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Development, assessment and application of a novel algorithm to automatically detect change of direction movement and quantify its associated mechanical load in elite Australian Football

A thesis submitted to Edith Cowan University in fulfilment of the requirements for the degree of

Doctor of Philosophy

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BSc (Hons)

School of Medical and Health Sciences
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USE OF THESIS

The Use of Thesis statement is not included in this version of the thesis.

Abstract

The ability to change direction rapidly and efficiently is critical to team-sport performance, including Australian football (AF), where a player's capacity to rapidly decelerate, move laterally and re-accelerate is critical when evading opponents, tackling, or reacting to the unpredictable bounce of the ball or movement of another player. The biomechanical loading requirements of change of direction (COD) movement are angle and velocity dependant. Cumulative COD movement can impart high levels of neuromuscular and metabolic fatigue which can adversely affect the efficiency of subsequent movement efforts. Despite widespread use of microtechnology devices (the vast majority containing a global navigation satellite system receiver and inertial sensors) in elite level team-sport, a valid solution to automatically detect COD events and quantify the associated biomechanical load of these movements on-field remains absent. This project served to develop an algorithm that can automatically detect COD events, quantify the angle of the COD event and quantify the associated biomechanical load of each COD event. Study 1 and 2 were primarily focused on assessing the validity and reliability of the detection and angle quantification portions of the algorithm in both structured (Study 1) and unstructured (Study 2) movement environments, whilst Study 3 introduced a COD biomechanical load quantification technique to profile the COD demands of match play and a variety of match simulation training drills, provide comparisons between playing positions, and assess any similarities or differences with existing proprietary locomotive metrics. Whilst both COD event detection and angle quantification were highly accurate in a structured environment (Study 1), the accuracy of the angle quantification was severely reduced during unstructured, match-simulation training (Study 2). Utilising the event detection and biomechanical load quantification portions of the algorithm together, without angle quantification, the COD demands of match play were significantly lower than three different training drill types when expressed relative to time, whilst several positional differences were also present in COD demands across an entire season (Study 3).

Study one assessed the validity and reliability of a novel algorithm to automatically detect and calculate COD angle for pre-determined COD events ranging from 45° to 180° in both left and right directions. Five recreationally active males ran five consecutive pre-determined COD trials each, at four different angles (45°, 90°, 135° and 180°) in each direction wearing a commercially available microtechnology unit (Optimeye S5, Catapult

Innovations). Raw inertial sensor data were extracted, processed using our novel algorithm to calculate COD angle, and compared against a high-speed video (remotely piloted, position-locked drone aircraft) criterion measure. Concurrent validity was present for the following angles; (Left: 135°= 136.3 ± 2.1° and Right: 45°= 46.3 ± 1.6°; 135°= 133.4 ± 2.0°; 180°= 179.2 ± 5.9°) with a mild bias (< 5° or 6%) present for remaining angles; (Left: 45°= 43.8 ± 2.0°; 90°= 88.1 ± 2.0°; 180°= 181.8 ± 2.5° and Right: 90°= 91.9 ± 2.2°). All measurement of angles demonstrated good reliability (CV < 5%), whilst greater mean bias (3.6 ± 5.1°), weaker limits of agreement and reduced precision were evident for 180° trials when compared with all other angles ($p < 0.001$). These results confirm the high-level of accuracy and reliability of our novel algorithm to detect COD events and quantify COD angle during pre-determined COD trials and further advocates the use of inertial sensors to quantify sports-specific movement patterns.

Study two assessed the validity and reliability of both the original COD algorithm (Study 1) as well as an enhanced version to automatically detect COD events during Australian football match simulation training. The accuracy of detected COD angles was assessed from both absolute angle and discrete categorisation through multi-rater video observation as the criterion measure. Twenty-five elite, professional male Australian footballers' completed a match simulation training drill on a modified playing area (140 m x 70 m) where video footage was recorded from multiple angles (rear and perpendicular to play) and a 3-minute portion of the drill was synchronised and chosen for the manual coding process to be performed by three different expert raters. Each rater was required to manually note the time-point that each player performed a COD event, whilst also required to document the direction (i.e. left or right), a precise COD angle (between 30° and 180°) and to subsequently categorise the COD angle into pre-determined angle zones (Zone 1: 30-60°, Zone 2: 61-90°, Zone 3: 91-120°, Zone 4: 121-150°, Zone 5: 151-180°). Sensitivity of the enhanced algorithm (95.1%) in correctly detecting COD events was greater than the original version of the algorithm (50.9%), however, the enhanced algorithm significantly underestimated mean COD angle (absolute) ($p < 0.01$, $d = 1.07 – 1.13$) and mean COD angle zone (discrete) ($p < 0.01$, $d = 0.84 – 0.91$) when compared against each of the expert raters, whom demonstrated excellent inter-rater reliability for both COD angle (ICC: 0.997, $p < 0.001$) and COD angle zone allocation (ICC: 0.993, $p < 0.001$). The COD event detection capacity of the enhanced algorithm remained high in unstructured, chaotic, match simulation training, whilst the COD angle detection accuracy was poor, likely due to the spontaneous nature of the training drill and individual biomechanical variation to pre-determined versus reactive COD movement. The accuracy

of the COD event detection portion of the algorithm provides an opportunity to further integrate sensor signal outputs in a different manner to obtain and track mechanical loading requirements of on-field COD movement during team-sport activity.

Study three provided a method to quantify the mechanical load associated with each COD event which was subsequently used to profile the COD demands of 3 different training drills for comparison against match play data. Positional differences in COD demands were also assessed across the season, whilst our newly developed COD metrics were compared against existing proprietary metrics to determine their novelty. Forty-five elite Australian footballers' provided player movement data via a commercially available microtechnology unit (Optimeye S5, Catapult Innovations) for both training and match play across the course of an entire AFL premiership season. Three different types of match simulation style training drills were compared to assess the effect that field size and player density has on COD frequency and load (and other proprietary movement metrics). Each of these drill types were also compared against match play to ascertain whether these drills meet the COD (and other movement) requirements of match play, where match play positional COD demands were also assessed across the course of a season. The relative COD demands (COD frequency and load relative to time) of each training drill type (Small-Sided Games (SSG), Mini Footy, Team Training) were greater than match play ($p < 0.01$), whilst the COD demands of each drill were proportional to field size and player density of each specific drill where SSG demonstrated the greatest demand for COD frequency and load, followed by Mini Footy, then Team Training. During match play, the relative COD requirements (CODAlg) were greater for inside midfielders when compared against mobile defenders ($p = 0.001$, $d = 0.90$, *moderate*) and tall forwards ($p = 0.031$, $d = 1.04$, *moderate*). Additionally, outside midfielders ($p = 0.048$, $d = 0.54$, *small*) and mobile forwards ($p = 0.027$, $d = 1.07$, *moderate*) accumulated significantly more COD events than mobile defenders. Inside midfielders recorded a significantly higher rate of COD load (CODLoadAlg) than mobile defenders ($p < 0.001$, $d = 1.33$, *large*), rucks ($p = 0.026$, $d = 1.25$, *large*) and mobile forwards ($p = 0.047$, $d = 0.03$, *trivial*). Both outside midfielders ($p = 0.008$, $d = 0.91$, *moderate*) and mobile forwards ($p = 0.003$, $d = 1.39$, *large*) recorded a significantly higher rate of CODLoadAlg than mobile defenders. CODAlg and CODLoadAlg were largely correlated ($p < 0.01$) with relative IMA-COD during each training drill as well as match play. Almost all relative physical output measures (except IMA-Decel) decreased during each subsequent period (quarter and half) of match play. The COD demands of three different types of match simulation training drills all exceeded the demands of match play, however, whilst at a lower rate, players are

required to sustain these COD demands for a far greater duration (i.e. across an entire match where physical output markedly changes), when compared with training drills. Differences in COD demands present across positions may provide unique information that enables individualised, position-specific training prescription to more closely align with the evident differences during match play. These novel COD movement metrics may provide an alternative insight into the movement demands of team-sports and ultimately enhance load monitoring practice to optimise performance and reduce injury risk.

These three experimental studies as a collective provide a valid solution to detecting COD events and quantifying the associated mechanical load of COD movement during on-field team-sport activity; as well as provides a unique insight into the COD prevalence and mechanical load requirements of AF training and match play. The findings of this thesis may extend beyond elite AF and have the potential to influence future practice in various other team-sport environments.

Declaration

I certify that this thesis does not, to the best of my knowledge and belief:

i. incorporate without acknowledgment any material previously submitted for a degree or diploma in any institution of higher education;
ii. contain any material previously published or written by another person except where due reference is made in the text of this thesis; or
iii. contain any defamatory material.

[redacted]

Aaron S. Balloch

26th November 2019

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Abbreviations

ACL	Anterior Cruciate Ligament
AF	Australian football
AFL	Australian Football League
AHRS	Attitude and Heading Reference System
ASCA	Australian Strength & Conditioning Association
au	Arbitrary Unit
CKF	Complementary Kalman Filter
COD	Change of Direction
CODAlg	Algorithm Detected COD Events
CODLoadAlg	Algorithm Detected COD Load
CoM	Centre of Mass
CV	Coefficient of Variation
EKF	Extended Kalman Filter
FFC	Fremantle Football Club
FP	False Positive
FN	False Negative
GCT	Ground Contact Time
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
GRF	Ground Reaction Force
Hz	Hertz
IKF	Interlaced Kalman Filter
ICC	Intraclass Correlation Coefficient
IMA-COD	IMA Detected COD Events
IMA-Accel	IMA Detected Acceleration Events
IMA-Decel	IMA Detected Deceleration Events
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
LoA	Limits of Agreement
LPS	Local Positioning System
m	Metre
m^2	Metre Squared

MARG	Magnetic Angular Rate and Gravity
MEMS	Micro-Electro Mechanical-System
min	Minute
min^{-1}	per Minute
$m.min^{-1}$	Metres per Minute
ms	Milliseconds
$m.s^{-1}$	Metres per Second
$m.s^{-2}$	Metres per Second Squared
no.	Number
OR	Odds Ratio
PL™	Player Load™
PL_{SLOW}	Player Load Slow
PL_{2D}	Player Load 2D
PL_{ML}	Player Load Medio-Lateral
PL_{AP}	Player Load Anterior-Posterior
PL_{VERT}	Player Load Vertical
RHIE	Repeat High-Intensity Efforts
RPE	Rating of Perceived Exertion
s	Second
SD	Standard Deviation
SEM	Standard Error of Measurement
SPRINZ	Sports Performance Research Institute, New Zealand
sRPE	Session Rating of Perceived Exertion
SSG	Small-sided Games
SWD	Smallest Worthwhile Difference
TE	Typical Error
TP	True Positive
UKF	Unscented Kalman Filter

Definitions

Body Fixed Frame	Frame of reference fixed to a rigid body
Body Load	Square root of the sum of the squared instantaneous rate of change in acceleration in each of the 3 vectors (*x*, *y* and *z*)
Earth Frame	Frame of reference centred at a point on the Earth's surface
Euler Angles	Represent the orientation of a rigid body using three angles in relation to a fixed coordinate system
Gaussian Kernel	A kernel for smoothing in the shape of a Gaussian (normal distribution) curve
Gimbal Lock	Loss of one degree of freedom in a three-dimensional space that occurs when two of three gimbals are driven into a parallel configuration
Hard Iron Bias	A piece of magnetic material that is physically attached to the same reference frame as the sensor causing permanent bias in sensor output
Inertial Frame	A reference frame that is either fixed or moving at a constant velocity
Impulse Load	Accumulated mechanical load equal to the sum of areas under the 3-axis accelerometry curves (N.s)
Inertial Movement Analysis	Algorithm uses a Polynomial least squares fit to smooth the original acceleration data at a known frequency and then overlay this smoothed curve over the original acceleration trace to detect that an 'event' has occurred. The magnitude of the event is then calculated as the 'sum of the medio-lateral and anterior-posterior' area under the curve of that event and expressed as a change in velocity (m/s) across the mediolateral and anterior-posterior acceleration area.
Iteration	Repetition of a process
Order of Approximation	The accuracy of an approximation numerically represented as an order of the power series representing the error
Orthogonal	At right angles (Cartesian coordinate system)
Player Load™	Square root of the sum of the squared instantaneous rate of change in acceleration across each of the three vectors (x, y and z); divided by a scaling factor of 100
PL_{2D}	Sum of medio-lateral (x) and anterior-posterior (y) acceleration axes (removal of vertical (z) acceleration axis)
PL_{SLOW}	Sum of all accelerations from the tri-axial accelerometer at speeds <2m.s-1

PL_{AP}	Individual Player Load™ vector (y-axis)
PL_{ML}	Individual Player Load™ vector (x-axis)
PL_{VERT}	Individual Player Load™ vector (*z*-axis)
Quantization	Process of converting a continuous range of values into a finite range of discrete values
Quaternions	An extension of complex numbers designed to define a four-dimensional volume using three 'imaginary' parts and one 'real' part
Soft Iron Bias	Deflections or alterations in the existing magnetic field depending upon which direction the field acts relative to the sensor
Vasti Group	Sum of vastus medialis, lateralis and intermedius

List of Publications

Balloch, A. S., Meghji, M., Newton, R. U., Hart, N. H., Weber, J. A., Ahmad, I., & Habibi, D. (2019). Assessment of a Novel Algorithm to Determine Change-of-Direction Angles While Running Using Inertial Sensors. *Journal of Strength and Conditioning Research*. Advanced online publication. DOI: 10.1519/JSC.0000000000003064

Meghji, M., **Balloch, A. S.**, Habibi, D., Ahmad, I., Hart, N. H., Newton, R. U., Weber, J. W., Ahmad, I., & Waqar, A. (2019). An Algorithm for the Automatic Detection of Athletes' Change of Direction Incidents Using IMU Sensor Data. *IEEE Sensors*. *19*(12): 4518-4527.

List of Conference Proceedings

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Statement of Contributors

Aaron Balloch, Jason Weber, Nicolas Hart and Robert Newton conceptualised and planned the research project and developed specific research questions. Aaron Balloch and Jason Weber collected all data.

Chapters 1 and 2: Aaron Balloch, Nicolas Hart, Timo Rantalainen, Jason Weber and Robert Newton contributed to the conceptual design and writing of these chapters.

Chapter 3: Aaron Balloch, Mahir Meghji, Nicolas Hart, Jason Weber and Robert Newton contributed to the design and development of the algorithm, study design, data analysis, interpretation and writing of the chapter.

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Chapter 1 Introduction

1.1 Background and Physical Demands of Australian Rules Football

Australian Football (AF) is a unique, multifaceted field-based sport comprised of two teams of 22 players that contest a game over four 20-minute quarters plus stoppage time (Gray & Jenkins, 2010; Pruyn et al., 2012; Rogalski, Dawson, Heasman & Gabbett, 2012; Watsford et al., 2010). Elite-level, professional footballers compete in a national competition known as the Australian Football League (AFL) where full-time training is implemented to provide an environment where athletes can further develop physical, technical, mental and tactical aspects of the sport (Gucciardi, Gordon & Dimmock, 2008; Piggott, 2008; Young et al., 2005). To be successful at the elite level, these players must possess a combination of these attributes to meet the increasing physical and technical demands of the modern game (Colby, Dawson, Heasman, Rogalski & Gabbett, 2014; Gray & Jenkins, 2010).

Modern AF has become progressively faster due to improvements in playing surfaces, rule changes, technical resources and tactical shifts and thus the physical requirements of the game are now more demanding and continually evolving (Gray & Jenkins, 2010; Norton, Craig & Olds, 1999; Orchard, Driscoll, Seward & Orchard, 2012; Wisbey & Montgomery, 2016). Fundamentally, elite level AF match play requires a high amount of absolute running volume comprised of intermittent bouts of high-intensity sprinting interspersed with recovery periods of walking and jogging (Dawson, Hopkinson, Appleby, Stewart & Roberts, 2004; Wisbey, Montgomery, Pyne & Rattray, 2010). In addition, these players are exposed to high levels of physical duress from frequent accelerations and decelerations, jumping and landing, rapid change of direction movement and heavy contact/collisions with the ground and other players (Coad, Gray, Wehbe & McLellan, 2015; Fortington et al., 2015; Hrysomallis, 2013; Young et al., 2005).

Scrutiny on both a player's performance and level of conditioning as well as added pressure within the AFL system to achieve success has substantially increased, which has magnified the focus on maximising a player's physical capacity to meet the ever-increasing demands of a competitive match (Mooney, Cormack, O'Brien & Coutts, 2013a; Piggott, 2008). In order to build a robust and resilient footballer with a high-level running capacity and level of conditioning that can withstand the rigours of elite level AF, these players are exposed to high volumes of pre-season training at an intensity that is intended to elicit

positive musculoskeletal and cardiovascular adaptations (Buchheit et al., 2013; Rogalski et al., 2012). However, due to their elite status and existing high-level physiological and musculoskeletal conditioning, a high-intensity, high-volume training approach is often utilised to elicit further adaptation and develop resilience (Buchheit et al., 2013; Colby et al., 2017; Coutts et al., 2015). However, the fitness, injury and fatigue (or dose-response) relationship is complex where an essential component of the clinicians and sports science team's role is to keep players' injury free whilst also prescribing sufficient physically intense training to adequately prepare them for the demands of competition (Gabbett, Hulin, Blanch & Whiteley, 2016). Essentially, the delicate aim is to find a balance between achieving sufficient training loads to improve player robustness whilst restricting excessive training loads whereby there is likely a ceiling that will pose a higher injury threat for each player if exceeded (Colby et al., 2014; Gabbett & Ullah, 2012).

Given the nature of high-intensity, high-volume training load required, the importance of load monitoring and management in reducing the risk of overtraining (illness, injury, fatigue) cannot be understated (Buchheit et al., 2013; Piggott, 2008; Rogalski et al., 2012). To achieve on-field success, it is imperative that coaching staff have as many of their player's available as possible, with an added emphasis on key player availability (Drew, Raysmith & Charlton, 2017; Hoffman, Dwyer, Bowe, Clifton & Gastin, 2019). Consequently, each AFL club heavily invests in multidisciplinary teams of physiotherapists, doctors, sports scientists and strength and conditioning practitioners to carefully monitor and individualise each player's workload, preparation, training and long-term athletic development. Given this substantial investment of time, money and resources, the importance placed on longitudinal performance enhancement and injury prevention practice to maximise player availability is clearly evident. Despite this considerable financial investment in staff, technology and equipment to facilitate comprehensive and multi-faceted load monitoring systems, both new and recurrent overall injury incidence remain high (AFL Doctors Association, AFL Physiotherapists Association & AFL Football Operations Department, 2017, 2018; Hrysomallis, 2013; Rogalski et al., 2012).

Professional Australian footballers are at a high risk of injury due to the complexity and unpredictability of movement demands, heavy tackles and collisions, along with the effect of accumulated metabolic and neuromuscular fatigue across the course of a match (Coutts et al., 2015; Gastin, McLean, Spittle & Breed, 2013a; Mooney, Cormack, O'Brien, Morgan & McGuigan, 2013b; Young, Hepner & Robbins, 2012). Given the high-intensity,

high-velocity, heavy-impact nature of the sport, some injuries are to an extent, unavoidable; however lower-limb intrinsic injury risk and severity can be reduced with tailored strength and conditioning interventions and consistent monitoring of individual workload (Colby et al., 2014; Gabbett, 2010; Opar et al., 2014). Wearable technology provides an opportunity for sports science and strength and conditioning practitioners to collate, store and analyse on-field movement data, which when used appropriately, has the capacity to enhance load monitoring and management practices.

Microtechnology units which house Global Navigation Satellite Systems (GNSS) or Global Positioning Systems (GPS) along with inertial sensors (accelerometers, gyroscopes and magnetometers) are permitted to be worn during AF competition and are used by all teams within the AFL (Delaney, Thornton, Burgess, Dascombe & Duthie, 2017). These devices provide sports science and strength and conditioning practitioners with objective locomotive data in 'real time' during training and competition and are often analysed in greater depth prospectively to provide sports science and coaching staff with physical performance reports. Global positioning technology has significantly improved since its inception into the sporting landscape, and is now used comprehensively across a variety of team-sports (Cummins, Orr, O'Connor & West, 2013; Li et al., 2016). Global positioning technology fundamentally uses satellite signal frequency to triangulate the position of the receiver (or unit) multiple times per second (sampling rate dependant), then determines speed and displacement using the rate of change in the satellites' signal frequency as a result of the movement of the receiver (Doppler shift) (Townshend, Worringham & Stewart, 2008).This provides instantaneous displacement and velocity outputs that can be used to compute more meaningful locomotive metrics such as metres per minute ($m.min^{-1}$), distance travelled within pre-determine speed bands (including high-speed distance), accelerations and decelerations, repeat high-intensity efforts as well as metabolic load estimations (Akenhead, French, Thompson & Hayes, 2014; Coutts et al., 2015; Gray, Jenkins, Andrews, Taaffe & Glover, 2010; Johnston, Watsford, Kelly, Pine & Spurrs, 2014; Varley, Fairweather & Aughey, 2012).

Despite the widespread use of GPS technology, there are some important accuracy limitations that must be understood when interpreting GPS data. Research has consistently demonstrated decreased validity and reliability when measuring distance and speed during short duration, high-velocity, explosive and multi-directional movement patterns (Akenhead et al., 2014; Duffield, Reid, Baker & Spratford, 2010; Jennings, Cormack, Coutts, Boyd & Aughey, 2010; Varley et al., 2012; Vickery et al., 2014); which comprise

a large portion of team-sport competition. In addition, despite the portable, lightweight and unobtrusive nature of this technology, its reliance on satellite connectivity means that it cannot be used for indoor sports and is vulnerable to adverse atmospheric conditions or external signal interference which can significantly impact the strength of the signal; and thus the accuracy of the data. In recent times, team-sport locomotive research has shifted more towards inertial sensor technology. These sensors are co-located within the same microtechnology unit as the GPS engine, yet operate independently and sample at much higher frequencies.

Fundamentally, accelerometers measure linear acceleration (Yang & Hsu, 2010), gyroscopes measure rotation or angular velocity (Abyarjoo, Barreto, Cofino & Ortega, 2015) and magnetometers measure orientation (relative to the Earth) (Aminian & Najafi, 2004). When combined, these sensors have the potential to determine segmental orientation and calculate kinematic data using advanced filtering and signal analysis procedures, without the lab-based constraints of human motion capture systems (Aminian & Najafi, 2004; Madgwick, Harrison & Vaidyanathan, 2011; Wang et al., 2017). Most commonly in team-sport applications, these sensors have been used to provide a measure of external workload using accelerometry with the intent to quantify the mechanical load based from tri-axial centre of mass (CoM) movement during training and competition (Boyd, Ball & Aughey, 2013; Gentles, Coniglio, Besemer, Morgan & Mahnken, 2018; Hulin, Gabbett, Johnston & Jenkins, 2018; Lovell, Sirotic, Impellizzeri & Coutts, 2013). However, these measures of 'Player Load' or 'Body Load' have consistently been shown to strongly correlate with GPS derived distance measures (Casamichana, Castellano, Calleja-Gonzalez, San Román & Castagna, 2013; Gentles et al., 2018; Polglaze, Dawson, Hiscock & Peeling, 2015; Scott, Lockie, Knight, Clark & Janse de Jonge, 2013a), bringing into question their supplementary value for outdoor team-sport application. Additionally, whilst uni-axial, bi-axial and low-velocity derivatives of these load metrics exist and can provide additional insight into non-running based movement demands (Hulin et al., 2018; Jaspers et al., 2018; Rowell, Aughey, Clubb & Cormack, 2018; Svilar, Castellano & Jukić, 2018a), these load measures ultimately lack the specificity to accurately the determine the frequency and mechanical load associated with more discrete, sports-specific movement demands.

Microtechnology manufacturers have subsequently created proprietary algorithms in an attempt to detect and quantify the magnitude of these sports-specific movements such as accelerations, decelerations, jumps and CODs (Catapult Sports, 2013a). These algorithms have been tested in a laboratory setting as well as on-field and whilst they have

been shown to be valid and reliable in detecting counts of instantaneous accelerations, decelerations and COD events in a closed testing environment, in more chaotic tasks typical of team-sport movement situations, and when these detected movements are further classified by magnitude and direction, their reliability is significantly reduced (Luteberget, Holme & Spencer, 2018a; Meylan, Trewin & McKean, 2017). Plus, these algorithms have not yet been validated in a team-sport match simulation training or competition environment which has prompted the need for alternative methods to quantify more explosive and mechanically demanding movement tasks such as COD events.

Change of direction movement is highly prevalent in team-sports (Bloomfield, Polman & O'Donoghue, 2007; Dawson et al., 2004) and when executed quickly and efficiently can provide a significant performance advantage in AF when pursuing or evading an opponent as well as trying to win possession of the ball (Hart, Spiteri, Lockie, Nimphius & Newton, 2014). The biomechanical loading requirements of COD movement typically involve sudden, whole-body changes in velocity which require high levels of braking and propulsive tri-axial impulses facilitated by high-levels of lower-limb muscle activation and joint loading strategies (Besier, Lloyd & Ackland, 2003; Harper & Kiely, 2018; Rand & Ohtsuki, 2000). As the frequency of these movements increase, the accumulation of neuromuscular and metabolic fatigue can lead to a reduction in movement efficiency and a subsequent increase in injury risk (Hader, Mendez-Villanueva, Palazzi, Ahmaidi & Buchheit, 2016; Havens & Sigward, 2015a; Sanna & O'Connor, 2008; Schreurs, Benjaminse & Lemmink, 2017). If such events can be detected and these changes in mechanical loading can be identified, quantified and examined on-field using wearable technology; more informative load management strategies may be developed to further enhance performance and reduce injury risk through improved and individually tailored conditioning interventions specific to the demands of AF.

Given the increasing physical demands of AF and high levels of injury incidence, more informed, individualised and multi-faceted load management systems are required to optimise performance and injury risk evaluation. Wearable technology provides a valuable source of contextual information in a restricted setting yet is currently underutilised given the paucity of research focused on using inertial sensors to analyse and detect discrete, sports-specific movements in an on-field, team-sport environment. Ultimately, when interpreting proprietary movement metrics, little transparency exists in relation to raw data processing and therefore utilising raw sensor signals with appropriate filtering and signal analysis techniques may prove more accurate and informative. More

specifically, a valid solution to detect the frequency and quantify the magnitude of COD movement remains absent, which provides a clear rationale to further investigate whether the use of inertial sensors can provide a measure of COD mechanical load to better understand the movement demands of AF and other team-sports.

1.2 Purpose of Research

This project aimed to develop an algorithm that is capable of automatically detecting COD events and subsequently quantify the associated mechanical load of COD movement during professional Australian football training and match play. Specifically, this project describes the initial development of a custom-designed algorithm using inertial sensor technology (accelerometer, gyroscope, magnetometer) from a commonly used and commercially available microtechnology device to automatically detect COD 'events', identify the direction (i.e. left or right) and quantify a precise COD angle. This algorithm was tested for validity and reliability in both a structured and unstructured (match simulation) environment, before a secondary algorithm was developed and applied for further testing in a match simulation training drill. This secondary algorithm was subsequently used to profile the mechanical load associated with COD movement during match simulation training drills and match play to complement and compare against existing proprietary load monitoring metrics. This project aimed to provide the ability to quantify the mechanical load associated with COD movement which may aid in developing more in-depth and effective load management models across Australian football and other team-sports.

1.3 Significance of Research

Given the known limitations associated with GPS technology (Castellano, Casamichana, Calleja-González, San Román & Ostojic, 2011; Coutts & Duffield, 2010; Jennings et al., 2010; Johnston et al., 2014), there is clear rationale for the use of inertial sensors to better quantify sports-specific movement for enhanced on-field load monitoring practice. Currently, there is a clear inadequacy concerning on-field, lower body load management with the absence of information pertaining to the frequency and magnitude of COD movement. Give the high prevalence of COD movement in Australian football and other team-sports (Dawson et al., 2004; Jennings et al., 2010; Luteberget & Spencer, 2017; Meylan et al., 2017; Svilar et al., 2018a) and the neuromuscular and metabolic cost associated with repeat, high-intensity COD movement (Harper & Kiely, 2018; Maniar,

Schache, Cole & Opar, 2019), the resultant fatigue may adversely affect movement technique and efficiency; consequently heightening the risk of injury (Hader, Mendez-Villanueva, Ahmaidi, Williams & Buchheit, 2014; Sanna & O'Connor, 2008; Zebis et al., 2011). Therefore, the series of studies within this project aimed to provide a solution that would allow sports science and strength and conditioning practitioners to quantify the frequency and mechanical load associated with on-field COD movement and integrate this information into current load management practice for performance enhancement and injury prevention purposes.

1.4 Research Questions

Study 1: Assessment of a Novel Algorithm to Determine Change of Direction Angles While Running Using Inertial Sensors

1. Can a custom-designed algorithm be developed by integrating inertial sensor signals from a commercially available, wearable, trunk-mounted microtechnology unit that is able to automatically detect COD events, determine COD direction and quantify a precise COD angle?

2. Is this algorithm valid and reliable in detecting single, pre-determined COD events between 45° and 180°, identifying the correct direction and reporting a precise COD angle?

Study 2: Detecting and Categorising Change of Direction Events During Australian Football Match Simulation Training - Validity of a Novel Algorithm

1. Is the original custom-designed COD algorithm (Study 1) valid and reliable in detecting COD events, reporting direction and quantifying a precise COD angle during a match simulation training drill?

2. Does a secondary custom-designed COD detection algorithm outperform the original COD algorithm in detecting COD events, reporting direction and quantifying a precise COD angle during a match simulation training drill?

Study 3: Quantifying and Assessing the Mechanical Load Associated with Change of Direction Movement During Australian Football Training and Match Play

1. Can a measure of 'COD mechanical load' be developed by further integrating inertial sensor signals in accordance with the event detection algorithm (Study 2)?

2. Do training drills with smaller field dimensions and higher player density elicit an increase in relative COD frequency and COD load when compared with larger and less congested training drills?

3. How do the relative COD frequency and load demands of three different match simulation training drills compare with AFL match play?

4. How do these custom-designed COD metrics (COD frequency and load) differ or relate to proprietary GPS and inertial sensor derived metrics commonly used in elite sport?

5. Are there any positional differences present across COD frequency, load and other movement demands during competitive AFL match play?

6. Do the COD frequency, load and other movement demands change across the course of an AFL game from quarter to quarter and half to half?

1.5 Research Studies

A series of three experimental studies have been developed to provide a valid and reliable solution to quantify the frequency and magnitude (load) of COD movement during on-field Australian football training and match play. The first study outlines the signal processing computation and decision techniques used to establish a custom-designed algorithm that can detect pre-determined COD events, identify the relevant direction of movement and calculate a precise COD angle; whilst concurrently assesses its validity and reliability. The second study compares the performance of the original algorithm against a secondarily designed COD algorithm in detecting COD events, identifying direction and calculating a precise COD angle during match simulation Australian football training. Whilst the third study outlines the addition of a 'mechanical COD load' measure and outlines/compares the COD prevalence and load demands during various match simulation training drills and match play, assesses the relationship of these new COD metrics to existing proprietary GPS and inertial sensor derived metrics, profiles and

compares the COD demands of all positions in AFL match play and finally analyses how the COD (and other movement) demands change across the course of an AFL game.

1.6 Limitations and Delimitations

1. The COD detection and load algorithms were developed and assessed using data from both recreationally active males and elite Australian football players. The applicability of this algorithm was only demonstrated on elite, male Australian football players from one team, and therefore the outcomes of this thesis may not be synonymous with players from different AFL teams or lower level Australian football leagues (state league or amateur), women's AFL or lower-level women's Australian football, and other men's and women's team-sports such as soccer, basketball, field hockey as well as rugby league and rugby union for example.

2. The COD detection and load algorithms were created using inertial sensor signals from a trunk-mounted, Catapult (Optimeye S5) microtechnology device. Therefore, the performance of this algorithm may vary in accordance with alternate placement of device (e.g. lumbar spine) and alternative wearable technology companies that manufacture microtechnology units housing different models of inertial sensors.

3. The training drills analysed in Study 3 were taken from the pre-season period (January) which is designed to be the most strenuous training period across the course of an entire season. Therefore, the COD (and other movement variable) demands may differ in-season where training becomes a secondary stimulus and is planned around optimising player preparedness for competition.

Chapter 2 Literature Review

Overview

This literature review initially discusses the prevalence and importance of COD movement in team-sport as well the biomechanical principles that underpin efficient COD execution. Secondly, inertial sensors and their functionality are discussed in detail in conjunction with the technical aspects of signal acquisition and analysis techniques that facilitate effective use of these sensor signals. A comprehensive overview of the application of inertial sensors in a team-sport environment is then provided, with a particular focus on their use during training and match play and their current contribution to load management in elite sport. Lastly, additional suggestions for their potential enhanced utility in AF is provided.

2.1 Change of Direction Movement in Team-Sport

Change of direction movement is highly prevalent in multidirectional sports (Bloomfield et al., 2007; Dawson et al., 2004) where an ability to rapidly decelerate, move laterally and re-accelerate is a critical mechanism to execute various movement elements within a game scenario, such as evading opponents, tackling, or reacting to the bounce of the ball or movement from another player (Hart et al., 2014). A player's ability to rapidly and efficiently change direction has been directly linked with performance success (Bloomfield et al., 2007; Faude, Koch & Meyer, 2012; Maniar et al., 2019). Whilst subtle differences may be present between pre-planned (in response to visual or auditory cues) and reactive (unplanned stimuli) (Jones, Stones & Smith, 2014; Lee, Lloyd, Lay, Bourke & Alderson, 2017) COD movement, the biomechanical loading requirements of COD movement are typically associated with sudden, whole-body changes in velocity (e.g. deceleration). These rapid velocity changes require high magnitudes of tri-axial (vertical, medio-lateral and anterior-posterior) impulses which are facilitated by high-levels of lower-limb muscle activation (Besier et al., 2003; Hader et al., 2016; Maniar et al., 2019; Spiteri, Cochrane, Hart, Haff & Nimphius, 2013; Weinhandl et al., 2014). In turn, the demand on the lower-limbs differs in accordance with COD angle and velocity (Havens & Sigward, 2015b, 2015c; Schreurs et al., 2017; Vanrenterghem, Venables, Pataky & Robinson, 2012).

2.1.1 Change of Direction Biomechanics

Change of direction 'events' involve a braking (or deceleration) phase and propulsive (or acceleration) phase which highlights the importance of eccentric-concentric muscle action for both force absorption and production, as well as a muscular endurance element as the number of directional changes (or COD events) increase (Brughelli, Cronin, Levin & Chaouachi, 2008; Dos'Santos, Thomas, Comfort & Jones, 2018). The braking or deceleration phase is heavily reliant upon the capacity of the knee extensor (quadricep) muscles to absorb ground reaction force (GRF) (Hader et al., 2016; Rand & Ohtsuki, 2000). The amount of deceleration needed preceding a COD event is largely related to the intended angle and velocity at which the movement is performed (Vanrenterghem et al., 2012). Sharper CODs have been associated with longer ground contact times (GCT) (Havens & Sigward, 2015c; Vanrenterghem et al., 2012), higher GRFs (Havens & Sigward, 2015c; Schot, Dart & Schuh, 1995; Sigward, Cesar & Havens, 2015) and longer deceleration distances (Hader et al., 2016) where these longer decelerative impulse demands are further increased at faster approach velocities (Nedergaard, Kersting & Lake, 2014; Vanrenterghem et al., 2012). However, the increased force absorption demands required to decelerate quickly for more acute and high-velocity COD events may not be evenly distributed, with research demonstrating a greater reliance on the knee (Havens & Sigward, 2015b)(greater peak knee extensor moments and peak posterior GRF) which can increase anterior tibial shear force (Sell et al., 2007), thus the load on the anterior cruciate ligament (ACL) (Markolf, Gorek, Kabo & Shapiro, 1990; Markolf, O'Neill, Jackson & McAllister, 2004; Shao, MacLeod, Manal & Buchanan, 2011). Therefore, the eccentric strength or capacity of the quadricep musculature is critical during this braking phase to enable the knee to withstand heavy loads (de Hoyo et al., 2016; Havens & Sigward, 2015b; Watts, 2015) and is a determinant of faster COD performance by aiding braking/propulsion efficiency (Dos' Santos, Thomas, Jones & Comfort, 2017; Jones, Thomas, Dos'Santos, McMahon & Graham-Smith, 2017; Spiteri et al., 2013; Spiteri et al., 2015a).

2.1.1.1 Braking Phase

During COD movement, the primary purpose of the braking phase is to reduce centre of mass (CoM) velocity to allow the athlete to get into a position where they can redirect their movement quickly and efficiently (Maniar et al., 2019; Sheppard & Young, 2006). Whilst the braking GRF during this deceleration phase is largely sagittal (anterior-

posterior) (Maniar et al., 2019), during the 'cutting' motion when the athlete is redirecting their CoM, the GRF is generated in a more medial direction (Maniar et al., 2019). Consequently, a shift in the lower-limb musculature and contraction type is required where greater hip abduction, trunk lean angle and hip adductor moments have been reported (Havens & Sigward, 2015b). As a result, co-contraction of the knee flexors (hamstrings) and extensors (quadriceps) is required to withstand the heavy GRF load and stabilise the knee to prevent anterior translation, thus reducing injury risk, particularly ACL damage, when changing direction (Besier et al., 2003; Havens & Sigward, 2015a; Sigward & Powers, 2007; Weinhandl et al., 2014). Maniar and colleagues (2019) examined this further and indicated that the gluteus maximus, gluteus medius and the 'vasti group' (sum of vastus medialis, vastus lateralis and vastus intermedius) act as the prime movers during medial acceleration of the CoM during sidestep cutting, whilst the gastrocnemius and adductors actually generate GRF laterally (opposing acceleration of the CoM in the intended direction) until the last 15% of stance. Whilst this increase in hip abduction has been previously reported as a biomechanical risk factor associated with knee abduction moments or valgus loading of the knee, thus ACL injury risk (Havens & Sigward, 2015a; Sigward & Powers, 2007), this higher range hip abduction is important in facilitating an optimal distance for planting of the lateral foot (Havens & Sigward, 2015b; Sigward et al., 2015) and subsequent medio-lateral propulsion for executing CODs at more acute angles, highlighting the proposed injury-performance trade-off (Dos'Santos et al., 2018).

2.1.1.2 Propulsive Phase

Following redirection, the propulsive phase aims to accelerate the CoM as quickly and efficiently as possible in the newly intended direction. Whilst the initial stages of the CoM medial re-acceleration (via a cut-step) are primary modulated by the vasti group and the gluteus maximus and medius, subsequent anteriorly directed propulsive GRF has been reported to be primarily generated by the gluteus maximus and hamstrings (during the first 60-70% of stance) during hip and knee extension, as well as the gastrocnemius and soleus (late stance) during ankle plantar-flexion (Maniar et al., 2019). When compared against the deceleration or braking phase, the absolute amount or total impulse of GRF that the lower limb is required to produce during propulsion is far less (Maniar et al., 2019), however, the metabolic demands of the acceleration or propulsive phase in fact outweighs that of the deceleration phase (Hader et al., 2016; Osgnach, Poser, Bernardini, Rinaldo & Di Prampero, 2010). This is mostly due to heavy eccentric muscle contraction demands during the deceleration phase, which are estimated to be 2-6 times less metabolically

demanding for the same amount of work utilising concentric muscle contractions (Ryschon, Fowler, Wysong, Anthony & Balaban, 1997).

2.1.2 Change of Direction Mechanical Load

As the frequency of these COD movements increase, eccentric muscle demands during deceleration can impart a high-level of lower-limb skeletal muscle damage (Harper & Kiely, 2018; Howatson & Milak, 2009; Proske & Allen, 2005), whilst the repeat accelerative demands can impart a heavy metabolic cost (Hader et al., 2016; Osgnach et al., 2010). This accumulative tissue microtrauma and energetic cost are powerful drivers of neuromuscular and metabolic fatigue both during and after physical activity which can adversely affect the capacity of an athlete to tolerate subsequent braking loads and technical proficiency during high-intensity movement, which may then have a negative effect on performance and have injury implications (Harper & Kiely, 2018; Howatson & Milak, 2009). The presence of both neuromuscular and metabolic fatigue have been demonstrated to have an effect on subsequent movement bouts or efforts, where alterations in movement strategies and acute changes in mechanical efficiency have been shown (Dolci et al., 2018; Hader et al., 2014; Mooney et al., 2013b), which can subsequently alter the mechanical loading profile of lower-body joints via suboptimal muscle activation strategy and inherently increase the risk of injury (Dempsey et al., 2007; Maffey & Emery, 2007; Sanna & O'Connor, 2008; Zebis et al., 2011). However, stronger athletes that can rapidly absorb or produce high levels of GRF whilst maintaining optimal COD mechanics are able to tolerate these higher loads (Jones et al., 2017; Spiteri et al., 2013), whereas beginner or novice athletes may not have the fundamental strength capacity to tolerate these mechanical loads proficiently and place themselves into the optimal position to re-direct their CoM, leading to sub-optimal COD biomechanics and a heightened injury risk (Dos' Santos et al., 2017; Spiteri et al., 2015a; Suchomel, Nimphius & Stone, 2016).

2.1.3 Change of Direction Mechanics and Injury

Change of direction movements are a common source of non-contact injury, owing to rapid isolated events leading to technical and tissue failure as a predisposition to injuries such as ligament sprain or rupture (Boden, Dean, Feagin & Garrett, 2000; Olsen, Myklebust, Engebretsen & Bahr, 2004), or cumulatively, with repetitious suboptimal techniques leading to degradation or strain of muscle or tendon post-competition (Franklyn-Miller et al., 2017; Maffey & Emery, 2007). In cases where COD technique and

conditions remain poorly executed over the long-term, non-contact injuries may extend to chronic issues, such as osteitis pubis, from repeated doses of high-intensity, high-load activity in the absence of adequate recovery (LeBlanc & LeBlanc, 2003). Lower limb muscular strength is critical to allow adequate support of the knee and prevent excessive valgus loading which is a known mechanism associated with increased anterior cruciate ligament (ACL) injury risk (Besier, Lloyd, Cochrane & Ackland, 2001; Boden et al., 2000; Dempsey et al., 2007; Vanrenterghem et al., 2012). Evidence suggests that the sharper the COD angle, the greater the GRF absorption requirements, valgus load, thus injury risk on the knee (Havens & Sigward, 2015b; Hewit, Cronin & Hume, 2013; Schreurs et al., 2017; Vanrenterghem et al., 2012). Therefore, strength is a critical factor to facilitate optimal COD mechanics, as stronger athletes are better able to adopt technically proficient positions, thus better able to demonstrate sufficient trunk control, pelvic rotation, joint stability (reduced knee valgus angle) and appropriate stride length/frequency adjustments (Dempsey, Lloyd, Elliott, Steele & Munro, 2009; Havens & Sigward, 2015b; Hewit et al., 2013; Jones, Herrington & Graham-Smith, 2015b) which will likely provide the greatest chance of resistance to injury along with optimal COD performance (Lauersen, Bertelsen & Andersen, 2014). The deceleration phase, CoM re-direction and subsequent accelerative effort of COD movement expose players to high levels of mechanical stress which have been suggested to be key contributors to overall mechanical load (Nedergaard et al., 2014; Vanrenterghem, Nedergaard, Robinson & Drust, 2017). However, the absence of research in this area indicates that COD movement may not be widely considered in typical load monitoring programs or procedures (Bourdon et al., 2017; Camomilla, Bergamini, Fantozzi & Vannozzi, 2018; Halson, 2014). This is likely due to the current lack of a valid measure or accurate detection method that has the capacity to analyse change of direction movement on-field and during competitive play; yet is inherently necessary to adequately monitor and improve load monitoring practices for performance tracking and injury prevention purposes.

2.2 Load Monitoring in Team-Sport

Current load management practices within team-sport often integrate Global Positioning System (GPS) data with various screening tools, physiological data, anthropometrics and self-reporting measures to provide an overview of a player's readiness to train or compete (Gray & Jenkins, 2010; Jaspers et al., 2018; McLellan, Lovell & Gass, 2011; McNamara, Gabbett, Naughton, Farhart & Chapman, 2013; Montgomery & Hopkins, 2013; Rogalski et al., 2012; Young et al., 2005). Objective measures of

absolute and relative (per minute (.min^{-1})) external workload such as GPS derived distance metrics (including distance within various speed bands) (Aughey, 2011; Colby et al., 2014; Varley, Gabbett & Aughey, 2014; Wisbey et al., 2010), high-speed running distance, accelerometry (Boyd et al., 2013; Gabbett, 2015b; Polley, Cormack, Gabbett & Polglaze, 2015), session time and internal workload such as heart rate telemetry (Buchheit et al., 2013) are commonly assimilated with and assessed against subjective measures including ratings of perceived exertion (RPE) (Casamichana et al., 2013; Fox, Stanton & Scanlan, 2018; Gallo, Cormack, Gabbett, Williams & Lorenzen, 2015; Gallo, Cormack, Gabbett & Lorenzen, 2016; Scott, Black, Quinn & Coutts, 2013b) and wellness measures including muscular soreness (Bahnert, Norton & Lock, 2012; Montgomery & Hopkins, 2013), sleep patterns (Dennis, Dawson, Heasman, Rogalski & Robey, 2015; Juliff, Halson & Peiffer, 2014), fatigue, and levels of 'stress' (Gastin, Meyer & Robinson, 2013b; Kellmann, 2010). Combined, these variables provide a valuable and rather extensive overview of an athlete's broad state of wellbeing. However, when trying to develop an overview of the external workload requirements of on-field training and competition, time-motion analysis methods have typically been adopted from notational video systems to semi-automated camera set-ups and more recently wearable GPS and local positioning system (LPS) technologies (Holme, 2015). However, there are some limitations associated with these wearable technology systems that must be considered.

2.2.1 Global Positioning System Technology for Monitoring On-Field Locomotion

Global positioning system technology for sporting application first became available in 2003 with the intent to measure locomotive distance (Aughey, 2011). This technology typically calculates a precise time and position by decoding radio signals from the network of 24 operational satellites that continuously orbit the Earth (Townshend et al., 2008). These signals are decoded by a GPS receiver which allows the calculation of distance to each satellite by multiplying the time taken for the signal to reach the receiver by the speed of light (Townshend et al., 2008). When distance to at least 4 satellites is known, a 3-dimensional position can be determined using trigonometry (Townshend et al., 2008). To measure speed of distance travelled for a continuously moving object (or human), the rate of change in the satellites' signal frequency is calculated relative to movement of the receiver; known as Doppler shift (Townshend et al., 2008).

Global positioning technology has been used extensively amongst a wide range of sporting applications as a source of objective data relating to the specific on-field

movement demands of team-sport athletes (Colby et al., 2014; Coutts & Duffield, 2010; Duffield et al., 2010; Edgecomb & Norton, 2006; Gray et al., 2010; Jennings et al., 2010; Johnston et al., 2014; Johnston et al., 2012; Murray & Varley, 2015; Rampinini et al., 2015; Varley et al., 2012; Varley et al., 2014; Vickery et al., 2014). Since inception, this technology has advanced enormously within the sporting landscape and with enhanced hardware and firmware, higher sampling rates and improved signal filtering techniques, now has the capacity to provide sports science and strength and conditioning practitioners with a variety of objective movement metrics that include high-speed running distance (Gray et al., 2010; Johnston et al., 2014; Waldron, Worsfold, Twist & Lamb, 2011), in fact, distance within multiple pre-determined speed bands (Coutts & Duffield, 2010; Jennings et al., 2010; Johnston et al., 2014), accelerations and decelerations (Akenhead et al., 2014; Delaney et al., 2016; Varley et al., 2012), repeat high-intensity efforts (RHIE) (Austin, Gabbett & Jenkins, 2011; Jaspers et al., 2018; McLaren, Weston, Smith, Cramb & Portas, 2016) as well as metabolic load estimations (Coutts et al., 2015; Delaney et al., 2016; Di Prampero et al., 2005; Kempton, Sirotic, Rampinini & Coutts, 2015a; Osgnach et al., 2010; Rampinini et al., 2015). Importantly, GPS data is also available in 'real-time' which provides the opportunity for sports science and strength and conditioning staff to gather information and make informed decisions during training and competition (Aughey & Falloon, 2010; Coutts, Quinn, Hocking, Castagna & Rampinini, 2010).

Despite the widespread use of GPS technology, there are inherent limitations associated with this tool that must be considered when interpreting the outputs. GPS technology within sport originally sampled at a frequency of 1Hz (Duffield et al., 2010; Edgecomb & Norton, 2006; Gastin & Williams, 2010; Jennings et al., 2010; Wisbey et al., 2010), progressed to 5Hz (Duffield et al., 2010; Jennings et al., 2010; Johnston et al., 2012; Varley et al., 2012; Vickery et al., 2014) and is now commonly 10Hz (Castellano et al., 2011; Johnston et al., 2014; Varley et al., 2012; Vickery et al., 2014); with some units able to sample at 15Hz (supplemented with accelerometer outputs) (Johnston et al., 2014; Vickery et al., 2014). Initial research has suggested that microtechnology units with higher sampling frequencies produce greater validity when measuring distance (Aughey, 2011; Jennings et al., 2010; Rampinini et al., 2015; Varley et al., 2012), particularly during longer duration activities (Castellano et al., 2011; Gastin & Williams, 2010; Jennings et al., 2010). However, to the contrary, Johnston and authors (2014) reported greater validity and inter-unit reliability in a 10Hz GPS engine when compared with a 15Hz sampling rate. In addition, numerous studies have reported significantly reduced validity and reliability when measuring distance and velocity during high-velocity movements (Delaney,

Cummins, Thornton & Duthie, 2018; Duffield et al., 2010; Jennings et al., 2010; Varley et al., 2012; Vickery et al., 2014) and is even further compromised when assessing multi-directional movement patterns (Coutts & Duffield, 2010; Duffield et al., 2010; Jennings et al., 2010; Vickery et al., 2014). Combined, these findings suggest that perhaps GPS technology is approaching its limits of monitoring capabilities.

Whilst a majority of human motion occurs at a rate of less than 20Hz (James, 2006), it is clear that much higher sampling rates are required for more detailed and complex movement features. Global positioning system technology has been comprehensively assessed, and whilst it principally has the capacity to provide basic locomotive objective data under steady velocity, linear conditions (Castellano et al., 2011; Johnston et al., 2012), the validity and reliability of this technology to quantify displacement and velocity demands during high-intensity, short-duration, non-linear, unstructured movement environments has been consistently and significantly reduced (Coutts & Duffield, 2010; Duffield et al., 2010; Jennings et al., 2010; Johnston et al., 2014; Petersen, Pyne, Portus & Dawson, 2009; Rampinini et al., 2015; Varley et al., 2012; Vickery et al., 2014). Similarly, the inaccuracies present when using GPS technology to quantify more specific movement requirements that involve rapid changes in velocity (such as accelerations, decelerations and RHIE) further questions the value of this technology (Akenhead et al., 2014; Buchheit et al., 2014; Delaney et al., 2018; Spencer et al., 2004; Varley et al., 2012).

To our knowledge, only one study has used GPS to identify COD angle (Rovan, Kugovnik, Holmberg & Supej, 2014). This study was primarily aimed at determining the pre and post COD step requirements at varying approach velocities and COD angles, yet reported a high correlation between the intended and actual turning angle (Rovan et al., 2014). However, the precise calculation to determine this COD angle was unclear. In addition, this study used a high-end Real Time Kinematics GNSS (sampling at 20Hz) with a nearby reference station and 1.64kg receiver encased in a backpack which was required to be worn during each trial by all participants (Rovan et al., 2014). Combined with the fact that this study did not include a COD ‘detection method’ (all steps were identified using high-speed video), the capacity to automatically detect and quantify the mechanical load associated with on-field COD movement remains absent.

The apparent inability of GPS technology to accurately measure and quantify non-running-based activities suggests that alone, this technology may not provide a true reflection of the physical demands of team-sport. Whilst portable, lightweight and unobtrusive; due to satellite reliance, GPS cannot be used indoors and given its reliance

on satellite connectivity, is susceptible to dysfunction from adverse atmospheric or environmental conditions as well as signal interference which can significantly impact the accuracy of positional calculations and therefore the accuracy of transposed locomotive information. These shortfalls provide a clear rationale for the use of alternative microtechnology, namely high-frequency inertial sensors (housed within the same microtechnology unit), to better identify and quantify the magnitude of sports-specific movement demands. Together, these sensors signals, when fused using advanced signal analysis techniques to provide orientation estimates, may be capable of detecting on-field COD 'events' and quantifying their associated mechanical load.

2.3 Inertial Sensors

Inertial sensors (accelerometers, gyroscopes, magnetometers) are self-contained technologies which have been used extensively in submarines, spacecrafts and aeroplanes to provide orientation relative to the Earth's fixed coordinate frame (Abyarjoo et al., 2015; Bachmann, 2000). The use of Micro-Electro Mechanical-System (MEMS) based inertial sensors has rapidly developed, primarily because of their miniature size, low cost, low power consumption and light-weight features (Abyarjoo et al., 2015). These features are particularly beneficial when using these sensors in physical applications where the sensor outputs are commonly processed by digital computers using sophisticated signal processing techniques to make a specific determination regarding the physical world (Bachmann, 2000). Whilst these inertial sensors have been used in countless human applications to classify, monitor or assess various forms of physical activity in clinical populations (Kozey, Lyden, Howe, Staudenmayer & Freedson, 2010), youth (Masci et al., 2013; Raya, Roa, Rocon, Ceres & Pons, 2010), ageing populations (Mannini, Trojaniello, Cereatti & Sabatini, 2016; Mariani et al., 2010), sedentary lifestyle habits (Awais, Palmerini & Chiari, 2016), workplace ergonomics (Prairie & Corbeil, 2014) and motion capture systems (Roetenberg, Luinge & Slycke, 2009) they are gaining significant momentum in elite sport (Chambers, Gabbett, Cole & Beard, 2015) as wearable technology where they are co-located within the same unit casing as the GPS engine in most commercially available microtechnology devices and place little to no burden on the athlete (Figure 2.1). These sensors are capable of providing unique and extremely useful data, however, there are some limitations (e.g. low resolution signals subject to high noise levels (Mahony, Hamel & Pflimlin, 2008)) associated with these low-cost IMU systems which must be considered when interpreting sensor outputs and accounted for when implementing signal processing techniques to derive practically useful information.

(a) (b)

Figure 2.1 (a) Catapult Optimeye S5 microtechnology unit; (b) Commercially manufactured vest demonstrating the placement of the microtechnology unit. Optimeye S5 microtechnology unit is 52mm x 96mm x 12mm, housing a 10Hz Global Navigation Satellite System antenna, along with a tri-axial accelerometer, gyroscope and magnetometer.Accelerometers

Accelerometers are motion sensors that detect forced linear acceleration along one or several axes along with the reaction force due to gravity (Bachmann, 2000; Yang & Hsu, 2010). Accelerometers are principally designed using a mechanical sensing element and proof mass (or seismic mass) to produce a change in a specific sensing scheme (e.g. electrical impedance) which is proportional to the applied acceleration with respect to that specific frame (Aminian & Najafi, 2004). These sensors can be designed in slightly different ways (each design with its own practical advantages and disadvantages (Yang & Hsu, 2010)) and are most commonly defined as:

- *Capacitive accelerometers:* where the use of a silicon diaphragm (to which mass has been added) bends under acceleration resulting in a change in distance between a stationary and moving electrode which is converted into a proportional voltage (Bachmann, 2000; Yang & Hsu, 2010).
- *Piezoresistive accelerometers:* consist of a proof mass suspended from thin cantilever beams. Under acceleration, a force is developed (force = mass x acceleration) which bends the cantilever beams and appropriately positioned (where the beams meet the support) piezoresistors are able to produce a voltage proportional to the detected acceleration (Bachmann, 2000; Yang & Hsu, 2010).

- *Piezoelectrical accelerometers*: the sensing elements bend due to the applied acceleration resulting in displacement of the seismic mass which again, produces a voltage proportional to the amount of acceleration detected (Yang & Hsu, 2010).

Practically, orthogonally mounted accelerometers can provide useful information as they allow the detection of three-dimensional (3D; *x*, *y* and *z*; medio-lateral, anterior-posterior and vertical axes respectively (Figure 2.2)) body movement outside of the laboratory; within the day-to-day environment of the subject (Aminian et al., 1998). Micro-Electro Mechanical-System accelerometers are most commonly *capacitive* in nature and are a popular choice in human applications given their small size, low cost and suitability to measure low-frequency motion, but are also DC coupled meaning they are unable to distinguish between linear acceleration and acceleration due to the Earth's gravity (Abyarjoo et al., 2015; Yang & Hsu, 2010). Therefore, there becomes a need to separate motion acceleration from the Earth's gravitational pull using appropriate filtering techniques (Abyarjoo et al., 2015).

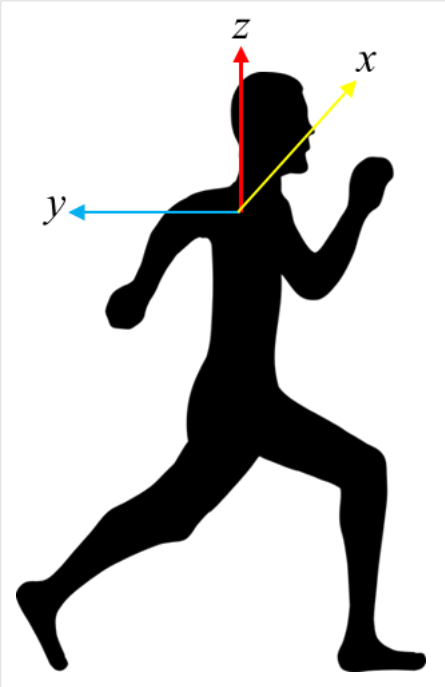

Figure 2.2 Visual representation of three-dimensional orthogonal axes of acceleration where *x* = medio-lateral, *y* = anterior-posterior and *z* = vertical.

2.3.2 Gyroscopes

Gyroscopes are motion sensors that measure rotation or angular velocity in one or more axes known as roll (*x*), pitch (*y*) and yaw (*z*) (Figure 2.3) (Abyarjoo et al., 2015). Micro-Electro Mechanical-System gyroscopes or angular rate sensors use the "Coriolis acceleration effect on a vibrating mass to detect angular rotation" (Abyarjoo et al., 2015). This Coriolis acceleration is derived from the 'Coriolis tuning fork principle' where the 'tuning fork' structure is originally set at a stable vibration frequency which generates a "sinusoidally varying procession where the amplitude of the generated sine wave is proportional to the input angular rate about the axis" (Bachmann, 2000). Gyroscope sensing schemes provide angular velocity quickly and accurately in proportion to the angular rate of rotation as derived from the Coriolis effect described above (Abyarjoo et al., 2015). Gyroscopes which use a vibrating mechanism to detect gyroscopic torques from the Coriolis acceleration (e.g. MEMS gyroscopes) are also considered more reliable and less expensive than those that use rotating bodies (Bachmann, 2000).

Gyroscopes can be used to estimate changes in orientation (angular position) by integrating angular velocity (e.g. trapezoidal), yet are inherently prone to drift which, if not correctly diminished, can magnify any inaccuracy with respect to orientation estimations (Luinge & Veltink, 2005). Hence, the combination of accelerometer and gyroscope signals, along with sophisticated filtering techniques can provide a more accurate estimation of orientation by correcting any offset (drift) in the vertical plane (Luinge & Veltink, 2005). Despite the susceptibility of gyroscope sensors to continual drift and noise accumulation, these sensors are not affected by the Earth's gravity (Abyarjoo et al., 2015).

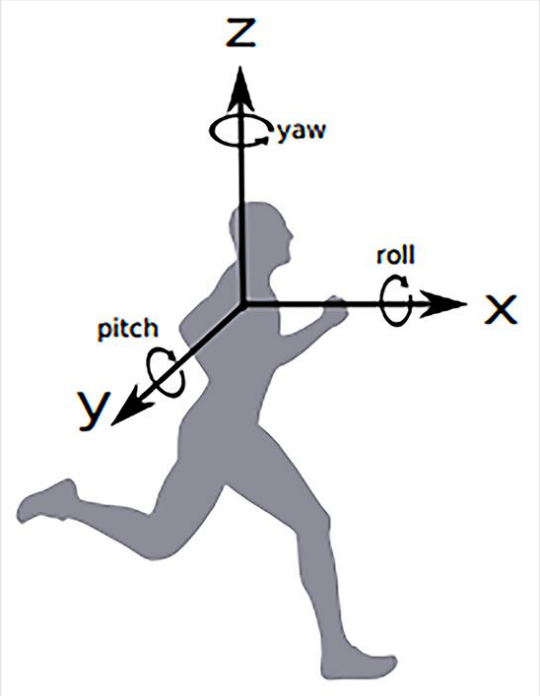

Figure 2.3 Visual representation of three-dimensional rotational axes of angular velocity (gyroscope) where rotation around the *x*-axis is known as roll, *y*-axis as pitch and *z*-axis as yaw.

2.3.3 Magnetometers

Magnetometers or electronic compass sensors are capable of detecting orientation "relative to the magnetic north (or compass north) direction" (Aminian & Najafi, 2004). Whilst noise generated from magnetometer signals is quite low, their high susceptibility to ferromagnetic disturbance can cause significant signal output error, and therefore, magnetometer data is considered less reliable than data from more robust inertial sensors (Bachmann, 2000; Mahony et al., 2008). Magnetometers measure magnetic flux density which is directly proportional to the strength of the Earth's magnetic field perpendicular to the magnetoresistive sensing elements within the sensor (Bachmann, 2000). Additionally, magnetometers have complementary features that can be used in conjunction with other inertial sensors. For example, magnetometer data can be used to correct gyroscopic sensor drift errors in the horizontal plane (Bachmann, 2000).

2.4 Signal Processing and Computation Techniques for Orientation Estimates

Inertial Measurement Unit's (IMUs) that comprise only accelerometers and gyroscopes are limited to measuring an object's orientation relative to the direction of gravity, and thus require input from a magnetometer (or GPS receiver) to provide a more

complete measure of orientation by referencing direction with respect to both gravity and the Earth's magnetic field (Madgwick et al., 2011). This hybrid IMU system known as magnetic angular rate and gravity (MARG) sensor arrays or an attitude and heading reference system (AHRS) requires the fusion of each sensor signal using an orientation estimation algorithm to arrive at an optimal orientation estimate (Madgwick et al., 2011). This algorithm initially assumes that the accelerometer will only measure gravity and that the magnetometer will only measure the Earth's magnetic field (Madgwick et al., 2011). Once the direction of the Earth's magnetic field is known in the earth frame (frame of reference centred at a point on the Earth's surface), a measurement of the Earth's field direction in the sensor frame can be used to express orientation of the sensor frame relative to the earth frame; thus providing a unique sensor orientation (Madgwick et al., 2011). Fundamentally, accelerometer and magnetometer data are used to create earth-fixed reference vectors; gyroscope rate sensor data is used to hasten orientation estimates (Bachmann, 2000). No single sensor is of sufficient quality to accurately determine orientation over an extended period and therefore it is necessary to combine the signal from several sensors to arrive at an accurate estimation of orientation.

2.4.1 Integrating Data from Multiple Inertial Sensors

Given that each sensor has complementary features relative to weaknesses of accompanying sensors, fusion algorithms and more sophisticated signal processing techniques combining data from multiple sensors provide more desirable, refined and accurate information in a range of applications (Abyarjoo et al., 2015; Camomilla et al., 2018). For example, integrating accelerometer and gyroscope data can provide a more precise measure of acceleration as the inclination of the unit and system is known with respect to gravity (Luinge & Veltink, 2005). Additionally, rotational measurements using only the accelerometer or gyroscope have not been proven accurate and also require the implementation of a sensor fusion algorithm (Abyarjoo et al., 2015).

One way to obtain the 3D orientation of a rigid body (x, y and z axes) is to calculate the yaw, pitch and roll angles (known as Euler angles) (Abyarjoo et al., 2015). Whilst rate sensors or gyroscopes can quickly and accurately detect 3D angular rotation and provide an angular velocity measurement, these sensors tend to drift over time and therefore must be continually corrected using complementary features from the accelerometer and magnetometer when calculating orientation (Bachmann, 2000). In order to obtain pitch (y) and roll (x) angles (by fusing the information from the noisy sensor signals) the

accelerometer signal is combined with the gyroscope sensor output and subsequently filtered to acquire ‘clean’ and stable (non-drifting) roll and pitch angles (Abyarjoo et al., 2015). Computing an accurate yaw (*z*) angle which is perpendicular to the Earth’s surface presents a more difficult challenge (Abyarjoo et al., 2015). The gyroscope alone is unable to accurately calculate this yaw angle (also known as the heading or azimuth) due to drift properties and whilst the magnetometer can measure heading accurately (in the absence of ferromagnetic materials) when parallel with the Earth’s surface (Caruso, 1997), this is unrealistic in most practical applications as the magnetometer will be attached and move with the object as it moves out of the horizontal plane leading to calculation errors proportional to the extent of magnetometer tilt (Abyarjoo et al., 2015). Consequently, a tilt compensation algorithm using tri-axial accelerometer and gyroscope derived pitch and roll angles (described above) can be integrated with the magnetometer signal to continually map the magnetometer data to the horizontal plane and thus provide an accurate heading calculation or yaw angle regardless of the magnetometer’s position (Abyarjoo et al., 2015; Pedley, 2013).

Alternatively, enhancing accelerometer measurement with GPS derived accelerations can provide estimates of pitch and roll angles. Assuming the object or aircraft is travelling at a sufficient velocity, GPS derived heading angle calculations can be used to periodically correct accelerometer and gyroscope derived inertial velocity (Kingston & Beard, 2004). However, human locomotion may not be continually fast enough to achieve accurate GPS derived heading angle calculations. In the absence of reliable GPS data, a magnetic compass or magnetometer can be used to calculate heading angle; albeit this requires additional hardware and computational complexity which could otherwise be avoided (Kingston & Beard, 2004).

2.4.2 Euler Angles and Angle Rates

Euler angles can be used to represent the 3D orientation of a body or an object using a combination of three rotations about specified axes (Bachmann, 2000). These axes can be defined as ‘roll’, ‘pitch’ and ‘yaw’ when referring to rotations about a north axis (*x*), east axis (*y*) and a down axis (*z*) respectively (Figure 2.3) (Diebel, 2006). In order to determine the orientation of a rigid body it is necessary to choose a coordinate system attached to an appropriate inertial frame (commonly the Earth’s coordinate frame), and then express all vectors relative to these coordinates (Bachmann, 2000). Additionally, a ‘body-fixed’ or rigid body inertial frame (also expressed as *x*, *y* and z) must be determined

which will allow the 3D orientation estimate to be expressed as the relationship between the inertial frame coordinates and the body-fixed frame coordinates (derived from point vectors of each axis) using a single rotation matrix (comprised of yaw, pitch and roll rotation matrices) (Figure 2.4) (Bachmann, 2000):

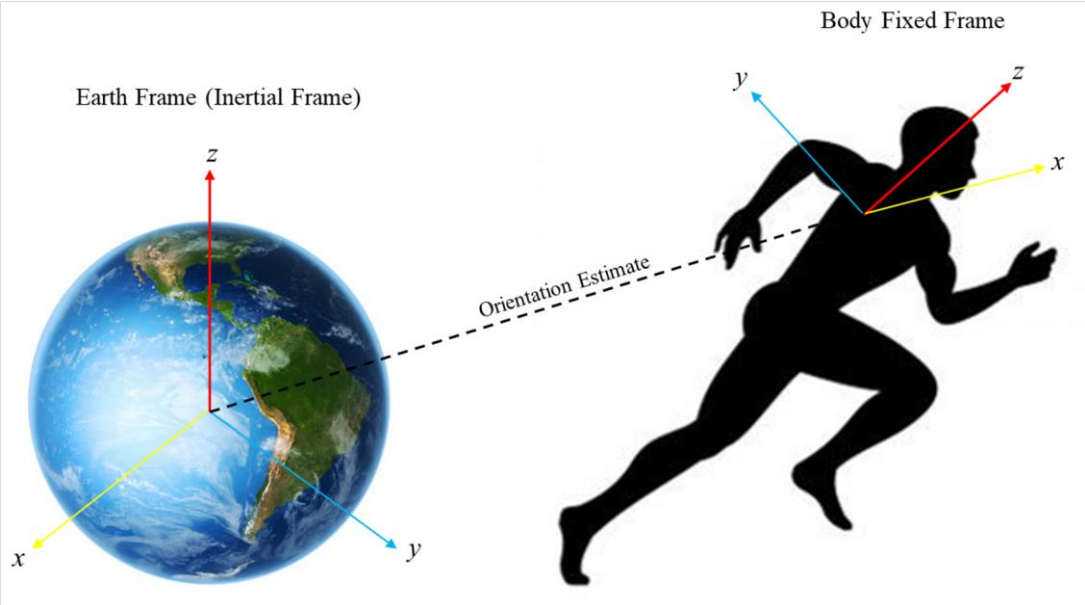

Figure 2.4 Example of mapping 3D orientation of a body-fixed frame to the Earth's frame.

Conversely, to determine inertial frame data (e.g. extracting linear acceleration data to determine velocity for tracking an object's position) relative to the body-fixed frame, inertial sensor (accelerometer, gyroscope, and magnetometer) data aligned with the body-fixed frame of reference can be used by simply performing a reversal of the rotational matrix (Diebel, 2006). This is quite straightforward for accelerometer and magnetometer data, however, becomes more complicated when converting rate gyroscope data to the inertial frame. Gyroscope derived body-frame rates (defined as p, q and r) cannot be integrated to obtain Euler angles in the global frame. Each angular rate must be converted between the different coordinate frames to estimate yaw, pitch and roll rates (Janota, Šimák, Nemec & Hrbček, 2015). This will allow the body-frame angular rate data to be accurately reported with respect to the inertial frame. However, when the orientation of an object points directly up or down (i.e. a pitch angle of ± 90°) the roll and yaw axes become collinear causing a phenomenon called 'gimbal lock' (loss of one degree of freedom in a three-dimensional space that occurs when two of three gimbals are driven into a parallel configuration) to occur which will lead to significant error when calculating orientation estimates (Janota et al., 2015). This singularity error is a well-known limitation of using

Euler angles and angle rates which can only be resolved by switching to a different numeric representation such as quaternions (Diebel, 2006).

2.4.3 Quaternions

A quaternion is essentially a four-element vector consisting of one 'real' part and three 'imaginary' parts and can be used to represent any orientation and rotation in a 3D coordinate system (Bachmann, 2000; Islam, Islam, Shajid-Ul-Mahmud & Hossam-E-Haider, 2017). Put simply, the three 'imaginary' parts describe a vector and the 'real' part expresses an angle of rotation about that vector (Bachmann, 2000; Kim & Golnaraghi, 2004). Similarly to transposed Euler angle rates, gyroscope derived angular sensor rates (p, q and r) can be used to find the orientation estimate of the body's fixed frame in relation to the Earth's fixed coordinate system expressed in quaternion form. These body-fixed rotational rates are essentially transformed into quaternion rates and integrated to get a quaternion representation of orientation (McGhee, Bachmann & Zyda, 2000). Whilst quaternions may be more complex and less intuitive than Euler angles, they are capable of determining all orientations without the limitation of singularities (i.e. gimbal lock) and therefore may be more appropriate for tracking the orientation of a body that can assume any orientation, particularly through the vertical plane. Additionally, robust quaternion attitude estimations can be converted into more simplistic Euler angle orientation estimations to allow the continual running or recovery of an estimator which can fail entirely when exposed to Gimbal lock if the estimator is solely reliant on Euler angle rates.

2.4.4 Vehicle Attitude and Heading Reference Systems

Attitude and heading reference systems have been well established in aerospace applications and continue to be used in underwater navigation and even motion capture (Markley, Crassidis & Cheng, 2005; Yadav & Bleakley, 2014). An AHRS involves the use of inertial navigation systems (INS) to measure the position, heading information and orientation of a moving body using data obtained from high-quality accelerometers, gyroscopes and magnetometers (Islam et al., 2017; Yadav & Bleakley, 2014). However, INS are generally reliant upon an initial calculation of position using an outside source (e.g. GPS satellite receiver) prior to the use of inertial sensor data inputs from tri-axial accelerometers and gyroscopes to determine subsequent position and orientation; a process called dead reckoning (Bachmann et al., 1996). For example, 'strapdown INS' are able to estimate the orientation of a body by integrating signal outputs from three

orthogonally mounted gyroscopes fixed to the body at a known orientation and drift-rate that can be accounted for in subsequent estimations (Foxlin, 1996). Position of the moving body can then be calculated using three orthogonally mounted linear accelerometers fixed to the moving body frame to measure the "total acceleration vector of the body relative to inertial space" (Foxlin, 1996). This acceleration vector can then be converted from the moving body frame coordinates to the Earth's coordinates using the "known instantaneous orientation" of the body determined by the AHRS (Foxlin, 1996). The effect of gravity is then removed and the measured acceleration is initially integrated to determine the inertial velocity of the measured body and then subsequently integrated using the known initial position to determine its current position (Foxlin, 1996). However, small errors in acceleration (accelerometer) and angular velocity (gyroscope) signals are compounded during sensor integration when calculating inertial velocity and must therefore be periodically corrected using an alternative navigation source (e.g. GPS satellite receiver, magnetic compass) (Kingston & Beard, 2004).

2.4.5 Determining Human Orientation or Attitude Using MEMS Inertial Sensors

Orientation tracking using MEMS based inertial sensors or inertial measurement units (IMUs) has been used in a vast array of applications from military endeavours, surgical aid, navigation systems to gaming, virtual reality, mobile robot design and even human tracking (Abyarjoo et al., 2015). To track the orientation of a rigid body, data from body mounted accelerometers, gyroscopes and magnetometers must be used in a complementary manner for optimal accuracy (both static and dynamic) (Bachmann, 2000). Whilst the integration of gyroscope derived angular rate data can provide an orientation estimate, as previously mentioned, these sensors are inherently prone to drift errors and small bias which would adversely affect subsequent calculations and therefore the use of other sensors (accelerometer (to sense the vertical inclination) and magnetometer (to sense the direction of the local magnetic field)) in combination with sophisticated filtering techniques is imperative to continually correct this orientation estimate (Bachmann, 2000). Therefore, to accurately estimate and track orientation, a separate accelerometer, gyroscope and magnetometer for each axis (x, y and z) of a rigid body is required.

Orientation algorithms have been successfully used in number of wearable 3D human tracking and movement analysis research applications (Bachmann, McGhee, Yun & Zyda, 2001; Luinge & Veltink, 2005; Madgwick et al., 2011; Roetenberg et al., 2009). These

algorithms are typically derived from multiple MEMS based inertial sensors strategically placed (at joints) to allow for limb and trunk segmentation which can provide highly detailed and useful data during fine movement tasks; but is also extremely useful to characterise more whole-body movement patterns when the signal from each sensor can be effectively combined. These sensors are highly suited to this environment given their high-level of accuracy, very low latency (allowing for immediate feedback) (Bachmann, 2000) and their ability to inherently capture the full details of relatively low-frequency (around 20Hz) peaks of human activity (James, 2006); and may therefore be highly beneficial in evolving current practice with regard to athletic performance tracking in a number of sporting contexts.

2.5 Data Filtering Techniques

When interpreting inertial sensor outputs for real-world applications, the best systems are able to process signal outputs from multiple sensors and use filtering algorithms to fuse these signals and arrive at an optimal value or estimate (Bachmann, 2000). The primary purpose of these filtering algorithms is separate the important features of the signal from the random noise. The sensors themselves have accuracy limitations which have been detailed in previous sections (2.3.1, 2.3.2 and 2.3.3) meaning that the raw data outputs from these sensors must be processed and analysed in a rigorous manner (Bachmann, 2000). For example, basic high and low pass filters can be used to separate low and high frequency noise respectively and has a subsequent 'smoothing' effect on the signal output.

When fusing sensor outputs to produce meaningful estimates of more complex state variables, more sophisticated filtering algorithms are needed to produce the best or 'optimal' outcome. There have been a number of different filter strategies used in relation to analysing and tracking motion (Abyarjoo et al., 2015; Madgwick et al., 2011; Roetenberg et al., 2009); each with its own pros and cons but all with a common goal; to optimise the accuracy of an orientation estimation (Yadav & Bleakley, 2014). Generally, an optimal filter is chosen based upon a probabilistic model from the derived signal and the overall algorithm or output to which it is related (Bachmann, 2000). Previously, Butterworth filters have been used to remove the noise from raw sensor data (Mayagoitia, Nene & Veltink, 2002), whilst a range of Kalman-based filters (Luinge & Veltink, 2005; Roetenberg et al., 2009; Wang et al., 2017) and particle filters (Yadav & Bleakley, 2014) have been frequently used in inertial based motion tracking applications. Additionally, complementary filters have been proven to be effective in calculating inertial sensor derived orientation estimates

(Bachmann et al., 2001; Mahony et al., 2008; Yoo, Hong, Yoon & Park, 2011) and do not require the heavy computational expense associated with alternative filters (i.e. Kalman filters in particular) (Madgwick et al., 2011). These filtering techniques often use gain scheduling as an approach to control non-linear systems by using the complementary (or robust) features of each sensor at different stages of the signal procession or algorithm to optimise accuracy during each stage (Yoo et al., 2011). This can be particularly useful in environments where ferromagnetic materials can cause distortion of the magnetometer sensor output and adversely affect the entire model.

2.5.1 Kalman Filtering Techniques

A Kalman filter (Kalman, 1960) can be described as "*a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimises the mean of the squared error*" (Welch & Bishop, 2006). In its simplest form, the discrete Kalman filter estimates the process state at a given time using vector modelling and uses noisy measurement data from that same time-point as feedback to correct the initial estimation. As such, Kalman filters are broadly made up of '*predictor* and *corrector*' equations (Welch & Bishop, 2006). Kalman gain is a critical element of the Kalman filter which involves continually assessing the residuals of the predicted and measured states and adjusting weighting priority according to the amount of error or noise present in the data to arrive at an optimal state estimate (Bachmann, 2000; Foxlin, 1996). For example, when the measurement error covariance approaches zero, the measured state residuals are given more weight, whereas when the predicted state error covariance approaches zero the measured state is given less weight and the predicted state becomes favourable (Welch & Bishop, 2006).

Kalman filtering techniques have been used in maritime and vehicle navigation, robotics and virtual environments to compute accurate orientation estimates (Foxlin, 1996). As mentioned previously, computing the yaw angle (or rotation around the Z-axis) is challenging and requires input from all three inertial sensors to provide accurate orientation estimations in most dynamic applications. Whilst orientation can be calculated by integrating angular rate measurements from a tri-axial gyroscope alone, or by integrating accelerometer and magnetometer signals, a drift and noisy/slosh free estimation of orientation can be obtained using a Kalman filter to weight these signals appropriately and make best use of the data from each sensor (Foxlin, 1996). Essentially, the Kalman filter uses the inclination or tilt difference (angle the estimated Z-axis makes with the real Z-axis)

along with the error model to estimate orientation and offset errors in a "statistical, most-likely manner" and use these estimates to correct orientation and offset at each time step (Luinge & Veltink, 2005). The tilt or inclination error from the raw data is dependent upon the gyroscope bias (caused by drift) and accelerometer 'slosh' (caused by transverse linear accelerations) (Luinge & Veltink, 2005), both of which have been successfully diminished using a Kalman filter, thus allowing an accurate and reliable estimate of orientation (Abyarjoo et al., 2015). Using a Kalman filter to calculate this inclination error has been shown to be superior when compared with low-pass filtering accelerometers (Luinge & Veltink, 2005).

The recursive nature of the Kalman filter is theoretically ideal when compared with alternate linear filtering techniques for fusing noisy data (assuming the noise components are *Gaussian*) from several indirect measurement sources to continually estimate desired variables that cannot be directly measured (Foxlin, 1996; Yadav & Bleakley, 2014). For example, the discrete Wiener filter must reprocess all previous data when deriving a new or updated state estimate, whereas the Kalman filter only relies on results from the estimate immediately prior to update the current state estimate (Bachmann, 2000). Whilst the dynamic model for error prediction and correction is a fundamental strength of the Kalman filter, in its original or basic form is not appropriate for non-linear system applications (Abyarjoo et al., 2015; Yadav & Bleakley, 2014). Additionally, Kalman filters can be difficult to implement which is reflected in the range of published solutions (Foxlin, 1996; Luinge & Veltink, 2005; Roetenberg, Luinge, Baten & Veltink, 2005; Sabatini, 2006; Wang et al., 2017) and the linear regression iterations (which are fundamental to the effectiveness of the filter) demand a heavy computational load which may limit its applicability to human movement and tracking applications where portability of any inertial sensor based system is critical to optimise its practicality (Madgwick et al., 2011). These limitations provide clear incentive for alternative filtering approaches to optimise human orientation tracking applications.

2.5.2 Non-Linear Filtering Methods

There have been several variants of the Kalman filter, such as the *Extended Kalman filter* (EKF) and the *Unscented Kalman filter* (UKF) proposed for non-linear system applications (Markley et al., 2005; Sabatini, 2006; Wan & van der Merwe, 2000; Yadav & Bleakley, 2014). The EKF has become a standard filtering approach to state estimation for a number of non-linear applications including attitude determination in aerospace applications and essentially works to linearise all non-linear models to allow effective

application of a standard linear Kalman filter (Julier & Uhlmann, 1997; Markley, 2003; Wan & van der Merwe, 2000). Whilst some of the earliest published EKFs were based upon the integration of Euler angles, the susceptibility of Euler angles to singularities can become problematic when a spacecraft strays from a reference attitude (being defined with respect to a local-vertical / local-horizontal coordinate frame) which is why quaternions are often preferred for kinematic applications (Markley et al., 2005). Fundamentally, the EKF works in a similar manner to the standard linear Kalman filter where the state estimate is recursively approximated using numerical iterations to achieve an optimal estimate by minimising the mean-squared error and then using 'first order' linearization to analytically propagate the non-linear system (Wan & van der Merwe, 2000). However, these 'first-order' approximations can introduce large errors in the posterior mean and covariance of the transformed (*Gaussian*) random variable which can cause sub-optimal filter estimations and even divergence (Wan & van der Merwe, 2000).

Alternatively, the UKF (based on the unscented transformation method (Julier & Uhlmann, 1997)) addresses the approximation issues of the EKF by estimating the state distribution using a select few specifically chosen sample points (or iterations) which best capture the true mean and covariance of the *Gaussian random variable* and are accurate to the 'third-order' for any nonlinearity (Wan & van der Merwe, 2000). Whilst the UKF is able to capture the posterior mean and covariance more accurately (third-order) than the EKF (first-order), the total number of computations is in fact the same, meaning that the UKF is able to consistently display a higher-level of accuracy when compared with the EKF; with both filters equally complex (Wan & van der Merwe, 2000). Another form of the Kalman filter known as the *Interlaced* (*Extended*) *Kalman Filter* (IKF) (Glielmo, Setola & Vasca, 1999) aims to reduce the computational load associated with the state estimation process for non-linear applications by running two 'pseudo-linear' models simultaneously (each estimating only a subset of the state) to comprise a final state estimation (Gasparri, Panzieri, Pascucci & Ulivi, 2009; Markley et al., 2005). The error associated with using this linearisation technique can be reduced by increasing the noise covariance matrices (Gasparri et al., 2009).

Particle filters are an umbrella term for a broad class of 'suboptimal non-linear filters' where the state distributions are approximated by weighted particles (random samples) that are generated using 'pseudorandom number generators' (Markley et al., 2005). Particle filters are suggested to be superior to other conventional non-linear filters for more difficult applications with non-linear and non-Gaussian distributions (Markley et al.,

2005). Particle filters make no assumptions around the linearity or noise distribution of a system and are therefore applicable to a wide range of applications (Yadav & Bleakley, 2014). Other non-linear filters include 'sigma-point' filters which are particularly useful when the nonlinearities of a measured state are severe, or when *a priori* data is of poor quality; and therefore a reliable *a priori* state estimation is not possible; and even the 'orthogonal attitude' (Markley, 2006) filter which is a predictive filter used for 'deterministic estimation', however its applicability to attitude estimation is still under investigation, and its advantages unknown (Markley et al., 2005).

Whilst both the IKF and the EKF are very effective in filtering gyroscope output noise during attitude determination applications, the IKF outperforms the EKF producing lower (25-35%) attitude rate estimation errors; likely due to the linearisations associated with the EKF (Algrain & Saniie, 1994). However, despite its limitations, the EKF remains the optimal choice for a range of attitude estimation applications due to its relative simplicity and flexibility to integrate numerous signals (Markley et al., 2005). Whilst non-linear filters (UKF, IKF) may be more appropriate and provide greater accuracy for certain applications, altering or 'tuning' a standard Kalman filter can be onerous and very time-consuming and therefore the benefits of implementing these filters must be weighed against their computational cost. Additionally, whilst several non-linear forms of the Kalman filter (particularly the 'multiplicative EKF' (Markley, 2003)) have been successfully used in a number of attitude determination applications, in some cases, their poor performance and susceptibility to divergence from the embedded linearisation techniques has led to the development of alternate filtering algorithms.

2.5.3 Complementary Filtering Techniques

Complementary filters are a specialisation of the broader Wiener filter classification. The complementary filter makes no assumptions about the structure of the signal and is based upon the use of multiple independent noisy measurements of the same signal (Bachmann, 2000). If the signal outputs have complementary 'spectral characteristics' then these transfer functions can be manipulated to optimise (or reduce) estimation error (Bachmann, 2000). Additionally, a wide variety of complementary filters exist, each with its own practical advantages which outlines the flexibility and applicability of this filtering approach (Mahony et al., 2008). Whilst more simplistic single-input single-output (SISO) complementary filters have been used for attitude estimation in unmanned aerial vehicles, this becomes problematic when vehicle dynamics become too great and the direction of

gravitational acceleration becomes difficult to determine (Yoo et al., 2011). It is important to be able to distinguish between gravitational acceleration and motion acceleration, yet this requires a filter which can cause a delay in the response and therefore must be integrated with the output from the gyroscope (Abyarjoo et al., 2015). Conversely, the gyroscope signal is inherently prone to bias or drift and must be corrected using complementary features from other sensor outputs (accelerometer, magnetometer) in order to provide an accurate orientation estimate. In this case, a 'gain-scheduled' complementary filter can be used which provides different weightings to the accelerometer and gyroscope signals depending on the amount of acceleration (Yoo et al., 2011). This is termed the 'crossover frequency' of a complementary filter which represents the value where both inputs are weighted equally (Bachmann, 2000). Subsequently, where the frequency of the filter is above or below this value, the signal from one sensor will be proportionally weighted in accordance with another (or multiple) sensor signal(s) to provide an optimal estimate (Bachmann, 2000).

When using a complementary filter to optimise AHRS, accelerometer and gyroscope signals are integrated for accurate estimation of roll and pitch (Yoo et al., 2011). Then, the gyroscope and magnetometer signals are combined to estimate the yaw (or heading) angle; thus providing an optimal estimate of orientation (Yoo et al., 2011). The fusion of these sensor signals can provide a less noisy attitude and heading estimation due to each sensor's complementary features, particularly under adverse circumstances where significant gyroscope measurement noise may provide inaccurate orientation estimates, when the accelerometer is not stationary, or the magnetometer has become disturbed due to ferromagnetic interference (Madgwick et al., 2011; Yoo et al., 2011).

2.5.4 Ferromagnetic Disturbance

Magnetometer signals can be significantly distorted by the presence of ferromagnetic materials, which have the potential to greatly affect orientation estimates (Madgwick, 2010; Yadav & Bleakley, 2014). Numerous correction equations embedded within various filtering algorithms have been used with the aim to offset associated inaccuracies derived from both hard and soft iron biases (see Definitions section) (Koo, Sung & Lee, 2009; Madgwick, 2010; Roetenberg, Luinge & Veltink, 2003; Yadav & Bleakley, 2014)

Yadav and Bleakley (2014) proposed a method which detects the presence of magnetic distortion using magnetic strength in conjunction with magnetic dip angle. The magnetic dip angle can be defined as "*the angle between the lines of flux of the Earth's*

magnetic field and the surface of the Earth" (Yadav & Bleakley, 2014) and is derived using accelerometer and magnetometer signals. An adaptive particle filter is then used to mitigate the effects of the distortion by reducing the weight of the magnetometer signal for orientation estimation and increasing the emphasis on dead reckoning using the signal from the gyroscope (Yadav & Bleakley, 2014). Furthermore, when magnetic disturbance is detected, accelerometer derived inclination estimates (in conjunction with magnetometer heading readings) are used for orientation estimates under quasistatic (or slower) movement conditions, whereas, under conditions of more rapid acceleration, the filter adapts moving away from erroneous accelerometer derived inclination estimates and instead uses the weighted sum of gyroscope and magnetometer heading estimates in accordance with the detected magnetic dip angle (Yadav & Bleakley, 2014). This adaptive cost function method has been shown to be equally applicable at all speeds of motion, and in particular, improves on previous orientation estimations under conditions of high acceleration (Yadav & Bleakley, 2014).

Alternatively, Roetenberg et al. (2003) developed a magnetic disturbance correction model within a Kalman filter to accurately depict human body orientation estimates under conditions of magnetic disturbance. Bachmann (2000) was also able to use a weighted least squares modification to his complementary attitude filter (quaternion based) and reduce the weighting of the magnetometer to allow more accurate orientation estimations for human body tracking (limb segments and resulting posture) to continue in the presence of fluctuating magnetic fields. Koo et al. (2009) demonstrated the superior performance of the particle filter in comparison with EKF when correcting heading error in aerospace applications under conditions of heavy bias. Madgwick et al. (2011) also developed a magnetic distortion compensation model within their novel orientation estimation algorithm (gradient descent) using the accelerometer signal as an additional reference of attitude to compensate for inclination errors in the Earth's magnetic field (Madgwick et al., 2011). This algorithm and compensation model, designed for a wearable inertial human motion tracking system ensures that any magnetic disturbance will only affect the estimated heading component of orientation and also eliminates the need for the user to predefine the direction of the magnetic field (Madgwick et al., 2011).

2.5.5 Filtering Techniques for Human Motion Applications

Whilst several studies have demonstrated the capability of MEMS inertial sensors combined with various filtering techniques to provide highly accurate and robust vehicle

AHRS at a relatively low computational expense (Kingston & Beard, 2004; Mahony et al., 2008; Yoo et al., 2011), these same types of sensors and filtering techniques have also been successfully used in human movement applications (Bachmann et al., 2001; Lambrecht & Kirsch, 2014; Luinge & Veltink, 2005; Madgwick et al., 2011; Roetenberg et al., 2009; Wang et al., 2017). Bachmann and colleagues (2001) used MARG sensor technology and complementary filtering to track the posture of an articulated rigid body (human body) by independently determining the orientation of each link (limb) relative to the Earth's fixed reference frame. This quaternion based method allows for continual orientation estimates through all attitudes using drift corrections and calibrations for misalignments between sensor and limb coordinates (Bachmann et al., 2001).

In addition, Madgwick et al. (2011) developed a wearable inertial human tracking system for rehabilitative purposes using a custom-designed gradient descent sensor fusion algorithm. When compared with a proprietary Kalman-based algorithm, Madgwick and colleagues (2011) novel algorithm was able to reduce much of the computational load (by reducing the number of iterations) and also incorporate a magnetic distortion compensation equation to mitigate any error from ferromagnetic interference. In addition, Wang and colleagues (2017) used a complementary Kalman filter (CKF) coupled with several miniature MARG or IMU sensors to develop a 3D human motion capture system. Characteristic of a Kalman filter, this adaptive model adopts a feedback mechanism using a Kalman gain matrix to compensate for any error in the state variable by using the current orientation estimate to correct the previously predicted estimate (Wang et al., 2017). This recursive process is able to continually correct for any orientation error caused by gyroscope offset, inclination estimates and magnetic disturbance whilst analysing all 16 IMUs to accurately determine orientation during basic human movement tasks (walking and squatting) (Wang et al., 2017). Wang and cpolleagues (2017) demonstrated that implementing a CKF when fusing raw sensor data to compute Euler angles for real-time orientation estimates in a human motion tracking system elicited a more stable output and significantly reduced the accumulated error (as task duration increased) when compared with an UKF.

2.5.6 Filtering Sensor Signal Data - Summary

When filtering inertial sensor outputs, the primary goal is to separate the important features from multiple noisy measurement signals to produce an optimal estimate or value of a system or variable within that system (Bachmann, 2000). No single inertial sensor signal can continually determine orientation accurately and therefore the sensor signals

must be combined using sophisticated signal processing and filtering techniques to best utilise the relative strengths of each sensor. When fusing raw data from inertial sensor outputs, the complementary and Kalman filter are the most broadly used techniques (Islam et al., 2017). The structure of these filters are well-suited to fusing low frequency positional measurements with high-frequency measurement signals for first order kinematic systems (Mahony et al., 2008).

Whilst a variety of sensor fusion filtering techniques have been adopted for orientation estimates during human tracking applications (e.g. limb or body segment tracking, posture assessment, gait analysis) (Bachmann et al., 2001; Madgwick et al., 2011; Mayagoitia et al., 2002; Roetenberg et al., 2009; Tao, Sun, Huang, Huang & Wu, 2011; Wang et al., 2017; Yadav & Bleakley, 2014), the Kalman filter or modified non-linear versions of the Kalman filter (e.g. EKF) have been described as 'ideal' filters when able to incorporate a dynamic model of the human musculoskeletal system combined with inertial sensor or MARG outputs (Bachmann, 2000). Kalman filters have become the accepted method for a majority of orientation algorithms and commercial wearable human inertial sensor applications (Luinge & Veltink, 2005; Roetenberg et al., 2009; Wang et al., 2017), yet depend on an accurate process model and complete statistical data set to compute accurate state estimates (Bachmann, 2000).

Modern approaches have focused on more simple sensor fusion filtering techniques that are not as computationally heavy, nor require any complex parameter tuning; often associated with Kalman-based algorithms (Madgwick et al., 2011). These simpler processing techniques, such as the complementary filter, have been shown to produce orientation estimates of equivalent accuracy to the Kalman filter, yet require far less computational load, are quicker to develop and can be considered more robust in the sense that this filtering approach is able to cope with missing data (Bachmann, 2000; Madgwick et al., 2011; Mahony et al., 2008). In particular, Bachmann and colleagues (2001) were able to develop a complementary filter with properties designed to continually track the orientation of each link (limb or body segment) of a rigid body through all attitudes (regardless of movement type) which make this approach particularly applicable to human tracking applications which often involve spontaneous and intermittent periods of high linear acceleration.

2.6 Edge Detection

2.6.1 Theoretical Background

Edge detection is a widely used technique in image processing (e.g. image enhancements, image segmentation, video coding and tracking) which primarily aims to simplify the analysis process of images by significantly reducing the amount of data to be processed, yet maintaining important boundaries (or edges) within an image to ensure all the objects within that image or scene can still be identified (Basu, 2002; Canny, 1986; Xu, Varadarajan, Chakrabarti & Karam, 2014). These edges or discontinuities within an image are abrupt changes in pixel intensity which are then classified as an 'edge' if the gradient exceeds a certain threshold (Maini & Aggarwal, 2009). Whilst there are many ways to perform edge-detection, each method generally sits under the 'gradient' category where edges are detected by looking for the maximum and minimum first derivatives of the image; or the 'Laplacian' category where the algorithm will search for zero crossings in the second derivative of the image to classify edges (Shrivakshan & Chandrasekar, 2012). Whilst there have been a number of customised edge-detection algorithms developed, (Canny, 1986; Marr & Hildreth, 1980; Prewitt, 1970; Sobel & Feldman, 1968) ultimately, the ability of the edge detector to successfully separate the background and objects within a scene or image (much like the human visual system) will fundamentally determine its success (Basu, 2002; Lopez-Molina, De Baets, Bustince, Sanz & Barrenechea, 2013). Edge orientation, noise characteristics, and the structure of the edge must all be considered with common problems of spurious or false edges detected, missing true edges, edge localisation and high computational time (Maini & Aggarwal, 2009).

The presence of noise and quantization of an original image can lead to false detection (i.e. locating intensity changes where they do not exist or missing existing edges); and therefore a successful edge detector will have a low error rate and well localised edge points (i.e. the distance between the points marked by the detector and the centre of the true edges should be minimised) (Basu, 2002). Edge localisation can become problematic during edge detection object recognition tasks as the presence of noise within an image can alter the position of the detected edge to be shifted from its true location (Basu, 2002). True edges contain sharp intensity transitions due to their high-frequency components which can become 'blurred' or 'distorted' during the filtering or smoothing process (Basu, 2002; Maini & Aggarwal, 2009). Low-pass filters are the most commonly used smoothing filters and are essential to assist in amplifying the high-frequency components of discontinuous

sharp edges (change in pixel intensity) and assist in differentiating between objects in an image or scene (Basu, 2002). The optimal amount of filtering will depend on the size or scale of the smoothing operator, but essentially works as a trade-off between error rate and localisation quality (Basu, 2002; Canny, 1986).

2.6.2 Gaussian Filter for Edge Detection

The Gaussian smoothing filter is the most widely used filter for edge detection applications, largely due to its simplicity and signal preservation capabilities (Basu, 2002; Lopez-Molina et al., 2013). The Gaussian operator, which has been used in a variety of edge detection applications (Canny, 1986; Sanjay, 2015; Xu et al., 2014) works to convolute (blur or sharpen) an image using a Gaussian kernel which varies in width (using a pre-calculated or chosen standard deviation) depending on the noise characteristics of an image and the size of the desired objects within that image (Basu, 2002). When the standard deviation is large enough to nullify any undesirable effects from noise and subsequently remove the probability of detecting false edges, the localisation of the true edges can become displaced (in some cases, severely) from their actual position and the clarity of these edged can begin to fade from this excessive smoothing; potentially compromising overall clarity of an image (Lopez-Molina et al., 2013). Conversely, edge localisation will improve with high-frequency operators, yet may be more susceptible to false detection (Lopez-Molina et al., 2013).

Whilst the smoothing or filtering process is vital, selecting a single 'scale' of smoothing to optimise all edges within an image can be challenging (Basu, 2002). The scale refers to the size of the area where the intensity changes are measured or the size of the smoothing filter applied prior to edge extraction (Lopez-Molina et al., 2013). Whilst small scale filtering can amplify fine details of intensity changes within an image, it can also be more susceptible to noise interference; conversely, larger scale filtering can extract coarse details and is more resilient to noise interference, yet some of these detected edges can have large localisation errors (Basu, 2002; Maini & Aggarwal, 2009). Basically, a single-scale filter approach may not have the flexibility to remove unwanted noise whilst maintaining good localisation.

Multiscale edge detection involves using a variety of smoothing filters of different sizes to extract multiple edges at different scales and subsequently combining all edge information to develop a more precise depiction of the actual edge representation of an image (Basu, 2002). Whilst multiscale edge detection aims to optimise the object

identification within an image or scene by assuming that different parts of that image will have varying degrees of noisiness and different types of edges; and should therefore be filtered accordingly, this approach can create issues around choosing the size or scale of the filters and how to best combine edge information from multiple scales to create a single edge map (Basu, 2002). Despite the lack of consensus in relation to automatically determining the optimal scale for a given edge detection method, both fine-to-coarse edge tracking (Sobel & Feldman, 1968) and neighbourhood-based evaluation (both fixed sized and modified sized) have been successfully used to determine the scope of the gradient or intensity changes within an image (Lopez-Molina et al., 2013). This includes Canny's (1986) approach to edge detection which involves aggregating the results from different scales, named *feature synthesis*. Edges are tracked from 'finer' scales where edges are detected with optimally accurate localisation to 'coarser' scales where smoothing of the image will greatly reduce the possibility of detecting spurious objects or false edges in the image (Lopez-Molina et al., 2013). Importantly, when implementing this method, the Gaussian filter has been proven to be the only operator that can remove existing edges (zero-crossings of the second derivatives) without creating new edges as the scale increases (Babaud, Witkin, Baudin & Duda, 1986; Yuille & Poggio, 1986). Additionally, algorithms have been designed to automatically determine the optimal filter scales for each pixel prior to the aggregation process to detect the final edge map (Deng & Cahill, 1993; Jeong & Kim, 1992; Marr & Hildreth, 1980). However, these algorithms have some performance limitations and are computationally expensive (Deng & Cahill, 1993; Jeong & Kim, 1992). Moreover, altering the Gaussian filter scale can affect the localisation or change the detected position of the edge, the orientation of the edge generally remains very similar (Lopez-Molina et al., 2013).

Whilst classical operators for gradient based edge-detection (Prewitt, 1970; Sobel & Feldman, 1968) are relatively simple and can detect edges and their orientation, they can be susceptible to noise interference which can degrade the magnitude of an edge leading to inaccuracies (Shrivakshan & Chandrasekar, 2012). Whereas Gaussian operators use a probability function for finding error rate, localisation and response and perform better in noisy conditions by using a thresholding method (Shrivakshan & Chandrasekar, 2012). However, Gaussian operators require more complex computational methods which can be time consuming and in some cases can detect false edges (Maini & Aggarwal, 2009). More specifically, the Canny (1986) edge detection algorithm (a Gaussian operator) relies mainly on the standard deviation for the Gaussian filter and its associated threshold values (Shrivakshan & Chandrasekar, 2012). A greater standard deviation value indicates a larger

scale Gaussian filter (more blurring) which is needed for noisy images, and to detect larger edges (Maini & Aggarwal, 2009). However, the larger scale Gaussian filter will be less accurate during edge localisation (Maini & Aggarwal, 2009). Whilst the Canny edge detection algorithm has been considered 'optimal' in image detection (Maini & Aggarwal, 2009), its superior performance must be weighed against the increased computational cost and time requirements when compared with other edge detection algorithms.

2.6.3 Canny Edge Detection

The Canny edge detector has been designed to handle the presence of Gaussian noise within known image features and encompasses three primary criterion for edge detection performance (Canny, 1986):

- **Good detection**: there should be a low probability of failing to mark real edge points, and low probability of falsely marking non-edge points
- **Good localisation:** the points marked as edge points by the operator should be as close as possible to the centre of the true edge
- **Only one response to a single edge:** if there are two responses to the same edge, one of them must be considered false

The third criterion was needed to completely eliminate the possibility of multiple responses to a single edge (Canny, 1986). Initially, the Canny edge detector works to smooth the image using a Gaussian filter; reducing or eliminating any noise. For two-dimensional applications, two filters representing both vertical and horizontal derivatives are used for optimal detection (Basu, 2002). In two dimensions, an edge also has an orientation, where if desired, the Canny algorithm can be adjusted to detect only edges of a particular orientation by creating an orientation specific two-dimensional mask using by convolving the image with a symmetric two-dimensional Gaussian kernel and then differentiating between the normal and desired edge direction (Canny, 1986). Once the noise has been optimally removed, the Canny algorithm will find the image gradient to detect regions within the image that contain high spatial derivatives to mark as possible edges (Maini & Aggarwal, 2009). From here, the algorithm then tracks along these detected regions performing non-maximum suppression. This essentially involves identifying an edge point (a jump in intensity from one pixel to the next) whose strength is locally maximum in the direction of the gradient and suppressing (set equal to zero) any pixel that is not considered to be a maximum in its neighbourhood (Maini & Aggarwal,

2009; Shrivakshan & Chandrasekar, 2012). This results in an image with zeros everywhere except for the local maxima points which have been preserved (Shrivakshan & Chandrasekar, 2012). However, the non-maximal suppressed image may still contain false edge fragments which can be caused by noise or the presence of small resolution or image intensity changes (Shrivakshan & Chandrasekar, 2012). These false edge fragments must be reduced using a thresholding procedure to suppress any remaining false edges and produce a new gradient array (Maini & Aggarwal, 2009; Shrivakshan & Chandrasekar, 2012). Canny uses a thresholding procedure called hysteresis (Canny, 1986) to track the remaining pixels which have not been suppressed and removes (setting to zero) any pixels with a magnitude below the lower threshold, marks any pixels with a magnitude above the higher threshold as a 'real edge' and any connected pixels within the contour that have a higher magnitude than the lower threshold are also marked as 'real edges' (Canny, 1986; Maini & Aggarwal, 2009). This thresholding procedure is critical in greatly reducing the possibility of 'streaking' which is defined as the "breaking up of an edge contour caused by the operator output fluctuating above and below the threshold along the length of the contour" (Canny, 1986). Additionally, the likelihood of detecting isolated false edges is greatly reduced as the magnitude of these edges must be above the higher threshold (Canny, 1986). The high and low thresholds are set according to statistics from the entire image (i.e. the amount of noise) which is determined by a pre-processed noise estimation procedure (Basu, 2002; Sanjay, 2015). Conversely, this thresholding procedure makes the Canny edge detection algorithm more computationally demanding than other edge detection algorithms but is also responsible for its superior performance under noisy conditions (Maini & Aggarwal, 2009; Sanjay, 2015). The pre-processing threshold requirements are critical for the accuracy of the algorithm, however this process also means that direct implementation of the Canny algorithm has a level of latency that is proportional to the size of the frame (or image) making it difficult to implement in real-time applications (Sanjay, 2015).

The accuracy or performance of the Canny algorithm is reliant upon the standard deviation or the size of the Gaussian filter along with the hysteresis threshold values (high and low), both of which are adjustable parameters (Maini & Aggarwal, 2009). The greater the standard deviation, the larger the size of the Gaussian filter becomes which essentially means more blurring is needed for noisy images and detecting larger edges (Maini & Aggarwal, 2009). As a consequence, the larger scale Gaussian filter will be less accurate when localising the edge in comparison with smaller scale Gaussian filters which will have greater localisation but are more susceptible to detecting false edges (Maini &

Aggarwal, 2009). Altering the size of the filter essentially becomes a trade-off between being able to accurately localise edge points and detecting spurious or false edges (Lopez-Molina et al., 2013). These parameters are able to be adapted to best suit shifting environments and provide an optimal result. Canny has also proposed a method to combine the outputs from various filter scale sizes using a 'fine-to-coarse' strategy termed *feature synthesis* (Basu, 2002).

More recently, Xu and colleagues (2014) and Sanjay (2015) have developed customised Canny edge detection algorithms known as 'distributed' Canny edge detectors. These solutions adaptively compute the detection thresholds (high and low) using block-based data (block type and local distribution of gradients in an image block) as opposed to the original Canny algorithm which uses frame-level statistics (Sanjay, 2015; Xu et al., 2014). Additionally, an alternate method ("low complexity non-uniform quantized histogram calculation") has been shown to be effective in computing the block hysteresis thresholds (Sanjay, 2015; Xu et al., 2014). This block-based version of the Canny algorithm is able to compute edges of multiple block simultaneously and thus displays a significant increase in speed to meet real-time requirements, increased throughput, and critically, no reduction in edge detection performance when compared with the original Canny algorithm (Sanjay, 2015; Xu et al., 2014). Whilst edge detection is a widely technique for a range of different image-processing tasks (Basu, 2002; Xu et al., 2014), to the author's knowledge, this technique has scarcely been used as a signal processing mechanism to analyse inertial sensor outputs, much less has had any previous applicability to detecting and classifying human movement characteristics from body-worn inertial sensors.

2.7 Human Motion Capture Systems

Human motion capture involves recording human movement and translating that movement onto a digital model (Tao et al., 2011). Micro-sensor or MEMS inertial sensor human motion capture systems are becoming more prevalent and are able to provide highly-accurate movement kinematics based on segmental orientation data from suitably placed IMUs coupled with sophisticated sensor fusion techniques (Bachmann et al., 2001; Roetenberg et al., 2009; Wang et al., 2017). These systems comprise signal outputs using each of the sensors (accelerometer, gyroscope, magnetometer) from multiple IMUs coupled with filtering algorithms to assess the position of each segment and rotations between segments under the assumption that each segment forms part of a linked

kinematic chain (Roetenberg et al., 2009; Tao et al., 2011). This, however, is not a simple process and requires pre-determined and individualised biological and anatomical details (e.g. limb length) to build a 3D human skeletal model which is able to compute accurate orientation estimates in real-time (Wang et al., 2017). More specifically, to accurately measure the rotation of joints and limbs, a four coordinate system made up of the *Global Coordinate System*, *Body Coordinate System*, *Sensor Coordinate System* and *Model Coordinate System* is required (Wang et al., 2017).

Whilst these systems are able to provide highly accurate body segment orientation and kinematic data during any movement task, and do not require external cameras, emitters or markers, they do require the subject or athlete to wear several IMUs carefully placed on each segment of the body derived from individual anatomical measures; of which the set-up and calibration process can be laborious and time-consuming. Additionally, whilst portable IMU motion capture suits exist (Roetenberg et al., 2009) and can be used both indoors and outdoors, these systems are best suited to a laboratory environment bringing into question their ecological validity or ability to provide an accurate depiction of legitimate field-based movement in a sporting context. These suits could be considered cumbersome for an athlete to wear during on-field training and are not designed to withstand the rigours of team-sport activity (e.g. falls, collisions, tackles, intense accelerations & decelerations, COD movement). Although perhaps not as comprehensive as whole-body motion capture systems, microtechnology embedded inertial sensors commonly worn in elite sport provide an opportunity to collect on-field kinematic data in both training and competition which can become both useful and insightful to advance knowledge of team-sport movement demands.

2.8 Inertial Sensor Use Within Elite Sport

2.8.1 The Application of Inertial Sensors and GPS Technology

Although advanced human motion capture systems can provide accurate information regarding 3D movement kinematics (Roetenberg et al., 2009), they are principally designed for laboratory-based assessments and are impractical for on-field use during team-sport activity. However, wearable technology has advanced rapidly whereby less cumbersome body fixed sensors housed within commercially available microtechnology units are now commonplace in elite sport and have the advantage of being able to record ambulatory measurements in the natural environment of the subject (Aminian & Najafi,

2004). Access to, and use of these devices during on-field training and competition enables a far more pragmatic approach to profiling the locomotive demands of a range of different sports, monitoring on-field training loads, distinguishing between sports-specific movements (for more in-depth analysis) and can provide 'real-time' locomotive data during both training and competition to evaluate the load each athlete is exposed to as it is occurring (Chambers et al., 2015; Cummins et al., 2013; Wixted, Billing & James, 2010).

Commercially available wearable systems are becoming more diverse and are now commonplace within the elite sporting landscape with more affordable options rapidly gaining momentum in sub-elite and recreational settings (e.g. semi-professional, college, high-school) (Casamichana et al., 2013; Chandler, Pinder, Curran & Gabbett, 2014; Cormack, Smith, Mooney, Young & O'Brien, 2014; Gentles et al., 2018; Polley et al., 2015; Vlantes & Readdy, 2017; Wellman, Coad, Goulet & McLellan, 2017). Generally, these microtechnology units are driven by a GPS engine which enables the accompanied proprietary software to produce a series of kinetic and kinematic movement variables that can be assessed in real-time, and prospectively reported using proprietary reporting solutions; or customised solutions designed and created by sports science and strength and conditioning practitioners. Commonly adopted in elite sporting environments, more advanced microtechnology units from well-known manufacturing companies (e.g. Catapult Sports, GPSports, Zephyr, StatSports, VX Sport) also contain one or more inertial sensors (accelerometer, gyroscope, magnetometer) co-located within the same unit casing as the GPS engine. Importantly, during on-field training and competition, these microtechnology units are typically worn on the posterior aspect of the trunk placed between the scapulae (upper back) embedded in a playing jersey or manufacturer supplied fitted-vest ensuring they place no burden on the athlete (Figure 2.1).

Whilst GPS technology has been thoroughly examined for validity and reliability in a multitude of different sports (Castellano et al., 2011; Duffield et al., 2010; Gastin & Williams, 2010; Jennings et al., 2010; Johnston et al., 2014; Petersen et al., 2009; Rampinini et al., 2015), in a variety of settings (e.g. lab-based, field-based) and for a wide array of movement patterns (accelerations, decelerations, distance, velocity, COD etc.), it is feasible to suggest that GPS technology may be a valid and reliable tool when aiming to quantify more basic human locomotion (e.g. total distance (Johnston et al., 2014; Johnston et al., 2012), or speed during steady velocity running (Varley et al., 2012; Waldron et al., 2011), yet is limited by its sampling rate (5 to 15 Hz) and reliance on satellite connectivity which becomes problematic when trying to assess more detailed and

refined sports-specific movement patterns. Accordingly, inertial sensors, which have the capacity to sample at a much higher frequency (>100 Hz) than GPS engines, may prove superior in their ability to detect subtle changes in movement within the 3D environment that GPS technology is presently incapable of (Chambers et al., 2015). Additionally, inertial sensors work independently of satellite reliant GPS, and can therefore be implemented indoors and without interference of environmental events such as solar flares (Chambers et al., 2015); superseding the previously outlined limitation of GPS engines when used in isolation.

MEMS based microtechnology or inertial measurement devices now contain multiple transducers working in tandem for each sensor which has allowed movement detection to become multi-dimensional (Li et al., 2016). Typically, tri-axial, these sensors are orthogonally mounted with each measure (or physical quantity) taken in accordance with the Cartesian coordinate system (*x*, *y* and *z*). More recently, with the addition of miniature electronic compass sensors (or magnetometers) providing orientation relative to magnetic-North, pieced together with vertical inclination measures derived from the accelerometer, 3D orientation can be obtained and monitored using sensor fusion algorithms (Kemp, Janssen & van der Kamp, 1998). Recent developments in the wearable technology space has vastly improved the affordability (and therefore access) of these commercial microtechnology devices with their sampling frequency now considered to be adequate when capturing most sporting applications (Lightman, 2016). The integration of these multi-axes sensors provides a platform where a variety sensor fusion strategies, techniques and subsequent algorithms can allow for more accurate quantification of on-field/in-competition movement kinematics to inform future technical and physical movement prescription (Camomilla et al., 2018). Yet, in elite sport, the ability to maximise the sampling capacity and complementary features of these sensors is principally limited by the lack of experience or inability of sports-science practitioners to apply sophisticated fusion algorithms (e.g. the ability to compensate for gyroscope drift errors) to integrate these sensor signals effectively. Consequently, this limitation in conjunction with other restrictions (unit placement, fusion ability, athlete compliance, and more) has led to a paucity of research using these sensors to produce effective and meaningful measures which can be used to inform future practice in elite sport.

2.9 Clinical and Technical Use of Inertial Sensors

In alignment with the growing trend of wearable technology in sport, the use of inertial sensors to assess gait (walking and running) (Bötzel et al., 2018; Lee, Mellifont & Burkett, 2010a; Li, Young, Naing & Donelan, 2010; Seel, Raisch & Schauer, 2014), posture (Alahakone & Senanayake, 2010; Lee, Desmoulin, Khan & Park, 2011; Li et al., 2009) as well as aid in rehabilitative exercise (Lee, Sutter, Askew & Burkett, 2010b; Sant'Anna, Wickström, Eklund, Zügner & Tranberg, 2012; Yang, Zhang, Novak, Brouwer & Li, 2013) has been established in a clinical setting and increasingly more commonplace in athletic environments. During treadmill and overground locomotion (walking and running), inertial sensors can be strategically placed on specific joints (e.g. ankle, knee, hip) to assess the range of motion in one or more planes and quantify the range (e.g. knee flexion/extension) that these joints have the capacity to function within (Cooper et al., 2009; Seel et al., 2014). In addition, symmetry changes between lower limbs during both running and walking tasks can be assessed using inertial sensors (Lee et al., 2010b; Moe-Nilssen & Helbostad, 2004; Sant'Anna et al., 2012). However, these assessments and subsequent analyses are heavily influenced by both the number and location of the sensors (Mendes Jr, Vieira, Pires & Stevan Jr, 2016; Salarian, Burkhard, Vingerhoets, Jolles & Aminian, 2013). During lower-limb kinematic assessments, inertial sensors are often attached to the lumbar spine to analyse movement of the hip; to the thigh and/or tibia to analyse knee angle during gait; and to each ankle to analyse movement and range of motion (e.g. dorsi/plantar flexion) (Favre, Aissaoui, Jolles, de Guise & Aminian, 2009; Mendes Jr et al., 2016; Tognetti, Lorussi, Carbonaro & de Rossi, 2015).

Inertial sensors can also provide highly detailed information during kinematic assessments and rehabilitative programs where subtle changes to an individual's gait pattern and movement signature can be tracked longitudinally to assess the effectiveness of rehabilitation interventions and ensure the person or athlete's gait similarly returns to a pre-injury pattern. Whilst video analysis can also assist in this endeavour, inertial sensors can pick up more subtle and detailed changes that may not be visible to the naked eye, and also have the capacity to provide objective information which can be used to inform future practice; such as acceleration data which can be transposed to force output and assessed unilaterally (Crowell & Davis, 2011; Lee, Ohgi & James, 2012).

Whilst there is an abundance of literature containing useful and practical information in this area, to conduct highly detailed analyses and obtain accurate kinetic and kinematic data, multiple IMUs are required. These sensors are placed in specific regions of the body

(e.g. joints) and are used in conjunction with sophisticated sensor fusion and filtering algorithms to enable accurate limb orientation and segmental analyses during locomotion. However, whilst highly detailed and appropriate for laboratory testing, the placement and attachment of multiple sensors is simply unrealistic and obtrusive to an athlete during on-field testing, training and competition. Additionally, wearable technology comprising restrictive garments and/or markers may alter the natural movement pattern of the athlete (Lee et al., 2012). This heavily restricts the utility of these methods to establish construct validity when assessing on-field movement, yet the ability to truly assess and classify movement activity in the natural environment of the athlete is highly valuable.

2.10 Inertial Sensors for Load Monitoring Purposes in Team Sports

While inertial sensors have been used in a wide array of environments and in countless applications, the major purpose of the present review is to assess their on-field use and utility in team-sports during training and competition where one or more sensors (accelerometer, gyroscope, magnetometer) housed within a single microtechnology unit (located on the upper thoracic vertebrae) are routinely used to profile certain training and game demands, quantify mechanical 'load' of certain sports and identify specific movements within these sports to improve/advance performance and load monitoring procedures and perhaps inform future practice regarding injury prevention strategies. The advantages are clear, these units do not require any complex setup procedure, are portable and easy to use, place no burden on the athlete, can be used indoors (inertial sensors works independently of satellite reliant GPS technology), can provide real-time feedback (when paired with enabling software) and have developed to the point where there now exists a range of different units with varying price tags to suit the needs of all athletes.

Principally, inertial sensors during on-field use in team-sports have been used to either:

a. Quantify a single/multiple form/s of mechanical load or energy expenditure, more as a 'holistic' summation of the requirements of a training sessions or game; or
b. Automatically detect, quantify and sometimes categorise more detailed sports-specific movement patterns within a training session or game environment.

Table 2.1 Summary of peer-reviewed research that has utilised one or more inertial sensor signals from a single microtechnology unit (positioned only on the upper thoracic vertebrae) to quantify multiple sources of mechanical or metabolic 'load' within a variety of team-sports during scheduled training and/or match play. Only data that utilised (or was compared against) inertial sensor signals is reported.

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Barrett et al., 2016)	Soccer	63 males, professional (English championship)	To determine the within match patterns of PL^{TM} and locomotor variables in competitive matches Assess any match related changes in players' locomotor efficiency patterns by calculating the ratio of total PL^{TM} to distance covered (PL:TDC)	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Between player (32.1 – 63.9%) and between-match (10.3 – 44.4%) variability was present for PL:TDC, PL^{TM} and individual accelerometer planes PL:TDC ratio (locomotor efficiency) increased in the last 15 minutes of both first and second halves in relation to the 0-15 minute period PL^{TM} accumulation was significantly greater in the 0-15 min stage of a match when compared with all other time periods
(Barron, Atkins, Edmundson & Fewtrell, 2014)	Soccer	38 males, sub-elite, youth	Investigate the external load (PL^{TM}) during competitive match play and assess any positional differences	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100 Hz)	CMF position accumulated greater total PL^{TM} than the CD position ($p \leq 0.04$) CMF also displayed greater anterior-posterior loading (y-axis) when compared with CD ($p \leq 0.01$)
(Boyd, Ball & Aughey, 2011)	Australian football	10 males, semi-professional	To determine the reliability of a tri-axial accelerometer vector magnitude measure (PL^{TM}) as a measure of physical activity demands during Australian football matches	MinimaxX 2.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Between device reliability of accelerometers during Australian football matches was 1.9% (CV) PL^{TM}: Noise (CV = 1.9%) lower than the signal (SWD = 5.88%) supporting use to reliably detect differences in physical activity demands during Australian football matches

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Boyd et al., 2013)	Australian football	40 males, elite (19) and sub-elite (21)	Assess 2 forms of external load measures using accelerometers (PL_{3D} (sum of all axes) and PL_{SLOW} (sum of all axes for movement < 2m/s)) during both Australian football training drills and matches Assess any differences between playing positions, playing level, training drills and matches for these external load measures	MinimaxX 2.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} varied between positions with midfielders accumulating the highest external load Ruckmen accumulated the highest PL_{SLOW} load when compared with all other positions Elite level Australian footballers accumulated more PL^{TM} than their sub-elite counterparts Small-sided games was the only training drill that equalled or exceeded the external load requirements of match-play
(Casamichana et al., 2013)	Soccer	28 males, semi-professional	Examine relationships between common internal training load metrics and objective measures of external training load	MinimaxX v4.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Very large correlation ($r = 0.72$, $p < 0.01$) between PL^{TM} and Edwards indicator of internal load (HR data) Very large correlation ($r = 0.76$, $p < 0.01$) between PL^{TM} and session RPE
(Chandler et al., 2014)	Netball	8 females, collegiate	The use of PL^{TM} to investigate the physical demands of netball match play and different training activities Investigate the physical demands of specific playing positions during netball match play	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	The movement demands of netball match play are best replicated by skills-based conditioning The C position recorded the highest total PL^{TM} and greatest PL^{TM} in each of the three axes, whilst the GK and GS positions recorded the lowest PL^{TM} during match play
(Colby et al., 2014)	Australian football	46 males, elite	Investigate the relationship between physical workload and injury risk	SPI Pro X, GPSports	Tri-axial accelerometer (100 Hz)	In-season, 3-weekly force loads of >5,397 AU were associated with a 2.5 times greater risk of injury when compared with <4,561 AU

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
			Assess the effects of increased 'Force Load' (force produced from foot strikes, collisions, jumps etc..) on subsequent injury risk during both pre-season and in-season periods			
(Cormack, Mooney, Morgan & McGuigan, 2013)	Australian football	17 males, elite	Assess the effect of neuromuscular fatigue on exercise intensity (relative contributions of each accelerometer axis (*x*,*y*,*z*) to external load accumulation) Assess the association between external load accumulation ($PL^{TM}.min^{-1}$) and alternative measures of running activity	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	In a fatigued state, the contribution of the vertical accelerometer (*z*) to external load accumulation was reduced when compared with non-fatigued players In a non-fatigued state, elite AF athletes with a high capacity appear able to accumulate a large percent of external load (LPM) by performing lateral movements
(Cormack et al., 2014)	Netball	32 females, sub-elite (17) and recreational (15)	To determine the differences in external load ($PL^{TM}.min^{-1}$) accumulation between different standards of netball match-play Assess differences in external load accumulation between playing positions and periods of play	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Sub-elite netballers produced greater external load measures ($PL^{TM}.min^{-1}$) across all positions when compared with their recreational counterparts (avg 31% higher) Higher standard players had a greater contribution from the vertical (*z*) axis, but lower contribution from the mediolateral (*x*) and anterior-posterior axes (*y*) Centre-court players produced the greatest external load No clear differences in the rate of external load accumulation ($PL^{TM}.min^{-1}$) throughout periods of a match in both sub-elite and recreational netballers

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Cummins & Orr, 2015)	Rugby league	26 males, elite	Investigate the forces of collision events during both attacking and defensive play Determine any positional differences in collision profiles during match play	SPI Pro X II, GPSports	Tri-axial accelerometer (100 Hz)	Hit-up forwards, wide-running forwards and adjustables experienced more collisions defending, whilst outside backs experienced more collisions during attacking play Hit-up forwards sustained 33.3% more collisions during match play than wide-running forwards, 60% more than adjustables, and 300% more than the outside backs Hit-up forwards produced a greater number of high-impact (zone 5 and 6) tackles and hit-ups per minute of match play than wide-running forwards (43%), adjustables (100%), and outside backs (263.6%)
(Cunniffe, Proctor, Baker & Davies, 2009)	Rugby union	3 males, elite	Assess the physical demands (body load and game impacts) of forward and back players during rugby union match play	SPI Elite, GPSports	Tri-axial accelerometer (100 Hz)	The forward player accumulated greater overall body load per minute (1,426 AU) than the back player (376 AU) The forward (1,274) accrued more total impacts than the back (798) The forward was involved in 60% more high-level impacts than the back
(Curtis et al., 2018)	Soccer	18 males, collegiate	To quantify the positional match demands of NCAA Division 1 men's soccer (PL™)	MinimaxX v4.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Centre midfielders very likely accumulated more total PL™ than defenders (147 ± 95) and wide midfielders (122 ± 95), as well as likely more total PL™ than forwards (119 ± 109)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Davies, Young, Farrow & Bahnert, 2013)	Australian football	14 males, elite	Quantify and compare the agility demands of 4 small-sided game (SSG) variations in elite AF training: PL^{TM}3D and PL^{TM}2D, *x* + *y* axes	MinimaxX3, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Larger area and lower player density SSGs led to moderately greater 3D PL^{TM} accumulation ($p = 0.121$, ES = 0.82), whilst smaller area and higher density SSGs led to largely greater 2D PL^{TM} ($p = 0.010$, ES = 1.22) Players produced substantially greater 3D ($p < 0.05$, ES = 1.53) and 2D ($p > 0.05$, ES = 1.44) PL^{TM} values when the number of players was reduced
(Douglas, Rotondi, Baker, Jamnik & Macpherson, 2019)	Ice hockey	25 females, world class	Compare external and internal loads across the 2 playing positions in the sport to provide information that allow coaches to make informed decisions regarding training volume and intensity in regard to match demands	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Forwards had higher PL^{TM} ($P < 0.001$, ES = 0.32), PL^{TM}.min^{-1} ($P < 0.001$, ES = 0.55) and IMA explosive efforts ($P < 0.001$, ES = 0.63) during training Forwards had higher PL^{TM} ($P < 0.001$, ES = 0.26), PL^{TM}.min^{-1} ($P < 0.001$, ES = 0.38) and IMA explosive efforts ($P < 0.001$, ES = 0.64) during competition Defenders accumulated significantly more PL^{TM} ($P < 0.001$, ES = 2.98), PL^{TM}.min^{-1} ($P = 0.016$, ES = 0.25) and IMA explosive efforts ($P < 0.001$, ES = 2.52) and forwards accumulated significantly more PL^{TM} ($P < 0.001$, ES = 2.63) and IMA explosive efforts ($P < 0.001$, ES = 2.08) during competition when compared to training
(Esmaeili et al., 2018)	Australian football	55 males, elite	Evaluate individual and combined effects of multiple factors on the risk of non-contact. soft-tissue injury	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	High 14-day smoothed PL^{TM} had the largest effect (hazard ratio 3.2, 90% CL 1.86-5.4) on the risk of soft-tissue injuries compared to other load measures

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
			Evaluate the effects of acute load and previous injury on high acute:chronic workload ratios			Injury-prone players displayed a 5x greater risk of injury compared to robust players after adjusting for 14-day smoothed PL^{TM} and previous leg injury (hazard ratio 5.4, 90% CL 3.6-12)
(Fox et al., 2018)	Basketball	15 males, semi-professional	Quantify and compare the external demands and internal responses between physical conditioning training (PCT) sessions, game-based training (GBT) and competition across different seasonal phases	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PCT and GBT produced statistically significantly ($p < 0.001$) higher absolute (AU) (PCT: 632 ± 139, d = 1.36; *large*, GBT: 624 ± 113, d = 1.54; *large*) and relative (AU.min^{-1}) (PCT: 6.50 ± 0.81, d = 2.44; *very large*, GBT: 6.10 ± 0.77, d = 2.14; *very large*) PL^{TM} compared with competition (abs: 449 ± 118, rel: 4.35 ± 1.09) Relative PL^{TM} was significantly (p = 0.003) higher during PCT (6.50 ± 0.81, d = 0.51; *small*) than during GBT (6.10 ± 0.77) Competition (1.58 ± 0.85) produced a significantly ($p < 0.001$) higher sRPE:PL^{TM} ratio than PCT (0.98 ± 0.22, d = 1.44; *large*) and GBT (0.91 ± 0.24, d = 1.90; *large*), whereas GBT (0.53 ± 0.0) produced a significantly (p = 0.021) higher SHRZ:PL^{TM} ratio than PCT (0.50 ± 0.08; d = 0.42; *small*)
(Gabbett, 2015b)	Rugby league	182 males, semi-professional	Investigate the relationship between PL^{TM}, PL$_{SLOW}$ (all accelerations from tri-axial accelerometer data at speeds < 2m.s^{-1}) and PL$_{2D}$ and collisions in rugby league players	MinimaxX Team S4, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Across all positions, poor relationships found between PL^{TM} and the number of collisions performed during match play

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
			Assess any positional differences in PL™ variances and collision demands			Weak relationships found between PL™ and collisions in the adjustable (r = 0.28, $p \leq 0.05$) and outside back (r = 0.19) positions, whereas these associations markedly improved in the forwards (r = 0.69, $p \leq 0.01$) and hookers (r = 0.65, $p \leq 0.01$) Relative PL™(PL™.min^{-1}), PL™, PL_{2D} and PL_{SLOW} were highest in the forwards and hookers
(Gabbett, 2015a)	Rugby league	104 males, semi-professional	Investigate the activity profiles of rugby league match-play, accounting for ball "in" and ball "out of play" periods	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	The frequency of collisions increased by 63% when expressed relative to ball-in play time (0.67 collisions per minute) Neither increases or decreases in total ball-in play time influenced collision activity
(Gabbett, Jenkins & Abernethy, 2012)	Rugby league	30 males, elite	Investigate the physical demands of rugby league match play using microtechnology Compare the physical demands of match-play with typical training activities	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Hit-up forwards (42, ES = 1.41-2.75) and wide running forwards (45, ES = 0.63-2.00) were involved in a greater number of collisions than the adjustables (34, 95%CI 28-40) and outside backs (28, 95%CI 23-32) Hit-up forwards and wide-running forwards were involved in a greater amount of absolute moderate and heavy collisions when compared with the adjustables and outside backs, and thus also had a higher match-play collision rate

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Game based training had similar mild, moderate, and overall collision frequency to competition, but lower heavy collision demands ($p < 0.05$) than match-play, whilst collision frequency during traditional conditioning and skill training activities was significantly lower than competition ($p < 0.05$)
(Gabbett, Polley, Dwyer, Kearney & Corvo, 2014)	Rugby league	22 males, elite	Investigate the physical demands of rugby league match-play in elite forwards (hit-up forwards, wide-running forwards and hookers) Assess the extent to which these demands differ between attack and defence, and in different field positions	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Trivial to small differences found in the frequency of collisions across different field positions Lowest frequency of collisions occurred in attack when players were attacking from their own try-line (0-30m zone) with moderately greater collision frequency in the middle third ($p < 0.001$; ES = 0.73 ± 0.15) and when attacking the opposition's try-line ($p < 0.001$; ES = 0.63 ± 0.15) Frequency of collisions were 2.4 times greater (very large) in defence than attack (1.9 ± 0.7 per min vs. 0.8 ± 0.3 per min, $p < 0.001$, ES = 1.38 ± 0.12)
(Gabbett, 2013a)	Rugby league	22 males, elite	Compare the activity profiles of players competing against high-ranked (Top 4) and low-ranked (Bottom 4) teams Compare the activity profiles of players when their team won or lost	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Number of mild, moderate, and heavy collisions were similar ($p < 0.05$, ES = 0.00 – 0.28) whether competing against Top 4 or Bottom 4 teams No difference ($p > 0.05$, ES = 0.00 – 0.23) between winning and losing teams for the number of mild, moderate and heavy collisions

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Gabbett & Seibold, 2013)	Rugby league	32 males, semi-professional	Determine which physical qualities could discriminate between state-based rugby league players competing for selection in semi-professional rugby league team Investigate the relationship between tests of physical qualities and physical match performance in these players	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Forwards engaged in greater number of collisions per minute of match play than backs ($p < 0.05$, ES = 2.53) Lower-body power, upper-body strength and endurance, and prolonged high-intensity intermittent running capacity discriminate between successful and less successful rugby league players; but are not associated with collision performance (number of collisions)
(Gabbett, 2014)	Rugby league	185 males, semi-professional	Investigate the physical demands and technical and tactical performance of rugby league teams and determine which variables discriminated successful from less-successful teams	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Total number of collisions performed was greater (P = 0.004, ES = 0.33 – 0.39) in Bottom 4 teams than in Middle 4 and Top 4 teams
(Gallo et al., 2015)	Australian football	41 males, elite	Examine the relationship between internal and external training load by exploring characteristics that may impact on session RPE (sRPE)	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Very large correlation between sRPE and PL^{TM} (r = 0.86, 95% CI: 0.83-0.89) and PL_{SLOW} (r = 0.80, 95% CI: 0.75-0.84)
(Gallo et al., 2016)	Australian football	36 males, elite	Examine the relationship between self-reported pre-training wellness measures and subsequent exercise intensity in skill-based training sessions Assess the impact of perceived wellness on external load parameters and external:internal load ratio	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Pre-training wellness (Z-score) had a significant negative effect on subsequent PL^{TM} (-0.45 ± 0.28 $au.min^{-1}$, $p = 0.002$) and PL_{SLOW} (-0.61 ± 0.28 $au.min^{-1}$, $p = < 0.001$) output during subsequent skill-based training The ratio of PL_{SLOW}:RPE was significantly impacted by pre-training wellness scores (-0.49 ± 0.29 $au.min^{-1}$, $p = < 0.001$), although this reduction may be trivial

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
Gastin et al. (2013a)	Australian football	20 males, professional	Describe and quantify the frequency, velocity and impact acceleration during tackling in Australian football Assess the ecological validity of accelerometer impact data against the criterion measure	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	352 tackles recorded across four matches comprising 173 tackles made (68 low, 100 medium, 5 high-intensity) and 179 tackles against (47 low, 118 medium, 14 high-intensity) Peak PL™ was significantly greater in high (7.5 ± 1.7 a.u.) compared to medium (4.9 ± 1.5 a.u) and low (4.0 ± 1.3 a.u.) intensity tackles Significant differences ($p < 0.01$) in peak impact accelerations were present (in all three planes) between high, medium and low intensity tackles
(Gaudino et al., 2015)	Soccer	22 males, elite	Identify the external training load variables that are most influential on RPE and RPE-TL (RPE x duration) during elite soccer training	Viper, STATSports	3-dimensional accelerometer (100 Hz)	Moderate correlation between RPE-TL and number of impacts (r = 0.451, 95% CI: .415 - .486, $p < .001$) Very large within-individual correlation between RPE-TL and number of impacts ($r = 0.729$, 95% CI: .708 - .749, $p < .001$)
(Gentles et al., 2018)	Soccer	25 females, collegiate (Division II)	Quantify the external and internal training loads of only locomotor-related events throughout a women's college soccer season Assess the relationship between accelerometer derived locomotor-only training loads against GPS and sRPE data	BioHarness, Zephyr™	Tri-axial accelerometer (100 Hz)	Team average Impulse Load (N.s) during practice (12,410 ± 4067), match warm-up (9,694 ± 1902) and match-play (20,120 ± 8609) Near perfect and very large correlation between Impulse Load and total distance ($r = 0.95$, $p < 0.001$) and Impulse Load and sRPE ($r = 0.84$, $p < 0.001$) respectively
(Gomez-Piriz, Jiménez-Reyes & Ruiz-Ruiz, 2011)	Soccer	22 males, professional	Assess the relationship between total body load and sRPE in soccer specific training and to determine any positional differences	SPI Elite, GPSports	Tri-axial accelerometer (100 Hz)	sRPE only accounted for 5% of the variance in total body load ($r = 0.053$)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						No significant effects of playing position on total body load $F(2,19) = 0.28$; $p = 0.76$, $\eta^2 = 0.03$
(Graham, Cormack, Parfitt & Eston, 2019)	Australian football	21 males, professional	Compare within individual predictive precision of model estimates of match exercise intensity with actual measures obtained across a pre-season Assess any differences in match exercise intensity precision accuracy between models constructed from internal and external loads	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Within-individual correlation between predicted and actual match exercise intensity for TRIMP scaled PL™ was very large ($TRIMPs_{PL}$: $r = 0.72$) TRIMPsPL comparative ability to predict pre-season fluctuations as $TRIMPs_{Dist}$
(Grainger, McMahon & Comfort, 2018)	Rugby union	38 males, elite	Compare absolute and relative number of impacts between nine positional groups	Viper, STATSports	Tri-axial accelerometer (100 Hz)	There was no significant difference in both absolute and relative impacts > 9.01G between forwards and backs Scrum halves were involved in the highest number of absolute 9.01-11G impacts (162 ± 82) and full backs the highest number of absolute 11.01-13G impacts (66 ± 27) and >13G impacts (87 ± 27), as well as the highest number of absolute impacts >9.01G (296 ± 99) Hookers experienced the highest relative number of 9.01-11G, 11.01-13G and >13G impacts
(Heishman et al., 2018)	Basketball	10 males, collegiate (NCAA Division 1)	Examine the relationship between measures of internal stress and external load Examine the effects of readiness and PL™ on countermovement jump (CMJ) performance	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Increased PL™ during the previous training exposure was associated with a decrease in subsequent CMJ height (58.1 ± 4.7cm vs. 60.4 ± 5.1cm, r = -0.67, $p = 0.035$)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						PL^{TM} and CNS (central nervous system) readiness were shown to have independent impacts on performance
(Heishman et al., 2017)	Basketball	10 males, collegiate (NCAA Division 1)	Examine the effects of morning vs. afternoon strength and conditioning training on an acute performance index of fatigue	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	CMJ height (58.8 ± 1.3cm vs. 61.9 ± 1.6cm, p = 0.009) and power (6378 ± 131.2W vs. 6622.1 ± 172.0W, p = 0.009) were lower during the morning compared with afternoon training, after PL^{TM} and session duration were matched
(Howe, Aughey, Hopkins, Stewart & Cavanagh, 2017)	Rugby union	30 males, professional	Determine the difference between GPS and accelerometer technology for detecting differences in measures of maximum mean movement between positions and halves during professional rugby union match play using a 600-s rolling average epoch	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Accelerometer derived PL^{TM} was more sensitive for quantifying declines in maximum mean movement between halves (up to a 17.6% decline) than both GPS derived Mean Speed and Metabolic Power Differences between backs and forwards more adequately quantified by accelerometers (moderate – large standardised differences) than GPS measures (unclear – less likely). Forwards produced greater PL^{TM} per unit of distance covered or metabolic power generated than backs
(Hulin et al., 2018)	Rugby league	25 males, elite	Examine the relationship between collision workloads and PL^{TM} in each anatomical plane during professional rugby league match-play	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	$PL_{2D}.min^{-1}$ (R^2 = .37, r = .61, large), $PL_{VM}.min^{-1}$ (R^2 = .30, r = .55, large), $PL_{AP}.min^{-1}$(y) (R^2 = .34, r = .59, large), $PL_{ML}.min^{-1}$(x) (R^2 = .38, r = .62, large), $PL_{V}.min^{-1}$(z) (R^2 = .20, r = .45, moderate), and $PL_{SLOW}.min^{-1}$ (R^2 = .22, r = .47, moderate) each demonstrated a distinct relationship from collision.min^{-1} workloads during match-play and should be treated as separate variables

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						$PL_{SLOW}.min^{-1}$ had a distinct relationship from total distance <2m.s^{-1}.min^{-1} (R^2 = .07, r = .26, small) No PL^{TM} variable provides a valid measure of collision workload in team sport
(Jaspers et al., 2018)	Soccer	38 males, elite	Predict RPE from a given set of external load indicators using machine learning Identify which external load indicators contribute most to RPE	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Some of the top 'importance scores' in relation to predictive RPE capacity: PL^{TM}: 0.487, PL_{ML}: 0.458 and PL_{2D}: 0.384
(Johnston, Gabbett & Jenkins, 2013)	Rugby league	15 males, junior	Determine physiological responses to an intensified period of junior rugby league competition Assess the relationship between markers of fatigue and match performance	Team S4, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Across the competition, forwards performed a greater number (ES = 1.20) and frequency (ES = 1.40) of collisions compared with the backs Moderate reductions in number and frequency of collisions in game 4, and frequency in game 5 for the forwards Increases in CK were significantly associated with a greater number of total collisions (r = 0.62; p = 0.01)
(Jones, West, Crewther, Cook & Kilduff, 2015a)	Rugby union	33 males, professional	Examine the positional movement patterns within elite rugby union match-play by assessing various physical performance metrics and temporal changes in movement	MinimaxX v4.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} values were significantly greater for loose forwards (625 ± 104AU) and half backs (617 ± 81AU) than tight forwards (528 ± 97AU, p < 0.05) Tight forwards (30 ± 15) were involved in a greater number of total contacts than outside backs (16 ± 8, p < 0.05), whilst loose forwards (38 ± 16) were also involved in a greater number of contacts than half backs (19 ± 9), inside backs (21 ± 11) and outside backs (16 ± 8, p < 0.05)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						PL™.min^{-1} was significantly lower in the second half (6.5 ± 0.9AU) compared with the first half (6.9 ± 0.8AU)
(Kempton, Sullivan, Bilsborough, Cordy & Coutts, 2015b)	Australian football	33 males, elite	Determine match-to-match variability for measures of physical and technical performance during successive seasons Examine the influence of playing position on these variables Assess changes in physical performance within competition seasons	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	No difference in PL™ between seasons PL™ accumulation was relatively stable across playing positions: Backs (CV: 7.2%, 95%CI: 6.3-8.6%), midfielders (CV: 10.5%, 95%CI: 9.4-12.1%) and forwards (CV: 9.5%, 95%CI: 8.1-11.8%) No difference in PL™ accumulation from the start of the season (1263, 95%CI: 1225-1301AU), to the middle (1266, 95%CI: 1236-1309AU) and at the end of the season (1246, 95%CI: 1215-1276AU)
(Lovell et al., 2013)	Rugby league	32 males, professional	Examine the internal and external factors that contribute to perceived exertion in rugby league training	SPI Pro, GPSports	Tri-axial accelerometer (100 Hz)	Large correlations between sRPE-TL with body load (r = 0.57) and impacts (r = 0.55) Moderate correlations between sRPE with body load/min (r = 0.42) and impacts/min (r = 0.45)
(Luteberget et al., 2018a)	Handball	12 males, elite	Assess the between-device reliability of a commercially available IMU to measure physical demands in team handball	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Total IMA counts showed a CV (1.8%) < SWD (2.5%), however this reliability decreased when IMA counts were categorised into intensity bands: Low: CV (2.7%) > SWD (2.3%) Medium: CV (4.6%) > SWD (3.0%) High: CV (5.3%) < SWD (5.6%)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Good to moderate reliability found for forward (CV: 6.6%) , back (CV: 5.5%), left lateral (CV: 3.9%) and right lateral (CV: 4.1%) IMA counts (CV > SWD% in all cases), which became further decreased when these IMA directional counts were also divided in to intensity bands The CV of PL^{TM} and its associated variables (PL^{TM}.min^{-1}, PL_{2D}, PL_{AP}, PL_{ML}, PL_{V}) were good (CV < 5%) and lower than the SWD
(Luteberget & Spencer, 2017)	Handball	20 females, elite	Investigate the position-specific high-intensity events (HIE) in international handball matches	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Differences in HIE present between all playing positions with backs accruing the highest number, followed by pivots and then wings Accelerations, decelerations and lateral CODs were extremely variable between positions with most differences large to very large in magnitude Backs and pivots had the highest PL^{TM}.min^{-1} values with the wing position slightly lower and the GKs substantially lower
(Luteberget, Trollerud & Spencer, 2018b)	Handball	31 females, semi-professional	Compare the intensity of game-based training drills with different player numbers (3v3 and 6v6) Compare the intensity of these training drills against match-play to assess position-specific demands	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Wings, pivots, and GK had greater HIE.min^{-1} in 3v3 than match-play with no HIE.min^{-1} differences in 6v6 compared with match-play for any position Backs, wings and pivots displayed greater PL^{TM}.min^{-1} during both 3v3 and 6v6 training drills when compared with match-play

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Fewer players resulted in higher $PL^{TM}.min^{-1}$ and $HIE.min^{-1}$ for all outfield positions
(McLaren et al., 2016)	Rugby union	28 males, professional	Determine the within-and between-player match loads for forward and backs Establish individual threshold values for interpretation of between-match changes in physical performance and match-loads	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Forwards accumulated more total impacts (78 ± 18 vs. 28 ± 12), PL^{TM} (590 ± 50 vs. 520 ± 90) and PL_{SLOW} (290 ± 30 vs. 230 ± 40) when compared with the backs Backs tended to show greater match-to-match variability for total impacts, PL^{TM} and PL_{SLOW}; both within and between-player A ~10% between-match change in PL^{TM} and PL_{SLOW} may be considered a likely substantial change, whereas impacts appear to be far more variable (26.4-41.7%)
(McLellan & Lovell, 2012)	Rugby league	22 males, elite	Examine the acute and short-term neuromuscular responses to the number, intensity and distribution of collisions during match-play	SPI Pro, GPSports	Tri-axial accelerometer (100 Hz)	No significant difference in the number of hit-ups between forwards (13.8 ± 5.2) and backs (11.7 ± 4.6), yet forwards (26.1 ± 15.3) completed significantly ($p < 0.05$) more tackles than backs (10.7 ± 8.9) Significant ($p < 0.05$) correlations between total number of impacts and reduced PRFD and PP 30 minutes post-match Number of impacts in Zones 4 (heavy), 5 (very heavy) and 6 (severe) were significantly ($p < 0.05$) correlated with reduced PRFD and PP (CMJ) 30 minutes post-match, whilst number of impacts in Zones 5 & 6 were significantly ($p < 0.05$) correlated with reduced PRFD and PP 24 hours post-match

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(McLellan et al., 2011)	Rugby league	17 males, elite	Examine the acute and short-term biochemical and endocrine responses to the number, intensity and distribution of impacts associated with collisions during match-play	SPI Pro, GPSports	Tri-axial accelerometer (100 Hz)	No significant difference between forwards and backs for total impacts (or impacts in each zone) during match-play or CK and cortisol levels after match-play Impact zones 5 (very heavy) and 6 (severe) were significantly correlated ($p < 0.05$) with increased levels of CK 30 minutes, 24, 48- and 72-hours post-match No significant correlation between cortisol levels and number of tackles, hit-ups or heavy-severe impacts by forwards or backs during match-play or throughout the next 120 hours of recovery
(McNamara et al., 2013)	Cricket	26 males, elite junior	Profile and identify pre-fatigue and workload variables of cricket fast-bowlers during a 7-week physical preparation period and 10-day competition period	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} greater (912 ± 481AU, *C*d = 0.32 ± 0.16, 96%) in fast-bowlers during competition (when compared against non-fast bowlers (697 ± 424AU), but unclear during the physical-preparation period (fast bowlers: 703 ± 450AU, non-fast bowlers: 598 ± 427AU; *C*d = 0.16 ± 0.2, 53%)
(Meylan et al., 2017)	Soccer	13 females, elite	Determine the variability of inertial-based parameters from match to match and compare the results against standard GPS metrics used in match analysis	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	High IMA events (CV: 14%, 95CI: 13-15%) were a more stable measure than GPS derived acceleration frequency (CV: 18%, 95CI: 16-21%) between matches Players may perform around 157 explosive actions (acceleration, deceleration, COD) during a 90-minute game

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Montgomery & Maloney, 2018)	Basketball	361 males & 208 females, elite senior and junior	Quantify and describe the physical and physiological demands of elite 3x3 basketball games, during international tournament play at junior, senior and professional levels, according to sex	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Movement demands are reduced (PL^{TM}) when compared with traditional basketball 3x3 competition requires frequent high-speed movements which contributes to the increase in PL^{TM} evident at more senior levels Volume of high-speed movements (>3.5m.s^{-1}) similar between males and females, yet the volume of accelerations during change of direction are greater for males
(Mooney et al., 2013b)	Australian football	17 males, elite	Assess whether NMF influences the relationship between yo-yo IR2 and match exercise intensity (PL^{TM}.min^{-1}) Assess whether NMF affects the relationship between PL^{TM} and other measures of exercise intensity	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	The importance of yo-yo IR2 capacity to the production of PL^{TM}.min^{-1} is very-likely reduced (Δr = -0.44 ± 0.26) from normal to fatigued states FT:CT moderates the effect of PL^{TM} accumulation (PL^{TM}.min^{-1}) on coaches' votes (large-trivial (ES: -0.67 ± 0.56) reduction in the 'fatigued' group) NMF had a very-likely (Δr = 0.43 ± 0.29) negative effect on the relationship between PL^{TM}.min^{-1} and HIR.min^{-1} accumulation (ES: -0.47 ± 0.56)
(Peterson & Quiggle, 2017)	Basketball	5 females, collegiate	Investigate longitudinal neuromuscular status of the lower extremity in relation to the associated external loads derived from accelerometry data Explore how internal load may be affected by both absolute and relative external load quantification	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	IMA^{TM} in the mediolateral plane (*RW* = 29.4%) displayed a high-level of importance in relation to adductor longus contraction time, comparable to total IMA^{TM} (*RW* = 30.5%), both far greater than PL^{TM} (*RW* = 5.6%). Similar results were found when radial muscle displacement was assessed (IMA^{TM} Med/Lat, *RW* = 25.8%; total IMA^{TM}, *RW* = 22.6%; PL^{TM}, *RW* = 15.9%)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						In absolute terms, internal load metrics (*Tc* and *Dm*) did not significantly differ from week to week, whereas external load metrics (PL™ and IMA™) did exhibit both high and low weekly values; yet in relative terms (week-to-week load changes), both internal and external metrics demonstrated meaningful fluctuations Positive correlations (r_{crit} = 0.38, p < 0.01) observed between aggregated muscle contraction time (internal) and external IMA™ metrics (total IMA™ (r = 0.43), Vert (r = 0.38), and Ant/Pos (r = 0.41))
(Polglaze et al., 2015)	Hockey	24 males, elite	Investigate the relationship between PL™ and total distance during both SSGs and match-play (and assess any differences) Investigate whether the relationship between PL™ and total distance differs between playing positions	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Very large correlation between absolute distance and overall PL™ (r = 0.868, p < 0.00001) and for all positions (r = 0.808 to 0.863, p < 0.00001) except for the strikers (large: r = 0.694, p = 0.0007) during match-play Very large correlation between absolute distance and PL™ during SSG training (r = 0.742, p < 0.00001) Relative PL™ lower (p = 0.043, d = 0.27) during SSG training (12.7 ± 2.2AU) than competition (13.2 ± 1.4AU) Relative PL™ to distance relationships differed between positions: STR: small, r = 0.132, p = 0.579 AMF: moderate, r = 0.441, p = 0.007 DMF: large, r = 0.627, p = 0.002

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						DEF: large, $r = 0.581$, $p = 0.001$
(Polley et al., 2015)	Lacrosse	15 males, state-level	Quantify the activity profile of top-level Australian lacrosse players in match-play using microtechnology	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Midfielders (9.9 ± 1.5AU) produced significantly higher ($p < 0.05$) PL^{TM}.min^{-1} values than both attackers (8.2 ± 2.1AU) and defenders (7.6 ± 2.7AU) PL^{TM}.min^{-1} output appears to decrease during all subsequent quarters when compared to the first quarter (across all positions)
(Reche-Soto et al., 2019)	Soccer	21 males, national level	Quantify and describe the situational relationship between PL^{TM} and metabolic power with soccer specific contextual variables Analyse the relationship between both indexes for external load quantification	WIMU PRO^{TM}, RealTrack Systems	Tri-axial accelerometer (100 Hz)	Higher player load demands during the first half than the second half ($p < 0.001$; $d = 1.16$) Midfielders produced the highest player load values (21.3 ± 3.45AU) whilst external defenders produced the lowest (17.7 ± 3.76) Player load was higher when the team was winning the match ($p < 0.001$; $d = 1.71$) and playing away ($p < 0.001$; $d = 0.98$) High correlation ($r = 0.918$, $p < 0.001$) between player load and metabolic power
(Ritchie, Hopkins, Buchheit, Cordy & Bartlett, 2016)	Australian football	44 males, elite	Quantify training load and competition load of an Australian football team across various stages of the season	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} was most likely higher in training during preseason 1 (1910 ± 770AU) and 2 (2060 ± 720AU) than during all in-season blocks PL^{TM} likely increased for training during in-season 3 (1130 ± 430AU) compared with in-season 1 (980 ± 380AU) and 4 (990 ± 320AU)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						PL^{TM} in games during preseason 3 (1010 ± 290AU) was most likely lower than during all in-season game blocks
(Roe, Halkier, Beggs, Till & Jones, 2016)	Rugby union	26 males, elite junior	Investigate the relationship between accelerometer metrics, and running and collision demands of rugby union match-play in forwards and backs and assess any positional differences	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	All PL variables demonstrated very large correlations (PL^{TM}: r = 0.727, PL_{2D}: r = 0.758, PL_{SLOW}: r = 0.701) with collisions in the forwards PL_{SLOW} demonstrated the largest correlation (r = 0.613) with collisions in the backs Correlation between all PL variables (PL^{TM}: r = 0.785, PL_{2D}: r = 0.817, PL_{SLOW}: r = 0.799) and collisions became stronger when scrum events were included for the forwards
(Rowell et al., 2018)	Soccer	21 males, elite	Assess the impact of preceding weekly load on SSG activity profile and matchday -1 NMF Assess the degree to which change in matchday -1 NMF impacts SSG activity profile Assess the impact of matchday -1 NMF and SSG activity profile on subsequent match activity profile	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Relatively high preceding weekly training loads resulted in a very likely increase in $PL^{TM}.m.min^{-1}$ (ES: 0.58 ± 0.19) and $PL_{SLOW}.min^{-1}$ (ES: 0.58 ± 0.33) during a standardised SSG A reduction in weekly FT:CT resulted in a likely reduction in SSG $PL^{TM}.min^{-1}$ and $PL_{SLOW}.min^{-1}$ Reduced FT:CT was correlated with an increase in PL_{ML}% contribution and a decrease in PL_{V}% contribution during subsequent match activity An increase in SSG $PL^{TM}.m.min^{-1}$ (above baseline) resulted in a reduction in PL_{ML}% contribution and an increase in PL_{V}% contribution during subsequent match activity

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Rowell, Aughey, Hopkins, Stewart & Cormack, 2017)	Soccer	18 males, elite	Determine the impact of football match load on CMJ performance, testosterone, cortisol and testosterone:cortisol ratio	Not stated	Tri-axial accelerometer (100 Hz)	Jump height was very likely reduced at 0.5h post (-15.8 ± 8.1%) and 18h (-8.7 ± 5.3%) post high PL^{TM} matches FT:CT was very likely and possibly reduced at 0.5h post high (-12.4 ± 6.6%) and medium (-5.0 ± 6.5%) PL^{TM} matches respectively, as well as likely and most likely reduced at 18h post high (-12.6 ± 10.3%) and medium (-17.0 ± 7.5%) PL^{TM} matches respectively Elevated testosterone (17.0% - 19.5%) and cortisol (54.6% - 165.4%) levels and a reduced testosterone:cortisol ratio (-27.2 - -54.4%) were observed at 0.5h post game in all match loads (low, medium and high PL^{TM})
(Sanders, Boos, Shipley, Scheadler & Peacock, 2018)	Volleyball	1 female, Division 1 college	Monitor athlete across season to assess neuromuscular fatigue (weekly) and assess which external loads contribute to neuromuscular fatigue and on-court performance	Catapult Innovations (model not stated)	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	IMA derived low-intensity decelerations, medium and high intensity accelerations, and low and high intensity jumps accounted for 91.7% of the variation in jump performance (r = 0.958, r^2 = 0.917, p < 0.001) Only high intensity jumps were significantly different between practices prior to winning and losing performances Athlete engaged in 20 fewer high-intensity jumps in practices prior to winning performance

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Scott et al., 2013a)	Soccer	15 males, elite	Compare the sRPE and 2 HR-based methods against measurements of player movements and accumulated accelerations (PL^{TM})	MinimaxX 2.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Large correlations ($p < 0.01$) between external training load (PL^{TM}) and various methods of internal load (sRPE: $r = 0.84$ (0.77-0.89), Banister's TRIMP: $r = 0.73$ (0.62-0.81), Edward's TRIMP: $r = 0.80$ (0.71-0.86)) Large correlation ($r = 0.93$) between PL^{TM} and GPS derived total distance
(Scott et al., 2013b)	Australian football	21 males, elite junior and semi-professional	Examine the validity of the sRPE method within AF using CR10 and CR100 scales as measures of intensity and investigate the relationship between these perceived intensity measures and external measures of training load	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Strong correlation between sRPE (both CR10 ($r = 0.83$) and CR100 ($r = 0.80$) scales) and PL^{TM} ($p < 0.05$)
(Sparks, Coetzee & Gabbett, 2017)	Soccer	13 males, collegiate	Individualise intensity zones to compare the external (velocity and PL^{TM}) and internal (HR) loads of match-play	MinimaxX V4.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} was significantly ($p \leq 0.01$) correlated with all velocity variables (*large-very large*; $r = 0.64 – 0.92$) and low-moderate intensity HR variables (*small-large*; $r = 0.24 – 0.61$)
(Suarez-Arrones et al., 2014a)	Rugby sevens	10 males, highly trained	Describe the physical match demands relative to positional groups (forwards and backs)	SPI Pro X, GPSports	Tri-axial accelerometer (100 Hz)	Players withstood an average of 25.6 ± 14.3 heavy impacts (7-8g), 15.2 ± 7.7 very heavy impacts (8-10g), and 2.5 ± 2.1 severe impacts (>10g) per match No difference ($p = 0.75$, ES: 0.16 ± 0.87) between forwards (45.1 ± 24.5) and backs (41.8 ± 20.7) in the number of impacts (>7g) during match-play

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Significant (large-*very large*; all ES > 1.4) differences between accelerometer derived impacts and video confirmed impacts with small to moderate (all $p > 0.05$) correlations (all $r < 0.42$) observed in relation to the magnitude (*g* force) of these impacts
(Suarez-Arrones et al., 2014b)	Rugby union	8 females, elite	Provide an objective description of the locomotive activities and exercise intensity during an international female rugby union match Compare the physical demands of match-play according to playing position	SPI Pro X, GPSports	Tri-axial accelerometer (100 Hz)	Players withstood an average of 63.5 ± 59.6 heavy impacts (7-8g), 43.8 ± 19.5 very heavy impacts (8-10g), and 5.6 ± 2.6 severe impacts (>10g) for the match The backs experienced substantially (all $p > 0.05$) more light (400.3 ± 65.1 vs 327.6. ± 231.5), moderate-heavy (77.3 ± 42.8 vs 50.6 ± 41.2), heavy (104.0 ± 91.3 vs 39.2 ± 31.0) and severe (6.3 ± 0.6 vs 5.2 ± 3.5) impacts when compared against the forwards No differences observed between first and second halves in relation to the total number of impacts (354.3 vs 350.5, $p = 0.971$; ES: 0.02 ± 0.84)
(Suárez-Arrones, Portillo, González-Ravé, Muñoz & Sanchez, 2012)	Rugby union	9 males, elite	Describe and quantify the movement patterns and physiological demands of an elite rugby team during competitive matches and assess any positional (backs and forwards) differences	SPI Elite, GPSports	Tri-axial accelerometer (100 Hz)	Forwards were involved in a larger number of total impacts when compared against the backs (1225 vs 883)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Forwards were involved in significantly more ($p < 0.05$) moderate-heavy (161.6 ± 107.0 vs 54.3 ± 28.9) and heavy (143.1 ± 122.0 vs 29.8 ± 9.0) impacts than the backs and tended to be involved in a greater number of high magnitude (heavy + very heavy + severe) impacts than the backs (220 vs 71)
(Sullivan et al., 2014)	Australian football	40 males, elite	Identify how the quarter outcome and margin of the score differential affect both physical activity and skill performance during AF matches	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	The win/loss result of the quarter had no effect ($p = 0.989$) on body load (AU/min) accumulation during that quarter (Win: 11.9 (11.7 – 12.1) vs Loss: 12.0 (11.8 – 12.3)) Players accumulated significantly ($n^2 = 0.006$, $p = 0.031$) more body load (AU/min) when the score margin was small (12.2 (11.9 – 12.4)) compared to when it was large (11.7 (11.4 – 12.0))
(Svilar et al., 2018a)	Basketball	13 males, elite	Establish the correlation among external training load variables, and external and internal training load parameters	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Very strong correlations ($r > 0.8$) between sRPE and all PL variables (PL^{TM}, PL_{AP}, PL_{ML}, PL_{VERT}) ($p < 0.01$) PL^{TM} showed a higher correlation with all total movement variables (tACC, tDEC, tCOD, $r = 0.60 – 0.76$) than compared with high-band movement variables (hACC, hDEC, hCOD, $r = 0.48 – 0.52$), except for the JUMP variable Higher correlations found between sRPE and tDEC ($r = 0.70$) and tCOD ($r = 0.76$) than tACC ($r = 0.60$) and tJUMP ($r = 0.38$)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Svilar, Castellano, Jukic & Casamichana, 2018b)	Basketball	13 males, elite	Investigate the structure of interrelationships among the external and internal training session loads to determine how they vary among different positions	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Across all playing positions, RPE and sRPE are highly correlated with the total amount of ACC (RPE: r = 0.480 – 0.605, sRPE: r = 0.614 – 0.710), DEC (RPE: r = 0.452 – 0.723, sRPE: r = 0.679 – 0.806) and COD (RPE: r = 0.585 – 0.679, sRPE: r = 0.760 – 0.779) Guards (hACC and hJUMP) and forwards (hDEC and hCOD) profiled more high-activity actions than centres (hJUMP) ACC and COD for centres, DEC and hJUMP for guards, and high and total amount of DEC and COD for forwards are demanded during training
(Twist, Highton, Daniels, Mill & Close, 2017)	Rugby league	15 males, professional	Understand training and match loads and any cumulative fatigue responses during a novel congested-fixture period	Viper pod 2, STATSports	Accelerometer (sampling rate not stated)	Accelerometer load before match 1 (days 1 to 4: 164 ± 94 AU) was similar to values between matches 1 and 2 (150 ± 30 AU; 9.8%, ES 0.16 ± 0.55, *unclear*) but lower between matches 2 and 3 (22 ± 10 AU; –83.4%, ES –2.32 ± 0.57, *most likely*) and matches 3 and 4 (122 ± 63 AU; –24.3%, ES –0.29 ± 0.25, *possibly*) Accelerometer load increased from match 1 (384 ± 200 AU) to match 2 (473 ± 188 AU; 30.6%, 0.51 ± 0.31, *likely*), was similar in match 3 (373 ± 163 AU; -3.0%, -0.05 ± 0.27, *unclear*), and was higher in match 4 (391 ± 168 AU; 7.4%, 0.11 ± 0.25, *possible*)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Varley et al., 2014)	Australian football, Rugby league and Soccer	94 males, elite (AF: 28, RL: 36 and SOC: 30)	Investigate and directly compare the activity profiles of soccer, rugby league and Australian football players	MinimaxX, Team 2.5, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Relative number of heavy and total collisions was 32 and 42% greater in RL compared to AF ($p < 0.001$); however, no difference when expressed as absolute values RL players demonstrated a reduction in total number of collisions.min^{-1} from first half to second half (0.35 ± 0.19 vs. 0.30 ± 0.21, $p = 0.015$; ES, -0.29) AFL players maintained number of collisions.min^{-1} across each half (0.20 ± 0.14 vs. 0.20 ± 0.16, $p = 0.287$; ES, -0.08)
(Vazquez-Guerrero, Reche, Cos, Casamichana & Sampaio, 2018)	Basketball	12 males, elite	Determine whether the rules during 5-on-5 scrimmage basketball drills had any effect on players' physical responses	WIMU PRO™, RealTrack Systems	Tri-axial accelerometer (100 Hz)	Players during the HALF drill (0.7 ± 0.1) exhibited lower (*very large*, ES = 2.79) player load (AU) values than during the FULL drill (1.00 ± 0.1) Players during HTRAN drill (0.9 ± 0.0) presented higher (*large*, ES = 1.88) player load (AU) values than during the HALF drill (0.7 ± 0.1)
(Vázquez-Guerrero, Suarez-Arrones, Casamichana Gómez & Rodas, 2018)	Basketball	12 males, elite	Compare accelerometer load, number of accelerations and decelerations and the accel:decel ration at different velocities between positions during competitive matches	ADXL326, Analog Devices, Inc.	Tri-axial accelerometer (100 Hz)	PF presented the lowest external total load of all specific playing positions (ES = 0.67 to 1.18, *likely* in all cases) All other positions (PG, SG, SF and C) exhibited similar external total loads
(Venter, Opperman & Opperman, 2011)	Rugby union	17 males, elite junior	Obtain information on elite under-19 rugby union forward and back players regarding movement patterns, as well as impacts from collisions experienced by these players	SPI Pro, GPSports	Tri-axial accelerometer (100 Hz)	Back row forwards experienced the highest amount of impacts (683.4 ± 295.04) during games, whilst the outside backs experienced the least number of impacts (474.33 ± 81.92)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Inside backs experienced the highest amount of severe (>10g) impacts (12.16 ± 3.18), whilst front row forwards experienced the least amount of severe impacts (8.00 ± 4.58)
(Vlantes & Readdy, 2017)	Volleyball	11 females, collegiate	Quantify the external and internal load experienced during women's collegiate volleyball matches Investigate the relationship between internal and external demands in a competition setting	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	The setter experienced significantly ($p \leq 0.01$, $d \geq 0.8$) greater mean PL™ and jumps for 3, 4 and 5-set matches when compared against other positional groups Middle blocker demonstrated the highest ($p \leq 0.01$, $d \geq 0.8$) mean HI PL™, % HI PL™ and explosive efforts, whilst also recording the second highest mean jump total when compared against all other positions Large correlation ($r = 0.54$, $p < 0.001$) between S-RPE and number of jumps and a very large correlation ($r = 0.73$, $p < 0.001$) between S-RPE and PL™ across the entire team (DS position excluded from jumps analysis)
(Walker, McAinch, Sweeting & Aughey, 2016)	Australian football	18 males, elite	Develop an algorithm utilising oxygen uptake and accelerometer data to measure the energy expenditure of players during training and matches	Minimax 4.0, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Average PL™ during match-play was (1235 ± 222 AU) which resulted in an absolute corrected EE of 5745 ± 1468 kJ (range: 4097 – 8621 kJ), 64.7 ± 16.5 $kJ.kg^{-1}$ or 0.66 ± 0.16 $kJ.kg^{-1}.min^{-1}$ per match Average PL™ during training was (565 ± 107 AU) which resulted in an absolute corrected EE of 2719 ± 666 kJ (range: 1789 – 3371 kJ), 30.4 ± 6.5 $kJ.kg^{-1}$ or 0.42 ± 0.08 $kJ.kg^{-1}.min^{-1}$ per training session

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Large correlation (r = 0.57) between PL^{TM} calculated EE and proprietary metabolic power calculated EE
(Ward, Tankovich, Ramsden, Drust & Bornn, 2018a)	American football	101 males, elite	Identify the relationship between inertial sensor training load metrics and non-contact injury incidence during training	Minimax S4, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	PL^{TM} (OR: 1.96, 90% CI: 1.22, 3.19, *very likely harmful*) and PL_{VH} (OR: 2.84, 90% CI: 2.06, 3.99, *most likely harmful*) were most strongly correlated to a greater risk of soft-tissue injury in comparison to all other PL variables IMA_{High} (OR: 5.89, 90% CI: 3.18, 11.4, *most likely harmful*) and $Impacts_{High}$ (OR: 2.66, 90% CI: 1.77, 4.11, *most likely harmful*) (per minute) were observed to have the strongest relationships with soft-tissue injury risk when compared against the same variables of lower-intensity The joint model of PL^{TM}, PL_{LOW} and $Impacts_{High}$ had the strongest overall relationship with non-contact soft tissue injury (OR = 6.48, 95% CI: 2.79, 15.8)
(Ward, Ramsden, Coutts, Hulton & Drust, 2018b)	American football	63 males, elite	Investigate the differences among position groups during an NFL training camp	Minimax S4, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Defensive backs and wide receivers performed the highest amount of PL^{TM} compared with other positional groups, with unclear differences observed between them (GD -4: 19 ± 41; GD -3: -2 ± 36 and GD -2: -11 ± 38 AU)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Lineman (offensive and defensive) were found to perform a larger volume of IMA actions compared to all other positional groups with unclear differences between them on GD -4 and GD -2 and OL performing more total IMA on GD -3 (-9 ± 9, *likely moderate*) Positional groups that oppose each other on offense and defense (DL & OL, WR & DB, LB & TE, LB & RB) mostly exhibited unclear differences in total IMA count (except for DL & OL on GD-3 (-9 ± 9, *likely moderate*) and LB & RB on GD-3 (7 ± 8, *possibly moderate*))
(Warman, Cole, Johnston, Chalkley & Pepping, 2019)	Hockey	16 males, elite	Quantify specific torso flexion/extension angles and time spent in this orientation between different positional groups Determine distribution of playing time that players spent with their torsos in different degrees of flexion/extension Investigate influence that playing position had on this distribution	MinimaxX S4 (13 units) or Optimeye S5 (3 units), Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Mean torso angle during match-play was 44.6 ± 23.7° with little difference between playing positions (Def: 43.5 ± 24.2°; Mids: 44.2 ± 22.7°; Strikers: 46.4 ± 23.8°) Players spend most of their playing time (89.26%) between 20° and 90° of torso flexion, with postured between 30-40° (26.39%) and 40-50° (26.28%) most prevalent Defenders spend more playing time in the 10-20° posture band than mids (6.2%) and strikers (6.3%). Mids spend more playing time in the 20-30° posture band than strikers (4.5%). Strikers spend more playing time in the 30-40° posture band than defenders (8.8%)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Weaving, Jones, Marshall, Till & Abt, 2017)	Rugby league	23 males, professional (English Championship)	Determine the structure of the interrelationships among measures of internal and external training load	Optimeye X4, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL™ (0.92) (or HREI) can represent 56.6% of the variance of four training load variables during skills training PL™ (0.80) (or HREI, or sRPE) can also represent 56.01% of the variance of four training load variables during conditioning training; with the addition of HSD (0.96) allowing 85.44% of variance to be accounted for PL™ was significantly ($p < 0.001$) correlated with sRPE and HREI during both skills (sRPE: $r = 0.47$, *moderate*; HREI: $r = 0.72$, *large*) and conditioning (sRPE: $r = 0.56$, *large*; HREI: $r = 0.55$, *large*) training
(Weaving, Marshall, Earle, Nevill & Abt, 2014)	Rugby league	17 males, professional	Examine the influence of training mode on common measures of training load	SPI Pro XII, GPSports	Tri-axial accelerometer (100 Hz)	Either body load (0.79) or total impacts (0.85) can account for 68.44% of the variance of five training load variables during small-sided games Body load (0.86) and total impacts (0.87) were the highest loading first principle components during skills training and accounted for 47.60% of the variance which then increased to 68.31% when combined with a secondary component (iTRIMP) Body load and total impacts were significantly correlated ($p < 0.0001$) in all training modalities ranging from *moderate* to *very large* ($r = 0.41 – 0.83$)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Wellman et al., 2017)	American football	33 males, Division 1 college	Examine positional impact profiles during competitive matches Determine if positional impact profiles exist within offensive and defensive teams	SPI HPU, GPSports	Tri-axial accelerometer (100 Hz)	Significant ($p \leq 0.05$) differences in number and intensity of impacts exist between many playing positions Most notable: *Offense:* -WR experienced more very light and light-moderate impacts than all other offensive positioning groups -WR and OL experienced more moderate-heavy impacts than RB -RB recorded greatest number of severe impacts *Defence*: -DB and LB involved in more very light impacts than all other positions -DT group recorded more moderate-heavy, heavy and very heavy impacts than all other defensive position groups
(White & MacFarlane, 2013)	Hockey	16 males, elite	Compare the impact of data-analysis procedures (derived from soccer) with sport-specific analysis procedures	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100 Hz)	No difference ($p > 0.05$) between FG (645 AU, 95%CI: 622 - 668) and TOP (631 AU, 95%CI: 606 - 656) methods of analysis for PL^{TM} accumulation No significant ($p > 0.05$, $r^2 = 27.5\%$) correlation between PL^{TM} accumulation and predicted VO_{2MAX} derived from the multistage fitness test
(White & MacFarlane, 2015)	Hockey	16 males, elite	Assess the 'active' time physiological demands of elite field hockey during competition and training	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Full training session (mean) (816 AU, 95%CI: 773 – 858) accumulated significantly ($p < 0.001$) more PL^{TM} than competition (631 AU, 95%CI: 602 – 661)

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
						Relative PL™ (per 70 min) was greatest ($p < 0.001$) during running drills (714 AU, 95%CI: 672 – 756), whilst tactical/technical drills (213 AU, 95%CI: 193 – 237, $p < 0.001$) and full training (mean) (524 AU, 95%CI: 520 – 531, $p \leq 0.05$) exhibited lower relative PL™ values than competition (589 AU, 95%CI: 562 – 617)
(Wik, Luteberget & Spencer, 2017)	Handball	18 females, elite	Examine activity profiles of international women's team handball matches with a particular focus on fatigue development	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	The first 10-minute period of the game elicited the highest PL™.min^{-1} value of the game across each outfield position and all outfield positions combined when compared against both middle and last 10-minute time-periods of the first-half, and the first period of the second half Where the player was involved in 2 or more consecutive 5-minute periods of field time, PL™.min^{-1} output subsequently decreased for each outfield position and all outfield positions combined Substantial declines in PL™.min^{-1} were present during both Post-5 and Post-10 5-minute time-periods (below the player's PL™.min^{-1} 5-min match average) immediately following the identified peak 5-minute PL™ time-period. Post-5 period was also substantially lower than pre-period

Authors(s)	Sport	Participants	Primary Aims	Unit Type	Sensors Used	Key Findings
(Wilkerson, Gupta, Allen, Keith & Colston, 2016)	American football	45 males, collegiate (Division I-BCS)	Analyse IMU-derived data worn during practice sessions to identify any associations of average inertial load or intraindividual inertial load variability metrics with the occurrence of musculoskeletal sprains and strains over the course of the season	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz)	Both IL CoV $\leq$0.15 (p = 0.030, OR = 8.21, 90% CI: 1.34, 50.25) and involvement in $\geq$ 289 game plays (p = 0.007, OR = 7.33, 90% CI: 2.10, 25.63) were strongly (but independently) associated with an increased injury occurrence Having either an IL CoV $\leq$0.15, involvement in $\geq$ 289 plays, or both risk factors combined, strongly discriminated between injured and uninjured players (χ^2 = 9.048; p = 0.004, OR = 8.04, 90%CI: 2.39, 27.03) Injury rates for players exposed to both risk factors was 26.4 per 1,000 player exposures, whilst those exposed to just 1 of the 2 risk factors was 30.0 per 1,000 exposures
(Young et al., 2012)	Australian football	15 males, elite junior	Determine whether there was an association between GPS variables describing movement demands of an elite junior AF game and post-match CK levels	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100 Hz)	PL^{TM} was significantly (42%) greater (p < 0.05, ES: 1.62, *large*) in the high CK group (1,519 ± 237 AU) compared with the low CK group (1,070 ± 311 AU) Within-group correlations between PL^{TM} were weak in both high CK (r = 0.227, *small*) and low CK (r = 0.083, *trivial*) groups

Inclusion criteria:

- Team-sports athletes only (tested on athletes during team scheduled on-field training/competition)
- Inertial sensor metric or variable must be independent of any GPS input (i.e. not integrated with GPS for distance measures) or any other contribution from another technology source
- Single, upper thoracic worn microtechnology unit
- Studies utilising 'match simulation' exercises were excluded due to the ability of coaches or high-performance staff to manipulate the training environment (and thus the physical demands)
- Team or club scheduled training and/or match play was included

As seen above, in Table 2.1, there are a plethora of studies that have used independently derived inertial sensor metrics to quantify mechanical, impact and metabolic demands of team-sport athletes during both training and competition. It is recognised that many additional studies that have assessed the validity, reliability and application of inertial sensor derived metrics in laboratory settings or closed-circuit training intended to simulate the demands of a game, however, the strict criteria of the above table served to include field-based research during official team-sport training and/or match-play where participants (or players) wore a single, trunk-mounted microtechnology device where inertial sensor derived metrics were used (independent of GPS contribution) to activity profile, track acute and/or chronic mechanical load, or as a correlate with alternative internal and external load metrics.

From Table 2.1, whilst every reviewed study utilised an accelerometer signal, only 27.9% and 12.8% of studies utilised the gyroscope and magnetometer sensors respectively. This is further supported in the 73.3% of reviewed studies that utilised tri-axial accelerometry to quantify an absolute or relative proprietary measure of 'Player Load' in their respective training or competition environments. On the other hand, only 31.4% and 14.0% of studies assessed impact/collisions and IMA multi-directional movement events respectively, of which a vast majority utilised (and require) input from the gyroscope and/or magnetometer for successful detection. Australian football, Rugby league and soccer were the most prevalent team-sports within the reviewed studies, where research from a total of 14 different team-sports met the inclusion criteria (Figure 2.5). A compelling 86.0% of these studies utilised male participants with only 15.0% recruiting female team-sport athletes (one study analysed both sexes). This finding exposes a major imbalance where there is a clear need for greater investment and research in to the mechanical and metabolic load demands of women's team-sport. As expected, a large majority of funding and research has been completed in a professional team-sport environment with elite senior athletes (68.6%). Elite junior (8.1%), collegiate (12.8%) and semi-professional (10.5%) athletes were relatively well represented, with only 3 studies published utilising sub-elite athletes (3.5%) within the search criteria. Catapult Innovations were the clear leader in microtechnology company representation (74.4%) where research has utilised proprietary Player Load™ (and PL™ derivatives), IMA and impact/collision algorithms, with GPSports a distant second (14.0%) where research using these units has typically involved their impact/collision and Body Load algorithms.

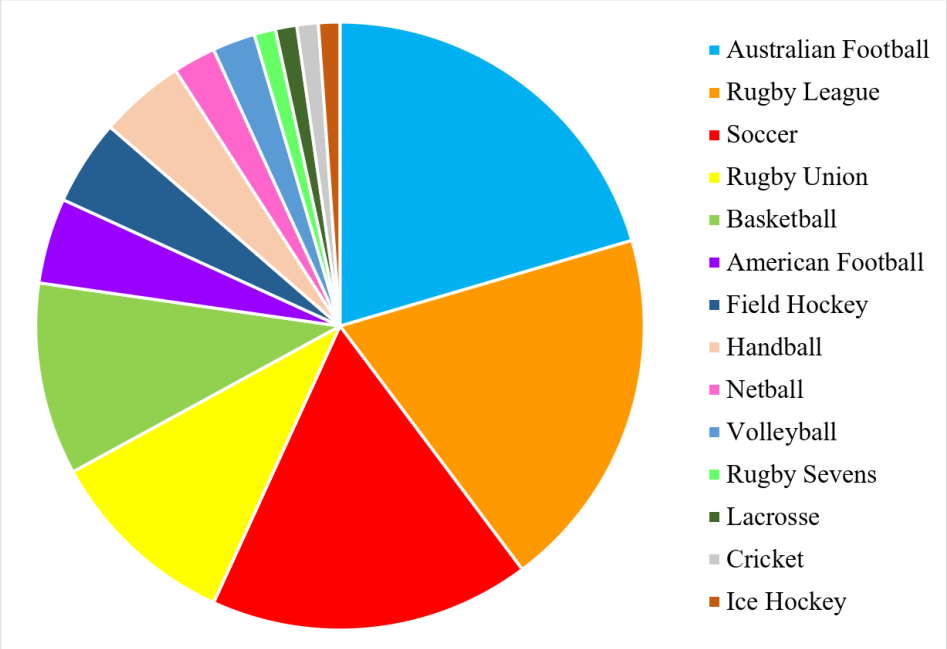

Figure 2.5 Team-sport prevalence for summary of peer-reviewed research depicted in **Table 2.1**.

The primary inertial-sensor derived load-monitoring tool (73.3% of analysed studies) was a measure of absolute or relative 'Player Load' which is calculated very similarly across numerous microtechnology models manufactured by a variety of companies (e.g. Catapult's 'PlayerLoad™' (PL™), GPSports' 'Body Load', RealTrack Systems 'PlayerLoad') (Boyd et al., 2011; Gentles et al., 2018; Lovell et al., 2013; Reche-Soto et al., 2019). Fundamentally, this variable is calculated as the square root of sum of the squared instantaneous rate of change in acceleration of each of three vectors (*x*, *y* and *z*), divided by the sampling frequency of the sensor (Boyd et al., 2011; Gentles et al., 2018). Whilst this percentage is extremely high, team-sport research has consistently demonstrated strong correlations between Player Load and GPS derived total distance during both training and competition (Barrett et al., 2016; Bartlett, O'Connor, Pitchford, Torres-Ronda & Robertson, 2017; Casamichana et al., 2013; Gentles et al., 2018; Polglaze et al., 2015; Scott et al., 2013a). This is likely due to the predominant contribution of acceleration in the vertical axis (*z*) during overground running when compared with the medio-lateral (*x*) and anterior-posterior (*y*) axes (Cormack et al., 2014; Rowell et al., 2018; Svilar et al., 2018a). Whilst this relationship is unequivocally strong, differences in magnitude have been shown between team-sports where rugby league (r = .79, R^2 = .62) has exhibited a weaker relationship when compared with both Australian football (r = .94, R^2 = .90) (Aughey, 2011) and soccer (r = .93, R^2 = .86) (Scott et al., 2013a); likely due to the increased collision/impact and acceleration demands and lower locomotor requirements in rugby league match play (Varley et al., 2014). Whilst PL™ has previously

been shown to be reliable both within and between device (Boyd et al., 2011) and may provide a useful measure of mechanical load as supplement for total distance for indoor sports where GPS satellite connectivity is not possible, the value and applicability of this specific metric in relation to profiling mechanical load may be limited in sports where GPS data is easily obtained and used, and team-sports with greater collision and impact demands (Barrett et al., 2016; Hulin et al., 2018).

2.10.1 Player Load Derivatives

For PL^{TM} to provide complementary information to GPS derived total distance, the vertical acceleration axis (*z*) should be removed (2D Player Load), and/or any accelerations at speeds above 2 m.s^{-1} (Player Load 'Slow') (Catapult Sports, 2013b). These PL^{TM} derivatives are designed to target the 'non-running' elements of team-sport movement and have been widely assessed across numerous sports (Davies et al., 2013; Gallo et al., 2016; Hulin et al., 2018; Jaspers et al., 2018; Luteberget et al., 2018a; McLaren et al., 2016; Roe et al., 2016), often coupled with more in-depth analyses looking at the contribution of each individual axis in relation to a number of different movement patterns during training and competition (Cormack et al., 2014; Hulin et al., 2018; Jaspers et al., 2018; Luteberget et al., 2018a; Rowell et al., 2018).

Multiple PL^{TM} derivatives (PL_{2D}, PL_{ML}, PL_{AP}, PL_{VERT}) have been shown to be reliable in the field (Luteberget et al., 2018a) and have exhibited increased potential to facilitate the quantification of alternative mechanical load requirements of team-sport. For example, Hulin and colleagues (2018) demonstrated a small correlation (r = .26, R^2 = .07) between PL_{SLOW} and total distance below the same velocity threshold (2 m.s^{-1}) during match-play which may be due to the heavy contact, tackles and acceleration/deceleration demands of rugby league. PL_{SLOW} has also exhibited sensitivity towards positional differences in rugby league (Gabbett, 2015b), rugby union (McLaren et al., 2016) and Australian football (Boyd et al., 2013). In addition, smaller area and higher density small-sided games has demonstrated greater increases in PL_{2D} accumulation when compared with the standard PL^{TM} metric in Australian football training (Davies et al., 2013).

Whilst the ability of PL^{TM} and its derivatives to differentiate between general locomotor activity appears strong, its relationship with collisions/tackles seems to be more clouded. One study has demonstrated large correlations between PL^{TM} and multiple of its derivatives (PL_{SLOW} and PL_{2D}) with collisions in rugby union, regardless of position, which was further enhanced when scrums were included (Roe et al., 2016). Whilst another

study found poor relationships between PL^{TM} and the number of collisions performed during match-play across an entire rugby league team, marked differences were present between positions, yet some meaningful correlations were present in certain positions (forwards and hookers) which typically require greater contact demands (Gabbett, 2015b). In contrast, another study has suggested that no PL^{TM} metric is suitable to indicate collision workload in rugby league due to the influence of running demands within these metrics (Hulin et al., 2018). Interestingly, one study used manual video coding to identify collision and impact events (Roe et al., 2016), whilst the studies that indicated mostly weak or poor correlations between PL^{TM} derivatives and collision events (Gabbett, 2015b; Hulin et al., 2018) used previously validated algorithms to quantify collision events during match-play (Gabbett, Jenkins & Abernethy, 2010; Hulin, Gabbett, Johnston & Jenkins, 2017).

2.10.2 Player Load Derivatives and Measures of Internal Workload

Internal load responses to the accumulation of PL^{TM} and its derivatives are somewhat unequivocal. For example, PL^{TM} accumulation has been highly correlated with heart rate and blood lactate measures in basketball (Montgomery, Pyne & Minahan, 2010), multiple measures (varied calculations) of heart-rate based training impulse (TRIMP) in soccer (Casamichana et al., 2013; Scott et al., 2013a), with alternate research only finding correlations of contrasting magnitudes (small to large) between PL^{TM} and low-moderate intensity HR variables, and no correlation at higher HR-intensities during soccer match-play (Sparks et al., 2017). Similarly, there is strong evidence to suggest PL^{TM} and its derivatives are strongly correlated with session rating of perceived exertion (sRPE) across a number of team-sports (Casamichana et al., 2013; Gallo et al., 2015; Scott et al., 2013a; Scott et al., 2013b; Svilar et al., 2018a; Vlantes & Readdy, 2017), however there is also some research that has displayed lower magnitude correlations in this area (Lovell et al., 2013), with one study describing the relationship between sRPE and Body Load as 'weak'(Gomez-Piriz et al., 2011). Interestingly, the latter two studies used a common microtechnology unit (SPI Pro, GPSports) whereby the usefulness of accelerometer-derived algorithms from this unit has previously been questioned due to the lack of inclusion of a gravity compensation formula (Alexander et al., 2016). Furthermore, some PL^{TM} derivatives (PL_{2D} and PL_{ML}) have actually shown a reduced capacity to predict RPE when compared with the standard PL^{TM} metric in professional soccer (Jaspers et al., 2018). Whilst in Australian football, pre-training wellness measures have been shown to have a significantly negative effect on both PL^{TM} and PL_{SLOW} accumulation in subsequent skill-based training sessions (Gallo et al., 2016).

Seemingly, PL^{TM} and its derivatives may also be sensitive to changes in diagnosed 'neuromuscular fatigue' or fatigue status. Research analysing professional soccer players found greater $PL^{TM}.m.min^{-1}$ and $PL_{SLOW}.min^{-1}$ accumulation during a standardised small-sided games (SSG) following high weekly training loads (Rowell et al., 2018). In addition, reduced weekly flight-time to contact-time ratios (FT:CT) during a countermovement jump were shown to have a negative effect on PL^{TM} and PL_{SLOW} accumulation during the same SSG (Rowell et al., 2018). Interestingly, this reduction in FT:CT also resulted in an increase in PL_{ML}% contribution and a decrease in PL_{VERT}% contribution during subsequent match-play (Rowell et al., 2018). Therefore, PL^{TM} and select PL^{TM} derivatives such as PL_{SLOW}, PL_{2D} and PL_{ML} may have the potential to reveal any fatigue driven changes in movement efficiency or strategy which may have implications from a load monitoring and injury prevention perspective.

2.10.3 Energy Expenditure

Only one known study has definitively used trunk-mounted accelerometry to assess the energy expenditure demands of team-sport movement (Walker et al., 2016), by developing an algorithm using laboratory based maximal aerobic power and the corresponding accelerometry data (during an incremental treadmill test) to estimate on-field energy expenditure (using PL^{TM} data). Walker and colleagues (2016) subsequently profiled the energetic demands of both training and match-play in elite Australian football, demonstrating a large correlation (r = 0.57) with estimated energy expenditure derived from Catapult's (Catapult Innovations, Melbourne Australia) proprietary metabolic power calculation which stems from previous work in professional soccer and considers both running speed and the energetic cost of acceleration (Di Prampero et al., 2005; Osgnach et al., 2010). These calculations have also been used in Australian football to assess positional differences in regards to energetic cost and metabolic power demands of match-play (Coutts et al., 2015). Unfortunately these measures appear to provide limited supplementary information to existing running-based metrics (Coutts et al., 2015), and are unable to differentiate between specific movement patterns that may provide more valuable information regarding mechanical load determinants. Additionally, previous research has advised that caution must be exercised when using trunk-mounted accelerometry within player tracking devices to estimate energy expenditure due to incidental acceleration data typically seen from poorly controlled methods of microtechnology unit attachment (e.g. loose-fitting vest, loose player guernsey pocket, etc.) (Edwards, White, Humphreys, Robergs & O'Dwyer, 2019).

2.10.4 Inertial Sensors to Profile COD Mechanical Load

Numerous studies have attempted to define mechanical load determinants associated with COD movement using inertial sensor outputs in both laboratory and field settings (Hulin et al., 2018; Luteberget et al., 2018a; Meylan et al., 2017; Nedergaard et al., 2017; Peterson & Quiggle, 2017; Svilar et al., 2018a). One study assessed sensitivities of all PL^{TM} variables in response to COD workload with PL_{SLOW} demonstrating the greatest sensitivity (Hulin et al., 2018). The authors also suggested practitioners consider using PL_{ML} and PL_{VERT} axes when looking to quantify the demands of COD movement (Hulin et al., 2018). Further to this, high-levels of PL_{ML} have previously been linked with greater RPE scores (Jaspers et al., 2018; Svilar et al., 2018a) and have also been shown to be sensitive to changes neuromuscular status where professional soccer players demonstrating reduced FT:CT during a CMJ seemingly altered their movement strategy in subsequent match-play with an increase in PL_{ML}% contribution and a decrease in PL_{VERT}% contribution (Rowell et al., 2017).

Other studies have used Catapult's proprietary generated 'Inertial Movement Analysis' (IMA) algorithm to detect and assess COD demands during team-sport activities (Luteberget & Spencer, 2017; Luteberget et al., 2018b; Meylan et al., 2017; Peterson & Quiggle, 2017; Svilar et al., 2018a; Svilar et al., 2018b; Ward et al., 2018a). This metric (IMA) is designed to detect and quantify accelerations, decelerations, CODs, free running events as well as jump height and frequency using Kalman filtering techniques to fuse accelerometer and gyroscope sensor outputs creating a non-gravity vector (Catapult Sports, 2013a). Essentially, this algorithm uses a Polynomial least squares fit to smooth the original acceleration data at a known frequency and then overlay this smoothed curve over the original acceleration trace to detect that an 'event' has occurred (Catapult Sports, 2013a). The magnitude of the event is then calculated as the 'sum of the medio-lateral and anterior-posterior' area under the curve of that event and expressed as a change in velocity (m/s) across the mediolateral and anterior-posterior acceleration area (Catapult Sports, 2013a). These magnitudes are defined in to 'low', 'medium' and 'high' brackets based on arbitrarily set velocity change rates but can be altered by the user. From there, direction is calculated to display the direction of the force applied and categorised in one of twelve 30° segments based on the angel of the applied acceleration which will define whether the movement is classified as a COD (left or right), acceleration or deceleration (Catapult Sports, 2013a; Luteberget et al., 2018a).

Multiple studies have assessed the reliability of this detection algorithm during team-sport activity in both laboratory and field settings (Luteberget et al., 2018a; Meylan et al., 2017). In a controlled laboratory assessment, IMA displayed good reliability (CV = 1.8%) when detecting the magnitude of all (total) well-controlled movement tasks (e.g. singular, isolated accel/decel or COD event), however this reliability was reduced (CV: 5.9-6.7%) in more chaotic tasks (successive start/stop and multi-directional tasks) which are more characteristic of typical team-sport movement patterns (Luteberget et al., 2018a). When this reliability study expanded to a field-setting, the IMA algorithms displayed good (CV < 5%) reliability for total IMA counts and were considered able to detect 'real and worthwhile' (CV < SWD) changes in movement activity (Luteberget et al., 2018a). This reliability was reduced when IMA events were categorised in to intensity bands (low, medium, high and medium-high(combined)) with only total, high and medium-high bands producing a CV less than the SWD (Luteberget et al., 2018a). Further, good-moderate reliability was present when these IMA events were categorised within directional bands (forward (CV: 6.6%), backward (CV: 5.5%), left lateral (CV: 3.9%) and right lateral (CV: 4.1%)) where the CV for all directions was greater than their equivalent SWD, bringing in to question the usefulness of this data (Luteberget et al., 2018a). Reliability became substantially compromised when directional IMA counts (forward, back, left and right) were also categorised into intensity bands (CV: 4.6 – 21.5%) where the usefulness of this metric to detect 'real and worthwhile' differences (CV < SWD) was largely not present (Luteberget et al., 2018a).

Another study assessed the validity of IMA detection and reliability of IMA magnitude during maximal sprinting and cutting manoeuvres, whilst concomitantly assessing the match-to-match variability of detected 'high' IMA events in professional soccer (Meylan et al., 2017). The IMA algorithm displayed a high-level of validity in detecting instantaneous accelerations, decelerations and COD events in a closed testing environment when synchronised against video footage, yet the ability of the IMA algorithm to accurately assess the magnitude of these events was not acceptable, with the authors of this study suggesting IMA is not appropriate to assess acceleration, deceleration and COD performance in sporting environments (Meylan et al., 2017). Similarly to Luteberget and colleagues (2018a), it was suggested that the use of IMA counts may be beneficial in identifying high-magnitude accelerations, decelerations and CODs, with the usefulness of quantifying the absolute magnitude of IMA efforts (or counts) dubious (high standard error of measurement (SEM)) when analysing the demands of match-play (Meylan et al., 2017). However, these high-magnitude IMA events (CV = 14%) were still

found to be a more stable measure than GPS-derived acceleration frequency (CV = 18%) which has been commonly used in previous team-sport research to further assess mechanical load requirements (Dalen, Jørgen, Gertjan, Havard & Ulrik, 2016; Russell et al., 2016). In agreement with previous findings (Wundersitz, Gastin, Richter, Robertson & Netto, 2015a), fusing raw accelerometer signals with appropriate filtering techniques may be more accurate than using proprietary manufacturer supplied algorithms such as IMA (Meylan et al., 2017).

In addition to reliability studies, IMA has also been practically assessed against other external and internal load measures in field settings (Peterson & Quiggle, 2017; Svilar et al., 2018a) and has even been linked with injury risk in American football (Ward et al., 2018a). Svilar and colleagues (2018a) demonstrated a large to very large correlation (r = 0.60 – 0.76) between PL™ and IMA-derived total acceleration, deceleration and COD counts. Interestingly, this correlation was stronger than when PL™ was assessed against the equivalent IMA counts (acceleration, deceleration, COD) in the high-banded IMA threshold (r = 0.48 – 0.52), further supporting the limitations of this variable in assessing the magnitude of these movements (Svilar et al., 2018a). Additionally, stronger correlations were present between sRPE and total COD (r = 0.76) and deceleration (r = 0.70) counts than accelerations (r = 0.60) and jumps (r = 0.38); further demonstrating the high physical cost of COD movement and advocating the importance of being able to accurately quantify the associated mechanical load.

Peterson and Quiggle (2017) explored this concept further and used tensiomyography (i.e. a non-invasive method to assess contractile and mechanical properties of skeletal muscle) to longitudinally assess the neuromuscular status of collegiate basketball players in relation to the external loads exposed to from week-to-week. While general correlations were present between external load IMA™ metrics and total muscle contraction time, both total IMA™ (*RW* = 30.5%) and IMA™ load accumulation in the medio-lateral plane (*RW* = 29.4%) displayed high-levels of importance in relation to adductor longus contraction time, both far superior to PL™ (*RW* = 5.6%) (Peterson & Quiggle, 2017). Similar results were evident when radial muscle displacement was assessed (Total IMA™ (*RW* = 22.6%), IMA™ medio-lateral (*RW* = 25.8%), PL™ (*RW* = 15.9%)), further outlining mechanical load requirements and subsequent neuromuscular and musculoskeletal cost (fatiguing nature) of movement in the medio-lateral (or frontal) plane, whilst also highlighting the potential importance of monitoring movement (such as COD) in this plane (Peterson & Quiggle, 2017).

In addition, Ward and colleagues (2018a) demonstrated that relative IMA_{HIGH} (>3.5 $m.s^{-2}$) (OR: 5.89, *most likely harmful*), $Impact_{HIGH}$ (>7g) (OR: 2.66, *most likely harmful*) and $PL_{VERY\text{-}HIGH}$ (>4g) (OR: 2.84, *most likely harmful*) had the strongest correlations with subsequent non-contact injury risk in American football, outperforming equivalent variables of lower intensity. This study did not evaluate individual accelerometer axes (or planes of movement) where more information may have added further knowledge and clarification around the ability of accelerometer-derived locomotion to inform subsequent soft-tissue injury risk. Interestingly, also in American football, Wilkerson and colleagues (2016) suggested that both accumulated inertial load (PL^{TM}) and low variability in average inertial load may be indicators of subsequent injury risk amongst contact sport athletes, outlining that this low variability may be representative of a '*deficiency in the ability to rapidly alter the direction of body mass movement in response to changing environmental conditions*' (Wilkerson et al., 2016). Wilkerson and colleagues (2016) went further, suggesting that players that are able to rapidly accelerate, decelerate and change direction will generate high levels of inertial load, of which the corresponding neuromuscular demands may provide a protective effect to injury risk.

2.10.5 Summary

Inertial sensors, mostly accelerometers, have been extensively used across a wide-range of team-sports in an attempt to quantify and profile the mechanical demands of training and competition. The validity, reliability, usefulness, relevance and importance of a number of the inertial sensor derived external load metrics has been assessed, with results varying between sports, athlete populations, microtechnology companies and sensor fusion techniques or algorithms. Further, the influence that these external load metrics appear to have varied relative to a range of internal load measures.

PL^{TM} and equivalent metrics from alternate microtechnology companies (e.g. Body Load) has been thoroughly explored in relation to mechanical load determinants of team-sport training and competition. Given the prevalence of research that has demonstrated extremely strong correlations between PL^{TM} and GPS derived total distance (Bartlett et al., 2017; Casamichana et al., 2013; Gentles et al., 2018; Polglaze et al., 2015; Scott et al., 2013a) this metric may provide a surrogate measure of locomotion indoors where satellite connectivity is not possible, however the applicability of this metric in sports where GPS data is readily available may be limited. Consequently, PL^{TM} derivative metrics (e.g. PL_{SLOW}, PL_{2D} and individual axes (PL_{AP}, PL_{ML}, PL_{VERT})) have been developed by the

manufacturer where the contribution of vertical acceleration (which is the predominant contributor during overground running, to quantify nonrunning elements) has been removed (PL_{2D}), along with PL_{SLOW} where only accelerometer activity below a velocity of $2m.s^{-1}$ is included (Catapult Sports, 2013b). However, these metrics are often based on arbitrary criteria thresholds which lack construct validity (Polglaze et al., 2015). Whilst PL™ and its derivative metrics have all been shown to be reliable in team-sport settings (Boyd et al., 2011; Luteberget et al., 2018a), and PL™ derivatives may provide an alternative mechanical load measure complementary to GPS locomotive data, these measures remain non-specific as they are unable to differentiate between sports-specific movements such as accelerations, decelerations, CODs, collisions, impacts and tackles that greatly contribute to the physical demands of movement (Hulin et al., 2018; Polglaze et al., 2015). Recent research has suggested that accelerations and decelerations may comprise up to 15% of PL™ (Dalen et al., 2016) however, further research is needed in this area for practitioners to be able to identify the effect that specific movement types and intensities may have on PL™ (and derivatives) accumulation. In addition, the use of GPSports 'Body Load' measure may not be a viable method of quantifying training load due to the absence of a gravity compensation formula within the software's algorithm (Alexander et al., 2016; Gomez-Piriz et al., 2011).

Catapult's IMA was accordingly developed to allow the detection and classification (based on magnitude) of more specific measures of mechanical load such as accelerations, decelerations, CODs and jumps. The manufacturer attempted to categorise these events into thresholds based on arbitrarily chosen changes in velocity across the course of the detected event. This results in discrete 'counts' of these events with further classification derived from the magnitude thresholds. Whilst these IMA 'counts' have been shown to be somewhat reliable across numerous sports in both training and match-play, this reliability was reduced when IMA 'counts' were categorised into directional bands, and became significantly weaker when classified by both direction and intensity (Luteberget et al., 2018a; Meylan et al., 2017). While IMA has been shown to be reliable in certain environments and situations when assessed as 'counts', and has demonstrated the sensitivity to display positional differences in multiple sports (Luteberget & Spencer, 2017; Svilar et al., 2018b; Ward et al., 2018b) only one study has attempted to validate the IMA algorithm (Meylan et al., 2017). This validation occurred in a controlled environment with single straight-line sprinting and COD efforts which may lack construct validity and is unlikely to replicate the unpredictable demands of team-sport movement. The validation process of the IMA algorithm is critical to the authenticity and level of practical application

of this increasingly used metric. Given the evident reduction in reliability and presence of false positives (e.g. detection of two small events vs. one large event) previously seen in more 'chaotic' movement tasks (Luteberget et al., 2018a) typical of team-sport activity, algorithm improvements along with additional validation procedures in a team-sport training or match-play environment would be highly beneficial. Synchronising IMA data with on-field training or match-play vision may be an appropriate strategy (Meylan et al., 2017).

2.10.6 Future Direction

While inertial sensors have been commonly used as an alternative solution to, and in synergy with GPS to quantify the mechanical demands of team-sport training and match-play, their use in detecting and quantifying sports-specific movement patterns has been scarce. Although manufacturer supplied proprietary movement algorithms are easily available and commonly used, these algorithms are unable to accurately differentiate between sports-specific movement patterns and provide a measure of magnitude or intensity which have varying demands on the neuromuscular, metabolic and musculoskeletal systems (Douglas et al., 2019; Hulin et al., 2018; Luteberget et al., 2018a; Meylan et al., 2017). Furthermore, inconsistencies between microtechnology devices and brands requires caution to be exercised when interpreting or comparing data (Alexander et al., 2016; Nedergaard et al., 2017), yet the ability to extract and utilise the raw sensor signals removes the unknown features of manufacturer treated data.

Recent research suggests that the extrapolation and use of raw inertial sensor data in conjunction with appropriate filtering and pattern recognition techniques may be able to provide more meaningful, task-specific information (Meylan et al., 2017; Wundersitz, Gastin, Robertson, Davey & Netto, 2015b), yet the full spectrum or capability of these sensors tend to be underutilised purely due to the inability of sports scientists, performance analysts and strength and conditioning practitioners having limited time, capacity or knowledge of signal processing capabilities to be able to fuse sensor signals into meaningful metrics or measures. Given the prevalence of these highly demanding movement patterns (such as COD movement) during team-sport activity (Dawson et al., 2004; Jennings et al., 2010), the importance of being able to accurately detect and the quantify the mechanical load associated with these types of movement cannot be understated. This valuable information may enhance future team-sport performance assessment and load monitoring practice to ultimately aid in injury prevention practices.

2.11 Inertial Sensors to Quantify Field-Based Sports Specific Movement Patterns

A vast majority of 'workload' quantification research has focused on the use and analysis of GPS and accelerometry data, with much less research focusing on the design of more complex, sports-specific 'detection' variables by fusing inertial sensor signals. Theoretically, trunk-mounted accelerometry can provide a measure of mechanical load from the CoM (Boyd et al., 2011), and has been shown to have the capability of quantifying the magnitude of contact-based movements (Gabbett et al., 2010; Hulin et al., 2017; Wundersitz, Netto, Aisbett & Gastin, 2013). However, recent research has questioned the validity of trunk-mounted accelerometry as a true indication of whole-body mechanical loading (Nedergaard et al., 2017). Nedergaard and colleagues (2017) found that trunk-positioned accelerometers consistently overestimated whole-body CoM acceleration during straight line running and COD movement tasks and demonstrated a weak relationship with corresponding ground reaction force data (Nedergaard et al., 2017). However, trunk-mounted accelerometry, whether commercial (Catapult: 100Hz) or higher-specification (1000Hz), were closest to peak CoM acceleration and impulse, outperforming both pelvic and tibial mounted accelerometers (Nedergaard et al., 2017). This may be due to the shock attenuation as the acceleration signal as travels up through the body (Hamill, Derrick & Holt, 1995) and also the fact that the trunk represents the largest proportion of whole-body mass (49.7%) when compared with pelvic (14.2%) and tibial (4.7%) segments (Dempster, 1955). This indicates that whilst not optimal, manufacturer designed microtechnology units commonly positioned on the posterior aspect of the trunk may best represent the accumulation of whole-body mechanical load during typical on-field, team-sport movement (Nedergaard et al., 2017).

Although a large amount of research has been undertaken to quantify workload of team-sports, there has been a distinct lack of research aimed at detecting sports-specific movement patterns and their associated mechanical load. This is likely because 'workload' variables typically used have been based solely on accelerometer data, whereas detection variables tend to include gyroscope data (Luteberget et al., 2018a). In a laboratory setting, accelerometers have demonstrated an acceptable level of validity (yet continue to overestimate) when quantifying peak impact accelerations for team-sport movement patterns such as collisions, jumps, sprints, jogging and COD (Wundersitz et al., 2015b; Wundersitz, Gastin, Robertson & Netto, 2015c). However, the integration of gyroscope and magnetometer sensor signals can provide angular velocity measures to determine

segmental orientation (e.g. torso lean, twist, flex for trunk-mounted devices) with the inclusion of this data significantly enhancing the prospect of being able to automatically detect these events, accurately report direction (where applicable) and quantify the associated mechanical load. The addition of more sports-specific detection variables would provide extremely valuable information in regard to 'workload' or mechanical load, yet the research is principally limited by the ability of sports science practitioners to use gyroscope and magnetometer data effectively (i.e. in conjunction with sophisticated signal processing techniques), amongst other factors.

Table 2.2 Summation of 'event detection' research which describes the formation of novel algorithms that have been designed to automatically detect and record a movement/s typical of team-sport and assess its performance *in the field*. Only research utilising inertial sensor signals derived from commercially available trunk-mounted (upper thoracic spine) microtechnology units has been included.

Author(s)	Sport	Participants	Event Detection Variable / Activity	Unit Type	Sensors Used	Key Findings
(Chambers, Gabbett and Cole, 2018)	Rugby union	30 males, elite	Scrum events during training and match play	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Good sensitivity (91%) and specificity (91%) for training and match-play events across all positions (front row, second row and back row) Greater accuracy for match-play (93.6%) events than training events (87.6%)
(Chambers et al., 2019)	Rugby union	12 males, elite	Tackle and ruck events in match play	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100Hz), tri-axial gyroscope (100Hz) and tri-axial magnetometer (100Hz)	Ruck events accurately predicted by the algorithm when an average of 79.4 ± 9.2% of the decision trees agreed that a ruck event had occurred (Backs: 79.8 ± 9.8%, Forwards: 79.1 ± 8.5%) 1v1 tackle events were accurately predicted by the algorithm when an average of 81.0 ± 9.3% of the decision trees agreed that a tackle had occurred (Forwards: 77.7 ± 12.2% demonstrated a significantly lower cut-off than backs: 85.3 ± 7.2%)
(Gabbett et al., 2010)	Rugby league	30 males, professional	Collision events (tackles, hit-ups, decoy runs, and support runs)	MinimaxX, Catapult Innovations	Tri-axial accelerometer (100Hz) and tri-axial gyroscope (100Hz)	Strong correlation ($r = 0.96$, $P < 0.01$)`between total collisions recorded via the minimaxX units and those coded from the video recordings No significant ($P > 0.05$) differences detected in the number of mild, moderate, and heavy collisions detected via the minimaxX units and those coded from video recordings of the events

Author(s)	Sport	Participants	Event Detection Variable / Activity	Unit Type	Sensors Used	Key Findings
			Defined as (i) mild (contact made with a player but able to continue forward progress/momentum out of the tackle), (ii) moderate (contact made with a player, forward progress/momentum continued until tackle) (iii) heavy (contact made with player, forward progress/momentum stopped, and forced backwards in tackle)			
(Gastin, McLean, Breed and Spittle, 2014)	Australian football	20 males, elite	Tackles (for and against) and collision impact events Tackles further categorised according to intensity (low, medium and high)	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz) and tri-axial gyroscope (100 Hz)	1510 "tackle events" detected by the MinimaxX with only 18% verified as tackles by the coded video footage 78% of observed tackles from the video coding were correctly detected as tackles by the manufacturer's software Tackles against (i.e. when the player is being tackled) were more accurately detected (90%) than tackles made (66%) 275 correctly detected tackles indicated a significant level of agreement (mean = 76%, range: 68-78%) between tackle intensity criterion measure (video observation) and peak PL™ (x^2 (1, n = 275) = 0.54, $P < 0.01$)
(Hulin et al., 2017)	Rugby league	8 males, professional	Collision frequency during match play	Optimeye S5, Catapult Innovations	Tri-axial accelerometer (100 Hz) and tri-axial gyroscope (100 Hz)	Microtechnology detected collision events were strongly correlated with video-coded collision events ($r = 0.96$) Sensitivity of 97.6% when detecting collisions during rugby-league match play

Author(s)	Sport	Participants	Event Detection Variable / Activity	Unit Type	Sensors Used	Key Findings
						When short duration (<1s) and low-intensity (<1 PL™ AU) events were excluded: - Specificity of microtechnology was 91.7% - Accuracy was 92.7% - Typical error of estimate was 7.8%
(Kelly, Coughlan, Green and Caulfield, 2012)	Rugby union	3 males, elite	Tackle/collisions during match play	SPI Pro, GPSports	Tri-axial accelerometer (100 Hz)	High recall (0.933) and precision rating (0.958) of automated collision detection system (using a learning grid approach) when compared against manually labelled collisions
(McNamara, Gabbett, Chapman, Naughton and Farhart, 2015)	Cricket	12 males, international, first-class and first grade	Bowling counts and events	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz) and tri-axial gyroscope (100 Hz)	No differences (P = 0.34) detected between bowling counts and MinimaxX detection counts in training or competition Strong correlation (r = 0.99) between direct bowling counts and bowling counts recorded by MinimaxX unit in training or competition Training: 448 bowling events observed, 99.0% sensitivity & 98.1% specificity Competition: 345 bowling events observed, 99.5% sensitivity & 74.0% specificity
(Murray et al., 2017)	Baseball	17 males, elite junior	Pitching and throwing events	MinimaxX S4, Catapult Innovations	Tri-axial accelerometer (100 Hz) and tri-axial gyroscope (100 Hz)	Pitching events detected with 100% sensitivity and 79.8% specificity in training Pitching events detected with 100% sensitivity and 74.4% specificity during competition Overall accuracy was 77.1% with the algorithm overcounting pitching and throwing events

The limited research that does exist has been largely successful in achieving high detection rates from custom-designed event detection algorithms. Of the 8 studies that met the selection criteria (Table 2.2), 5 were designed to automatically detect tackle or collision event in rugby league (Gabbett et al., 2010; Hulin et al., 2017), rugby union (Chambers et al., 2019; Kelly et al., 2012) and Australian football (Gastin et al., 2014). Both Gabbett and colleagues (2010) ($r = 0.96$, $p < 0.01$) and Hulin and colleagues (2017) ($r = 0.96$) reported strong correlations between microtechnology device recorded collisions and video-coded collisions. Interestingly, these studies used different microtechnology devices, however they were manufactured by the same company. The same tackle and collision impact detection algorithm did not have the equivalent success in Australian football where only 18% of microtechnology recorded tackle events were verified by the coded video footage (Gastin et al., 2014). Despite these false positives, 78% of video-coded tackle events were correctly detected by the algorithm, and 76% of these correctly identified tackle events demonstrated agreement between video-determined and algorithm derived tackle intensity categorisation (low, medium and high) (Gastin et al., 2014). The relatively poor performance of this algorithm in AF is likely because this algorithm was designed for and trained on rugby league players to detect rugby league tackles (Gastin et al., 2014). There are clear differences in tackle dynamics between these codes (e.g. front on tackling in rugby league versus 360° tackling in AF) where a 'successful' tackle in rugby league requires the player to be taken to ground or to bend over and touch the ball on the ground whilst being held, whereas in AF, the purpose of a tackle is to impede the opposition player's capacity to effectively pass the ball to a teammate, hold up play, or even win the ball back, without the opposition player necessarily having to go to ground (or that player could already be on the ground). The algorithm requires a significant change in torso orientation to detect that a tackle has occurred, which lends to the evident difference in detection performance between rugby league and Australian football.

The collision detection system (Kelly et al., 2012) and tackle event detection system (Chambers et al., 2019) developed in rugby union took a slightly different approach using decision trees (a form of machine learning) to determine whether a collision or tackle event had occurred. Both studies reported high-level accuracy under certain decision model conditions when compared against manually coded video footage (Table 2.2). Excluding Kelly and colleagues (2012), all of these collision and/or tackle detection algorithms required the combination of accelerometer and gyroscope data to assess both impact and

body lean (change in torso orientation) which likely contributed to the high detection rates. Interestingly, Kelly and colleagues (2012) only achieved high precision and recall rates when utilising a combination of standalone classifiers in a learning grid approach. These standalone models did not perform well in isolation, instead, this algorithm performed optimally when each classifier learned a unique aspect of the tackle motion to complement the learning features of the other classifier models in a learning grid approach (Kelly et al., 2012). In this scenario, the addition of gyroscope data may have allowed the authors to differentiate between collision and tackle events which may have improved the detection rate of collisions using single classifiers.

Chambers and colleagues have also recently developed algorithms to automatically detect ruck events (Chambers et al., 2019) and scrums (Chambers et al., 2018) in rugby union. Again, a decision tree approach was used to successfully detect ruck events using temporal and spatial features extracted from accelerometer and gyroscope signals evident in the dataset used to train the classification model (Chambers et al., 2019). Whereas the scrum detection algorithm was dependant on the orientation of the microtechnology unit and was subsequently calculated using accelerometer and gyroscope sensor fusion techniques, as well as machine learning classifiers, and demonstrated high detection sensitivity and specificity (Chambers et al., 2018). The other event detection algorithms have been developed to automatically detect fast bowling events in cricket (McNamara et al., 2015) as well as pitching and throwing events in baseball (Murray et al., 2017). McNamara and colleagues (2015) developed an algorithm that triggered a fast-bowling event when specific accelerometer (change in anterior-posterior acceleration) and gyroscope (torso rotation peak speed above 500°/s) criteria were met, whilst Murray and colleagues (2017) were able to detect pitching events using a combination of raw accelerometer and gyroscope date to analyse peak angular velocity about the longitudinal axis, and throwing events (fielding) by analysing oscillations and small angular velocity peaks immediately prior to the throwing motion. Each of these studies reported exceptionally high sensitivity in both training and competition (99-100%), and whilst McNamara and colleagues (2015) demonstrated high specificity in training (98.1%), this was significantly reduced during competition (74.0%), attributed to the random nature of competition and the addition of ‘bowling actions’ occasionally evident when players are fielding or warming-up. Murray and colleagues (2017) demonstrated similarly low specificity values during training (79.8%) and competition (74.4%) and also attributed the presence of false positives to random events such as batting and warm-up movements.

There is clear evidence inertial sensor signals derived from trunk-mounted microtechnology units can be used to develop algorithms that are capable of accurately and reliably detecting sports-specific movement events during team-sport competition. The inclusion of gyroscope data to complement the acceleration signal, as well as the integration of these sensors in multiple axes of movement to estimate orientation has provided the capacity to quantify these movement events, however the paucity of research in this area suggests that the opportunity to utilise this data more effectively may be limited by the knowledge or ability of sports scientists to process these raw sensor signals in a meaningful way. These sports-specific movements are not only critical to team success (Bradshaw, Young, Russell & Burge, 2011; Chambers et al., 2018; Gabbett, 2013b; Hulin, Gabbett, Kearney & Corvo, 2015), but the automatic detection and tracking of both frequency and magnitude of these movement events may allow load monitoring protocols to better represent the true demands of the sport. Despite a recent shift in research from GPS technology to exploring the potential of inertial sensor signals, more research in this area is still required, and notwithstanding the recent development of solutions to detect some sports-specific movements, there currently remains no valid and reliable solution to automatically detect and quantify the mechanical demands of COD movement on-field during team-sport training and match play.

2.12 Overall Importance and Potential Implications of Being Able to Monitor Change of Direction Movement

The ability to change direction rapidly and efficiently has been suggested as a critical success factor in multi-directional team-sport athletes (Brughelli et al., 2008; Sheppard & Young, 2006; Young, Dawson & Henry, 2015). Multiple components such as GRF absorption and production (Harper & Kiely, 2018; Spiteri et al., 2015a), muscle activation (Maniar et al., 2019; Rand & Ohtsuki, 2000) and even cognitive abilities (Lee et al., 2017) contribute to COD performance and have varying levels of associated neural and metabolic cost (Hader et al., 2014; Harper & Kiely, 2018; Zebis et al., 2011). Importantly, there is strong evidence outlining the trade-off between COD angle and velocity where sharper CODs will require a more rapid deceleration phase (slower approach velocity) and thus generate slower acceleration (exit velocity) (Hader, Palazzi & Buchheit, 2015; Schot et al., 1995; Vanrenterghem et al., 2012). Therefore, the COD angle and velocity will govern changes in COD kinetics and kinematics which subsequently alter GRF requirements, muscle activation strategies, joint-loading, physiological demands, perceptual response, and ultimately, lower-limb mechanical loading (Buchheit, Haydar & Ahmaidi, 2012;

Dos'Santos et al., 2018; Hader et al., 2016). Given the high prevalence of COD movement in multi-directional team-sports (Bloomfield et al., 2007; Dawson et al., 2004), along with the neuromuscular and metabolic cost of repeat COD movement on subsequent performance potential (Hader et al., 2016; Harper & Kiely, 2018; Howatson & Milak, 2009; Zebis et al., 2011), the capacity to detect and quantify the mechanical load associated with COD movement during on-field training and competition, and integrate this information in to load management practice, may allow sports science and strength and conditioning practitioners to more effectively reduce injury risk and enhance COD performance through targeted training interventions that endorse chronic COD-specific neuromuscular adaptations. Given the widespread use of wearable technology now present within team-sport environments, including microtechnology units which house inertial sensors, it may be possible to develop an algorithm using advanced signal processing techniques and orientation estimates that is capable of detecting on-field COD 'events' and their associated mechanical load.

Chapters 3, 4, 5, 6 and 7

are not available in this version of the thesis

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APPENDICES

Appendices A and B are not available in this version of the thesis

Appendix C Conference Poster – ASCA (2016) – Melbourne, AUS

USING WEARABLE MICROTECHNOLOGY TO MEASURE PRECISION OF PRE-DETERMINED CHANGE OF DIRECTION INCIDENTS OF VARYING ANGLES

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INTRODUCTION

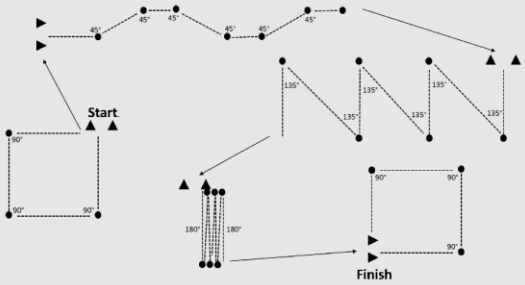
Cumulative change of direction incidents can elicit high levels of musculoskeletal and neuromuscular fatigue which may alter mechanical loading on lower-body joints and subsequently reduce mechanical efficiency, underpinning an increased risk of injury[1,2]. Inertial sensors have previously shown the capability to accurately identify and differentiate between a variety of sports-specific movements[3,4]. Therefore, the aim of this study was to determine whether an accurate and reliable algorithm could be developed to calculate the precise angle from a range of pre-determined change of direction incidents.

METHODS

EXPERIMENTAL DESIGN:

Six recreationally active males (***Age***: 29 ± 0.5 years, ***Height***: 181 ± 5.6 cm, ***Body Mass***: 79.4 ± 5.3 kg) completed 2 laps of a pre-determined change of direction course. Each lap consisted of 3 change of direction incidents in each direction (left and right) at 4 different angles (45°, 90°, 135°, 180°) for a total of 288 change of direction incidents. Participants were fitted with a commercial microtechnology unit (accelerometer, gyroscope, magnetometer; Optimeye, S5, Catapult Innovations, Melbourne, Australia) posteriorly trunk-mounted in a manufacturer supplied vest.

Figure 1. A visual representation of the change of direction course. Each participant was required to compete 2 laps.



STATISTICAL ANALYSIS:

Tri-axial data from the accelerometer, gyroscope and magnetometer were extracted using manufacturer supplied software before a complementary filter was applied to integrate data from each of the 3 inertial sensors. The data was then subject to a series of signal processing techniques (Gaussian filter, edge detection filter and a non-maximal suppression stage) before the precise angle from each turn could be determined. Reliability was assessed using absolute Typical Error (TE) and sensitivity evaluated by calculating Smallest Worthwhile Change (SWC) to determine whether the algorithm was capable of accurately detecting minor variations in change of direction angle.

RESULTS

Table 1. Reliability and descriptive measures for all subjects between four pre-determined change of direction angles.

	45°			90°		
	Mean ± SD	**TE**	**SWC**	**Mean ± SD**	**TE**	**SWC**
Left	39.5 ± 3.4°	0.56	0.67	89.2 ± 3.4°	0.57	0.68
Right	40.2 ± 3.8°	0.63	0.76	84.8 ± 3.8°	0.64	0.76
	135°			**180°**		
	Mean ± SD	**TE**	**SWC**	**Mean ± SD**	**TE**	**SWC**
Left	136.6 ± 4.4°	0.74	0.89	180.7 ± 3.3°	0.55	0.65
Right	138.4 ± 2.6°	0.44	0.52	181.7 ± 2.8°	0.46	0.55

Note: TE: Typical Error of Measurement
SWC: Smallest Worthwhile Change .

Smallest Worthwhile Change (SWC) was greater than the Typical Error (TE) for all angles in both directions.

DISCUSSION

From preliminary data, this novel algorithm is capable of accurately detecting minor variations in change of direction angle when all participants are instructed to run an identical change of direction course (TE < SWC)[5]. Additional data will provide a more accurate depiction of reliability; between-subject reliability will be of particular interest to clarify whether this algorithm is applicable to a greater variety of running techniques. However, it must be taken in to account that there is almost certainly a degree of human error present when participants are instructed to change direction at an 'exact' angle.

PRACTICAL APPLICATIONS

Change of direction movement is highly prevalent in a range of team-sports, and to our knowledge, is unable to be reliably distinguished from other running variables using a commercially available microtechnology unit. The development of a novel algorithm to accurately identify changes in mechanical loading (angle) during change of direction incidents may present a new perspective in athlete monitoring for performance enhancement and injury prevention purposes.

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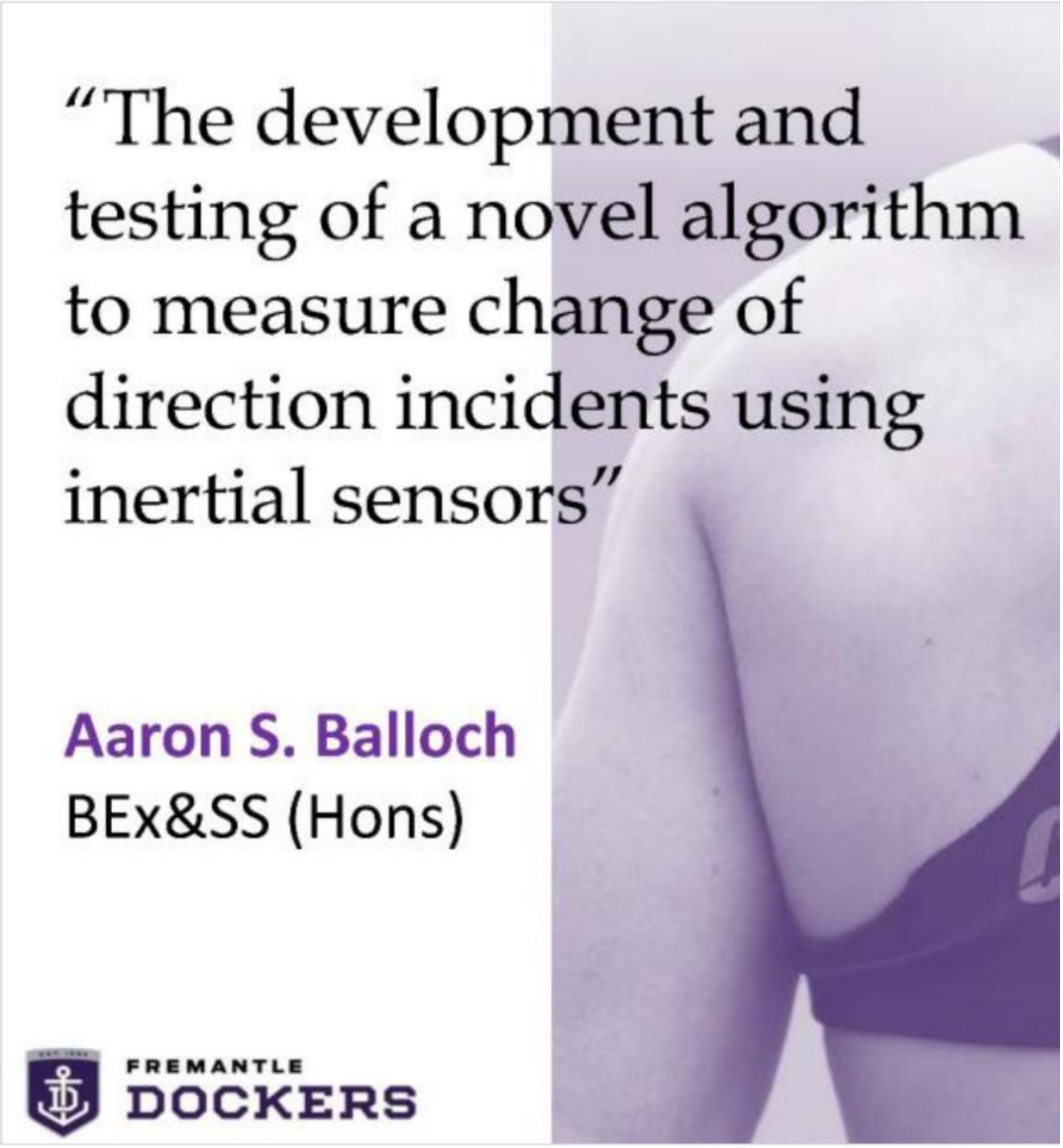
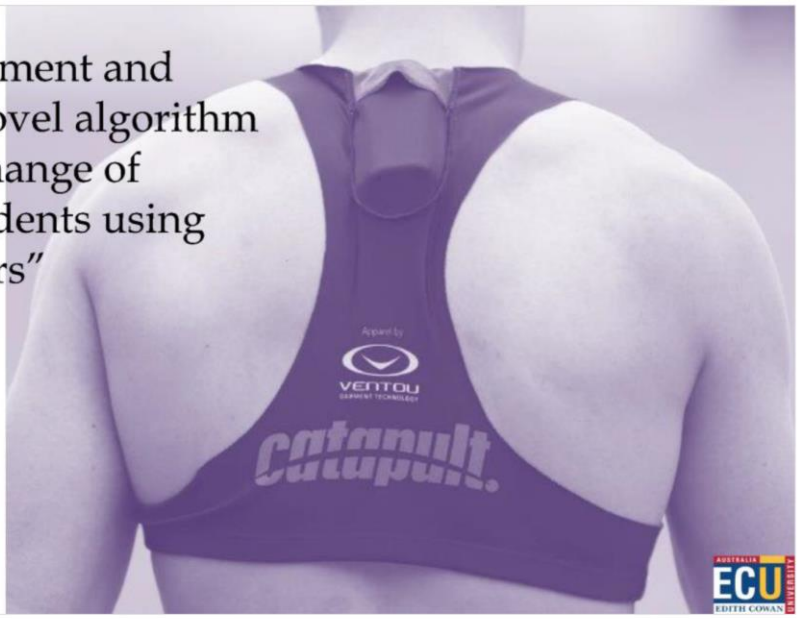
Appendix D Conference Presentation – SPRINZ (2017) – Auckland, NZ



"The development and testing of a novel algorithm to measure change of direction incidents using inertial sensors"

Aaron S. Balloch
BEx&SS (Hons)



FREMANTLE DOCKERS

ECU EDITH COWAN

BACKGROUND

The Idea….

- Internal validity testing of a proprietary algorithm
- Clear lack of measurement and absence of information concerning the **frequency** and **magnitude** of COD movement
- Evade opponents, positional advantage
- >50% of match sprints incorporate at least one change of direction (Dawson et al. 2004)

BACKGROUND

Injury mechanism…?

Cumulative Change of Direction Load

↓

↑ muscle damage & ↑ neuromuscular fatigue

↓

Altered movement strategy changes mechanical loading patterns

↓

↑ Injury incidence??

WHAT ARE INERTIAL SENSORS??

- **Accelerometers:** Linear Acceleration (g)
- **Gyroscopes:** Angular Velocity (deg/sec)
- **Magnetometers:** Earth's magnetic field (orientation relative to 'magnetic north') (µT or T)
  - ✓ 3D
  - ✓ Sample at 100Hz+
  - ✓ Capable of detecting and quantifying sports-specific actions

ALGORITHM CREATION

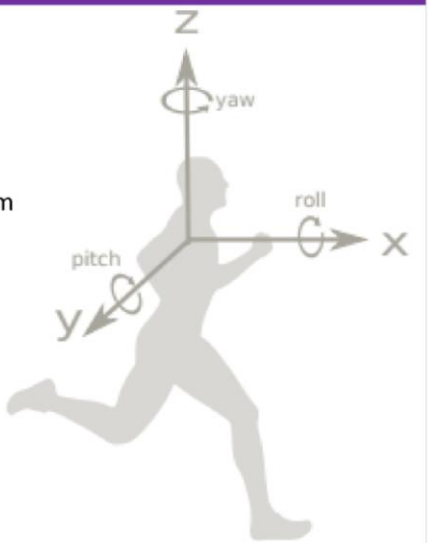
Computing the **Yaw** angle…

- Combination of **tri-axial** data from multiple sensors
  - e.g. gyroscope prone to drift

✓ **Step 1**: Calculate angular rotation about x, y, z axes from known initial orientation
  - Euler Yaw angle

✓ **Step 2**: Measure heading via Earth's magnetic field
  - Axial sensitivity changes when athlete tilts

✓ **Step 3**: Application of complementary filter
  - Gyroscope + Magnetometer Yaw angles

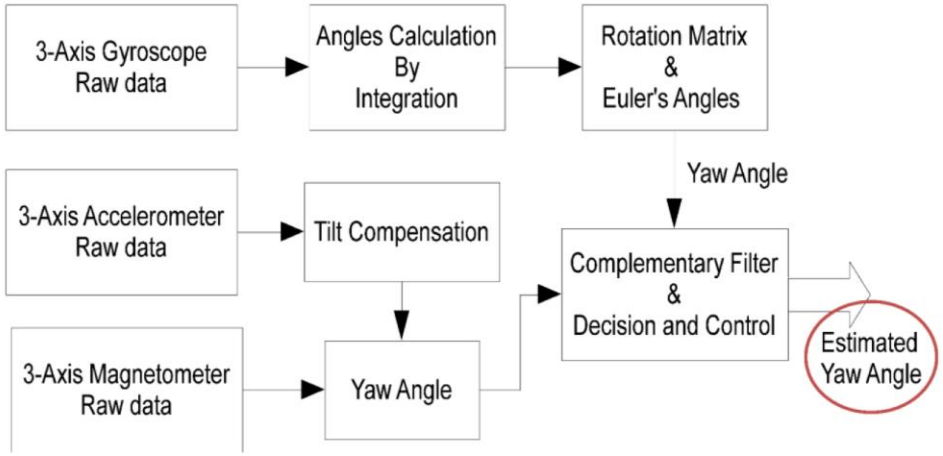


ALGORITHM CREATION

And finally…….

- Computation and decision technique stages
  - ✓ Gaussian smoothing
  - ✓ Edge detection
  - ✓ Non-maximal suppression
  - ✓ Threshold procedure

SUMMARY



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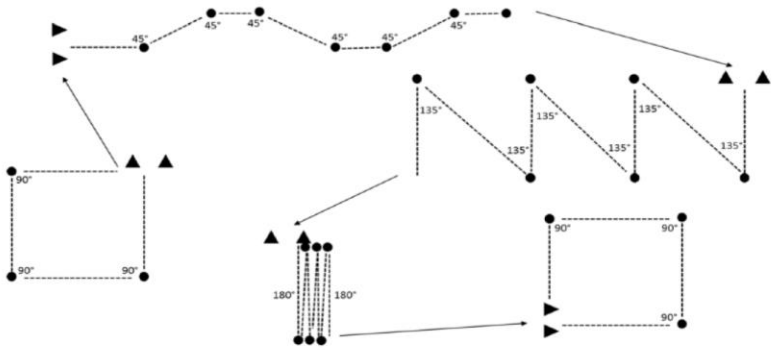
VALIDITY / RELIABILITY TESTING

Study Design #1

- ✓ 6 recreationally active males
- ✓ 5 laps of COD circuit
- ✓ 15 CODs at each angle in each direction
- ✓ Total of **720** CODs



VALIDITY / RELIABILITY TESTING

Results

	45°		90°	
	Mean ± SD	**CV (%)**	Mean ± SD	**CV (%)**
Left	43.6 ± 1.7°	3.9	89.0 ± 2.5°	2.8
Right	44.7 ± 2.0°	4.6	90.4 ± 3.4°	3.8
	135°		**180°**	
	Mean ± SD	**CV (%)**	**Mean ± SD**	**CV (%)**
Left	135.3 ± 2.8°	2.1	180.3 ± 4.4°	2.5
Right	133.5 ± 3.3°	2.5	183.1 ± 3.5°	1.9

KEY POINTS

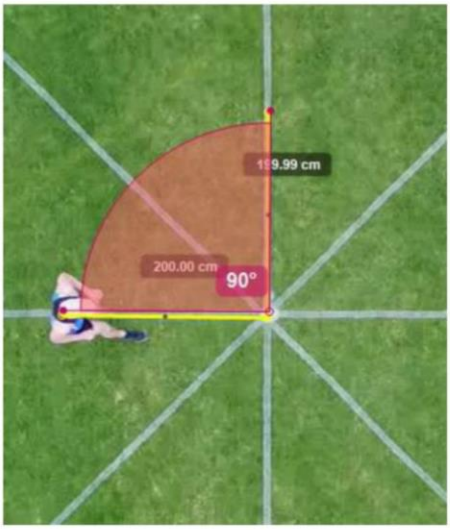
- ✓ All CVs <5%
- ✓ Human error or machine error?

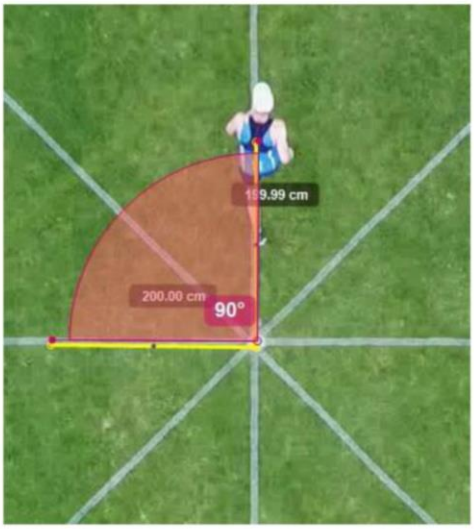
VALIDITY / RELIABILITY TESTING

Study Design #2

- ✓ 6 recreationally active males
- ✓ 5 CODs in each direction at each angle
- ✓ Total of **240** CODs

VALIDITY / RELIABILITY TESTING





VALIDITY / RELIABILITY TESTING

Initial Results

	Algorithm	Video	Mean Difference
45°L	43.6 ± 2.1°	46.3 ± 2.0°	-2.7°
45°R	46.2 ± 1.6°	46.7 ± 1.6°	-0.5°
90°L	88.1 ± 2.0°	89.4 ± 1.8°	-1.3°
90°R	91.9 ± 2.2°	90.8 ± 2.3°	1.1°
135°L	136.3 ± 2.1°	135.8 ± 1.9°	0.4°
135°R	135.2 ± 2.8°	134.0 ± 2.1°	1.1°
180°L	182.1 ± 2.8°	180.2 ± 3.0°	1.9°
180°R	180.8 ± 3.8°	179.4 ± 3.2°	1.4°

A WORK IN PROGRESS.....

What now.....

- ✓ Papers under review
- ✓ Additional data analysis
- ✓ Not all CODs are equal!!
- ✓ ~~GPS~~
- ✓ Profile AFL
- ✓ Application for variety of team-sports

ONLY A PIECE OF THE PUZZLE.....

Monitoring Tools @ FFC

- **Internal** & **External** Load Metrics
  - Distance (Speed-zones)
  - TE & TRIMP
  - TSB
- **Gymaware**: Strength & Power Profiling
- **Force Plate**: CMJ – Eccentric Components
- **Subjective** Measures

AMTI FORCE AND MOTION · GA · FIRSTBEAT · CATAPULT

THANKYOU....

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Appendices E and F are not available in this version of the thesis