This is in-line with other frequency domain research, which often utilises data points in the 95th or 99th percentile as a feature (Pintelon & Schoukens, 2012). Movement paths were defined as the X-Y coordinates of a player within an effort. An effort was defined as the five seconds leading up to, including and following distance covered in the players' 99th percentile of velocity. A five second threshold was heuristically chosen after visualising bout thresholds of between one and ten seconds. Instances where a player decelerated, before again covering speed in their 99th percentile of velocity in the five seconds following the initial bout, were included as a single effort. The results for a single player were visualised to compare high intensity movement paths in matches with match simulation.

6.4 Results

6.4.1 Drill sequencing

The mean Euclidean distance of each training drill to each match segment is shown in Appendix 1. Drills were optimized to have the lowest mean Euclidean distance for each match segment to inform drill sequence. Figure 6.1 depicts drills sequenced through their similarity to match segments. The density plots in a) demonstrate how velocity changes for a player in a given match. The density plots of drills in b) have been sequenced to minimise their Euclidean distance from each match segment. All drills follow a similar distribution to their respective match segment. In the drills; *Full Ground Bulldog Ball*, *1v1* and *Ball Security Circuit*, players spent more time at 0 $m \cdot s^{-1}$, than in their respective match segments.

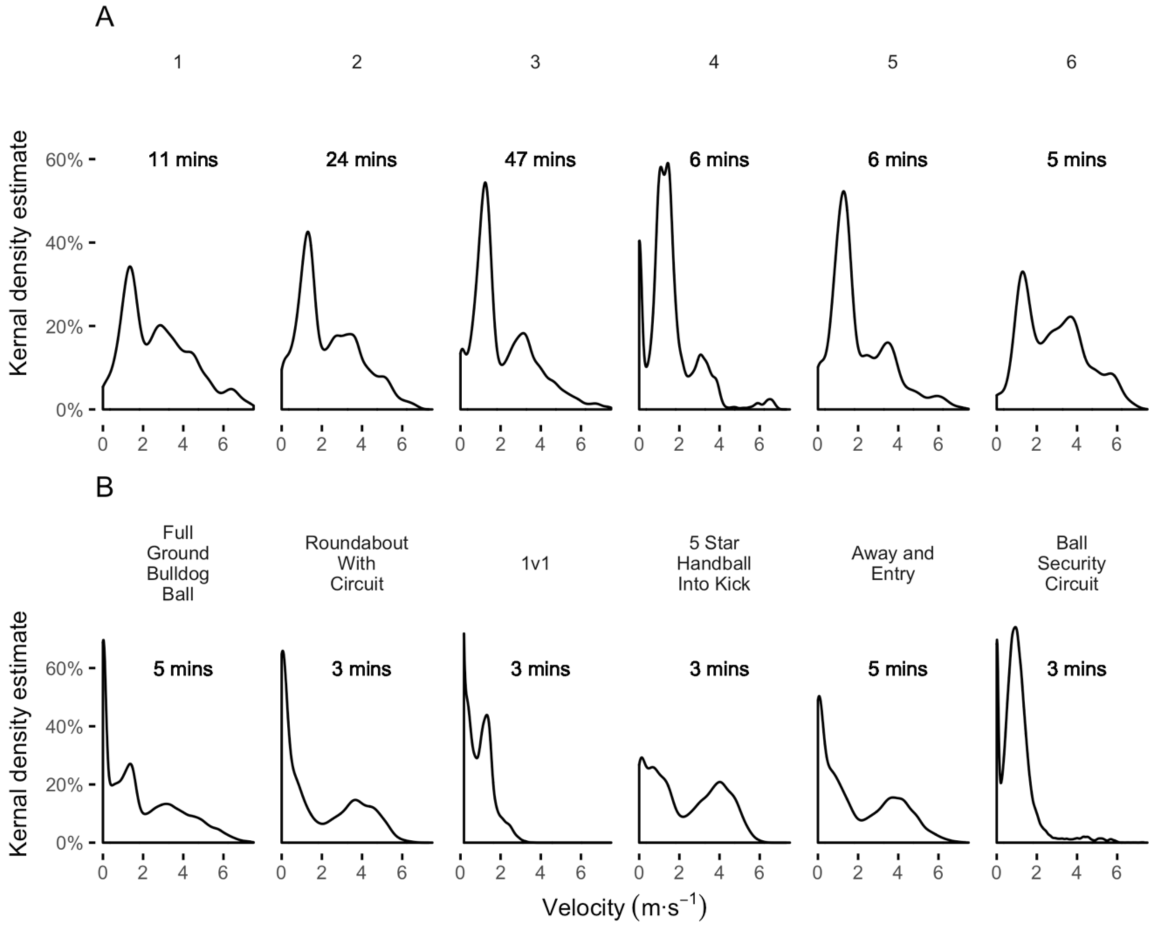

Figure 6.1-- A density plot depicting the relative frequency of data points recorded at each velocity in match segments (A), and drills selected through their Euclidean distance to each match segment (B). Data is for a single player.

6.4.2 Challenge point analysis

Figure 6.2 depicts the average length of 10 frequently recurring training drills. Additionally, it shows the location of the challenge point, which divided velocity data points into two segments. Challenge point location is also expressed as a percentage of drill length. Challenge point location varied considerably depending on drill. For example, in *Cascade Handball*, the challenge point occurred with less than one-minute remaining in the drill. In *3 Kick Variation,* the challenge point occurred more than halfway through the drill, with six minutes until drill completion.

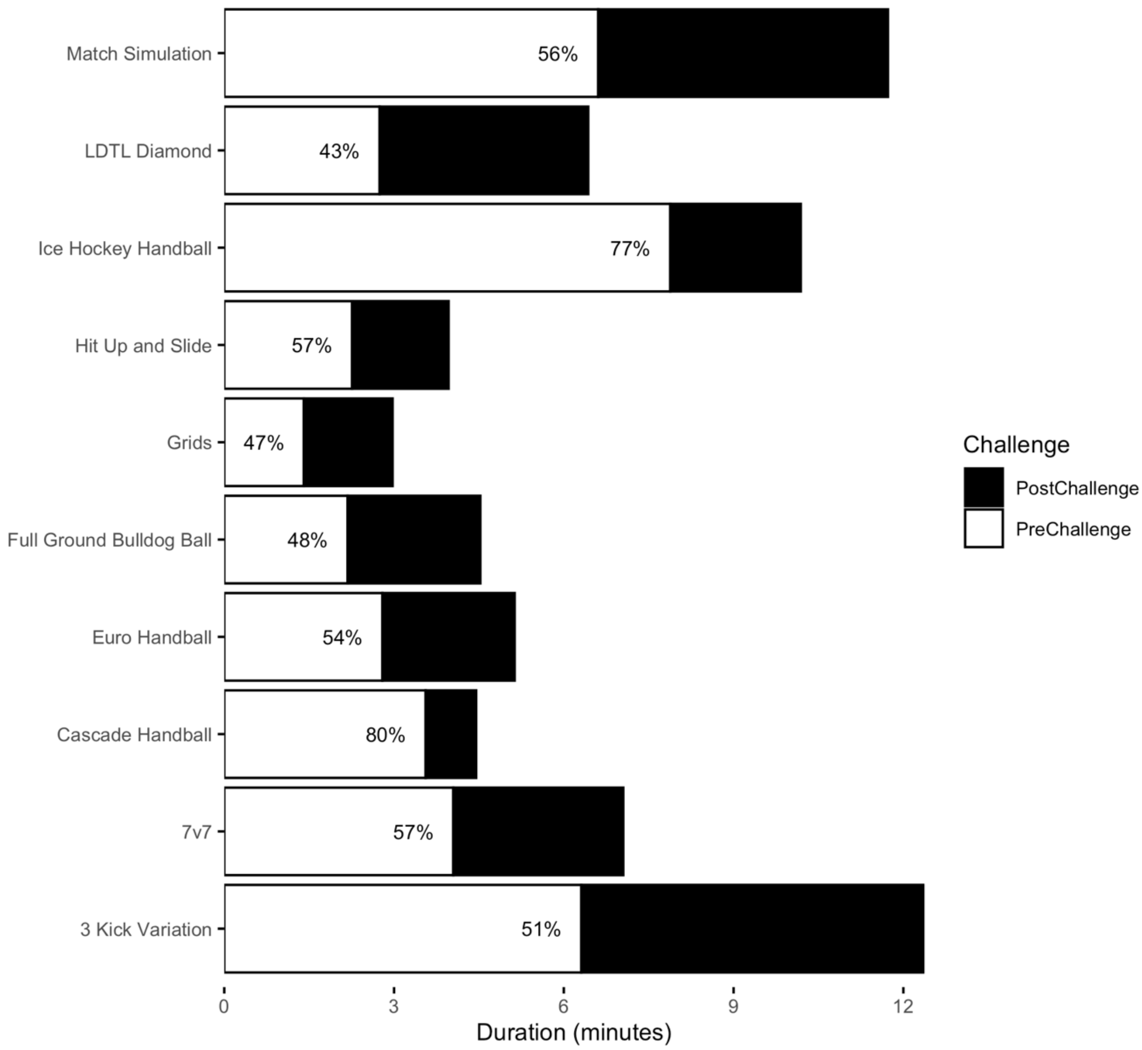

Figure 6.2 -- Average challenge point location across the team for 10 frequently occurring drills. Portions of the bar in white depict time pre-challenge point. Portions of the bar in black depict time post-challenge point. Challenge point location is also expressed as a percentage of total drill duration.

Figure 6.3 depicts the distribution of velocity before and after the challenge point for 10 frequently occurring training drills. Across most drills, there was a lower central tendency post-challenge point. This was particularly prominent in drills including *Ice Hockey Handball*, *Euro Handball, Hit Up and Slide*. For a small number of drills, the central tendency of velocity appeared higher post change point. These drills included *Grids* and *Cascade Handball*.

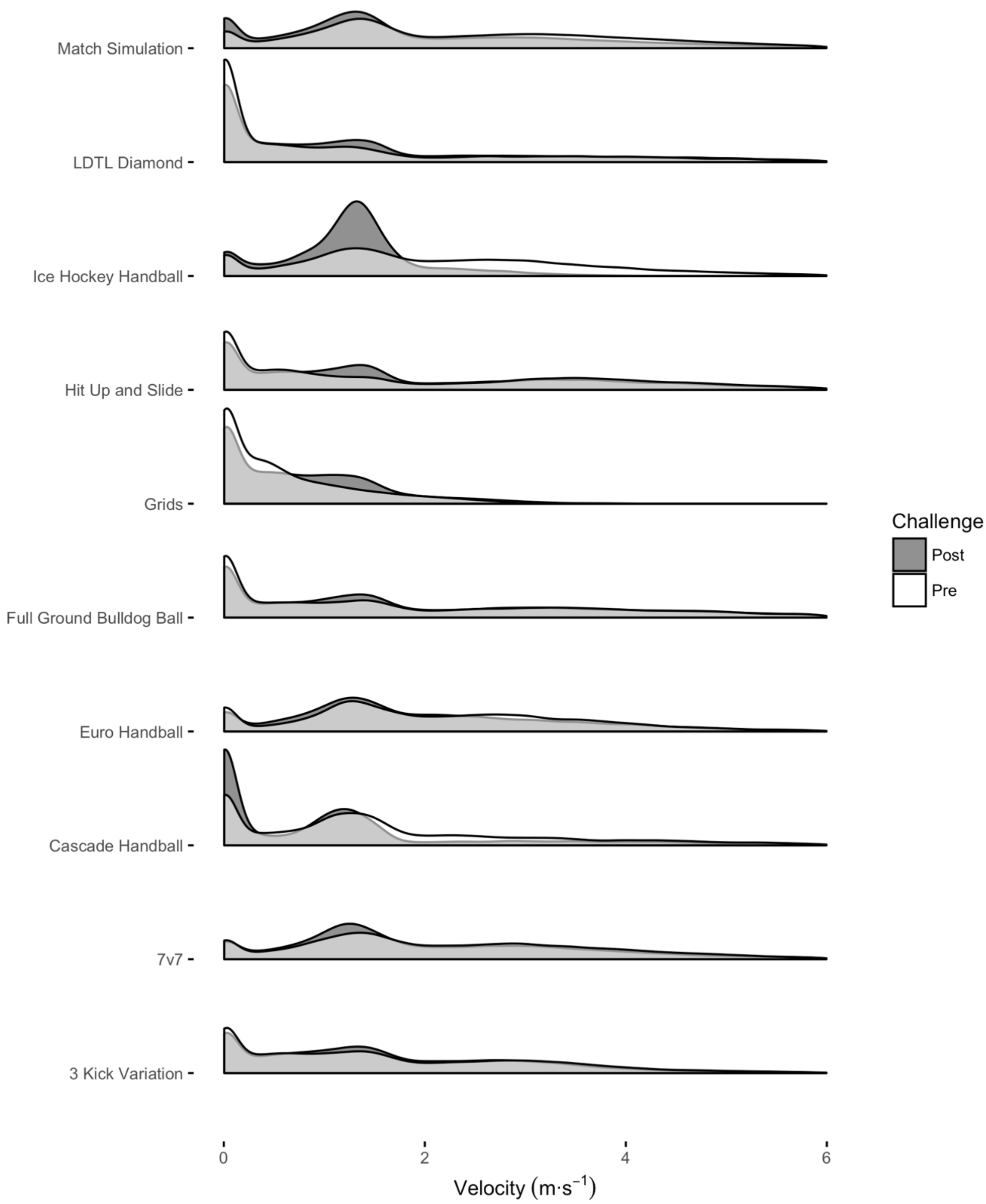

Figure 6.1-- A density plot depicting the relative frequency of data points recorded at each velocity, for 10 frequently occurring drills. Data points in white are velocities occurring pre-challenge point. Data points in dark grey are velocities occurring post challenge point.

6.4.3 High intensity movement path specificity

Figure 6.4 depicts 10 movement paths for an exemplar player, with velocities in their 99th percentile. This figure demonstrates the differences in very high intensity running patterns for the player, between match simulation and actual match conditions. In match conditions, efforts appeared more discrete and required the player to maintain a higher velocity. In match simulation, however, efforts required the player to maintain higher velocities briefly, interspersed with periods of lower velocity. These efforts also typically required a higher acceleration and were performed in closer succession than in matches.

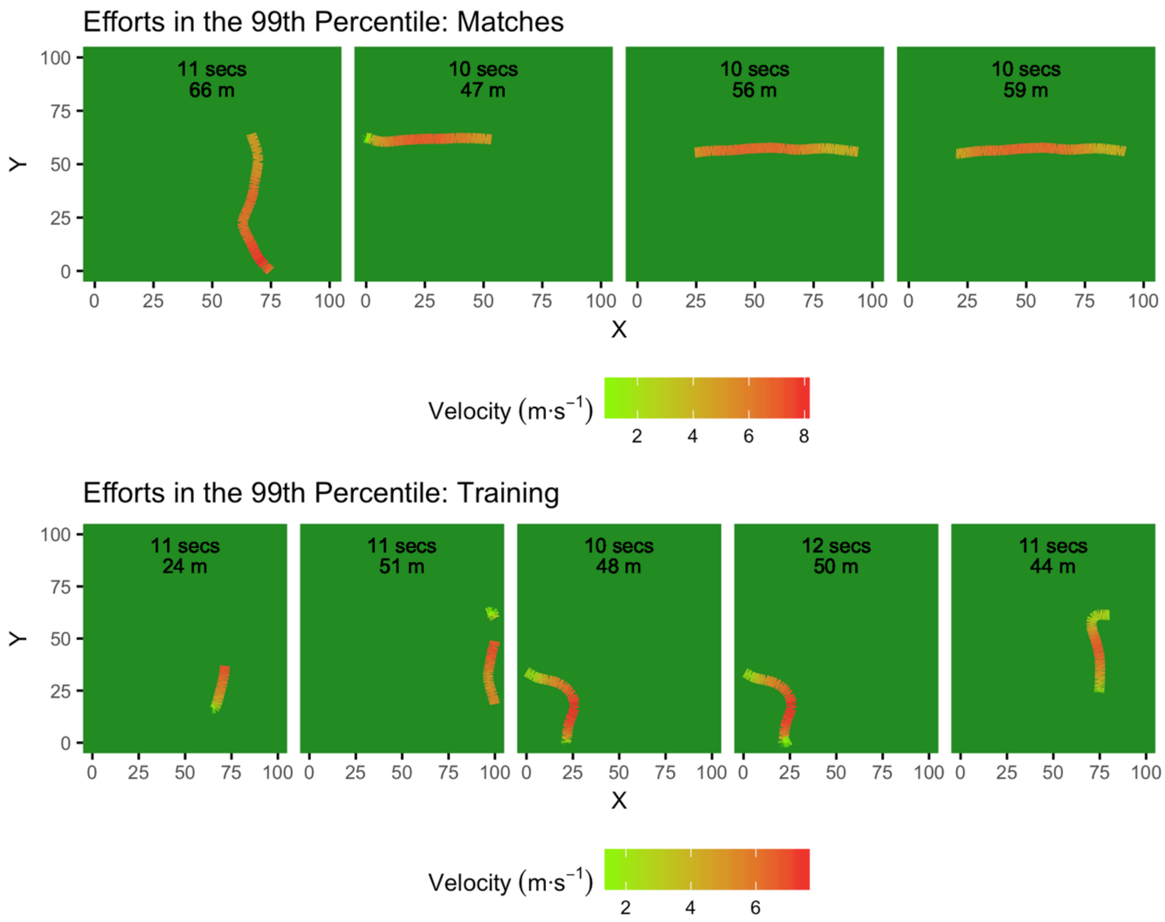

Figure 6.2-- Exemplar movement paths, visualising efforts in a player's 99th percentile of velocity as X-Y coordinates. Green data points denote a slower velocity. Red data points denote a faster velocity.

6.5 Discussion

This study aimed to illustrate how a time-series/ frequency-domain approach can be applied to physical output to assess the sequence, specificity and difficulty of team-sport training drills. The similarity of training drills to various match segments was utilised to determine a specificity-based drill sequence. Furthermore, a binary segmentation change point algorithm was run for velocity data in all training drills, to identify how physical output changes as a function of time. Movement paths were also visualised, to examine the similarity of maximal intensity efforts in training and matches. These methods were able to quantify physical output for each drill, as well as how output changes over time.

By condensing velocity data from training drills into a similarity metric from match segments, a drill sequence resembling physical output at differing points of a match was generated. This allows for a specific physical stimulus to be delivered to players, at a similar time to when they would in a match. Typically, high intensity drills are performed in an unfatigued state towards the beginning of training sessions (Little & Williams, 2006). However, practitioners may utilise the methods presented in the current study to deliver a physical stimulus at time points specific to the players' match profile. Consequently, these methods could be pertinent in increasing the specificity of training sessions, where drills are pre-set due to coaching or load monitoring concerns (Corbett et al., 2018). When specificity may not be a training objective (Robertson & Joyce, 2015), for example in early pre-season or when reintegrating injured players into training drills (Rogalski, Dawson, Heasman, & Gabbett, 2013), other constraints may be applied to inform training drill sequence. For example, features reflecting considerations, including limiting the level of high-speed running or starting and finishing a session with lower intensity drills, could also be utilised instead of the similarity-based metrics used in this study.

The visualisations used to compare the features of training drills to match segments may also be useful in training drill modification. Although velocity within training drills followed a similar distribution to their respective match segments, drills may still be modified to further increase their specificity to match segments (Travassos, Duarte, Vilar, Davids, & Araújo, 2012). For example, in *Ball Security Circuit, Full Ground Bulldog Ball* and *1v1*, players spent considerably more time stationary than they would in a match. Although there are instances where this is unavoidable, including the delivery of concurrent feedback (Schmidt & Wrisberg, 2008), practitioners may use this information to find opportunities to increase the total physical output of players. This may be achieved through modifications including changing the dimensions of the training drill, or reducing the number of players in each group to minimise idle time (Hodgson, Akenhead, & Thomas, 2014). Similarity metrics could also be calculated between training drills. This could identify drills which are specific in their physical output, but provide variety from a skill perspective (Corbett et al., 2018).

Another novel method presented in this study was the application of a challenge point framework to measures of physical output in team-sport training drills. Other literature has established peak match intensities and utilised these results to prescribe training-drill benchmarks of varying durations (Delaney et al., 2015). Similarly, time points where the physical output of matches have also been identified (Corbett et al., 2019). However there is no research, examining how peaks in physical output, extracted from match data can be replicated in training drills (Carling et al., 2018). Therefore, this study expanded upon these methods, by identifying a challenge point, where the physical output of training drills changes. Challenge point location varied substantially by drill. Whilst drills such as *3-Kick Variation* and *Match Simulation* had a challenge point approximately halfway through the drill, *Cascade Handball'*s challenge point occurred towards the end of the drill. These results highlight the importance of analysing changes in physical output within training drills, to determine training drill length. This is because aggregate parameters of physical output cannot identify intensities at differing periods within and across training drills (Carling et al., 2018).

Current drill prescription systems emphasise metrics such as metreage per minute, which assume a linear increase in training volume as a session progresses (Corbett et al., 2018). Change in physical output over time has been examined in matches (Aughey, 2010a; Montgomery & Wisbey, 2016). In the present study, the features of training drills were found to differ before and after their respective challenge points. In most drills (eg. *Ice Hockey Handball*, *7v7*) players had a tendency to reach and maintain higher velocities. Consequently, practitioners may modify or shorten these types of drills post-challenge-point, if wishing to maintain the drill at a higher intensity. Conversely, there were some training drills where players maintained higher velocities post-challenge-point (eg. *Grids*, *Hit Up and Slide*). In these situations, practitioners may wish to avoid shortening training drills, as doing so may cause an unexpected reduction in a player's total physical output. This method may be used in conjunction with existing profiling methods (Delaney et al., 2015), to identify the efficacy of different training drills in attaining differing physical outputs (Carling et al., 2018). To gain a more sophisticated understanding of how physical output changes over time, practitioners may specify a greater number of challenge points. Subsequently, the physical output of altering duration for a given drill could be monitored. This method may be utilised to identify the potential impact of manipulating training drill duration.

Specificity of training is currently evaluated using either aggregate parameters (Corbett et al., 2018) or via peak moving averages extracted from match data (Delaney et al., 2015). This study expanded upon these methods, by visualising on-field match and training movement paths. Consequently, the specificity of how players accrue total distance was examined. This study found that high intensity sprint efforts in matches were generally discrete, linear and required players to maintain high velocities for a number of seconds. Sprint efforts were defined as efforts in the 99th percentile of velocity for training drills and matches. However, this similar output was achieved differently in training sessions, than in matches. Specifically, sprint efforts in training, were generally shorter, performed in closer succession, non-linear and required the players to reach a higher velocity before decelerating. This suggests that, the specificity of training drills to match outputs, could be further improved by examining movement paths (Corbett et al., 2018). Indeed, the paths in this study were able to identify differences between match and training movements that are not available using existing parameters including effort count, effort duration or effort distance (Sweeting, Cormack, Morgan, & Aughey, 2017). The visualisations in this study provide a means for practitioners to inspect the shape, duration and distance covered in team-sport running paths. These observations may then be used to modify movements within training drills or to design more specific rehabilitation and conditioning sessions. This may be important from both a fitness improvement (Gabbett, Kelly, & Sheppard, 2008) and injury prevention perspective (Rogalski et al., 2013).

The methods in this study can also be used to increase the sophistication of training drill evaluation and monitoring. The frequency domain analysis presented in the present study utilised percentiles to quantify the intensity of training, relative to the individual. Specifically, very high intensity efforts were examined as the 99th percentile of efforts for each player. This removes the need to pre-set velocity thresholds (Sweeting et al., 2017), and adds to the growing body of literature, aiming to individualise measures of physical output in team-sports. Furthermore, the movement paths analysed in this study, may be utilised to explore how players accrue total volume measures such as total distance. Further research should utilise time-series and frequency domain analysis to monitor physical output in other training situations such as rehabilitation or individual sports.

This study presented a method to assess the specificity, sequence and difficulty of training drills using physical output. This study was limited by the validity and reliability of wearable technologies, in measuring acceleration (Luteberget et al., 2018). As the reliability of devices improves, an acceleration time-series could be used to give a greater understanding of physical output. Further research should integrate measures of skilled output, such as involvements, to develop a holistic drill prescription system. Additionally, this study focussed on evaluating movement paths and drill sequence through their specificity to match outputs. Further research may adapt these methodologies, to achieve other training outcomes such as variety and progressive overload.

6.6 Conclusion

This study illustrated how a time-series/frequency-domain can be applied to physical output to assess the sequence, specificity and difficulty of team-sport training drills. Frequency domain features were utilised to sequence training drills, through their specificity to physical output at varying points of a match. Furthermore, this study adapted the challenge point framework, to examine the influence of time on physical output in training drills. Finally, movement paths were visualised, to examine the specificity of movement paths to match outputs. These methods could be utilised by practitioners, to provide an evidence base for decisions related to training drill prescription.

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CHAPTER 7 – Discussion and Conclusions

7.1 Thesis Overview

In team-sport, physical and skilled output is typically described using aggregate volume (eg., total distance (Coutts & Duffield, 2010) and metabolic power (Buchheit, Manouvrier, Cassirame, & Morin, 2015; Coutts et al., 2015)) and intensity (eg., peak velocity (Coutts & Duffield, 2010), metreage per minute (Corbett et al., 2018)) parameters. Skilled output is also described using aggregate parameters, including coach's ratings (Kempton, Sullivan, Bilsborough, Cordy, & Coutts, 2015) and Champion Data^{TM} player rankings (McIntosh, Kovalchik, & Robertson, 2018; Robertson, Gupta, & McIntosh, 2016). However, aggregate parameters could not identify changes in physical and skilled output within a session (Dillon, Kempton, Ryan, Hocking, & Coutts, 2017). This thesis presented a time-frequency approach to team-sport output profiling (Corbett, Sweeting, & Robertson, 2019). Further, this thesis demonstrated the efficacy of a time-frequency approach to match profiling. It illustrated how a time-frequency approach may be utilised to address training considerations, including the duration and sequence of training drills, which are not possible using aggregate parameters. Consequently, this thesis presents a complementary method to aggregate parameter profiling to understand the physical and skilled output of team-sport athletes.

7.1.1 Study One

"Weak Relationships between Stint Duration, Physical and Skilled Match Performance in Australian Football"

Study One examined the relationship between physical and skilled output and time in team-sport using aggregate parameters. This study integrated involvements (defined as the sum total skilled actions completed by a player) alongside aggregate parameters including meterage per minute (total distance relative to time). Study One expanded upon the literature by utilising random intercept and random slope models to account for differences in physical and skilled output between players and games. This study was also utilised conditional inference trees, as a non-parametric method to model the relationship between physical and skilled output and time. Consequently, Study One was the first to examine how physical aggregate parameters may interact to change skilled output in team-sport.

Regardless of the modelling technique, Study One identified a weak relationship between physical and skilled output and time (RMSE 10 - 11 involvements/match; conditional R^2 0.14-0.23). In the random intercept and random slope models, aggregate parameters could positively or negatively relate to skilled output depending on the player. Furthermore, in the conditional inference tree, splits were dominated by external factors such as Round and Player ID, and utilised only duration and meterage per minute. This was likely due to several factors. First, aggregate parameters do not account for individual differences between players (Sweeting, Cormack, & J., 2017). For example, a static threshold of 25 km/hr^{-1} as “very high intensity running”, may be commonly or seldom reached depending on the player. Secondly, aggregate parameters cannot identify time-points when physical and skilled output change within a match (Dillon et al., 2017). Therefore, analyses exploring the relationship between output and time, are restricted to repeated measures designs. The key limitation of this study was its reliance on aggregate parameters. These findings laid the foundation for Study Two to develop a method to identify changes in physical and skilled output within team-sport matches.

7.1.2 Study Two

“A change point approach to analysing the match activity profiles of team sport athletes”

Study Two bridged the analysis of aggregate parameters in Study One, with Studies Three and Four which applied a time-frequency approach to team-sport match profiling and training drill design. This study expanded upon moving averages (Delaney et al., 2018b), by utilising change point analysis which does not require a “duration windows” to identify peak intensities.

Additionally, change point analysis could also identify fluctuations in physical and skilled output, as well as their temporal occurrence within a match. Binary segmentation was selected as a fast, valid change point method to identify segments of physical and skilled output in team-sport matches. Subsequently, frequency domain features were computed for individual match segments. This study was the first to use frequency domain features to quantify physical output.

Study Two simulated the impact of different change point quotients on the frequency domain features of match segments. From this, it was determined that between 4 and 7 change points could adequately describe the most distinct segments of a match. Change points occurred independently of stint interchanges (r = 0.21), highlighting the advantage of time-series methods in identifying change in physical and skilled output over time over stints as aggregation windows. This study suggested hyperparameters to be used in Studies Three and Four, which would utilise the proposed time-frequency in both match and training drill prescription settings. The key limitation of this Study was that frequency domain features are unfamiliar to practitioners. Consequently, both Study Three and Four aimed to overcome this limitation, by outlining how frequency domain features may be practically used to inform match profiling and training drill design.

7.1.3 Study Three

"Profiling individual team-sport athlete physical and skilled output with frequency and time-series domain analysis"

Study Three illustrated how a combined time-frequency approach could be used to profile physical and skilled output in team-sport matches. As part of a growing body of literature examining both physical and skilled output, this study compared aggregate parameters and the combined time-frequency approach presented in Study Two to match profiling. This study created a dual match analysis system, whereby segments of team-sport matches could be analysed as a function of time (time series segmentation) and based purely on their physical and skilled output (*k*-means clustering).

This dual classification system was able to identify changes in physical and skilled output within a match, which is not conceptually possible using aggregate parameters. Furthermore, this approach was able to identify differences in physical and skilled output between matches. For a given match, aggregate parameters (total distance, high intensity running, very high intensity running and metreage per minute) were all within one standard deviation for a given player. However, a time-frequency approach revealed less time spent stationary for the given player, and more time spent at velocities > 5.0 $m.s^{-1}$. This study laid the foundation for Study Four, by improving match profiling in team-sport. Specifically, by demonstrating how a combined time-series/frequency domain approach may overcome the limitations of moving averages and output bands. This would later be crucial, for the representative task design framework utilised in Study Four (Correia et al., 2012). The key limitation of this study was its small sample size. An exemplar athlete was utilised to illustrate the efficacy of a combined time-series/frequency domain approach to match profiling. However, future research could utilise a larger sample size to better compare players' outputs.

7.1.4 Study Four

"Methods for prescribing drill sequence, specificity and difficulty in team-sport training using player physical output"

Study Four combined the methods from both Studies' Three and Four to improve training drill prescription in team-sport. This study built upon previous drill classification systems (Corbett et al., 2018; Loader, Montgomery, Williams, Lorenzen, & Kemp, 2012)., by illustrating how a time-frequency approach to analysing physical output could be used to prescribe training under a representative task design framework. This study computed frequency domain features for each training drill and compared them to match segments for all players (computed in Studies' Three and Four). This was achieved by summarising frequency domain features for all drills, based on their similarity to each match segment. This study computed a single binary change point for all training drills as a proxy for "challenge points". Change points occurred anywhere between 43% and 80% of elapsed drill time dependent on training drill. Physical output post-change point was not necessarily impaired and increased in many drills. This highlighted the potential limitations of utilising linear work rates such as metreage per minute to infer physical output at differing durations. Finally, this study compared running paths in the 99th percentile of velocity for players between match simulation and actual matches. In training, players completed shorter efforts and spent less continuous time at near-maximal intensities. Collectively, Study Three and Four illustrated how the added insight gleaned from a combined time-frequency approach, may improve match profiling and training drill prescription. Skilled output data was not included in this study, as its' applications related to replicating the physical output of matches. However, future research may integrate skilled output data to develop a more holistic understanding of training drill prescription.

7.2 Thematic Discussion

7.2.1 Limitations of Aggregate Parameters

This thesis highlighted how analysing physical and skilled output beyond aggregate parameters, may increase our understanding of team-sport athletes. Future research may utilise time-series analysis to investigate problems where insight may be gleaned from data changing over time. For example, in endurance sports such as track-cycling where pacing is a strategic consideration (Corbett, 2009), time-series segmentation may be used to identify segments of competition. This is because track-cycling is less intermittent than team-sport (Corbett, 2009), and thus, segments are likely characterised by more sustained changes in physical output.

Consequently, time-series segmentation could be used to characterise fatigue or better understand when opponents physical output changes. Additionally, in sports requiring frequent travel including basketball and cricket, time-series segmentation may be used to identify high stress travel periods across the year (Fowler, Duffield, Howle, Waterson, & Vaile, 2015). Additionally, time-series segmentation may be used to identify for changes in playstyle over time. This would allow practitioners to better evaluate players in the context of their time period when making decisions related to list management and recruiting. Furthermore, time-frequency approach could be applied to other datasets, such as IMU devices to better understand physical output in off-field training settings (Huang et al., 2012). This would allow practitioners to quantify output on a global level, which is usually only possible using internal measures including RPE and heart rate (Alexiou & Coutts, 2008; Bartlett, O'Connor, Pitchford, Torres-Ronda, & Robertson, 2016).

Despite their limitations, aggregate parameters are easily interpretable by practitioners (Cummins, Orr, O'Connor, & West, 2013; Delaney, Cummins, Thornton, & Duthie, 2018a). Conversely, frequency domain features do not relate to a concrete quantity, and thus, summarise physical and skilled output in more abstract terms (Tedesco, Urru, & O'Flynn, 2017). This thesis utilised density plot visualisation, as a means to communicate frequency domain features. However, this approach may still not be as interpretable as aggregate parameters for some practitioners. For this reason, it is recommended that a combined time-frequency approach be used to complement aggregate parameters. Specifically, broader questions related to periodisation may be better addressed using aggregate parameters. For example, aggregated differences in load from session-to-session and week-to-week are important for maximising adaptation and reducing injury risk (Bourdon et al., 2017; Gabbett, 2015; Murray, Gabbett, Townshend, & Blanch, 2017). In these settings, aggregate parameters complement the periodisation lexicon used by parameters, and thus, assist with decision making (Ritchie, Hopkins, Buchheit, Cordy, & Bartlett, 2016). Conversely, within match and training considerations may be better addressed with a combined time-frequency approach. No study has been able to identify a clear relationship between physical output, skilled output and time (Dillon et al., 2017). Therefore, a time-frequency approach is warranted to uncover nuanced differences in physical and skilled output within a match. Although this thesis proposed a method to identify fluctuations in physical and skilled output, it is unknown to what extent these fluctuations are due to fatigue, the influence of the opposition or changes in match tactics.

7.2.2 Understanding Physical and Skilled Match Profiles

Prior to this thesis, there was a limited body of research, examining how physical output changes within stints themselves. Moving averages, were a common within-stint method reported in the literature (Delaney et al., 2016a; Delaney et al., 2016b; Delaney et al., 2018b). However, moving averages were limited by their inability to identify the frequency and temporal occurrence of peak intensities (Carling, McCall, Harper, & Bradley, 2018). Similarly, phase-of-play analysis aimed to analyse physical output within contextual actions. By utilising time-series segmentation, this thesis identified peak intensities for each player, and how intensity fluctuated across the course of a match. Furthermore, the methods in this thesis may identify whether a player completes high physical output segments later in matches. This could be used to design specific rehabilitation and conditioning sessions, which may potentially increase performance and prevent injury in matches.

Future research may utilise the methods in this thesis to understand the profiles of team-sport athletes in greater depth. For example, it is increasingly common for athletes to play multiple or ambiguous positions in team-sport (Jackson, Polglaze, Dawson, King, & Peeling, 2018; Luteberget, Spencer, & Gilgien, 2018; Varley, Jaspers, Helsen, & Malone, 2017). A time-frequency approach combined with clustering, could be used to ascertain player archetypes based on their physical and skilled output. This would allow for training groups to be objectively prescribed. Additionally, the physical preparation required for players who either have no data or are changing on-field roles could be estimated using this method. Furthermore, differences in physical output based on competition level could also be investigated. This would allow for athlete development, which considers the output required to progress to higher levels of competition (Brewer, Dawson, Heasman, Stewart, & Cormack, 2010). Conversely, the impact of ageing on the physical and skilled output of players could be explored using this method. This may assist practitioners to identify declines in physical and skilled output with age, which may inform list management and contract decisions. Furthermore, the relationship between physical output, subjective measures of physical output and injury occurrence could be investigated to better understand on-field injury mechanisms. Future research should also examine the underlying contextual factors leading to changes in physical and skilled output in team-sport matches. Finally, the relationship between physical change points and tests of physical fitness could also be examined. This would allow practitioners to examine the relationship between physical output and capacity.

7.2.3 Understanding Training Drills

Studies exist to aid practitioners with drill selection (Corbett et al., 2018; Loader et al., 2012). However, other considerations, including the sequence of training drills within a session, the difficulty/length of training drills and the specificity of high velocity movement paths to match outputs were unexplored. Each of these considerations contributes to the specificity and physical intensity of a training session, and therefore, are important to evaluate when designing training. Consequently, this thesis explored how a time-frequency approach could be integrated with skill acquisition frameworks, to design training sessions which are specific to match outputs.

Representative task design contends that maximal performance benefits occur when learning environments most closely resemble performance environments (Dicks, Davids, Button, MacMahon, & Farrow, 2009; Pinder, Davids, Renshaw, & Araújo, 2011). Consequently, this thesis illustrated how a combined time-frequency approach could be utilised to not only select specific drills (Corbett et al., 2018), but also to design training sessions which replicate fluctuations in physical output experienced by players in matches (Study Four). Theoretically, this would allow for the greatest cognitive and physical adaptations for players, as they would be practicing in similar circumstances to which they perform. Consequently, future research should investigate the impact of training drill sequence on player performance to validate/invalidate this framework. Additionally, further resources should be directed towards notating skilled data during training sessions. This would allow future research to integrate skilled output measures to the methods proposed in this thesis. In turn, this would allow for more specific training session evaluation and design

This thesis drew upon the challenge point framework to inform training drill length. Under this framework, there was a hypothesised challenge point, after which physical output would be altered. In this thesis, physical output was not necessarily impaired post-challenge point. This demonstrated how linear work rates such as average acceleration and meterage per minute may over or under-estimate estimates if used to simulate the impact of drill length on physical output. Consequently, future research and practice may utilise time-series segmentation to understand phases of training drills. This may be integrated with contextual factors, including coach’s direction and drill modification, to better explain why output changes within training drills.

The challenge point and representative task design frameworks illustrate how a combined time-frequency approach may be combined with skill acquisition to better prescribe training drills. However, specificity may not always be a training objective. For example, in many team-sport, physical overload is prioritised, with specific match simulation drills often not being introduced until mid-late pre-season (Fry, Morton, & Keast, 1992). Consequently, practitioners may alter the methods presented in this thesis to prescribe drills in-line with their training objectives. For example, the similarity metrics utilised in Study Four may be replaced with features such as spectral energy to describe the overall physical output of training drills. This information may be used to gradually increase the intensity of training drills over a training block (Ritchie et al., 2016). Furthermore, training drills could be arranged based on increasing physical output in order to train players in a fatigued state.

7.2.4 Technological Progression

Machine learning methodologies were used in all four studies of this thesis. In Studies One and Two, conditional inference trees and random forests were used to model a non-linear relationship between physical output, skilled output and time. These methods require minimal hyper-parameter tuning (Sardá-Espinosa, Subbiah, & Bartz-Beielstein, 2017), and are thus, extremely accessible to practitioners. Similarly, the *k*-means algorithm utilised in Study Three and Euclidean distance calculated in Study Four, required only one hyper-parameter to be tuned (Jain, 2010). Consequently, these methods were relatively fast and easily interpretable. However, it should be noted that additional classification/predictive accuracy may be possible, with reductions in model interpretability. For example, neural networks may better learn the relationship between physical and skilled output and time (Lu, Chen, Little, & He, 2018). However, this output could not be deciphered (Ofoghi, Zeleznikow, MacMahon, & Raab, 2013). This is because neural networks typically calculate a single output given a set of inputs and cannot describe the interactions and relative strengths of dependent variables on independent variables (Ofoghi et al., 2013). Consequently, the methods utilised in this thesis, including random forests and decision trees, provided a balance between interpretability and predictive performance. This was important, to ensure the methods could be translated to match profiling and training drill prescription practices.

This thesis leveraged wearable technologies to better understand physical output in team-sport training sessions and matches. Specifically, velocity time-series was the primary data set for Studies Two to Four. However, due to questionable validity (Akenhead, French, Thompson, & Hayes, 2014; Barrett, Midgley, & Lovell, 2014), features were derived exclusively from velocity to quantify physical output. Consequently, although defensive involvements such as tackles were analysed, acceleration, deceleration and micro-movements were not quantified in this thesis. The time-frequency approach presented could be applied to acceleration time-series' when the validity of devices improves. This would allow practitioners to encompass other aspects of physical output which may enrich match activity profiles and our understanding of training drill characteristics (Cummins, Orr, O'Connor, & West, 2013; Delaney et al., 2018a). Additionally, the current lack of automation in skilled movement detection (Lu et al., 2018), means manual tagging of events is still necessary in many team-sports. As automatic event detection becomes ubiquitous, there is greater potential to analyse skilled actions in both training sessions and matches. Collectively, these developments may allow practitioners to better understand the interactions between all aspects of physical and skilled output in team-sport matches and training.

In AF practitioners currently utilise GNSS devices to measure physical output during training sessions and matches (Dillon et al., 2017; Ryan, Coutts, Hocking, & Kempton, 2017; Vella et al., 2021). Conversely. LPS devices are used to measure physical output during indoor matches (Dillon et al., 2017; Ryan et al., 2017; Vella et al., 2021). This means, it can be difficult to compare physical output between training drills and matches. In Chapters Three and Four, this limitation. was overcome by specifying Round Number as a random effect (mixed effects model), or by utilising Round Number as a dependent variable (conditional inference trees, random forests.) Consequently, any error introduced by utilising different devices was accounted for in these Chapters. Chapters Five and Six proposed new methodologies, and utilised LPS and GNSS systems interchangeably for match profiling and training drill design. This was done, as all comparisons were performed within individual matches. However, for future researching aiming to use these methods for inferential questions, it is recommended that practitioners account for the random effect measurement tools may have on measured phenomenon. As LPS and optical based devices become more ubiquitous, the need to utilise different devices will likely be reduced.

Developments in cloud data storage and computing power may allow practitioners to better leverage the methods presented in this thesis (Ofoghi et al., 2013). For example, a season of 10 Hz GPS data in team-sport comprises millions of rows of data. At present, such data cannot currently be stored locally or easily joined with other datasets. Further, processing large-scale locational data is currently unfeasible using local computing power. As a result of these technical limitations, Chapters Five and Six analysed only a small pool of players. Further, many of the methods utilised in this thesis were selected due to being computationally inexpensive in addition to validated. For example, binary segmentation is less powerful than recent segmentation algorithms such as energy divisive (James & Matteson, 2013) and prophet (Medina, Montaner, Tárraga, & Dopazo, 2007). However, it was advantageous due to its fast processing speed which allowed more players to be analysed in Study Two. Similarly, neural-network based dimensionality reduction including Uniform Manifold Approximation and Projection (McInnes, Healy, & Melville, 2018) may have better preserved global differences between match segments in Study Two. Conversely, computing power and cloud storage is rapidly evolving (Zhang, Zhang, Chen, & Huo, 2010). Consequently, there will be greater potential for practitioners to implement, productionalise and develop many of these methods in the future.

7.3 Summary

This thesis highlighted the limitations of aggregate parameters to measure the relationship between physical output, skilled output and time in team-sport (Chapter Three). A combined time-frequency approach to measure physical and skilled output was then proposed (Chapter Four). These techniques were then applied to match profiling, to understand changes in physical and skilled output both within and between matches (Chapter Five). The proposed time-frequency approach was then applied to training in order to evaluate the specificity, sequence and difficulty of different drills. Overall, this thesis illustrated how a combined time-frequency approach may give greater insight into match and training outputs than are currently available. Future research should further examine the interplay between physical and skilled output in training drills and apply the methodologies in this thesis to other sports.

7.4 Practical Applications

The main practical applications of this thesis are:

1. Change point analysis may be utilised to understand when meaningful changes in physical output occur during team-sport matches. This could be pertinent in sports including track cycling, where increasing or decreasing velocity is a tactical decision
2. Frequency domain analysis may be utilised to understand physical and skilled output at varying points of a match. This can allow practitioners to determine benchmarks to reach within training sessions.
3. A combined time-frequency approach may be utilised to identify more nuanced changes within and between matches, than are apparent from aggregate parameters. This could be utilised to identify matches with high or low match outputs and assist with decisions related to increasing or decreasing training load in subsequent weeks.
4. A combined time-frequency approach may be utilised to inform the sequence and duration of training drills if specificity is a desired training outcome. This would allow practitioners to manipulate training drill sequence to best emulate match outputs, where drill selection may be static.

7.5 Conclusions

The specific conclusions of this thesis are:

1. There is a weak relationship between physical output, skilled output and time, as quantified using aggregate parameters in professional Australian football
2. A better understanding of physical and skilled output in Australian football may be gained utilising change point and frequency domain analysis.
3. Aggregate parameters may be unable to identify meaningful and practically useful changes in athlete profiles between matches in team sport.
4. Physical output is not accumulated in a linear fashion in training drills. Current work rates may over or under-estimate the physical output of training drills if used prescriptively.

7.6 References

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APPENDIX

Appendix 1-- Involvements included in this thesis

Involvement Category	Reason for usage
Disposals (Boundary Kick Ineffective, Kick In Short, Handball Effective, Handball Ineffective, Kick Effective, Kick In Long, Handball Clanger, Handball, Boundary Kick Long, Ground Kick Ineffective, Kick Long To Advantage, Kick Ineffective, Kick Backwards, Kick Inside 50, Kick Short, Kick Long,	Measure each time the player interacted with the ball
Offensive Actions (Mark Contested, Knock On Effective, Centre Bounce Clearance, Gather, Ball Up Hitout To Advantage, Loose Ball Get, Mark From Opp Kick, Free For, Mark Lead, Inside 50, Mark, Mark Lead, Mark Uncontested, Mark Play On, Handball Received, Shark, Hitouts to Advantage)	Measure every action which the club deems important in contributing to a goal
Defensive Actions (Block, Smother, Smotherer After Disposal, Run Down Tackle Dispossessed, Pressure Credit, Chase, Tackle, 1-on-1 Contest Defender, Spoil Gaining, Spoil Defensive, Hold	Measure each time a player contributed to the team by potentially preventing the oppositions' goal.

Appendix 2 – Aggregated Euclidian Distance (AU) across all players for each training drill to each segment

Drill	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
1v1	1751	1166	1074	1182	1081	1926
2 Way Shape	8750	9281	9358	9265	9358	8607
3 Kick Variation	70496	71051	71132	71035	71131	70343
3 Way Handball	7898	8423	8500	8407	8499	7757
3 Way Handball Euro Handball	29642	30200	30282	30183	30281	29488
3 Way Handball Squares - Shuttles	12845	13395	13476	13379	13475	12694
3 Way Kick	28613	29161	29241	29145	29240	28463
3v3 Grids	6101	6614	6690	6599	6689	5966
3v3v3 Kicking Game	11025	11564	11643	11548	11642	10879
5 Star Handball Into Kick	1361	1647	1697	1635	1700	1338
5 Star Into Roundabout	21701	22248	22329	22232	22328	21551
6v6	20484	21032	21112	21016	21111	20334
6v6 Corridor Footy	15275	15831	15913	15815	15912	15122
7v4	51242	51795	51876	51779	51875	51090
7v4 Kick	8785	9315	9393	9299	9392	8642
7v4 Kicking	25869	26417	26498	26401	26497	25719
7v5 Kicking	17507	18053	18133	18036	18132	17358
7v7	74624	75177	75259	75161	75257	74471
Away and Entry	1293	1630	1687	1617	1689	1252
Ball In Motion Kick	12563	13105	13184	13089	13183	12416
Ball Security	12794	13332	13410	13316	13410	12649
Ball Security Circuit	1508	1839	1894	1826	1896	1463
Ball Security Grid	13341	13879	13958	13863	13957	13195
Bulldog Ball	940	1051	1088	1042	1092	995
Bulldog Ball In Pairs	13759	14303	14383	14287	14382	13611
Cascade Handball	6549	7072	7148	7056	7148	6411
Check Mate	55088	55642	55723	55626	55722	54936
Contest Stoppage To Fwds	24721	25268	25348	25252	25347	24571
D50 Walkthrough	2261	2670	2733	2657	2734	2175
Deception Kick	9749	10282	10360	10266	10360	9605
Euro Handball	17194	17739	17819	17723	17818	17046
Extras	245342	245897	245979	245881	245977	245189
Full Ground Bulldog Ball	47501	48052	48133	48036	48132	47349
Full Ground Bulldog Ball in Pairs	16705	17252	17332	17236	17331	16556
Game of Cones	14988	15532	15612	15516	15611	14840
Goal Kicking	270264	270819	270901	270803	270899	270111
Goal Kicking Circuit	32941	33494	33575	33477	33574	32789
Grid	2127	2596	2667	2581	2667	2019
Ground Balls	1829	2228	2290	2214	2292	1752
Half Ground Bulldog Ball	11977	12516	12595	12500	12594	11830

Half Ground Transition	129244	129798	129879	129782	129878	129091
Handball Ice Hockey	29442	29991	30072	29975	30071	29291
Handball Ice Hockey 3 Way Handball	27811	28366	28447	28349	28446	27658
Handball Ice Hockey Euro Handball	13574	14133	14215	14116	14214	13421
Handball Squares	10315	10849	10928	10833	10927	10171
Handball Squares Cascade Handball 3v3v3	29056	29611	29693	29595	29692	28903
Hit Up and Slide	35770	36320	36401	36304	36400	35619
Ice Hockey Handball	23755	24306	24387	24290	24386	23604
In Out In	18056	18599	18679	18583	18678	17907
Initiative Squares	4857	5374	5450	5359	5450	4722
Kick Warm up	344244	344799	344881	344783	344879	344091
Kicking Volume	6469	6987	7063	6972	7063	6333
Large Cascade Handball Game	31580	32129	32210	32113	32209	31429
LDL Diamond Into F50	29278	29828	29908	29811	29907	29128
LDTL Diamond	10764	11304	11383	11288	11382	10618
Lines (Backs)	34172	34724	34805	34708	34804	34020
Lines (Fwds)	34597	35149	35230	35133	35229	34445
Lines (Mids)	45234	45787	45868	45771	45867	45082
Lines Warm up (Backs)	36066	36619	36700	36603	36699	35914
Lines Warm up (Fwds)	39213	39766	39847	39749	39846	39061
Lines Warm up (Mids)	42618	43171	43252	43154	43251	42465
MAS Test	54668	55223	55304	55207	55303	54515
Match Simulation	497404	497960	498041	497943	498040	497251
Match Simulation #2	23149	23698	23779	23682	23778	22999
Quad Colour Decision Kick	32394	32945	33026	32929	33025	32243
Reel and Go Kick	8167	8696	8773	8680	8773	8025
Roundabout and 5 Point Link Up	10534	11073	11152	11057	11151	10388
Roundabout Into 5 Star	27855	28403	28483	28386	28482	27705
Roundabout With Circuit	1036	1027	1046	1021	1052	1119
Roundabout with Cutback	14776	15319	15399	15303	15398	14628
RTP	419638	420195	420277	420178	420275	419484
Shape to Coach Into Goal	2147	2594	2662	2580	2663	2047
Shape To Goal	26303	26850	26930	26834	26929	26153
Shuttle	16203	16742	16821	16726	16820	16057
Shuttles	2691	3123	3188	3109	3189	2593
Small Into Big Bowtie	7885	8418	8497	8402	8496	7742
Soccer	49090	49643	49724	49627	49723	48938
Strides	3727	4201	4271	4186	4272	3609
Take Off Drill	4350	4860	4935	4844	4935	4218
Team Competition	1953	2385	2452	2371	2453	1862
Transition Runs Into Goal	3321	3850	3929	3834	3928	3183
Warm up	772898	773453	773535	773437	773534	772744
Warm up and Strides	34947	35500	35581	35484	35580	34795

Warm up Game Prep with Scenarios	25374	25928	26009	25911	26008	25222

Appendix 3 – Ethics—Information to Participants

INFORMATION TO PARTICIPANTS INVOLVED IN RESEARCH

You are invited to participate

You are invited to participate in a research project entitled "Temporal analysis of physical and skilled performance in elite Australian Rules football'

This project is being conducted by a student researcher David Corbett as part of a Doctoral thesis at Victoria University under the supervision of Dr. Sam Robertson from ISEAL, College of Sport and Exercise Science at Victoria University and the Western Bulldogs.

Project explanation

It is likely that both the number of involvements and the physical intensity of matches and training sessions decline as a function of time. However, there are currently very few methods to measure these reductions in performance. Specifically, there is currently no way to know how long on-field stints or training drills should last, before player performance begins to decline.

The aim of this study is to develop and apply a range of methods, to measure short-term changes in both physical output (as measured through wearable technologies, such as GPS), and skilled output (as measured using Champion Data performance statistics, as well as coding conducted within the club) The methods developed in this study will allow for the creation of game-day strategies, which consider how long you are able to spend on field or in a certain position, before your physical and skilled outputs begin to decline. Additionally, these methods will allow for a more targeted approach to training drill design, which identifies how long a drill needs to go for before coach objectives are met.

What will I be asked to do?

You will not be required to do anything outside of your normal training and match day participation. For the purposes of this project, we would like to access the data from the wearable technologies (ie., GPS devices, and LPS devices for indoor games) used during training sessions and matches. We would also like to access your Champion Data statistics, and the notational analysis performed upon you. This will allow us to quantify your physical and skilled output on a 'minute by minute' basis.

What will I gain from participating?

By participating in this study, you will contribute the development of methods to identify performance changes within training drills and matches. These methods will provide coaches and performance staff a way to monitor your physical and skilled outputs on a minute-by-minute basis, and will allow for the design of match-day strategies which maximise your on field involvement. Additionally, they will be used to gain a greater understanding of how different drill durations impact your physical and skilled outputs. This will allow coaches and performance staff to design more efficient training sessions, with optimized drill lengths.

How will the information I give be used?

The data from your wearable technologies will be analysed, to see if we can find a way to identify drop offs in your physical output as a function of time. Similarly, the notational analysis performed upon you by both

Champion Data and the clubs Performance Analysts will be analysed on a minute by minute basis, to gain a greater understanding of how your skilled output changes during a training drill or match. These analyses will then be used to build a range of decision making tools, which allow coaches and performance staff to better monitor your on field performance, and to design training drills which best cater to your strengths and weaknesses.

What are the potential risks of participating in this project?

There are no perceived risks associated with this study. If you do not wish to participate in this study there will be no ramifications in terms of the level of service and delivery with regard to coaching and skill learning prescription. Nor will findings from the study it have any influence on squad selection.

How will this project be conducted?

We will use the outputs from your GPS (outdoor sessions and matches) and RFID (Etihad matches) devices. We will also use the results from the notational analysis conducted by Champion Data and within the club. This data will then be analysed using a range of different techniques by Student Investigator David Corbett. All of the results will be securely stored at Whitten Oval.

Who is conducting the study?

The study is conducted by personnel from the Institute of Sport, Exercise and Active Living (ISEAL) at Victoria University and sports science staff at Western Bulldogs.

Chief Investigator: Sam Robertson
Mobile Number: 0424 980 643
Email: sam.robertson@vu.edu.au

Student Investigator: David Corbett
Mobile Number: 0488 404 747
Email: david.corbett@live.vu.edu.au

Any queries about your participation in this project may be directed to the Chief Investigator listed above.
If you have any queries or complaints about the way you have been treated, you may contact the Ethics Secretary, Victoria University Human Research Ethics Committee, Office for Research, Victoria University, PO Box 14428, Melbourne, VIC, 8001, email researchethics@vu.edu.au or phone (03) 9919 4781 or 4461.

Appendix 4 – Ethics-- Consent Form

CONSENT FORM FOR PARTICIPANTS INVOLVED IN RESEARCH

INFORMATION TO PARTICIPANTS:

We would like to invite you to be a part of a study into changes in the skilled and physical outputs of elite Australian Rules footballers, during football matches and training sessions.

This project will develop methods to identify how skilled performance (as measured through statistics collected by Champion Data), and physical performance (as measured through Catapult Sports', global and local positioning systems GPS and LPS), changes as a function of time. These methods will then be applied to match day decision making, in order to identify optimal time on ground for each players. They will also be applied to training data, in order to prescribe optimal durations for training drills. Your 2016 and 2017 GPS and LPS data, as well as your performance statistics from Champion Data will be accessed. This data will be coded and re-identifiable during this process.

CERTIFICATION BY PARTICIPANT

I, ________________________________))
of ________________________________))

certify that I am at least 18 years old* and that I am voluntarily giving my consent to participate in the study: "Temporal analysis of physical and skilled performance in elite Australian Rules football" being conducted at Victoria University by: Associate Professor Sam Robertson and Mr. David Corbett

I certify that the objectives of the study, together with any risks and safeguards associated with the procedures listed hereunder to be carried out in the research, have been fully explained to me by:
Associate Professor Sam Robertson and Mr. David Corbett

and that I freely consent to participation involving the below mentioned procedures:

- Access to 2016 and 2017 GPS/LPS data for all training sessions and matches
- Access to performance coding, within the club, for all training sessions in 2016 and2017
- Access to performance coding, conducted by Champion Data, for all matches in 2016 and 2017

I certify that I have had the opportunity to have any questions answered and that I understand that I can withdraw from this study at any time and that this withdrawal will not jeopardise me in any way.

I have been informed that the information I provide will be kept confidential.

Signed: ____

Date: ____

Any queries about your participation in this project may be directed to the researcher
Associate Professor Sam Robertson
0439 392 881

If you have any queries or complaints about the way you have been treated, you may contact the Ethics Secretary, Victoria University Human Research Ethics Committee, Office for Research, Victoria University, PO Box 14428, Melbourne, VIC, 8001, email Researchethics@vu.edu.au or phone (03) 9919 4781 or 4461.