# DEVELOPMENT AND VALIDATION OF MICROTECHNOLOGY-BASED ALGORITHMS FOR QUANTIFYING COLLISIONS IN RUGBY UNION

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DOCTOR OF PHILOSOPHY

By

## **RYAN MATTHEW CHAMBERS**

SUPERVISORS:

PROFESSOR TIM J. GABBETT

DR MICHAEL H. COLE

DR ANDREW D. TOWNSHEND

DR RICHARD D. JOHNSTON

SCHOOL OF BEHAVIOURAL AND HEALTH SCIENCES

AUSTRALIAN CATHOLIC UNIVERSITY

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### Declaration

This thesis contains no material published elsewhere or extracted in whole or in part from a thesis by which I have qualified for or been awarded another degree or diploma. No parts of this thesis have been submitted towards the award of any other degree or diploma in any other tertiary institution. No other person's work has been used without due acknowledgment in the main text of the thesis. All research procedures reported in the thesis received the approval of the relevant Ethics/Safety Committees (where required).



Name: Ryan Chambers

Date: 4<sup>th</sup> February 2020

### Published Works by the Author Incorporated into the Thesis

The following is a description of the contribution of the main and co-authors for each of the published manuscripts supporting this thesis:

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Author	Roles	Contribution
Ryan Chambers	Conception of manuscript	70%
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Dr. Tim Gabbett	Conception of manuscript	15%
	Revision of manuscript	
Dr. Michael Cole	Conception of manuscript	14%
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Ryan Chambers	Conception of manuscript Preparation of initial draft of manuscript	60%
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Ryan Chambers	Conception of manuscript	60%
	Preparation of initial draft of manuscript	
Dr. Tim Gabbett	Conception of manuscript	10%
	Revision of manuscript	
Dr. Ritu Gupta	Algorithm development	10%
	Revision of manuscript	
Mr. Casey Josman	Algorithm development	5%
Mr. Rhodri Bown	Revision of manuscript	4%
Mr. Paul Stridgeon	Revision of manuscript	1%
Dr. Michael Cole	Conception of manuscript	10%

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	Revision of manuscript	
Mr. Ciaran Miller	Data analyses and interpretation	5%
Mr. Rhodri Bown	Revision of manuscript	4%
Mr. Paul Stridgeon	Revision of manuscript	1%
Dr. Michael Cole	Conception of manuscript	15%
	Revision of manuscript	

I hereby declare that my contribution to each of the four published/submitted manuscripts, as outlined above, to be accurate and true.





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#### Abstract

Rugby union requires players to perform high-intensity locomotor and contact efforts, interspersed with low-intensity activity. Locomotor efforts include accelerations, running and sprinting, while collision efforts include ruck, tackle scrum and maul events. Recent research has quantified the demands of Rugby Union using player-worn microtechnology that contains global positioning systems (GPS) and tri-axial microsensors including accelerometers, magnetometers and gyroscopes.

To date, research has extensively reported the locomotor demands of Rugby Union match-play using GPS, documenting total distance covered, high-speed distance, accelerations and running efforts. However, there is a lack of research on the contact events of match-play. A number of authors have investigated the contact demands of Rugby Union using microtechnology and applying non-specific algorithms to determine the number of collision events in Rugby Union. However, two major limitations exist in this approach. Firstly, while these algorithms have been validated for other collision sports (i.e. Rugby League), the unique collision events of Rugby Union mean they are unsuitable for this sport. Secondly, the developed algorithms do not delineate among contact events (i.e. ruck, scrum and maul), resulting in an underestimation of the contact demands of Rugby Union and all collision events being considered equally demanding. Therefore, the total physical demands of Rugby Union match-play are being under reported.

Based on the identified gaps in the literature, the purpose of this thesis was to 1) conduct a systematic review of the use of microsensors to quantify sport-specific movements and determine if such devices are potentially capable of detecting collision events in Rugby Union (Study 1), 2) develop a valid algorithm to detect scrum events in training and match-play (Study 2); and 3) develop an algorithm to determine ruck and one-on-one tackle events in Rugby Union (Study 3). This program of research was subsequently brought together by the final study (Study 4), which applied the newly developed algorithms with existing methods to uniquely quantify the locomotor and contact demands from both winning and losing teams in 12 elite matches. Results of this research provides a novel insight into the contact demands of elite Rugby Union and additionally provide validated methods to delineate each collision type. Results of this research provide a detailed overview of total physical demands of Rugby Union and provide insight into the different locomotor and collision profiles of winning and losing teams.

This research demonstrates a unique application of microsensors and specific algorithms to quantify the collision demands of elite Rugby Union training and matchplay. For the first time, the total locomotor and contact demands of elite Rugby Union match-play, including those of winning and losing teams have been documented. Performance staff can use this information to more effectively monitor the training loads of players and design sport-specific conditioning programs to prepare players for the most demanding passages of match-play.

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### **Chapter 1: General Introduction and Review of Current Literature**

### 1.1 Overview of Rugby Union

Rugby Union is a team sport that is alleged to have been founded in 1823 by William Webb Ellis, a student of Rugby School in Warwickshire England, who supposedly picked up the ball during a game of football (soccer) and ran with it (1). For the first five decades, the sport was played predominantly by schools and universities, but in 1873, the first Rugby Union international took place between England and Scotland. Although this first international match involved 20 players per team, the formation of the World Rugby governing body in 1886 led to the creation of specific rules and laws that included the number of players permitted on the field at one time being reduced to 15 per side (1,2). Since its origins, the popularity of Rugby Union has grown significantly, with the governing body estimating that more than 8.5 million people across 121 countries participate in the sport (2). While Rugby Union has been contested domestically and internationally for many decades, it was not until 1987 that the inaugural World Cup was hosted by New Zealand and Australia, with New Zealand winning the competition (1,2). In 1995, the sport of Rugby Union became professional, which subsequently led to the introduction of other prestigious competitions, both internationally and domestically (3). With this significant change, media coverage also increased, particularly at the elite level, with Rugby Union attracting large spectator and television audiences, with an estimated 120 million people watching the 2015 Rugby World Cup final (4).

A game of Rugby Union is contested by two teams, each with 15 players and 8 substitutes, who compete over two 40-minute halves separated by a 15-minute rest

interval. Unlike other codes of football, which may add a period of stoppage time to the length of each half (or quarter), Rugby Union makes no allowances for stoppages, except in the event of an injury (2,3). Generally, the ball is in play for an average of 35% of total match time (i.e. between 30 and 40 minutes) (3,5), with the ball being out of play for the remaining match time due to various scenarios, such as scoring, infringements (e.g. penalties for illegal manoeuvres etc.) and the ball being out of the field of play. As outlined by the sport's governing body, each player within a team is allocated a specific number, which corresponds with their playing position on the rugby field. Specifically, players can be identified as; 1) loose-head prop; 2) hooker; 3) tighthead prop; 4) left lock; 5) right lock; 6) blind-side flanker; 7) open-side flanker; 8) number eight; 9) scrum-half; 10) outside half; 11) left wing; 12) inside centre; 13) outside centre; 14) right wing; and 15) full back.

These 15 playing positions are subsequently grouped into 'forwards' (players 1 to 8) and 'backs' (players 9 to 15), before being further sub-divided into smaller specialist groups. The specialist groups formed by different teams often share some similarities, but generally the specific naming and assignment of player to each sub-group can be quite varied. While each player has a specific role within a team, all players are required on-field throughout the course of a game. Since the turn of the professional era, there has been an increased focus on developing the physical qualities of players to better prepare the athletes for the overall demands of the game (3). However, to achieve this goal, it is necessary to have a clear understanding of physiological demands associated with Rugby Union match-play, both on average and under 'worst-case' conditions (6). The following section provides an overview of the literature that has assessed the

physical demands associated with elite Rugby Union match-play to provide some context regarding the physicality of the sport.

### **1.2 Match Demands in Elite Rugby Union**

Rugby Union players are required to perform high-intensity locomotor activities, such as running, sprinting and accelerations, while also engaging in high-intensity collision events over an 80-minute period (3,7,8). Of these collision-based events, all players are likely to engage in rucks, tackles, and mauls during typical match-play scenarios, while forwards are also required to perform in scrums (3,7). Although both mauls and scrums are integral to the identity of Rugby Union match-play, rucks and tackles occur far more frequently than the other collision types.

Tackles occur when the ball carrier is impeded by one or more defenders (Figure 1.1) and while different tackles may share some similarities, the specific technique used by the tackler(s) will often vary. In general, most defenders seek to wrap their arms around the attacker's waist; allowing their arms to slide down around the attacker's legs to prevent them from gaining ground. By preventing the attacker's legs from moving, the defender brings the ball carrier to the ground, which ultimately leads to a second type of contact event, known as a ruck, being formed.



*Figure 1.1 – A completed tackle* (*Image taken from: https://laws.worldrugby.org/?highlight=Tackle&law=14*)

Ruck events occur following tackles that result in the attacking player going to ground (Figure 1.2). These contests require at least one player from either team to be involved in an intense physical competition for the ball whilst on their feet, with the objective of the attacking player to retain possession and prevent the defender from stealing the ball.



*Figure 1.2 – A formed ruck* (Image taken from: <u>https://laws.worldrugby.org/?highlight=ruck&law=15</u>)

However, some tackle events involve techniques where the defender wraps their arms around the upper body of the attacker, either preventing the attacker from passing or attempting to hold the attacker upright without allowing them to gain ground. Tackles that do not result in the ball-carrier being taken to ground, but rather have them being held up by the defending players, ultimately transition to a maul. Like the aforementioned collision-based events, these events can take place anywhere on the field and consist of the ball carrier and at least one player from each team who are bound together and on their feet. For a collision-based event to be classified as a maul and the attacking team to retain possession, the physical contest between the two teams must involve the ball being advanced in the direction of the attacking team (Figure 1.3). If the defensive team advances, and the ball is unplayable then the game is restarted with a scrum and a change in possession. During this contest, the defending team attempts to steal the ball from the attacking team or prevent the ball from advancing in favour of the attacking players (i.e. to stop the maul). A maul can appear as a reasonably static effort, but requires players to exert high forces to overpower their opposition. If the ball is deemed unplayable by the referee, then a minor infringement has occurred.



*Figure 1.3 – A maul* (*Image taken from: https://laws.worldrugby.org/?highlight=maul&law=16*)

Following such minor infringements (e.g. knock-ons, players being offside, ball unplayable from maul) or match stoppages due to major infringements (penalties being awarded following an illegal manoeuvre or action (e.g. dangerous play) the game is frequently restarted with a scrum. Scrums represent the fourth type of contact-based event and require all forwards from both teams to engage in a physical battle. A scrum occurs when the eight forwards from one team bind to form three rows, each comprising three, two and three players respectively, before interlocking with the opposition players (Figure 1.4). While in this interlocked position, the two opposing teams exert very high isometric forces to compete for possession of the ball, with the objective being to push the other team backwards off the ball.



*Figure 1.4 – A scrum formation* (*Image taken from: https://laws.worldrugby.org/?highlight=scrum&law=19*)

These four contact incidents combined with higher intensity locomotor actions are classified as high-intensity events, which are interspersed throughout a game with lower intensity activity (jogging and walking) and rest (9,10).

A substantial amount of research has provided significant foundational knowledge of the physiology of Rugby Union players, describing the physical characteristics, capacities and time motion analysis of match-play (3,10-12). Duthie and colleagues (3) evaluated the match demands of elite Rugby Union using video-based analysis to quantify work to rest periods and identify the distinct movement patterns of players. The researchers concluded that players spend 85% of the playing time during a match performing low-intensity aerobic activities, while considerably less time is spent performing high-intensity activities (3,7). Forwards were found to spend more time involved in contact situations than backs, suggesting that these players were more likely to be required to perform repeated high-intensity locomotor efforts and short acceleration bouts. Backs were found to perform more high speed running and also covered greater distances. Although this research provided initial insight into the match demands of elite Rugby Union, the use of video technology to quantify these demands is known to be very subjective, time consuming and potentially erroneous (12). The significant improvements in technology, specifically microtechnology, over the last decade has allowed practitioners and researchers to more accurately quantify the demands of Rugby Union (7,13,14). Specifically, the use of wearable microtechnology has reduced the need for video-based analyses at the elite level, thereby providing greater objectivity around the analysis of match demands.

Commercially available microtechnology devices containing global positioning system receivers (GPS) and microsensors (accelerometers, gyroscopes and magnetometers) are frequently worn by participants in a specifically designed harness and commonly used to quantify the physical demands of various team sports including Rugby Union (7,15). Recent research has examined the demands of elite level Rugby Union match-play, predominantly using global positioning systems and video tracking to provide greater insight into the demands of the sport (13,16,17). Specifically, via the use of such technology, it has been possible to objectively evaluate total distance covered, highintensity running distances and the number of accelerations performed by each player; ultimately allowing practitioners to understand the variation that exists between different playing positions on the field (6,13,18). Quantifying the demands of elite level Rugby Union is of benefit to practitioners, as it allows training methods to be improved, which will help to facilitate better athlete preparation for match-play. Having an improved understanding of the physical demands of the game not only allows coaches and sports scientists to ensure that their athletes are appropriately prepared for competition, but also allows them to develop improved injury prevention strategies and better monitoring techniques for players who are returning from injury.

Early application of wearable GPS technology allowed quantification of basic demands of elite Rugby Union (Table 1.1). Some research has found players can cover distances of approximately 7,000m each game (7), and highlighted that Backs cover over 1,000m more distance than Forwards during a typical game (7). Total distance is a metric that reflects a player's or sub-group's movements throughout the entire game, including stoppage periods. In contrast, the relative measure of distance per minute (m<sup>-</sup>min<sup>-1</sup>) provides an indication of the movement speed and/or intensity over a specific period; whether that be a game or training session. Relative distances covered by Forwards have generally been reported to be between 64.6 m<sup>-1</sup> and 71.6 m<sup>-1</sup> over the course of a match, compared with Backs who have been shown to cover between 71.9 and 81.0 m<sup>-1</sup> (7,13,19). Despite this difference, it should be noted that these data represent the average demands across all high-intensity ball-in-play bouts, as well as out of play activities; hence, the data will include recovery activities such as jogging, walking and standing. Although such analyses are useful for providing information about the total demands of rugby union match play, separate analysis of the ball-in-play demands may provide further insight into the players' workloads during active periods of competition.

With respect to comparing the activities of players from different positional groups, data collected for Backs have indicated that these players not only cover greater distances, but also perform greater absolute and relative locomotive activity at higher speeds (striding, running and sprinting) than Forwards. Furthermore, Backs also performed more efforts at higher speeds and executed more intense accelerations than forwards (7,8,10,12,13,20).

Table 1.1 illustrates the consistencies and points of differences amongst the existing literature that has quantified the total match demands of elite Rugby Union. Generally, the description of the total locomotor demands of Rugby Union has been consistent for both the forwards and backs positional groups. However, studies often differed with respect to the way in which they represented locomotor activity at higher speeds. Specifically, some of the research presented in Table 1.1 measured distances at higher speed thresholds using either an absolute speed threshold (7,8) or a relative speed

threshold (10,12,18) method, with the outcomes presented as a distance using a percentage of an individual's maximum velocity. Another limitation of the research in Table 1.1 is that it has primarily only considered the locomotor demands of the sport. Those studies that have reported collision data have used various methods, with some using subjective and potentially erroneous video-based analyses (10,12,20), while others have applied non-validated algorithms to microtechnology data (7,8).

Study	Standard and Number of Players	Tournament Level	Techno Use	ology ed	Main Findings
Austin et al.	20 Elite	Domestic	Video	tracking	The mean (±SD) total distances covered by the front row forwards, back-row
(20)			(Software	not	forwards, inside backs and outside backs during each match of a 7-game period
			reported)		were 4,662 $\pm$ 659 m, 5,262 $\pm$ 131 m, 6,095 $\pm$ 213 m, and 4,774 $\pm$ 1,017 m,
					respectively. All positions covered most of the total distance at slower running
					speeds, with Forwards completing greater distances at these speeds than Backs. Of
					the player groups, Backs, specifically inside backs, performed the greatest sprinting
					distance.
					High-intensity activity was considered to include locomotor activities, such as
					striding and sprinting and contact activities such as tackling, static holds and
					scrummaging (scrums, rucks and mauls). Although the findings were in accordance
					with other research and showed that Forwards produced more efforts than Backs,
					the difference between Forwards and Backs was markedly lower than other studies.

Table 1.1 Summary of studies concerned with match demands of senior men's Rugby Union.

Study	Standard and Number of Players	Tournament Level	Technology Used	Main Findings
Cahill et al.	120 Elite	Domestic	SPI-Pro	Forwards covered a median distance of 5,850 m, with the relative distance reported
(12)			(GPSports,	as 64.6 m <sup>-1</sup> . Median maximum speed was 26.3 km <sup>-1</sup> with forwards covering
			Canberra,	the majority of distance below 50% of their predetermined individual maximum
			Australia)	running velocity (Vmax). Forwards tended to cover only around 37 m at speeds
				above 80% of their Vmax.
				Backs covered a median of 6,545 m at a relative distance of 71.1 mmin <sup>-1</sup> with 86%
				of the total distance being covered at speeds below 50% of an individual's Vmax.
				Backs covered a slightly greater distance (50 m) at speeds above 80% of Vmax.
				The wearable devices contained accelerometers, but collisions were not reported.
Coughlan et	2 International	International	SPI-Pro	The Back covered a greater distance (7,002 m) than the Forward (6,427 m).
al. (8)			(GPSports,	Individuals performed nearly 75% of the total distance at lower velocity speed
			Canberra,	bands. The Back covered a greater percentage of the distance at speeds above 18
			Australia) and	km <sup>·</sup> hr <sup>-1</sup> .

Study	Standard and Number of Players	Tournament Level	Technology Used	Main Findings
			Sportscode video tracking (Warriewood, NSW, Australia)	The total number of accelerometer-detected impacts for the Forward was 838, compared with 573 for the Back. Scrum and tackle events were manually coded using video technology and matched alongside accelerometer data to calculate impact load using accelerations. The Back was involved in more tackle events (n=12) than the Forward (n=10), although the Forward was also involved in scrums (n=5). No validation of accelerometer-detected collisions with respect to the actual (video-based) contact events was provided.
Cunniffe et al. (7)	3 Elite	Domestic	SPI-Pro (GPSports, Canberra, Australia)	Only 2 of the players involved completed a full match (1 Forward and 1 Back). The Back covered 7,227 m with a relative distance of 71.9 m min <sup>-1</sup> , covered 524 m of sprinting (above 20 km hr <sup>-1</sup> ), and completed 34 efforts above this threshold. Majority of total distance (4,758 m) was covered at $\leq$ 12 km hr <sup>-1</sup> or slower. The Back attained a maximum velocity of 28.7 km hr <sup>-1</sup> .

Study	Standard and Number of Players	Tournament Level	Technology Used	Main Findings
				The Forward completed 6,680 m with a relative distance of 66.7 m min <sup>-1</sup> . Similar to the Back, most of total distance was covered at speeds $\leq 12$ km hr <sup>-1</sup> (4,285 m). Sprinting distance was lower than the Back, with only 313 m covered at speeds above 20 km hr <sup>-1</sup> . The Forward attained a maximum velocity of 26.3 km hr <sup>-1</sup> . Using an accelerometer, 1,274 and 728 collisions were recorded for the Forward and Back, respectively. However, impacts related to foot strike were not differentiated from collision-based events and the methods were not validated against video footage.
Lacome et al. (10)	30 International	International	Amisco Video tracking (Marlborough, MA, USA)	Backs covered 7,944 $\pm$ 659 m during match-play, compared with Forwards who cover 7,006 $\pm$ 356 m. Forwards covered more distance at slower speeds than Backs, while Backs covered a greater distance at velocities above their maximal aerobic speed.

Study	Standard and Number of Players	Tournament Level	Technology Used	Main Findings
				Scrums, rucks, mauls and standing tackles were all classed as 'static activities'. Forwards were involved in more static activities than Backs, although the specific nature of the activities and frequency of their occurrences were not reported.
Reardon et	36 Elite	Domestic	Optimeye S5	Across 20 games, Forwards covered an average of $5,639 \pm 762$ m per game, while
al. (18)			(Catapult sports, Melbourne,	Backs covered an average of $6,172 \pm 767$ m. Relative distances were also lower for Forwards compared with Backs, with these groups recording $72 \pm 10$ m min <sup>-1</sup>
			Australia) Video tracking	and $81 \pm 10$ mmin <sup>-1</sup> , respectively. Backs covered greater distances at higher speeds than Forwards, irrespective of whether a relative or absolute threshold was
			(Software not reported)	applied. In absolute terms, Backs covered $698 \pm 198$ m at speeds greater than 5 m s <sup>-1</sup> , compared with Forwards who covered $269 \pm 172$ m. Similarly, Backs
				covered greater distances $(570 \pm 171 \text{ m})$ at slow to moderate speeds ( $\leq 60\%$ of Vmax) than Forwards ( $355 \pm 99 \text{ m}$ ). The mean ( $\pm$ SD) total distances covered by the front row forwards back-row forwards inside backs and outside backs during
				the front fow for wards, back-fow for wards, inside backs and butside backs during

Study	Standard and Number of Players	Tournament Level	Technology Used	Main Findings
				each match of a 7-game period were $4,662 \pm 659$ m, $5,262 \pm 131$ m, $6,095 \pm 213$
				m, and $4,774 \pm 1,017$ m, respectively. All positions covered most of the total
				distance at slower running speeds, with Forwards completing greater distances at
				these speeds than Backs. Of the player groups, Backs, specifically inside backs,
				performed the greatest sprinting distance.

Note: Vmax = Maximum velocity

More recently, novel research has focused on the ball-in-play demands of Rugby Union. Although total ball-in-play time during international Rugby Union has been shown to be approximately 46% of total match time, single ball-in-play bouts can potentially last for more than 160 seconds (17). These extended activity cycles usually involve high locomotor or high contact demands (sometimes both), which rapidly increase fatigue and ultimately represent the most demanding passages of play (or "worst-case scenarios") for players (6). Such "worst-case scenarios" can require forwards to cover up to 156.6 m·min<sup>-1</sup> (38.3 m·min<sup>-1</sup> at high speeds), while backs can cover up to 177.4 m·min<sup>-1</sup> (69.9 m·min<sup>-1</sup> at high speeds) (21). However, average ball-in-play demands require Forwards and Backs to cover 106.0 m·min<sup>-1</sup> and 108.6 m·min<sup>-1</sup>, respectively. Of these relative distances, Forwards and Backs respectively complete 8.9 m·min<sup>-1</sup> and 19.0 m·min<sup>-1</sup> at higher speeds (>5m.s<sup>-1</sup>); with a single hard acceleration required nearly once every minute. Although this research provides sports scientists, coaches, conditioners and physiotherapists with much-required insight into the match-play demands of elite Rugby Union, it only describes the locomotor demands that are placed on the athletes.

During both training and match-play situations, the fatigue resulting from the runningbased demands of Rugby Union are compounded by the exertion involved with imparting or enduring the forces associated with physical collisions. Specifically, research shows that Forwards are required to perform at least one collision-based effort during every minute of play, while Backs generally perform one collision-based effort for every two minutes of ball-in-play time (6). The contact demands of Rugby Union have also been alluded to by research, but these studies have generally grouped all collisions under one category; describing them as either 'static activities', 'static exertions' or 'impacts' (10,12,22,23). In a separate study, the number of 'impacts' experienced by each player was recorded using the accelerometers encased within the microtechnology devices routinely worn by players during match-play (6). While this novel approach had the potential to provide an improved understanding of the collisionbased demands experienced by Rugby Union players, the researchers relied upon impact detection methods that were not validated for this sport. As such, the results presented by the authors tended to over-estimate the number of impact-based events experienced by each player, possibly due to the wide range of contact and non-contact situations that lead to large accelerations during Rugby Union match-play. For example, according to Coughlan and associates (8), players may experience large accelerations (e.g. up to 10g) during aspects of match-play that are not related to tackling (8), such as when the feet make contact with the ground during running and/or when the athletes rapidly change direction. As such, it seems reasonable to suggest that algorithms that seek to identify collisions based on accelerations alone may be limited in their capacity to discriminate tackle-related accelerations from the accelerations resulting from other forms of player activities (8).

Collectively, this body of literature highlights the shortcomings of previous attempts to quantify collision-based events in elite Rugby Union. Given that the success of a team is not only dependent on their capacity to perform the intense locomotor demands, but also to endure the repeated physical contacts associated with the sport (24), there is a clear need for better methods to quantify collisions and their influence on a player's performance and injury risk. Future studies should seek to explore the potential for combining accelerations with other microsensor data (e.g. gyroscopic data) to improve the validity and reliability of collision-detecting algorithms in Rugby Union. Furthermore, there is currently a lack of research that has distinguished between tackles,

rucks, scrums and mauls; the four different types of contact events that characterise Rugby Union. The development of algorithms that can discriminate one collision type from another would allow the physical demands of Rugby Union match-play and training to be better evaluated in the future.

### **1.3 Review of Microsensors**

Commercially available microtechnology devices commonly contain one or multiple microsensors, including accelerometers, gyroscopes and magnetometers. These are frequently referred to as microsensors, microelectromechanical sensors (MEMS) or inertial measurement units (IMUs). Such devices are frequently added to wearable technology devices that have extensive applications and may include detecting variations in activities and movements in laboratory, clinical and high-performance sporting environments.

Wearable technology devices containing accelerometers have been used in a number of ways in the general health setting, including the detection of static orientations during standing, sitting, and lying down, as well as the quantification of dynamic movements, such as walking and jogging (25,26). Such devices can assess movements by using specifically designed algorithms that recognise a combination of accelerometer-based outcomes and device orientation. Using these algorithms, it was possible to calculate the speed of low-intensity locomotor movements that were performed at  $\leq 4.8 \text{ m.s}^{-1}$  when devices were placed on the hip and thigh of participants (25). These algorithms have been integrated into commercially available wearable devices that can be used to detect the number of steps an individual completes (i.e. activity monitoring) or to log any disruptions in a person's sleep patterns (26,27). Furthermore, these devices provide

information that can be used to monitor changes in the intensity of locomotor behaviour, while also facilitating more detailed gait analyses (26,28-30).

Despite their widespread use in specific disciplines, the application of wearable microsensors in sport has been somewhat varied. For example, these sensors have been used to assess the patterns of running gait in a group of 10 elite national runners (31). In this study, runners were stratified into low-speed (10-12 km.hr<sup>-1</sup>), medium-speed (13-15 km.hr<sup>-1</sup>), and high-speed (16-19 km.hr<sup>-1</sup>) runner groups to evaluate the validity of microsensor-based measures of stride, step and stance durations with respect to an infrared motion analysis system (31). The results indicated that the temporal measures derived from the microsensor were, on average, 0.0008 seconds different to the optoelectronic motion analysis system; suggesting that a single sensor can be used to validly quantify stride, step and stance durations. From a practical perspective, this finding indicated that practitioners can accurately quantify the temporal aspect of running gait outside of the laboratory in more ecologically valid environments (31). Other studies have used wearable microsensors to evaluate movement intensity in team sports, particularly those that are performed indoors where other locomotor measurement systems, such as GPS, are not viable. For example, the demands of basketball training have been quantified using accelerometers, with the magnitude of the accelerations used to establish differences in the intensity of various drills and games (32). Further to this, Boyd and associates (33) explored the use of triaxial accelerometers to measure activity in team sports, creating an arbitrary unit called 'Player Load'. The 'Player Load' (Equation 1.1) is determined by calculating the square root of the sum of the squared instantaneous change in the three acceleration vectors (i.e. a<sub>x</sub>, a<sub>y</sub>, a<sub>z</sub>) divided by 100 (33). To date, research has used 'Player Load' to gain

further information about the physical demands of sports, such as Australian Rules football (34), netball (35-37) and junior soccer (38). The 'Player Load' measure has been found to be highly reliable when using data from Catapult S5 devices (Catapult Sports, Melbourne, Australia), however, the data that are input into this algorithm are known to be heavily filtered within the manufacturer's software (39). Therefore, it is recommended that such an accelerometer-derived outcome that are based on arbitrary units may be best suited to evaluating workload changes in individual athletes (39).

Player Load = 
$$\sqrt{\frac{(a_{y1} - a_{y-1})^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}{100}}$$

With the increasing need to quantify workload demands, most commercially available wearable devices include GPS hardware and at least one other type of microsensor. Generally, the wearable devices used in sport include a range of sensors (i.e. accelerometers, gyroscopes, magnetometers, GPS), such that participants only need to wear a single device, often positioned between the shoulder blades in a purpose-built harness, to evaluate a wide variety of performance-based outcomes (7,40,41). Recently, research has demonstrated the capacity for such devices to detect and classify a number of sport-specific movements in Rugby Union (42), Rugby League (41) and cricket (40); highlighting the potential for these devices to extend upon the more traditional appraisals of movement demands. For example, such devices have been used in cricket to develop validated methods to quantify fast bowling events in both training and match-play situations (40,43). The results of this research demonstrated that fast bowling could be automatically detected and monitored with high sensitivity in both

training (99.0%) and match-play (99.5%), thereby improving the monitoring of workload in cricketers.

Similarly, Rugby League tackle events have been successfully quantified using a specifically designed microsensor-based algorithm that was validated against manually-coded events from training sessions and a trial match (41,44). The algorithm's detection of tackle events used data from the wearable unit's gyroscope to determine that the athlete was not in a vertical position and data from the accelerometers to detect an instantaneous spike in the 'Player Load' measure. In addition to allowing the overall number of tackles to be determined, the presented algorithm also recorded high correlations with respect to differentiating tackles of mild (r=0.89), moderate (r=0.97) and heavy (r=0.99) intensity, based on the recorded accelerations (41).

Researchers in Rugby Union have used microsensor-based algorithms to quantify players' running-based workloads (11,45,46) and/or to attempt to delineate these locomotor demands from the collision-based demands (6,9). However, due to various limitations, the methods used to identify collisions in Rugby Union have been inadequate to discriminate one collision type from another (9,42). A separate study attempted to use a microsensor-based algorithm developed specifically for Rugby League to evaluate tackle events during Rugby Union match-play (42). The results of this study showed that tackle events could be identified via peaks in the accelerometer data; however, other collision-based (i.e. rucks, mauls, scrums) and non-contact events (e.g. jumping, running, falling) produced similar acceleration profiles. To improve the predictive capacity of the algorithm, tackles were detected by analysing the acceleration signal characteristics during the tackle events and applying a minimum cut-off for the
g-force detected during the collision. Although the final algorithm was capable of detecting tackle events, the researchers suggested that using other microsensor data, such as those from gyroscopes and magnetometers, may have improved the algorithm's accuracy (42).

In a research setting, it is evident that wearable microsensors have enhanced the capacity to monitor movements in healthy populations, clinical sub-populations and sporting groups (13,47). Investigations have demonstrated the possibilities to use this technology to detect specific movements to further understand the physical demands of sport; providing practical insight into how athletes should be trained and monitored. Initial research highlights the potential capabilities for wearable microsensors to detect sport-specific movements using purpose-built algorithms that are based on particular data signals and patterns. However, to date, estimates of the physical demands of Rugby Union have been limited to non-contact skills, such as running, while the influence of collisions on a player's physical workload have been largely disregarded. Given the widespread use of wearable microtechnologies in elite sports, such as Rugby Union, there is potential for these devices to be used to quantify the collision-based demands of the game, in much the same way as it is possible to quantify the non-contact demands of the sport.

### **Chapter 2: Statement of the Problem**

To date, research has generally reported exclusively on the locomotor demands of Rugby Union, providing an in-depth analysis of the distances covered by athletes, the relative intensities, high-speed activity and accelerations (3,6,17). Although an assessment of the running demands of Rugby Union match-play provides important insight into the physical demands of the sport, the physicality of collision-based events, such as tackles, rucks, scrums and mauls are overlooked. Traditionally, many researchers have monitored collisions subjectively using labour-intensive methods, such as video-based analysis, or with commercially available microtechnology devices. However, such research has neglected to differentiate types of collisions in Rugby Union. By developing an improved understanding of both the locomotor and contactbased demands of Rugby Union match-play, it would be possible to gain important insight into the specific physiological demands placed on these athletes and highlight any variations between different positional groups. Such information would better inform the coaches, sport scientists, physiotherapists and strength and conditioning coaches who are working with these players to ensure they are receiving the most appropriate physical preparation for competition and injury prevention.

It is clear that rucks, tackles, mauls and scrums are integral components of Rugby Union and are associated with the final outcome of a match along with injury rates (48). Tactically, there is a significant emphasis placed on teams winning the physical contests that characterise Rugby Union, and conditioning athletes for these physical collisions is considered imperative for overall team performance. However, collision-based activities are responsible for the greatest loss of playing time, with tackles contributing the greatest amount to the high number of injury occurrences (48). Due to the fatiguing nature of collisions, it is important to find a balance between the minimum number of skill involvements required to improve a specific skill (e.g. a tackle) and the maximum number of skill involvements that can be tolerated before injury risk is unnecessarily increased (41,49).

Commercially available microtechnology devices are becoming an increasingly popular way to determine the physiological demands of team sports. Many devices contain GPS tracking, allowing researchers and sport scientists to determine the running-based demands of the game (13). However, these devices also contain tri-axial microsensors (i.e. accelerometers, magnetometers and gyroscopes), which potentially provide an opportunity to evaluate other characteristics of a player's workload. Accelerometers are devices that measure acceleration and, hence, can be used to measure overall activity and various aspects of a player's motion. Magnetometers measure the direction, strength and relative change of magnetic fields and provide information about direction of travel, while gyroscopes measure angular velocity. Collectively, these devices facilitate real-time detailed movement analysis and potentially provide additional insight into player workload without the need for labourintensive video coding. For example, some sporting microtechnology companies have attempted to describe the "workload" exerted by an athlete by quantifying the sum of the individual tri-axial accelerometer vectors. Such measures of player workload are marketed under different names by different manufacturers, with the term 'Player Load' used by Catapult Sports (Melbourne, Victoria,), 'Body Load' used by GPSports Systems (Canberra, Australian Capital Territory, Australia), and 'Dynamic Stress Load' used by STATSports (Newry, Northern Ireland) (33,50,51). This growing body

of literature seems to demonstrate the capabilities of microtechnology to automatically detect sport-specific movements in a variety of individual and team sports. Nevertheless, the field would likely benefit from a systematic review that synthesises the available evidence and provides clarity on the extent to which wearable microsensor data are being used to support the sports science discipline.

Specifically designed algorithms that utilise microtechnology data have been used to automatically detect tackle events during match-play and training in contact-based sports, such as Rugby League (41). However, more recent research has demonstrated that such algorithms are highly specific to the sport for which they have been developed and, hence, have relatively poor transferability to other contact sports (52-54). To date, few studies have investigated the collision demands of Rugby Union and there are currently no validated algorithms that use commercially available microtechnology devices to quantify the contact demands of this sport. In a single study that sought to quantify the number of tackles performed by Rugby Union players using microtechnology data (42), it was shown that tackles were distinguished by a peak in the acceleration data recorded by the player-worn sensor. However, despite these encouraging findings, the researchers reported similar acceleration peaks for other contact and non-contact events experienced by the players during match-play and concluded that the algorithm's performance may have been improved if data from the gyroscope and/or magnetometer had been used (42,50,51). By making better use of the various data sources provided by modern-day wearable microsensors, it may be feasible to develop collision-detection algorithms that are specific to Rugby Union and provide both valid and reliable outcomes.

### **Chapter 3: General Aims and Hypotheses**

Although research has detailed the locomotor demands of elite Rugby Union, there is an absence of research accurately quantifying the collision-based demands of this sport. Within the existing literature, there are studies that have attempted to use microsensor data to quantify the frequency of tackle events in Rugby Union; however, the resulting algorithms grossly over-estimated the number of collisions and were not capable of discriminating the four types of collisions that are common to the sport. A limitation of not being able to discriminate between collision types is that it is assumed all events pose an equal physiological demand on players. Furthermore, during match-play, some collision types (e.g. scrums) are only experienced by players who are part of a specific sub-group (i.e. forwards), while others apply more universally to the athletes. Given these points, it was deemed to be beneficial to develop a specific algorithm for the collisions involving only a subset of players (i.e. scrums) and a separate algorithm to evaluate the collisions experienced by all players in Rugby Union (e.g. tackles, rucks) (52). Based on the work completed in other sports (Rugby League, cricket, swimming), it is evident that microsensors and microsensor-based algorithms could be used to automatically detect and discriminate collision types in Rugby Union.

The proposed program of research provides a unique opportunity to investigate potentially new applications for the data derived from player-worn microsensors and to further explore any likely limitations of using this technology to detect sport-specific events in Rugby Union. The four inter-related studies outlined in this thesis (Figure 3.1) broadly aimed to:

- (i) Synthesise the available evidence to better understand the ways in which microsensor-based data have been applied to algorithms to detect sportspecific movements (*Study 1*).
- (ii) Develop and validate an algorithm for automatically detecting scrum events in Rugby Union match-play and training using player-worn microsensor data (*Study 2*).
- (iii) Develop and validate an algorithm for automatically detecting ruck events and one-on-one tackles in Rugby Union match-play using player-worn microsensor data (*Study 3*).
- (iv) Describe the differences between winning and losing teams in elite Rugby Union with respect to the locomotor and collision-based demands of matchplay using microsensor data and the algorithms developed in Studies 2 and 3 (*Study 4*).

### Study 1

• The use of wearable microsensors to quantify sport-specific movements: A systematic review

#### Study 2

• Validity of a microsensor-based algorithm for detecting scrum events in Rugby Union

### Study 3

•Automatic detection of one-on-one tackles and ruck events using microtechnology in Rugby Union

## Study 4

•Microtechnology-based locomotor and collision profiles of winning and losing elite Rugby Union teams

Figure 3.1: Summary of the program of research

It was hypothesised that wearable microsensor data will have been used in previous literature to develop and validate movement prediction algorithms and to quantify and monitor movement in a wide variety of individual and team-based sports (Aim 1). Given this point, it was further hypothesised that it would be possible to develop and validate (Aims 2 and 3) collision-detecting algorithms that could be successfully applied to monitoring workloads in elite Rugby Union (Aim 4). By creating more robust and validated player and game profiles, the findings of this research will significantly advance the methods used by coaches, sports scientists and sports medicine practitioners to monitor player loads and injury risk. In turn, these improved methods will benefit the athletes, by facilitating the provision of more targeted and individualised training programs that will not only improve their performance, but also enhance their overall welfare. Although this research focuses on these attributes in an elite playing population, the results will also be of benefit to athletes playing at the developmental levels of the game.

# Chapter 4: The Use of Wearable Microsensors to Quantify Sport-Specific Movements: A Systematic Review

This study has been published following peer-review in Sports Medicine and the full reference details of the manuscript are:

Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine*. 2015 Jul 1;45(7):1065-81.

Given the rapidly growing use of wearable microsensors in the applied sports science field, there is an obvious need to synthesise the existing literature to better understand the current applications for microsensors in applied sports and to identify potential future applications for this equipment. For these reasons, a systematic review was considered necessary to establish the extent to which wearable microsensors have been used to quantify sporting movements, to highlight their potential pitfalls, and to determine their potential utility for other applications, such as collision detection in Rugby Union. The outcomes of this review are presented in this section and provide a summary of the literature that ultimately helps to identify those areas that require further attention to move this field of research forward.

## **4.1 Introduction**

The use of global positioning system (GPS) devices has become an integral part of sporting performance analysis, allowing coaches and support staff to understand the physical demands on team sport athletes. Commercially available microtechnology units have been used extensively to describe the physical movement demands of Rugby Union (7), Rugby League (55), Australian Rules football (34,56) and several other team sports (13). Such studies have described the distance, intensity and frequency of various match-play demands; this information is subsequently used to assist in the physical preparation of athletes and the prevention of negative consequences that might be associated with excessive or inappropriate training loads (57). Most commercially available microtechnology units contain microsensors that include the use of accelerometers, gyroscopes and magnetometers with some commercially available inertial measurement units (IMUs), such as microelectromechanical sensors (MEMS) containing one or a combination of these sensors. Most commercially available GPS devices now contain IMUs, which are housed in a small case then worn in a small purpose-built pocket or strapped to the athlete during training and competition. These devices, commonly referred to as wearable sensors, facilitate real-time detailed movement analysis and provide an alternative to labour-intensive video coding (7,13,24). As previously noted, many researchers have used GPS to quantify the physical demands of sport (13) with some also using accelerometers to identify activity profiles (32,33,36,37), although few have used this technology to identify sport-specific movements. Recent research has utilised this technology to assess running gait (31) and other continuous movements, but such movements are not sport-specific.

Several studies have described the use of accelerometers to detect the physical activities and movement patterns of the general population (58). Other types of accelerometers, such as actigraph technology have been used to detect movement and sleep patterns of the general population, by assessing the displacement of the accelerometer to determine stages of sleep and daily activity (59). Given that sensors can have a sample rate of up to 500 Hz (32,33,36,37,51) and can measure occurrence and magnitude of movement in three dimensions (anterior-posterior, medial-lateral and vertical) (33), such IMUs have been applied in elite sporting populations to further understand movement demands, particularly in indoor sports, where GPS signal is unavailable.

Some sporting microtechnology companies have attempted to describe the "workload" exerted by the athlete by quantifying the sum of the individual tri-axial accelerometer vectors. Various "workload" terminologies exist in these commercially available software programs, including 'Player Load' (Catapult Sports, Melbourne, Victoria,) and 'Body Load' (GPSports Systems, Canberra, Australian Capital Territory, Australia). The 'Player Load' that is calculated using the Catapult Sports equipment is an arbitrary unit defined as an 'instantaneous rate of change of acceleration divided by a scaling factor' (see Equation 1.1, p.25) utilising the highly responsive accelerometers within the three planes of movement to quantify movement intensity (33). Similarly, the 'Body Load' measure, as implemented by GPSports Systems is described as an 'arbitrary measure of the total external mechanical stress as a result of accelerations, decelerations, changes of direction and impacts' (51) and is calculated from the square root of the sum of the squared instantaneous rate of change in acceleration in the vertical, anterior-posterior and medial-lateral vectors. Athlete demands can be quantified by the aforementioned workload terminologies by applying formulas to

inertial data (33), providing a different perspective to that of other technologies such as GPS (13).

Physical activity has been measured by MinimaxX units (Catapult Sports, Melbourne, Victoria, Australia) using 'Player Load' to describe the physical demands of sports such as Australian Rules football (33,34), Basketball (32), and Netball (36,37). Boyd et al. (33) found that the accelerometers offered good reliability in quantifying the low and high intensity components of Australian Rules football activity and that the technology could be confidently applied to assess changes over multiple time periods or to assess differences between players. Boyd et al. (33) also found strong relationships between MinimaxX devices (r=0.996-0.999) for high intensity activity, although it was acknowledged that current practice fails to account for skill-based and contact-based activities (passing, jumping, kicking, marking, tackling and blocking). These findings indicate that the overall physical activity of Australian Rules football players may be underestimated, highlighting the potential for these devices to quantify additional movements other than locomotion.

Similarly, Rugby League researchers have quantified the relationship between measures of internal (heart rate and perceived exertion) and external (high-speed distance, 'Body Load' and impacts) loads associated with training (51). The authors found that the internal and external load measurements provided useful methods of quantifying various training modalities, with impacts and 'Body Load' contributing the highest loadings for skill sessions. However, it was also stated that further investigation was required to examine the derived measures of 'Body Load' and impacts using GPSports microsensors, as training demands may be underestimated using current methods.

Microsensors have the capability to automatically detect various movements and intensities (47). Bonomi and colleagues found that activities ranging from lying, sitting, standing, dynamic standing, cycling, walking and running could be detected using algorithms and decision trees (47). Using data from a tri-axial accelerometer, activities were categorised by the dominance in intensity of accelerations occurring along a particular axis. For example, accelerations that were predominantly medial-laterally directed were primarily used to categorise lying, sitting and standing. Intensity was also categorised by quantifying the speed of movement and the resultant accelerometer traces that were produced.

Accelerometers have also been used to assess movements such as jumping, with research (60) demonstrating the validity of this technology against a Myotest force platform (Myotest SA, Sion, Valais, Switzerland). The accuracy of the accelerometers was measured against the force platform with participants wearing a microsensor on their hip and measuring vertical force and power as well as leg stiffness and the reactivity index. Results of a five hop protocol, countermovement jump and squat jump demonstrated a high degree of reliability for the accelerometer system in comparison to the force platform (coefficient of variation <10%) (60).

Specific skill-based activities and movements can distinguish the physical demands of one sport from another. Currently there are relatively few studies that have assessed the reliability and validity of inertial sensor technology for detecting and assessing

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sport-specific skills. To date, current research (13) has demonstrated that it is feasible to use microsensors to quantify work rate patterns and metabolic differences between athletes. However, this research has been heavily dependent on the use of wearable GPS devices to evaluate the locomotor demands associated with specific contact and noncontact sports (see Cummins et al. (13) for a review). Given that a large number of sports include physically-demanding activities that involve few locomotor demands (e.g. volleyball jumping, Rugby Union tackling, and soccer goalkeeping), it is likely that research that has focussed solely on characterising the locomotor demands of team sport has underestimated the 'true' physical demands of the sport (13). As such, sport scientists now employ wearable sensors to identify sport-specific movements and activities in an effort to better evaluate the demands of a sport and to assist with physical preparation, injury prevention, and technical analysis of these activities. The aim of this review was to provide an overview of the use of microsensor technology, such as accelerometers, gyroscopes and magnetometers to detect non-locomotor activities that are specific to a particular sport.

### 4.2 Methods

### 4.2.1 Literature Search Strategy

This review investigates the use of microsensors to identify sport-specific movements. Articles for this review were systematically identified through the search of electronic academic databases that included Academic Search Complete, CINAHL, PsycINFO, PubMed, SPORTDiscus and Web of Science. These databases were searched using the combinations of the following key words: (i) 'accelerometer'; 'inertial'; 'sensor'; 'measurement unit'; 'IMU'; 'microsensor'; 'gyroscope'; 'wearable'; (ii) 'event'; 'movement'; 'detection'; 'specific'; 'analysis'; (iii) 'sport'; 'athletes'; 'game'; 'match'. Terms were connected with 'OR' within each of the three combination groups and these three search categories were combined using 'AND'. The search was restricted to fulllength articles written in English, published after 2008 and articles included were limited to those where search terms were included in the title or abstract.



Figure 4.1 Flowchart of the selection process for inclusion of articles in the systematic review

# 4.2.2 Selection Criteria

The process used for selecting articles is outlined in Figure 4.1 Duplicate articles were eliminated from the initial search results and the titles and abstracts of remaining articles were then independently reviewed by three assessors (RC, TJG and MHC) for relevance to the review. For the purpose of the review, articles included were required to have used wearable sensors to detect and assess a skill or movement that was specific to a sport (e.g. throwing, tackling, tennis strokes). As such, articles that attempted to categorise activity (e.g. running intensities) of athletes using microsensors or that solely attached microsensors to equipment were excluded. Other criteria for exclusion from

this research consisted of review articles, abstracts and studies that used accelerometers to assess movements that are generic to many activities (e.g. running gait). Any disagreements between the three independent reviewers were discussed and resolved. Once articles were selected, the complete manuscript was assessed for inclusion using the same criteria. The references of the selected articles were then scanned to detect any potentially relevant articles not identified by the original search.

# 4.3 Results

A total of 2,395 studies were initially retrieved from the six databases, of which 441 were duplicates, 293 were conference abstracts and three were review articles, leaving 1,658 unique research articles. After screening the titles and abstracts of these papers, 1,611 were excluded and 47 remained for full-text review. After full-text review, a further 19 were removed (Figure 4.1). Therefore, 28 articles remained for inclusion in this review. Eight articles addressed the use of microsensors in individual sports (61-68) including tennis (n=2), track and field (n=2), golf (n=2) trampolining (n=1) and weightlifting (n=1) (Table 4.1). Seven articles addressed the use of microsensors in team sports (40-42,53,54,69,70), which incorporated baseball (n=2), Australian Rules football (n=2), Rugby League (n=1), Rugby Union (n=1) and cricket (n=1) (Table 4.2). Eight used microsensors in water sports (71-78), reporting on detection of various technical elements of swimming (Table 4.3) and five used microsensors in snow sports (79-83) involving ski jumping (n=2), alpine skiing (n=1), snowboarding (n=1) and cross country skiing (n=1) (Table 4.4). The manufacturer of microsensors differed between studies although 'MinimaxX' device was the most common (n=7) followed by the 'Physilog inertial measurement unit' (BioAGM, La Tour de Peilz, Vaud, Switzerland) (n=5). Studies used microsensors either to detect sport-specific movements (n=19), analyse sport-specific movement (n=8) or detect and analyse movement (n=1). Sampling frequencies of the devices used ranged from 30 Hz to 500 Hz, although some articles did not report the type or sampling frequency of the sensors used (65,69,78). Articles varied with respect to the number and type of sensors used, although the selection of the equipment for each study was specific to the research question being addressed and the movement being analysed.

Study	Sport and sport- specific movement	Sample	Microsensor used	Method	Findings
Adelsberger	Weightlifting,	Sixteen athletes	ETHOS IMU (Zurich,	Each athlete equipped with three	Algorithm designed to classify
and Tröster	"thruster"	participated (four female	Zurich, Switzerland)	sensor devices: left ankle, lower	"thruster" movements. System
(61)	movement	and twelve male),		back and left wrist. Athletes	found to have an accuracy of 94%
		experience levels were		performed three sets of "thruster"	when differentiating experts and
		assigned and ranged		movements, first two sets at a	beginners based on 2 IMUs (ankle
		from beginner to expert		freely chosen weight, the final set	excluded) and individual instances
				consisted of three repetitions of	defined with above 93% accuracy.
				maximum weight. Final set used	
				to provide some data for	
				exhaustion detection.	
Ahmadi et al.	Tennis, serve	Four right handed, male	ADXRS300 Inertial	Players performed 30 successful	Significant correlation between
(62)		tennis players (one	Sensor (Kionix,	slow motion serves in a	inertial sensor and marker-based
		amateur, two sub-elite	Brisbane, Queensland,	controlled environment wearing	data for serve trends. Only slow-
		and one elite)	Australia)	microsensors located on chest,	motion serves were used as

Table 4.1 Summary of results from studies investigating sport-specific movements using wearable sensors within individual sports.

	[		upper arm and hand to identify	microtechnology used could not
			rotation and flexion. Also wore	provide feedback on power serves.
			marker-based technology	
			(Vicon).	
Tennis,	Eight tennis players	TennisSense, Wireless	Single sensor place on player's	Wireless IMU was able to
classification of	(three advanced players,	IMU - based on	dominant forearm during a game	recognise tennis stroke
strokes	three intermediate and	Tyndall's 25mm Mote	in order to register spike in	performance with 90% accuracy
	two novice)	Platform (Cork,	accelerometer data due to ball	when using information from all 3
		Munster, Ireland)	impact. Stroke classified as	sensors (accelerometers,
			serves, backhands or forehands.	gyroscopes & magnetometers).
			Accelerometer data above 3g	Accuracy rate was 10% higher
			were classed as tennis stroke	than that of accelerometer, which
			events, below 3g were classified	contributed highest single sensor
			as non-stroke events. Stroke	classification.
			recognition was trained on 7	
	Tennis, classification of strokes	Tennis, Eight tennis players classification of (three advanced players, strokes three intermediate and two novice)	Tennis, Eight tennis players TennisSense, Wireless   classification of (three advanced players, IMU - based on   strokes three intermediate and Tyndall's 25mm Mote   two novice) Platform (Cork,   Munster, Ireland) Munster, Ireland)	upper arm and hand to identify rotation and flexion. Also wore marker-based technology (Vicon).Tennis,Eight tennis playersTennisSense, WirelessSingle sensor place on player's dominant forearm during a game in order to register spike in accelerometer data due to ball impact. Stroke classified as serves, backhands or forehands. Accelerometer data above 3g were classed as tennis stroke events, below 3g were classified as non-stroke events. Stroke recognition was trained on 7

				players and then tested on an	
				unseen player.	
Ganter et al.	Track and field,	One male sports student	MTx (Xsens,	Athlete performed three discus	Body angles and velocities of 22
(64)	discus throw	(former decathlete)	Enschede, Twents,	throws (indoors; 1kg discus)	joints analysed, with movement
			Netherlands)	whilst wearing suit comprising	broken down into 6 critical phases.
				17 inertial sensor units and two	Demonstrated capability of
				transmission units. All throws	kinematic analysis using full body
				filmed in high speed. All data	inertial measurement system
				from inertial sensors were	emphasising potential of approach
				exported for further processing	when analysing other complex
				using MATLAB.	movements.
Ghasemzadeh	Golf, golf swing	Three male subjects, one	Microtechnology not	Five sensors used, three located	Body sensor networks
et al. (65)		female	reported	on each subject (right wrist, left	demonstrated application to a
				arm and lower back) other two	quantitative feedback model.
				located on golf club (club head	Results provided good reliability
				and grip). Subjects performed 10	of model with respect to angle of

		[		golf swings, addressing the ball	wrist rotation when sensors
				with varying degrees of wrist	sampled above 30 Hz. The overall
				rotation. Each trial divided into	value of absolute mean error was
				four segments (take-away,	reported as 9.2, 7.7, 6.6 and 6.5
				backswing, downswing, follow-	degrees for take away, back swing,
				through) and processed using	down swing and follow through
				five-point average moving filter	respectively which introduces an
				to remove effect of noise. 50% of	average error of less than 10
				trials were used to build	degrees for all segments.
				quantitative model, 50% were	
				used to evaluate model.	
Helten et al.	Trampoline, jump	Four female non-	MTx (Xsens,	Seven inertial microsensors worn	Microsensors provided automatic
(66)	classification	professional athletes	Enschede, Twents,	on trunk, forearms, upper legs	segmentation and classification of
		with intermediate skills	Netherlands)	and lower legs. Athletes	jumps. Used (1) inclination of a
				performed eight predefined	limb, (2) the enclosed angle
				routines and 2 self-selected	between limbs and (3) the angular

	[	[		routines with each routine	velocity of sensors. Algorithms
				performed two to three times.	developed to assist in the
					automatic segmentation of
					movements.
Lai et al. (68)	Golf, golf swing	10 golfers (six beginners	MTx (Xsens,	Four inertial sensors were	Results showed that inertial data of
		and 4 skilled low	Enschede, Twents,	attached to the swing lead hand,	low-handicapped golfers achieved
		handicap golfers)	Netherlands)	swing lead arm, pelvis and upper	higher mean peak acceleration
				back of each subject. Players	energy and also achieved higher
				performed 10 successful drives	accuracy than that of the
				towards a net. A successful trial	beginners. In all 10 trials, the
				was recorded when the ball hit	professional group showed less
				the net, a miss trial was recorded	variation in peak acceleration.
				otherwise. Trials were	Inertial sensor data can be
				segmented into back swing,	successfully used to differentiate
				down swing and follow-through	swing patterns between low-
				during pre-processing phase.	handicap golfers and beginners.

Lee et al. (67)	Race walking,	Seven race walkers (five	MTx (Xsens, Enschede,	Single inertial sensor placed	High-speed footage compared
	walking technique	male and two female)	Twents, Netherlands)	directly on skin over sacral	with the sensor-captured data on
				vertebra. Each athlete performed	the same steps. 300 total gait
				four trials of three walking	events were tested (i.e. 50 heel
				styles: (a) walking legally at	strikes and 50 toe offs) and
				submaximal pace; (b) walking	repeated three times. The inertial
				illegally at submaximal pace and	sensor was 91% accurate. Seven
				(c) walking legally at maximal	incorrectly identified steps
				pace. Analysis of high-speed	occurred with a time change less
				camera footage was performed.	than human eye detection.

IMU – Inertial measurement unit

MEMS – Microelectromechanical sensors

Study	Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Ghasemzadeh	Baseball, baseball	Three male subjects, no	Microtechnology not	Three sensor nodes placed on	Inertial node data was shown to
and Jafari (69)	bat swing	previous swing training	reported	subjects' chest, right wrist and	have the capability to provide
				hip and asked to execute 20	feedback on coordination of
				baseball swings with varying	segmented areas. Inertial
				timing and sequences of	coordination data correlated
				identified key events (hip	positively with that of video data.
				rotation, shoulder rotation and	
				arm extension). Raw sensor	
				readings passed through five-	
				point moving average filter to	
				reduce effect of high frequency.	
				Twenty-two good swing trials	
				were used to train system, thirty-	
				eight trials (22 good trials, 16	

Table 4.2 Summary of results from studies investigating sport-specific movements using wearable sensors within team sports.

				improper trials) were used for	
				validation. Data contributed to	
				designing and validation of an	
				algorithm for analysing the	
				baseball swing technique.	
Gabbett et al.	Rugby League,	Thirty male professional	MinimaxX S4	Units worn in a small vest on the	MinimaxX units found to
(41)	tackle	Rugby League players	(Catapult Sports,	upper back of participants.	provide a valid method of
			Melbourne, Victoria,	Collision events from 21 training	quantifying collision load.
			Australia)	appearances and one trial match	Strong correlation between video
				filmed and coded. To detect	coded data and unit automated
				collision unit was required to be	detection of mild (r=0.89),
				in non-vertical position and	moderate (r=0.97) and heavy
				require a spike in player load.	(r=0.99) contacts.
				Collisions were classified as	
				mild, moderate and heavy.	

Gastin et al. (53)	Australian Rules	Twenty professional	MinimaxX S4	MinimaxX units worn in playing	Total of 352 tackles recorded
	football, tackle	male Australian Rules	(Catapult Sports,	jersey located on upper back.	comprising 173 made and 179
		football players (four	Melbourne, Victoria,	Data relating to tackle events	against. Majority of tackles were
		defenders, five forwards	Australia)	from 4 AFL matches in 2011	medium intensity (61%) only 6%
		and eleven midfielders)		season. Tackles made by a player	were high intensity. Significant
				or when tackled by an opponent	difference found between the
				were coded from video footage.	three tackle intensities for peak
				Tackles were classified as low,	velocity and all accelerometer
				medium or high intensity based	variables. Suggests ecological
				on criteria that considered an	validity of tri-axial
				observed speed and impact.	accelerometers to assess impact
					forces in tackles.
Gastin et al. (54)	Australian Rules	Twenty elite male	MinimaxX S4	Cross-validation approach used	78% of tackles were correctly
	football, tackle	Australian Rules	(Catapult Sports,	to evaluate the effectiveness of	detected. Tackles against were
		football players	Melbourne, Victoria,	MinimaxX in detection of tackle	more accurately detected (90%)
			Australia)	and collision impact events. Unit	than tackles made (66%). 77

			worn in pocket located in playing	tackles were not detected;
			jersey. Unit worn in four AFL	majority of these (74%) were
			games during 2011 season.	classified as low intensity.
			Tackles made by a player or	
			when tackled by an opponent	MinimaxX versus observed play
			were automatically detected	event showed detection of 1578
			using commercially available	events in the four matches. Of the
			software and coded from video	1510 events (68 not captured on
			footage. Instances were then	video) only 18% were verified as
			matched with MinimaxX data to	tackles, the other 82% were
			determine if a "tackle" event had	incorrectly identified. Fifty-
			occurred. Allowed assessment of	seven percent of these were from
			true positive, true negative, false	contested ball situations. Of the
			positive and false negative tackle	1510 events, 385 (25%) detected
			events.	events where no contact was
				evident.
1	1	1	1	

Koda et al. (70)	Baseball, throwing	Five male volunteers	ADXL193 (Analog	Two sensors mounted on	Body mounted sensor indicate
		(two of whom were	Devices, Norwood,	subjects (forearm and upper arm)	use to analyse motion of arm
		former professional	USA), ADXL320	who were asked to perform	swing, flexion/extension of
		baseball players)	(Analog Devices,	pitching motion several times	elbow and hanging of arm during
			Norwood,	each. All trials analysed using	pitching motion. Data used to
			Massachusetts, USA)	Vicon systems.	estimate trajectories of throws
			(both accelerometers);		and show agreement from
			Murata ENC03M		position measured from Vicon,
			(Nagaokakyo, Kyoto,		although it was suggested that
			Japan), Microstone		body acceleration had possibility
			MG3-01Ab (Nagano,		to cause error.
			Nagano, Japan) (both		
			gyroscopes)		
Kelly et al. (42)	Rugby Union,	Seven elite Rugby	SPI Pro (GPSports	Device worn in purpose-built	Automatically detected
	collision	Union players game data	Systems, Canberra,	harness located between	collisions were compared to
		used for testing models.		shoulder blades. Indicators	manually labelled collisions and

Four players assisted	Australian Capital	drawn from changes in temporal	a set of performance measures
creation of classifiers of	Territory, Australia)	pattern and individual	classified using true and false
tackle and non-tackle		acceleration planes spanning	positives and true and false
during training.		from before to after the collision.	negatives. Precision and recall
		Other features included impact	analysis of results was also used.
		peaks in accelerometry signals.	Learning grid method provided
		Artificial learning models used.	greatest number of true positives
		Analysed 4 models to detect	with strong precision and recall
		contact: learning grid, support	scores, with static window
		vector machine (static window),	features providing low precision
		support vector machine (impact	and recall scores.
		region) and hidden conditional	
		random field. Models were	
		selected to learn the relationship	
		between source and target data.	

McNamara et al.	Cricket, fast	Twelve highly-skilled	MinimaxX S4	Participants were asked to	Results from this study proved
(40)	bowling	bowlers, ten	(Catapult Sports,	execute normal bowling training	the unit used accurately detected
		professionals (two	Melbourne, Victoria,	to a batter in a net situation, and	fast bowling events using the
		international, eight first	Australia)	then perform a series of non-	algorithm. The unit provided
		class) and two in first		bowling events such as run	very strong sensitivity for
		grade competition.		throughs ending in a single	counting bowling events in
				bound and run through with a	training (99.0%) and competition
				return throw whilst wearing a	(95.0%) using elite fast bowlers.
				microtechnology unit in a small	The unit was also able to detect
				vest located on their upper back.	non-bowling events, although
				Competition events were also	better performance was observed
				recorded using five bowlers. The	in training (98.1%) as opposed to
				aim of the study was to develop	competition (74.0%).
				an algorithm to automatically	
				detect fast bowling events.	

- AFL Australian Football League
- GPS Global positioning system
- IMU Inertial measurement unit
- MEMS Microelectromechanical sensors

Study	Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Beanland et al.	Swimming, stroke	Twenty-one high level	MinimaxX S4 (Catapult	Criterion validation study.	Strong correlations between
(71)	count of butterfly	participants (12 males	Sports, Melbourne,	Swimmers completed three 100	stroke count observed on video
	and breaststroke	and nine females)	Victoria, Australia)	metre efforts in outdoor pool	and data gathered from the unit
				wearing GPS device with	(r>0.99 for butterfly; r>0.98 for
				integrated triaxial	breaststroke). Acceleration data
				accelerometer located on the	provided clear pattern of
				head to obtain mid-pool	undulatory and cyclical
				velocity and stroke count.	mechanics of breaststroke and
				Video footage of each effort	butterfly body position.
				was captured allowing velocity	
				and stroke count to be obtained.	
Dadashi et al.	Swimming, front	Eleven elite swimmers	Physilog IMU	Each swimmer equipped with a	Variability assessment showed
(72)	crawl	(six male, 5 female) and	(BioAGM, La Tour-de-	single inertial sensor located on	the range of velocity between
		nineteen recreational		sacrum. SpeedRT was attached	

Table 4.3 Summary of results from studies investigating sport-specific movements using wearable measurement sensors within water sports.

		swimmers (twelve male,	Peilz, Vaud,	to waist of swimmers just	inertial sensor and SpeedRT was
		seven female)	Switzerland)	beneath lower end of the	less than 3.9%.
				sensor. Swimmers completed	
				consecutive twenty-five metre	
				trials increasing in velocity	
				from 70% to 100%.	
Dadashi et al.	Swimming, front	Seven well-trained	Physilog IMU	Waterproof units placed on	Adaptive change algorithm
(73)	crawl	national level swimmers	(BioAGM, La Tour-de-	both forearms and sacrum of	applied to inertial signals to
		(5 male and 2 female)	Peilz, Vaud,	swimmer whilst performing	detect phases of arm stroke using
			Switzerland)	three 300 m trials. Verbal	peak of angular velocity curve.
				instructions given during trial	Study validated algorithms
				(e.g. glide more or less) in order	providing automated feedback of
				to perform each trial under	stroke.
				different co-ordination mode to	
				test system in broad range of	
				coordination. Swim speed was	

				controlled using Aquapacer.	
				All trials filmed underwater	
				from 2 angles.	
Fulton et al. (74)	Swimming,	Twelve Paralympic	MiniTraqua (version 5,	Sensors worn on the thighs of	Using an algorithm to detect
	freestyle	swimmers (eight males	Australian Institute of	participants. Swimmers	swimming movements, strong
		and four females)	Sport, Canberra,	performed a maximal-effort	correlations of 0.96 for
			Australian Capital	100m freestyle swim time-trial	swimming trials and 1.00 for
			Territory, Australia)	and a 100m kicking only time-	kicking only trials were found
				trial within 24 hours of each	between video and microsensor.
				other. All trials were filmed	Gyroscope traces of troughs
				underwater from one angle.	allowed for semi-automated
					analysis of trials. Standard error
					of kick count validity was found
					to be higher in swimming trials
					(coefficient of variation 5.9%)

					than in kicking only trials (coefficient of variation 0.6%).
Fulton et al. (75)	Swimming,	Fourteen Paralympic	Single inertial system	Sensors were worn on the calf	Small to moderate decreases in
	freestyle	swimmers (eight males	containing triaxial	of the dominant leg to quantify	kick rate were associated with
		and six females)	accelerometer and	kick-count and kick-rate.	reductions of swimming speed.
			gyroscope.	Swimmers performed 100m	Sensor identified kick-rate
				freestyle swimming and 100m	differences and temporal pattern
				kicking only time-trials.	changes between the 2 trials.
James et al. (76)	Swimming, front	Female triathlete	MEMS triaxial	Three accelerometers were	Data analysed using MATLAB
	crawl		accelerometers, MEMS	placed on forearm, lower back	(Massachusetts, USA). Primarily
			pitch, yaw and roll	and lower leg. Participant	used accelerometer data from
			gyroscopes.	completed three; two lap trials	medial-lateral axis for event
				at two race pace settings: 400m	identification of movements.
				and 100m, respectively.	Results reported distinct
					classification of hand entry,
					glide, catch and recovery phases

					of front crawl from
					accelerometer trace. Spikes from
					the trace results made lap data
					identifiable allowing for
					potential future ability for
					automatic detection.
Jensen et al.	Swimming, stroke	12 German 2 <sup>nd</sup> league	SHIMMER sensor	Sensor node placed on the	Demonstrated a high accuracy of
(77)	classification and	swimmers (five female,	platform (Dublin,	occiput of subject underneath	turn events and swimming styles
	turn detection	seven male)	Leinster, Ireland)	swimming cap. Subjects were	with a head worn kinematic
				required to swim 200 metre	sensor. Swimming style
				medleys within 80% of their	classification returned results of
				best time. Pattern recognition	95%. Misclassifications were
				methods used for turning and	registered for the butterfly and
				swimming style detection.	breaststroke swimming styles.
					Turn detection had an overall
					classification rate of 99.8%;
					algorithm detected a single
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					misclassified turn.
Stamm et al.	Swimming, push-	Seven male swimmers	Microtechnology not	Sensor was taped to lower back	Raw acceleration data converted
(78)	off		reported	of swimmers along with	into gravitational units. Near
				SP5000 tether. Each swimmer	perfect correlation (r=0.94)
				used their feet to push-off, and	between tether and sensor
				once in the glide position,	derived velocity. Single inertial
				remained in the same relative	sensor offered a valid
				body position until out of	measurement method of push-off
				breath or no longer moving	velocity.
				forward. Twelve total	
				repetitions were performed at	
				three effort levels (slow,	
				medium and fast).	

GPS – Global positioning system

IMU – Inertial measurement unit

MEMS – Microelectromechanical sensor

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Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Alpine skiing,	Six alpine skiers (three	Physilog IMU	Each skier wore four wireless	Wearable system presented
comparison of	professional instructors,	(BioAGM, La Tour-de-	inertial modules located on	knee angle measurements and
cross-over and	three experienced skiers)	Peilz, Vaud,	middle length of thighs and	robust detection of events
cross-under turns.		Switzerland)	behind ski boots. Each skier	based on 3D acceleration and
			performed two cross-over and	3D angular velocity. System
			two cross-under techniques in a	showed high sensitivity
			regular slope in their own skis.	regarding timing periods and
			Each run was recorded by video	allowed identification of
			camera and synchronised.	parameters for intra-turn and
				the whole run.
Ski jumping,	Thirteen young ski	Physilog inertial	Each skier wore four IMU	Could identify temporal
identify temporal	jumpers from national ski	measurement unit	devices attached to thigh and	patterns of ski jumping phases
patterns of in-run,	junior team (five athletes	(BioAGM, La Tour-de-	shank of both legs. Indoor	using an inertial-based system.
take-off, early			validation of different jumping	Relative system precision was
	Sport and sport specific movement Alpine skiing, comparison of cross-over and cross-under turns. Ski jumping, identify temporal patterns of in-run, take-off, early	Sport and sportSamplespecific movementSampleAlpine skiing,Six alpine skiers (threecomparison ofprofessional instructors,cross-over andthree experienced skiers)cross-under turns	Sport and sport specific movementSampleMicrosensor usedAlpine skiing,Six alpine skiers (threePhysilog IMUcomparison ofprofessional instructors,(BioAGM, La Tour-de-cross-over andthree experienced skiers)Peilz, Vaud,cross-under turns.Switzerland)Switzerland)Ski jumping,Thirteen young skiPhysilog inertialidentify temporaljumpers from national skimeasurement unitpatterns of in-run,junior team (five athletes(BioAGM, La Tour-de-	Sport and sport specific movementSampleMicrosensor usedMethodAlpine skiing,Six alpine skiers (threePhysilog IMUEach skier wore four wirelesscomparison ofprofessional instructors,(BioAGM, La Tour-de-inertial modules located oncross-over andthree experienced skiers)Peilz, Vaud,middle length of thighs andcross-under turns.Switzerland)behind ski boots. Each skierperformed two cross-over andFrequenciesperformed two cross-over andtwo cross-under turns.FrequenciesFrequenciesSki jumping,Thirteen young skiPhysilog inertialEach skier wore four IMUidentify temporaljumpers from national skimeasurement unitdevices attached to thigh andpatterns of in-run,junior team (five athletes(BioAGM, La Tour-de-shank of both legs. Indoortake-off, earlyIIII

Table 4.4 Summary of results from studies investigating sport-specific movements using wearable sensors within snow sports.

	flight, stable flight	used for indoor validation	Peilz, Vaud,	techniques was required.	calculated at 7% for indoors
	and landing phases.	of jumping techniques)	Switzerland)	Athletes performed simulated	and less than 9% for outdoor
				jumps using 5 m ramp and a	conditions. System
				wheeled board. Forty jumps	automatically and precisely
				were recorded and analysed by	detected durations of three
				Vicon motion capture system.	movements within a ski jump.
					System proved to be robust
				For outdoor validation, thirteen	enough to accommodate
				athletes performed a maximum	differences in jumping
				of three jumps on a HS-77	durations between indoor and
				jumping hill. Video camera	outdoor conditions.
				captured all athletes and was	
				analysed using Dartfish.	
Chardonnens et	Ski jumping,	Thirty-three male athletes	Physilog inertial	Five IMUs were worn by	Demonstrated the ability of
al. (81)	Coordination of	of different performance	measurement unit	athletes located on thigh, and	IMU to assess inter-segment
	lower limbs and	level (twenty junior, nine	(BioAGM, La Tour-de-	shank-thigh segments	coordination of the shank-thigh
	I	1	1	1	l

	jump length	Continental Cup, four	Peilz, Vaud,	bilaterally and sacrum.	and thigh-sacrum pairs during
	performance	World-Cup) from Swiss	Switzerland)	Between one and three jumps	the take-off and extension in ski
		national ski jumping team		were recorded for each athlete	jumping using the CRP. IMU
				on HS-117 jumping hill. Data	data of CRP showed significant
				collected from total of 87	relationship of athletes
				jumps.	attaining longer jumps with
					those who had more symmetric
					movement of the thighs and
					sacrum.
Harding et al.	Snowboarding,	Ten athletes	MinimaxX S4 (Catapult	Sensor was situated	Mathematically-derived
(82)	aerial acrobatics		Sports, Melbourne,	approximately 5 cm to the left	algorithms used to
			Victoria, Australia)	of spine. Athletes wore unit	automatically detect air-time
				during training of 80 m half-	and air-angle to measure
				pipe runs. Video footage of	rotational magnitude of
				training was analysed using	acrobatic manoeuvres (180,
				Dartfish software. Data of 216	

				acrobatic manoeuvres was	360, 540, 720 or 900 degrees of
				collected.	rotation).
Marsland et al.	Cross country	Two groups of	MinimaxX S4 (Catapult	Participants wore single micro-	The microsensor was found to
(83)	skiing, movement	participants: international	Sports, Melbourne,	sensor unit and were filmed	be useful in identifying cyclical
	patterns and	group (three male, one	Victoria, Australia)	using a stationary camera from	movement patterns of major ski
	techniques	female) and Australian		side-on performing classified	techniques. A combination of
		group (three male, one		ski techniques. Skiers	inertial data enabled skiing
		female)		performed sessions lasting	actions such as kicking to be
				three to four minutes per athlete	clearly identified.
				and instructed to ski at	
				"moderate intensity slightly	
				faster than their normal easy	
				distance skiing pace."	

CRP – Continuous relative phase

IMU – Inertial measurement unit

MEMS – Microelectromechanical sensor

## 4.4 Discussion

The aim of this systematic review was to investigate published literature on microsensors and their ability to quantify and detect sport-specific movements. From the 28 studies identified, it was apparent that single or multiple sensors (i.e. combining accelerometers, gyroscopes and magnetometers) have the capacity to identify sport-specific movements in a variety of individual and team sports and can even be effectively utilised in the water or snow. The use of microsensors to detect sport-specific movements offers an exciting and innovative approach to performance analysis by improving practitioners' understanding of the physical and technical demands of sporting activities. Furthermore, accelerometers, gyroscopes and magnetometers have very high sensitivity allowing detection and analysis of movements that may not be easily identified by a coach.

# 4.4.1 The Use of Microsensors to Detect Movements in Individual Sports

Microsensors have had varied uses for detection of specific movements within individual sports. The use of IMUs in tennis has shown that these sensors are capable of detecting specific strokes during training and competition (62,63). Connaghan et al. (63) used TennisSense devices (based on Tyndall's 25mm Mote platform, Cork, Munster, Ireland) containing accelerometers, gyroscopes and magnetometers, placed on the arm to detect different strokes (serve, forehand and backhand) and non-stroke events. Accelerometer magnitude was used to determine a stroke event, while the addition of gyroscopes and magnetometers improved stroke detection to within 90% accuracy (the use of gyroscopes and magnetometers alone resulted in 88% accuracy of stroke detection). Although Connaghan et al. (63) discussed the use of accelerometer magnitude to identify strokes, no information was provided on the role the magnetometers and gyroscopes played within the stroke detection model. Ahmadi and colleagues (62) found a significant correlation between gyroscope sensors and markers positioned on the arm, hand and chest for detecting serving trends in tennis, accelerometers were located within the device used but it was not revealed as to why these sensors did not contribute to the research. However, as only slow motion serves (not game speed) were performed, it is unclear whether inertial sensors could accurately detect power serves. Ghasemzadeh et al. (65) provided a similar analysis by detecting wrist-rotation errors in golf using microsensors, although the specific nature of the devices used was not reported. Using five microsensors (three located on the participant and two on the club) that were sampling at 30 Hz, Ghasemzadeh et al. (65) created a model to provide feedback based on inertial detection of the different phases of the golf swing. Half the trials performed by the four subjects were used to create the model; the other half was used to test how well the model could detect the movement (i.e. the sensitivity of the model). The model could successfully determine wrist angle during the golf swing and provide feedback on the length of back swing, swing plane and club head speed, although the low sampling frequency of the microsensors may have impaired the detection accuracy of high-frequency events, such as ball impact. A limitation of this study, however, was that the playing ability of the participating subjects was unclear, and the framework used to identify the "correct" technique was also not reported.

Adelsberger and Tröster (61) conducted the only research in weightlifting using IMUs to detect completed 'thruster' movements and exhaustion, using three microsensors placed on the ankle, lower back and wrist (although the ankle data was subsequently deemed irrelevant and excluded). Using 75% of the data from the completed 'thruster'

movements, Adelsberger and Tröster (61) created an algorithm within a support vector machine to automatically detect successful 'thruster' movements. The remaining 25% of the trials were then used to test the algorithm's accuracy for detecting successful 'thruster' movements. The reliability of the detection algorithm was reported to be greater than 93%, which demonstrated the suitability of microsensors for detecting and assessing weightlifting movements, although the unused sensor at the ankle could have been relocated to another limb, potentially providing greater detection accuracy of movements.

Similarly, Lee et al. (67) used IMUs containing accelerometers, gyroscopes and magnetometers to detect legal and illegal movements in seven race walkers, positioning a single device on the lower back of participants. Compared to high-speed camera footage, the IMU devices were able to detect illegal walking technique in 91% of the gait cycle data collected, providing support for the use of microsensors to assist coaches and judges with providing feedback on performance. Nevertheless, despite the high detection accuracy demonstrated for race walkers, the speed of the walkers was not reported by the authors. As such, it is difficult to confirm the suitability of these devices during competition scenarios.

Helten et al. (66) advanced the use of sport-specific movement detection by using a series of seven MTx IMU devices (Xsens, Enschede, Twents, Netherlands), which incorporate accelerometers, gyroscopes and magnetometers to classify different trampoline jumps. Movements were automatically divided into segments based on the inclination of a limb, enclosed angles between limbs and the angular velocities of the sensors during the routines. Similarly, Ganter et al. (64) assessed a former decathlete

performing a discus throw using a suit that was fitted with 17 IMU devices. Synthesis of the data from the 17 independent devices allowed the authors to calculate kinematic variables, such as joint angles and velocities for 22 joints during the performance and detect phases of the throw solely using IMUs. Ganter et al. (64) suggested that IMUs can easily provide feedback for athletes that video-based systems cannot (e.g. determining the velocity of the throwing arm during the discus throw would be labour-intensive when using video-based systems). Collectively, these studies suggest that IMU devices, which incorporate accelerometers, gyroscopes and magnetometers, can be used for the detection of movements and error, as well as the provision of feedback in individual sports.

## 4.4.2 The Use of Microsensors to Detect Movements in Team Sports

Accelerometers, gyroscopes and magnetometers have been used in team sports to detect sport-specific movements and to provide feedback on performance. Ghasemzadeh and Jafari (69) evaluated the baseball swing using three sensor nodes placed on the chest, wrist, and hip, but the specific sensor type(s) used was not reported in their article. Nevertheless, the authors initially used twenty-two trials to develop and refine a signal processing model and a further thirty-eight trials were used to validate the accuracy of the model. Data was passed through a five-point filtering system to reduce high frequency noise and used to discriminate between 'a swing with proper sequence and timing of motions' and 'a bad swing with improper sequencing of key events'. Although the researchers suggested that this novel method could be used to train a player in baseball, it should be noted that the three participants used had 'no previous swing training' and no elite athletes were used. The demands of baseball were further examined by Koda et al. (70) who investigated the throwing motion using two accelerometer and gyroscopic sensors mounted on the upper and lower arm. Five participants, who included two former professionals, performed several throwing motions. Although the main objective of this research was to analyse the biomechanics of the baseball throw (trajectories of acceleration and angular velocity) this could only be done once the accelerometer and gyroscopic sensors had detected the throw. Therefore, the authors primarily discuss the biomechanical analysis of the throw rather than the reliability of throw detection.

Researchers have also used one MinimaxX S4 device containing an accelerometer, magnetometer and gyroscope in cricket to detect fast-bowling events (40). Highly skilled fast bowlers performed bowling and non-bowling events during training and competition to validate an algorithm capable of differentiating between bowling and non-bowling events. The algorithm demonstrated 99.0% sensitivity and 98.1% specificity with respect to correctly identifying bowling events during training, but the performance of the algorithm during competition was somewhat reduced (99.5% sensitivity, 74.0% specificity). McNamara et al. (40) suggested that the low specificity during competition could be due to players bowling the ball back to a bowler even when they were not the designated bowler.

Collision sports such as Rugby League (41), Rugby Union (42) and Australian Rules football (53,54) have used commercially available microsensors to automatically detect the non-running demands of their respective sports. Gabbett et al. (41) used MinimaxX S4 devices to automatically detect collisions in elite Rugby League. To achieve this goal, the authors developed an algorithm that relied on gyroscopic data to recognise when the unit was in a non-vertical position and accelerometer data to identify a spike

in 'Player Load'. Collision data were then classified as mild, moderate or heavy depending on the magnitude of the spike in 'Player Load'. All collision events recorded by the MinimaxX S4 device were compared against video notational analysis. Of the 237 events recorded, significant correlations were found between video and automatically-detected events for mild (r=0.89), moderate (r=0.97) and heavy (0.99) collisions. Researchers in Rugby Union (42) used an SPI Pro device (GPSports Systems, Canberra, Australian Capital Territory, Australia) to detect collisions. These researchers used a training set of physical 'contacts' and applied a mathematical learning grid (learning grids were established to classify specific accelerometer data signals of tackle and non-tackle events to create algorithms) and static window features (static window was determined as 128 frames either side of peak detection of collision using accelerometry data). The SPI Pro device used in this research (42) only contains accelerometers, demonstrating that a single inertial sensor is sufficient to detect collisions in Rugby Union, although it is possible that had gyroscopes and magnetometers been used, the authors may have found greater specificity for collision detection (e.g. tackles, scrums, rucks and mauls).

Using MinimaxX S4 units, Gastin et al. (53) used the formula proposed by Gabbett et al. (41) to quantify tackle demands in Australian Rules football. Three hundred and fifty-two tackles were recorded, comprising 173 tackles made and 179 tackles against. Of these recorded tackles, most were classified as medium intensity tackles (61%) while 33% were low intensity tackles and 6% were high intensity collisions. In a subsequent investigation, Gastin et al. (54) scrutinised the effectiveness of MinimaxX S4 devices when analysing 'observed tackles versus the MinimaxX device' and 'MinimaxX device versus observed play events' during four Australian Rules football matches. Observed tackles were detected with 78% accuracy by the MinimaxX device, accurately recording 66% of tackles made and 90% of tackles against. However, when the 1,578 "tackle events" recorded by the MinimaxX S4 device was compared against the observed play events, only 18% were correctly identified as tackles, while 82% were incorrectly identified. Movements such as ruck contests, smothering, and shoulder bumps comprised 57% of the incorrectly identified movements, whereas the remaining 25% involved no evident contact or collision. A possible reason for this high percentage of incorrectly identified events in this study was that the algorithm that was used to identify the collision events was specifically produced for Rugby League (41). Compared to Australian Rules football, the collisions associated with Rugby League tackles are likely to be different to those experienced in Australian Rules football due to opposing teams 'facing off' rather than playing 'man-on-man'.

As such, while the ability to distinguish non-contact events from contact events is of great significance in a wide variety of sports, it seems that it may be important for researchers to develop algorithms that are specific to each sport. Given the contrasting results (41,54), clearly further research is required to validate the ability of IMUs to distinguish tackles in collision sports from other contact events such as the ruck, maul and scrum in Rugby Union.

# 4.4.3 The Use of Microsensors to Detect Movements in Water Sports

Eight of the twenty-eight studies focused on the use of microsensors to detect movements in swimming. A single accelerometer placed on the head of the swimmer, has been shown to provide reliable accuracy of stroke and turn detection (71). Detection of turns demonstrated a classification rate of 99.8%, whereas detection of all four main

swimming strokes (butterfly, backstroke, breaststroke and freestyle) returned classification results of 95%, although some misclassification was acknowledged between breaststroke and butterfly styles due to similar head movements and positioning of the unit. Beanland et al. (71) applied accelerometer trace data gathered by MinimaxX S4 devices located on the head of swimmers to determine valid automated stroke detection of butterfly (r=1.00) and breaststroke (r=0.99). Quantification of freestyle swimming has also been carried out by Dadashi et al. (72,73), Fulton et al. (74,75), and James et al. (76). Fulton et al. (74) used gyroscope data obtained from sensors located on each thigh and shank of Paralympic swimmers to detect a valid and reliable form of kick count and kick rate, enabling quantification of the demands of freestyle. Data collected from gyroscope traces located on the shanks were strongly correlated with under water video of swimming trials (74). James et al. (76) also applied IMUs to understand the demands of freestyle by positioning units on the forearm, trunk and leg. Accelerometer data from the arm provided detection of hand entry, glide, and the catch and recovery phases of freestyle swimming.

Dadashi et al. (72) found that accelerometers encased in Physilog IMUs were accurate for measurement of swimmers' speed when compared with a commercially available tether. Stamm et al. (78) demonstrated similar capabilities of microsensors for detecting the velocity of push-offs, by positioning a single IMU on the participants' lumbar spine, although the specific sensor was not reported. Research conducted by Dadashi et al. (72) and Stamm et al. (78) reported valid and reliable methods of velocity measurements derived from data collected using microsensors when located on lumbar spine. These findings demonstrate that microsensors provide novel methods of measuring stroke and kick detection, allowing practitioners to quantify stroke and kick rate, and velocity of push-offs in swimming.

## 4.4.4 The Use of Microsensors to Detect Movements in Snow Sports

Snow sports accounted for 18% (5 of 28 articles) of the research included within this systematic review. Chardonnens et al. (79) applied Physilog IMUs to detect crossover and cross-under turn events in Alpine skiing, providing feedback on acceleration and angular velocity of the detected incidents. Accelerometers and gyroscopes, encased within Physilog IMUs, were applied in ski jumping and were able to detect temporal patterns of jumps from kinematic signals (80). The microsensors were able to automatically-detect temporal phases and durations of ski jump sequences of both indoor training sessions and outdoor conditions. Physilog IMUs have also been used to characterise lower-limb coordination during ski jumps (81), by determining the relationship between the position of the shank-thigh and thigh-sacrum segments during take-off. The biomechanical analysis of raw data detected from the IMUs placed on the sacrum and the thigh demonstrated that the movements of these segments during take-off were significantly correlated with the length of the jump (81).

Aerial acrobatics of snowboarders were evaluated using accelerometer and gyroscopic data obtained from a MinimaxX S4 device (82). Mathematically-derived algorithms derived from these data were able to detect the amount of air-time using gyroscopic data, which determined the magnitude of rotation for the participants. However, it was reported that acrobatics that involved rotations greater than 720 degrees were often incorrectly classified when compared to video analysis. The authors suggested that wearable sensors provided a novel method for coaches and judges to objectively

evaluate a snowboarder's acrobatics when the skill that is being assessed involved rotations of 540 degrees or below. These findings are important, as snowboarders are assessed on their performance of these skills in competition, yet they are difficult to assess with the naked eye. Nevertheless, it is important to note that the research conducted by Harding et al. (82) predominantly used data from one axis that only provided detail on flat spins and rotations and not acrobatic activities that included inversion movements. Given that the authors used a MinimaxX S4 device, which contains a three-dimensional accelerometer, gyroscope and magnetometer, it is reasonable to suggest that the data they collected could also be used to provide feedback in other sports that involve rotations, inversions and/or acrobatics (e.g. skateboarding, surfing).

Marsland et al. (83) applied a MinimaxX S4 device containing a three-dimensional accelerometer, gyroscope and magnetometer to identify cross-country skiing movement patterns. Cyclical ski patterns and kicking and skating actions on each side of the body were clearly identified by single sensors. Collectively, these results suggest that microsensors, coupled with sophisticated algorithms, can be used to detect movements in snow sports.

## 4.4.5 Directions for Future Research

The reviewed research demonstrates the ability of microsensors to accurately detect sport-specific movements in a wide range of environments. The specific aim of the research (e.g. to identify correct or incorrect technique or further understand the demands of a sport), will dictate the potential number of sensors used and their application for practitioners. The majority of team sports use single sensors to quantify the running demands placed on athletes during training and competition. As such, further research is required to determine whether movement patterns can be accurately detected during competitive games using a single sensor or whether multiple sensors would be required. This is particularly important in collision sports, given the conflicting results (41,54) reported in this systematic review. Multiple sensors also provide a unique approach to biomechanical performance analysis of movements as demonstrated by research conducted within individual sports by not only detecting movements but detecting errors.

To date, researchers have collected data from participants ranging from recreational to elite. It would be advantageous to understand the demands of elite sports in greater detail, as well as the biomechanical differences between sub-elite and elite populations for sport-specific movements. Furthermore, it would also be beneficial for authors of future research to use a common language for microsensors, by defining the manufacturer and the sensors used (e.g. accelerometer, gyroscope and magnetometer) and the sampling frequency, as much of the research uses various terminologies to describe microtechnology and may not reveal the type or sampling frequency of the microsensor employed.

# 4.4.6 Conclusion

This paper provides a comprehensive review of the ability of microsensors to detect sport-specific movements. The presented results demonstrate that commercially available microsensors have potential to detect sport-specific movements and are capable of quantifying sporting demands that other monitoring technologies may not detect. Furthermore, multiple sensor models have the ability to provide researchers with

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a tool to understand specific movements in greater detail and provide coaches or judges with feedback on correct and incorrect techniques.

### **Chapter 5 – General Methodology for Experimental Studies**

The results of the systematic review (Chapter 4) provided evidence of the widespread use of wearable microsensors to automatically identify and/or detect sports-specific movements. As previously outlined, a team's capacity to contest and win the physical collisions that characterise Rugby Union match-play are fundamental to their success in competition. However, in the absence of validated and automated methods for monitoring such collision-based events, sport scientists rely on largely subjective and time-consuming video-based methods of analysis. To address this need and make a clear and significant contribution to this field of science, the remaining three studies of this dissertation sought to; i) develop and validate microsensor-based algorithms to quantify collisions in Rugby Union (Studies 2 and 3); and ii) apply these methods to better understand the differences in workload demands between winning and losing teams (Study 4). Although many of the methods used for these studies were specific to addressing their individual aims, some methodological attributes were consistent. The methods that were common across the three experimental studies are outlined in this section, with the more specific methodological aspects explained in the individual studies.

#### 5.1 Participant Recruitment

For the purposes of Study 2 (Chapter 6), 30 elite Welsh Rugby Union players who played as Forwards were recruited to devise a scrum-detecting algorithm based on microsensor data. For Study 3 (Chapter 7), similar player-worn microtechnology data were collected from 12 elite Rugby Union players and used to develop and validate an algorithm to detect one-on-one tackles and ruck events. To address the aims of Study 4 (Chapter 8), data were collected from 185 players from four Welsh Rugby Union teams

who participated in the elite 'Pro12' competition during the 2016/17 season (Blues, Dragons, Ospreys and Scarlets). Due to the league structure, teams were required to play one-another twice (once home and once away); the four teams selected therefore play a combined 12 matches over the same season, each team participating 6 times. For each match a team of 23 injury-free players, comprising 15 starting players and 8 substitutes, were selected for either side. Although each of the experimental studies addressed a unique series of research questions, it should be noted that some participants featured in multiple studies.

To be eligible for inclusion in this research, participants in Studies 2 and 3 were required to have been selected by the Welsh Rugby Union coaching team to be involved with the elite international squad between June 2014 and June 2016. Furthermore, included subjects were required to be able to perform tackle and ruck movements with a high degree of technical proficiency as determined by national coaches for squad inclusion, with specific players in the 'Forwards' positional sub-group also needing to exhibit a competent scrum technique. For inclusion in Study 4, starting players were required to have played more than 60 minutes of total match duration, while substitutes were required to have played more than 5 minutes. Participants who did not meet these criteria were removed from the analysis. Using the specified teams allowed comparison of metrics between winning and losing teams. Lastly, for all 3 experimental studies, only those data files collected from players who were healthy and injury-free as determined by team physiotherapists at the time of measurement were included in this research to limit any potential bias in the match-play and/or training datasets.

The experimental procedures underpinning this program of research were reviewed and approved (#2014-135Q) by the Australian Catholic University's Human Research Ethics Committee prior to the study's commencement (Appendix A). The approved procedures required that all participants be provided with an information sheet that outlined the purpose, expected risks and benefits of the research program prior to their involvement (Appendix B). Interested participants were subsequently required to complete and sign a consent form to indicate their permission for their data to be included in the presented research studies (Appendix C). It should be acknowledged that no participants requested to be removed from the research and no injuries were reported as a result of this research.

# 5.2 Data Collection

#### 5.2.1 Video-Based Methods

To facilitate activity coding and assist with the validation of the microsensor-based collision detecting algorithms, all training sessions and competitive matches were video-recorded. Specifically, those training sessions that focused more on skills were recorded using two high-definition Sony FDR-AX100 cameras, while team sessions that included more tactical content and required a full training pitch necessitated a third Sony FDR-AX100 camera. To maximise player visibility throughout the training sessions, cameras were generally positioned to ensure that they monitored the players' activities from an elevated vantage point. However, for periods of training that involved scrums, cameras were placed at ground level with one being situated behind the players and another being positioned lateral to the point of contact. Following each session, video footage from each camera was transferred to an Apple MacBook Pro and cropped to exclude dead time (time that involved no instruction from coaches and was not

deemed to be rugby-related) and the pre- and post-training periods. Files were then stored to a secured storage server in a ".mp4" file format.

For the competitive matches, all video data were obtained using a live feed from the host broadcasting company at each match and venue. Due to each match being televised, multiple feeds were available from a variety of different angles. Despite this, most of the footage used for this research was taken from the standard television view, which is generally taken from an elevated position along the sideline of the pitch. All match footage was obtained in a high-definition format and similarly stored on a secure server in an ".mp4" format following the removal of dead time and pre- and post-match periods.

# 5.2.2 Wearable Microtechnology Procedures

For Studies 2 and 3, participants were required to wear a vest that held a Catapult Optimeye S5 device (Catapult Sports, Melbourne, Australia) between their scapulae for all training sessions and matches during the international periods within a typical season (Figure 5.1). Similarly, the participants involved in Study 4 were required to wear the same devices, but only during each of the 12 selected matches.



Figure 5.1 – Catapult Optimeye S5 device

The Catapult Optimeye S5 device is a commercially available device that contains GPS and other microsensor types (Figure 5.2). The device records global positioning data at a sampling rate of 10 Hz and locomotor-based outcomes derived from these units (e.g. speed, distance, position and accelerations) are reported to have acceptable reliability (84,85). The microsensors embedded within the Catapult Optimeye S5 device include tri-axial accelerometers, magnetometers and gyroscopes, which record data at a sampling rate of 100 Hz. Tri-axial accelerometers are highly-sensitive equipment that are capable of measuring accelerations in the vertical, anterior-posterior and lateral directions. Magnetometers use magnetic fields to provide information about the orientation of the unit, which assists with determining the direction of a movement, while gyroscopes measure the rate of angular change (i.e. angular velocity) of the unit. Importantly, the data derived from these different types of microsensors have been shown to be both valid and reliable for assessing sporting performances (39,86-88).

Prior to all activities, each player was assigned a device that had a unique identification number, which assisted with post-activity analyses. For training sessions, all devices were turned on while outdoors and were left untouched for a minimum of 5 minutes to allow satellite connectivity for global position systems. After this period, the units were inserted into the harness and applied to the athletes. For match-play, devices were turned on a minimum of 30 minutes before kick-off, while outdoors on the stadium's pitch to ensure good satellite connectivity. These devices were then taken back into the changing areas and inserted into the purpose-built player harnesses. Players then applied the harness immediately after warm-up, before the commencement of the match. All devices were on for the whole activity duration and turned off when returned by the participant.

The data from the players' wearable devices were collected via Catapult's Openfield software (versions 1.15 to 1.17), which allowed specific items of interest to be marked (i.e. coded) on the data files in real-time. Specifically, the items of interest during training sessions included the drill name, the drill duration, and details regarding the players involved in each of the drills. During match-play situations, the timing of player substitutions was coded in real-time to assist with post-match analyses.

#### 5.3 Data Analysis

Following the completion of each training session or competitive match, tri-axial microsensor data were exported and further analysed in Microsoft Excel (Microsoft Corporation, USA). For the training sessions, video data were synchronised with microtechnology data by manually identifying specific points in the data (e.g. 40-metre straight line run during the warm-up) using QuickTime version 10.5 (Apple, USA) and Openfield. To synchronise data collected during match-play, a point that could be readily identified in both the microtechnology and video data and video for matches

was established by having a point whereby the data started as did the video, for example, the ball being dropped for kick off. Once a synchronisation point was established, the data were extracted by using a unique video time stamp for each tackle, ruck and scrum event. Video timings of all movements during matches and training were then cross-referenced with corresponding microsensor data. Each event's data and video footage were extracted in a 20-second window (i.e. including 10 seconds before and after the point of contact) for tackles and ruck events and a 30-second window for scrum events (i.e. including 15 seconds before and after the point of contact).

For study 4, the microtechnology devices containing the GPS, accelerometer, magnetometer and gyroscope data, were connected to a PC using a USB-B cable and downloaded in a file format defined by the manufacturer (.raw) for each player. Files were then cropped to isolate the significant portions of the data files, processed and analysed using a specifically designed software package (Openfield, version 1.17.0). Specifically, data collected during competitive matches were cropped to establish the relevant data, for example each half of the matches was identified (identify the start and end), while training sessions were cropped to allow monitoring of player activities between the warm-up and the last instruction given by the coaches. Data outside of these periods were not used, as they contained non-rugby movements or were not captured by video cameras to verify the existence of rugby-specific movements.

Once the specific time periods were identified, GPS and microsensor data were analysed, these data were exported into Excel as ".csv" files for further analysis. The first export included summary data for all players for the entire activity duration (whole match or training) or session) of set periods (i.e. first and second half or drill). A second export only included GPS data at 1-minute intervals; this was performed for matches only and only included first half and second half data. Finally, an individual export containing microsensor data (sampled and exported at 100hz) was performed for training and match-play activities.

### 5.4 Statistical Analysis

Given their highly specific aims, there were few similarities between the three experimental studies with respect to the statistical methods used. Nevertheless, a brief explanation of the methods used for each study are provided here, with further detail about the specific statistical approaches provided in the chapters pertaining to each study. To facilitate the development and validation of the scrum-detection algorithm (Study 2, Chapter 6), a random-forest classifier method was used. Specifically, this approach included a preliminary event identifier method to identify scrum events using the microsensor data.

The algorithm developed to detect ruck and tackle events (Study 3, Chapter 7) using the player-worn microsensor data was similarly devised using a random forest method (89). However, unlike the scrum-detection algorithm, which sought to detect events that were preceded by a reasonably uniform set of player movements, the accurate detection of tackles and rucks required the use of a sliding-window method to systematically analyse the data in 2-second time intervals.

For the final study (Study 4, Chapter 8), which sought to provide detailed insight into both the running-based and collision-based physical demands of elite Rugby Union match-play, traditional GPS-based outcomes were considered in tandem with outcomes derived from the microsensor-based algorithms. To determine the potential role of running-based and collision-based workloads on match performance, magnitude-based inference methods were used to contrast these attributes between winning and losing teams (90,91).

# Chapter 6 - Validity of a microsensor-based algorithm for detecting scrum

# events in Rugby Union

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Although Rugby Union is characterised by high running demands, it also requires players to endure many collision-based events during a typical period of training or match-play. To date, a small number of studies have sought to better understand the physical toll that is placed on players as a result of these collisions, but none have been able to delineate one collision type from another. Given that each collision type is highly specific in nature, it seems unreasonable to assume that all collisions are associated with the same physical workload and subsequent injury risk. This emphasises the importance of developing methods to efficiently delineate one collision type from another. The results presented in Study 1 (Chapter 4) indicated that wearable microsensor data can be used to discriminate one movement type from another; hence, Study 2 of this thesis sought to develop a scrum-detection algorithm that used the accelerations and angular orientations from player-worn microsensors.

This chapter outlines the rationale and procedures involved in developing the scrumdetection algorithm, presents the results of the algorithm's validation and discusses the application and possible limitations of this method.

# **6.1 Introduction**

Commercially available microtechnology devices containing global positioning systems (GPS) and microsensors (accelerometers, gyroscopes and magnetometers) are commonly used to quantify the physical demands of Rugby Union (7). During match-play and training, players are divided into subgroups of forwards and backs and are required to perform repeated bouts of high-intensity locomotor activity (sprinting, running, accelerations) separated by low-intensity activity (standing, walking, jogging) (3,7,8,10,11,20). In addition to the locomotor demands of match-play, players are frequently involved in high-intensity physical contacts and collisions such as mauls, tackles and rucks, with forwards also required to compete in scrums (12,22). Scrums are used to restart play after a minor infringement and involve all eight forwards from each team, forming three interconnected rows of players. While facing each other, the players forming the front row for each team lock heads and shoulders with the opposition forwards and attempt to produce a greater force than their opponents to gain possession of the ball (92).

Despite researchers accurately quantifying the locomotor demands of elite Rugby Union, contact events such as scrums, rucks, mauls and tackles are usually combined and defined as 'impacts' when using microtechnology (7,8,12). Similarly, research evaluating contact events via video-based time-motion analysis has typically categorised these incidents as 'high-intensity efforts'(20) or 'static exertions' (3,11,22). Success in Rugby Union frequently depends on the players' ability to tolerate contact events (24). However, research summarising the physical contribution of contact events (scrums, tackles, rucks and mauls) during match-play, either provide a count of the total number of contact events, a rating of the force involved (7), or the total time attributable to collisions (22). To date, no research has differentiated between scrums, rucks, mauls and tackles, which inadvertently implies that each form of contact poses an equal physiological stress to the players (52). Classification of each contact would contribute to an improved understanding of the unique stresses associated with each of these collision types. In turn, this would potentially assist to improve player preparation and help to reduce the risk of injury and/or re-injury during training and competition.

Microsensors have been used to quantify the demands of sport-specific movements in team sports, snow sports, individual sports and water sports (52). Validated algorithms have been applied to microsensor data to automate the collection of sport-specific movements, such as cricket fast bowling (40), baseball pitching (93), and Rugby League tackling (41,44,52). To date, researchers have only used microsensors to quantify the tackle in Rugby Union (42), whilst scrums, rucks and mauls have been neglected (52). Researchers have highlighted the injury risk associated with scrums (94), predominantly in match-play (48). Currently there is no other valid method of quantifying scrum workload during training or match-play apart from using videobased time motion analysis, which is a labour-intensive process (52). Many researchers have highlighted the need to further investigate contact movements in Rugby Union, as they generally require the body to endure very high forces that are imparted over a relatively short time period. However, despite the relatively short duration of each contact event, the repeated collisions involved in a typical training or match-play scenario make a significant contribution to the players' total workload. Of the contact movements performed during regular match-play, scrum events occur around 25 times per game, while depending on playing position, each player will complete approximately 30 rucks and tackles per match (9,46,95).

Given the need for more time-efficient and accurate methods of evaluating the incidence and physical demands of contact events in Rugby Union, this research sought to establish the validity of a microsensor-based algorithm for the automatic detection of scrum events during training and match-play. Based on the demonstrated capabilities of inertial devices to quantify other aspects of sports performance (52,96), it was hypothesised that scrum events could be accurately detected using wearable microsensors.

## 6.2 Methods

## 6.2.1 Subjects

Thirty elite forwards (mean  $\pm$  SD age; 28.3  $\pm$  4.0 yrs), including players from all positions of the scrum (Front Row, n=16; Second Row, n=8; Back Row, n=6) were recruited to develop and validate the scrum-detection algorithm. At the time of testing, all participants were free of injury and had no known medical conditions that would compromise their participation or influence the recorded outcomes. All participants received a clear explanation of the study's requirements and provided written consent prior to their involvement. The Institution's Human Research Ethics Committee approved all experimental procedures (Approval #2014-135Q).

# 6.2.2 Phase 1 – Algorithm Development

To facilitate the initial development and training of the scrum detection algorithm, data were collected for the 30 participants using a Catapult S5 Optimeye device (Melbourne, Victoria, Australia) positioned between the players' shoulder blades in a purpose-built vest. Each device contained an array of inertial sensors (i.e. tri-axial accelerometer,

gyroscope, magnetometer), which captured data at 100 Hz during a series of competitive matches (n=46) and training sessions (n=51). A total of 97 data files (Front Row, n=49 files; Second Row, n=25 files; Back Row, n=23 files) that captured 1057 scrum events were required to develop and optimize the final scrum-detecting algorithm. Timestamps of the scrum instances were manually identified using video data, which were coded alongside Opta Sports events when available (i.e. during matchplay).

The development of an algorithm to detect scrum events involved two separate, but inter-related processes. Firstly, given the unique posture adopted by players while performing scrums, orientation of the device was estimated using a proprietary sensor fusion algorithm that included accelerometer and gyroscope data (Catapult; Melbourne, Victoria, Australia) within a match-play or training session. According to research, accelerations and the orientations determined from microsensor data using fusion-based methods have excellent reliability and concurrent validity (97-99). While the wearable sensors provided an array of measures, the following criteria were shown to have the ability to identify all scrum instances in the training set and, hence, were the two orientation measures consistently used in the scrum detection algorithm:

- The orientation of the device was below 25 degrees compared to the horizontal plane for at least 4 s. When this criterion was met, the algorithm established this time period as a potential event window.
- ii. The event was recorded only if the orientation of the device went below the horizontal plane during the event window.

For data to be considered to potentially represent a true scrum event during training or match-play, both of these orientation criteria were required to be met. This was typically met by participants in preparation for the scrum so that even if a scrum collapsed it would enter the second step of the algorithm and be classified as one scrum event. These two initial criteria were intended to remove other non-relevant contact instances. All possible scrum instances within the time-series data were then classified as true and false scrum instances based on video analysis conducted by Opta Sports (http://www.optasports.com) statistics. The windows of the classified events were then created for the inertial data and window mid-points were then extracted to become the event timestamp. This first step of the algorithm development aimed to efficiently transform the data from a time series into a classification problem using the orientation criteria. The second step extracted features of the accelerometer and gyroscope signals from each event. These calculations included summary statistics using different time windows around the event timestamp and formed the 33 variables for the machinelearning process. Variable selection was then performed using the R statistical software package's Variable Selection Using Random Forests (VSURF) function (100). Based on a 10-fold cross-validation mean classification accuracy, 11 signal features were eventually selected from the accelerometers and gyroscopes and included in the final version of the random forest classifier (89). R statistical software package (http://www.r-project.org/) was used throughout the development of the algorithm.

A scrum confidence scoring was attached to the algorithm based upon the number of trees in the random forest agreeing that a scrum event had taken place. If only the minimum orientation measures were met, then the algorithm would return a confidence of 0%. In contrast, when a larger number of trees in the random forest reported detecting

a scrum event based on the 11 signal features (Table 6.1), the algorithm returned a higher confidence rating (maximum 100%).

Feature Name	Feature Description		
Horizontal Position 5	To detect how long the estimated orientation of the device		
	is below 5 degrees (i.e. forward flexion)		
	To detect how long the estimated orientation of the device		
Horizontal Position 15	is below 15 degrees (i.e. forward flexion)		
	To detect how long the estimated orientation of the device		
Horizontal Position 25	is below 25 degrees (i.e. forward flexion), which		
	corresponds with scrum activity		
Raw Player Load Q75	75th percentile of raw player load during the scrum activity		
Rotation Median	Median of smoothed total rotation during the scrum activity		
Smooth Player Load 75	75th percentile of smoothed player load during the scrum		
Shiooti i layer Load 75	activity		
Raw Player Load Q90	90th percentile of raw player load during the scrum activity		
Raw Player Load Median	Median of raw player load during scrum activity		
Inertial Side O10	To detect how long the estimated orientation of the device		
	is below 5 degrees (i.e. forward flexion)		
	Normalised cumulative PlayerLoad 30 sec prior to the start		
Raw Player Load Pre 30	of the "scrum activity". It is normalised by the length of		
	the interval, i.e. 30sec or less if truncated.		
	Normalised cumulative rotational PlayerLoad 30 sec prior		
Raw Rotation Player Load Pre 30	to the start of "scrum activity". Normalised by the length		
	of the interval, i.e. 30sec or less if truncated.		

Table 6.1 List of scrum algorithm signal features

### 6.2.3 Phase 2 – Algorithm Validation

To validate the random-forest classifier-based algorithm, a testing set of 21 participants (Front Row, n=9; Second Row, n=5; Back Row, n=7) from the same cohort were monitored using Optimeye S5 devices across 11 international matches (143 full match files) and 9 training sessions (167 full training files). Training session scrums included events against opposition (8 vs. 8) or against a scrum machine (front 3 against machine, front 5 against machine and 8 against machine). A total of 261 scrum instances (international matches, n=169; training, n=92) were manually coded using video data and the timing of each scrum instance was noted according to video, time of day and time on the Catapult raw file. Video coded instances were compared to those detected by the algorithm. Scrum algorithm confidence scoring was set to the lowest possible setting, 0%, therefore incorporating all 4833 instances. Each instance was then matched with the relevant time stamp and false positives were thoroughly checked against video coded scrum events.

# 6.2.4 Statistical Analysis

True positive and negative results and false positive and negative results (Table 6.2) were determined to calculate algorithm accuracy, precision, specificity and sensitivity. Receiver Operating Characteristic (ROC) analyses were conducted to determine the sensitivity and specificity of the algorithm's confidence in predicting scrum events. The predictive confidence value that yielded the best sensitivity and specificity was selected as the optimal cut-off score and represented the point that simultaneously maximised both on the ROC curve. All statistical analyses were conducted in the Statistical Package for the Social Sciences (SPSS v24).

Table 6.2 Criteria of algorithm results.

	True	False
Positive	Scrum event and scrum correctly detected	No scrum event, scrum event incorrectly detected
Negative	No scrum event and no scrum event detected	Scrum event and no scrum event detected

# 6.3 Results

To evaluate the performance of the scrum detection algorithm when only the two initial orientation criteria were applied without considering the results of the machine-learning model (i.e. the non-optimised algorithm), the sensitivities and specificities associated with an algorithm confidence of 0% were examined. When data for all positions (i.e. front row, second row, back row) and all sessions (i.e. training, competitive matches) were considered, the non-optimised algorithm identified 3904 possible scrum instances. Of these instances, only 25 true negatives were recorded, yielding a sensitivity of 99.5%, a specificity of 31.5% and a precision of 47% (Table 6.3). Overall, algorithm performance was slightly better for match-play (sensitivity 99.8%, specificity 35.0%) than training (sensitivity 98.9%, specificity 28.1%).

Using the 11 signal features identified during the model learning process, the algorithm's predictive capacity was improved, and this was reflected in the higher predictive confidence values (i.e. the optimised algorithm). Table 6.3 demonstrates the algorithm confidence cut-offs that returned the best results for the entire dataset and for the three positional groups during the training and match-play sessions based upon receiver operating characteristic analysis (Figure 6.1). On the basis of these results, the predictive confidence threshold that yielded the best combination of sensitivities and

specificities for the entire cohort was 50%, while the optimal cut-off for matches (37%) was somewhat lower than determined for the training data (54%) (Table 6.3). When the study cohort was subdivided into positional groups, it was shown that the optimal cut-off for front row players was 27% for training and 51% for match-play, compared with 91% and 49% for the second row. In contrast the predictive confidence values that provided the best sensitivities and specificities for back row players during training and match-play were 63% and 21%, respectively.

Various training scenarios were observed during data collection, involving three, five and eight players against a scrum machine and opposed "eight verses eight" scrums. Importantly, the first two scenarios were only included in the validation phase. Scrums involving the front row only had the lowest sensitivity (50%) and specificity (97%); this improved when including both the front row and second row (i.e. for five player scrums), with both positions attaining sensitivity and specificity of 100%. Eight-man scrums against a scrum machine had the highest sensitivity and specificity for all positions: respective sensitivity and specificity values; front row, 98% and 99%; second row, 100% and 100%; and back row, 100% and 100%. Opposed scrums in training involving 16 players (8 vs. 8) also demonstrated high sensitivity and specificity for all 3 positions (front row, sensitivity 98% and specificity 99%; second row, sensitivity 100% and specificity 100%; back row, sensitivity 99.5% and specificity 99.7%).
		Optimal				
	Accuracy (%)	AUC (%)	Cut-Off	Sensitivity	Specificity	
Scrum Identification						
Probability for All Data	91.0	95.8	50%	0.91	0.91	
Data Source						
Probability for Training Data Only	87.6	92.9	54%	0.89	0.87	
Probability for Match Data Only	93.6	98.2	37%	0.94	0.94	
Position						
Probability for Front Row Only	90.4	95.1	41%	0.91	0.90	
Probability for Second Row Only	94.4	97.1	83%	0.94	0.93	
Probability for Back Row Only	89.8	95.8	36%	0.91	0.91	
Position by Data Source						
Probability for Front Row in Training	83.8	88.6	27%	0.84	0.83	
Probability for Second Row in Training	91.4	95.3	91%	0.90	0.90	
Probability for Back Row in Training	90.6	96.1	63%	0.91	0.91	
Probability for Front Row in Matches	95.9	99.1	51%	0.96	0.96	
Probability for Second Row in Matches	98.1	99.7	49%	0.98	0.98	
Probability for Back Row in Matches	89.6	96.6	21%	0.90	0.92	
Position by Data Source (Limited)						
Probability for Front Row in Training	85.2	90.5	39%	0.86	0.86	
Probability for Second Row in Training	91.3	95.3	91%	0.90	0.90	
Probability for Back Row in Training	90.8	96.2	63%	0.91	0.91	

Table 6.3 – Accuracy, Area Under the Curve (AUC), Optimal algorithm cut-off, sensitivity and specificity for each position during each scenario



Figure 6.1 – Receiver Operating Characteristic (ROC) analyses for Front Row (A, B), Second Row (C, D) and Back Row (E, F) players during the training and competitive match scenarios, respectively. **AUC:** Area under curve; **Sens:** Sensitivity; **Spec:** Specificity.

## 6.4 Discussion

This is the first study to investigate the use of microtechnology and associated algorithms to automatically detect scrum events in elite Rugby Union. Our results demonstrate that scrum events were best detected with high sensitivity and specificity when algorithm confidence level was at 50%, although algorithm performance was better during match-play than training. In training, scrums that involved a minimum of 8 players (8 against a machine or contested scrums involving 16 players) returned higher accuracy than those scenarios that involved 3 or 5 players. This finding can be explained by the lack of the latter scenarios in the training phase of the algorithm. Accuracy was best for the front row, with detection of scrum events poorest in the back row. These findings provide a practical and valid method of quantifying scrum events in professional Rugby Union match-play and training sessions.

False negatives during training were only recorded during 3-man scrums performed against a machine. This may have been due to the activity duration being insufficient to satisfy the algorithm's minimum requirements, thus affecting the overall sensitivity and specificity for the front row players during training sessions. Other false negatives in training occurred when scrums collapsed (front row falls to floor) or were reset (incorrect positioning) affecting both the front row and back row. During match-play, all false negatives were attributable to players in the back row who did not maintain a horizontal position for an adequate period of time to satisfy the algorithm's least common denominators before a scrum collapse. As shown in the results for these players, the tendency for back row players to change their trunk orientation prior to a scrum collapse significantly affected the algorithm's sensitivities and specificities for this positional group. Although the results for the back-row players were negatively

affected by this phenomenon, they do suggest that the physical exertion exhibited by these individuals during a particular scrum event may be quite different to that of front and second row players, even if a scrum is completed or collapses.

The comparisons of video-based notational analysis and the scrum algorithm demonstrated the best results with a 50% threshold cut off. The overall outcome of the algorithm was better for match-play than training. Fewer scrum variations occur in match-play (i.e. each scrum is always contested by 16 players), whereas training activities may involve contested '8 vs. 8' scrums, eight players against a scrum machine, or the front five (involving front row and second row) and front row positions only, which may account for the differences in algorithm performance in different scenarios. Further analysis of the different types of scrum-based technical drills utilized during training indicated that the algorithm performed worse for drills involving only three or five players. Although these results suggest that the algorithm's performance may be improved by including such drills in the "learning" phase of the algorithm, it could be argued that scrums involving 5 or fewer players are aimed more at developing technique, rather than specifically preparing the athletes for the demands of match-play. As such, the specific differences between these training-based drills and actual scrum events may contribute to these incidents not being identified as a scrum using the specified algorithm criteria.

We found that algorithm performance differed among positions during match-play and training. Optimal sensitivity and specificity for all positions occurred when the algorithm confidence rating was set at 37% for match-play and 54% for training (Table 6.3. Due to the differences in algorithm performance among positions, setting

confidence thresholds of 51%, 49% and 21% during match-play and 27%, 91%, and 63% during training for the front row, second row, and back row, will likely produce optimum results, although caution must be taken when extrapolating these results to other independent data sets. False positive events (threshold set to 50%) totalled 168 and 1668 true negative events (predominantly scoring below 5% confidence) were present across the validation data set. Most events were off camera, although events scoring the highest confidence rating were from rare static maul events where players were not moving and positioned in a similar posture to that observed during a scrum.

The results of the scrum algorithm are in agreement with a recent systematic review that evaluated the use of microsensors for the detection of sport-specific movements (52). This technology has been applied in cricket to count balls bowled (40) and bowling intensity (101), baseball throwing (93), tennis serves (102), and several individual (66-68), snow (80,81,83), and water-based sports (71-73). Microsensors and associated algorithms have been used to detect tackles in Rugby League (41) with accuracy improving with greater impact forces and longer duration of events (44). However, this technology has previously been shown to be less useful for detecting tackle events in Rugby Union (9) and Australian football match-play (54). A possible explanation for the poor performance of the algorithm in Australian football and Rugby Union match-play is that the tackle algorithm was trained on Rugby League players, to identify Rugby League tackles. The differences in tackles between Rugby League and that of Australian football and Rugby Union may explain the differences in accuracy and show the importance of the representativeness of the training data set for developing movement specific algorithms. Given the differences in findings among Rugby League, Rugby Union, and Australian football, and the present findings that 3and 5-man scrums were less accurate than 8-man scrums, we would recommend only using the scrum algorithm for detecting scrum events involving 15-a-side Rugby Union.

Although this algorithm advances the ability of sport scientists to automatically detect scrum events in elite Rugby Union, there are some potential limitations to the research. The algorithm was designed using two elite level teams and tailored primarily for front row players due to their role within scrum events. This may account for the slight, but incremental decrease in algorithm performance for the second row and back row positions, respectively. Elite male players were used to train the algorithm; consequently, the algorithm may be less applicable for younger and smaller junior Rugby Union participants, or female players, due to possible difference in microsensor signals. Finally, at present, the scrum algorithm only detects the number of scrum events and does not account for the forces applied during these events. Despite these limitations, this study demonstrates the potential for microsensor technology in the detection of Rugby Union-specific collision events provided an adequate (i.e. specific and representative) training data set. While the demonstrated success of the presented algorithm suggests that practitioners will be better able to detect scrum events in training and match-play to monitor players' total training loads, it is important to acknowledge that the scrum is one of many contact types experienced in Rugby Union. Hence, despite the algorithm success, a complete understanding of a player's match demands and total training load would require the development of alternate, but complementary methods to identify rucks, tackles and mauls using microtechnology.

# **6.5 Practical Applications**

The majority of rugby union GPS analyses have focussed on the locomotor demands (i.e. low-speed activities, high-speed running, and sprinting) of the game (7,8,10,20). However, disregarding the physically demanding collision events that may result in very little locomotor activity, may severely underestimate the physical demands of match-play. The development and validation of a scrum algorithm to automatically detect scrum events during training and match-play improves the understanding of an important component of Rugby Union. Previously, this type of analysis would require time consuming video-based notational analysis. The automated detection of scrum events using data provided by the GPS units worn by players allows practitioners to more easily quantify the occurrence of scrum events during regular training and match-play situations. By improving the efficiency of this process, it becomes far more viable for sports scientists to determine the physical load associated with these contact events, which should ultimately improve player preparation and reduce the risk of injury. Further research investigating the use of this technology to quantify the ruck, tackle and maul is warranted.

#### **6.6** Conclusion

In conclusion, we investigated the use of microtechnology and associated algorithms to automatically detect scrum events in elite Rugby Union. Receiver Operating Characteristic analyses provided optimal random forest algorithm confidence thresholds to generate best sensitivity and specificity (typically >90%). Algorithm performance was better during match-play than training for front row and second row, although conversely, results revealed better performance for the back row during training than match-play. In training, scrums that involved a minimum of eight players

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were readily detected, while scrums involving three players were less accurate. Scrums involving five players or more attained markedly better results than back row players in matches, however results between the three positions are closer in training due to the controlled environment. Overall detection was best for the second row, with decreased detection in the front row, with back row positions performing comparatively lower in training and match. These findings provide a practical and valid method of quantifying scrum events in professional Rugby Union match-play and training.

# Chapter 7 - Automatic detection of one-on-one tackles and ruck events using microtechnology in Rugby Union

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The results presented in Study 2 (Chapter 6) demonstrated that data derived from player-worn microtechnology can be used to accurately record the frequency of scrum events during elite Rugby Union training and match-play. However, scrum events only involve players assigned to the Forwards positional group and generally follow a strict structure during preparation and execution. In contrast, other collision-based events, such as tackles and rucks, are performed by all players on the pitch and impose different, but similarly important workloads and injury risks on players.

To address this need, Study 3 (Chapter 7) of this thesis sought to develop and validate an algorithm that could use wearable microsensor data to automatically detect one-onone tackles and ruck events during elite Rugby Union training and match-play. The findings of this study were expected to build upon the findings of Study 2 by developing a tool that would further assist sport scientists to discriminate tackles and rucks from other collision-based events in Rugby Union.

#### 7.1 Introduction

Commercially available microtechnology devices containing global positioning systems (GPS) and microsensors (accelerometers, magnetometers and gyroscopes) are extensively used to quantify the activity demands of various sports, including Rugby Union (10,13,18,52,103). Rugby Union is a high-intensity sport involving demanding bouts of intense locomotor activity (running, sprinting and accelerations) and requires players to perform a range of high-intensity collisions (rucks, tackles, mauls and scrums) (10,18,103), interspersed with activities that have lower locomotor demands (standing, walking and jogging) (16,18,52). Physical demands of Rugby Union have frequently been reported using video-based time motion analysis and more recently with the use of microtechnology (9,22). Recent research using microtechnology predominantly focuses on positional match-play demands of Rugby Union reporting locomotor metrics, such as distance covered, high-speed running and accelerations assisting with athlete physical preparation and injury prevention (16,22,24).

In combination with customised algorithms, microtechnology devices have demonstrated a capacity to detect sport-specific movements in individual sports such as snow and aqua sports (52), as well as team sports reporting fast bowling and intensity in cricket (40,101), and throwing in baseball (93). Furthermore, a small number of studies have focused on the non-running demands of contact sports (42). Specifically, such studies have determined whether these microtechnology devices have the ability to detect tackles in Rugby League (41,44), Rugby Union (42) and Australian Rules football (53,54). Studies have shown that tackles performed in Rugby League can be reliably detected using wearable microsensors (mild collisions: r = 0.89; moderate collisions: r = 0.97; heavy collisions: r = 0.99) (41) with high sensitivity (97.6%  $\pm$  1.5) and specificity (87.6%  $\pm$ 1.2) (44). Attempts to apply the same algorithm for tackles in Australian Rules football and Rugby Union were unsuccessful due to

obvious variations between contact events in these sports. Specifically, when applied to these sports the Rugby League tackle algorithm had a tendency to over-estimate the number of tackle events, incorrectly classifying some rapid changes of direction and other contact events as tackles (9,53,54).

Interestingly, recent research investigated whether existing algorithms developed for Rugby League can be adapted for Rugby Union (9). This study has shown that manipulation of g-force parameters within the algorithm was inadequate to provide an accurate tool for automatically recording collisions in Rugby Union; possibly due to the wide variety of tackle types (9). Other encouraging results in Rugby Union used an accelerometer-based tackle detection algorithm that was developed by incorporating a limited training set of 'contacts' (42). However, researchers concluded that the algorithm's performance might be improved if accelerometer data were complemented with magnetometer and gyroscope data (42,52).

Of the various types of contact events experienced during rugby match-play, rucks and tackles are reported to be the most frequent (24,103,104). On average, tackles and rucks are performed 116 times by each team during a competitive match, with front-on one-on-one tackling the most frequently occurring tackle type (22,105,106). Competition success is usually dependent on a team's ability to endure repeated collision events that characterise the sport (7,22,42).

A Rugby Union tackle is similar to that of other collision-based sports when a defender successfully brings an opposing ball carrier to the ground (105,107). Other techniques include a standing tackle when an attacker is not brought to ground and can potentially become a maul (108). The ruck, as performed in Rugby Union, is a unique event that occurs when at least one player from either team competes in a physical contest for possession after a completed tackle

for the ball that is on the ground (106). Although these collision-based events may involve only a single player from each team, they often escalate involving numerous players from one or both teams (107). Forwards predominantly perform greater tackle and ruck events during competitive matches than backs, a player's involvement in these events is not restricted and, hence, any player may be exposed to these situations during training or match-play (109).

As there is currently no validated algorithm capable of detecting tackles in Rugby Union, current practice involves manually counting and subjectively classifying tackle events using video footage. This process is time-consuming and labour-intensive and often prone to many inaccuracies (9,52). This early work can be further improved upon by seeking to develop methods that can differentiate tackles from other contact events in Rugby Union (e.g. rucks, scrums, mauls), as combining these events in a single category implies that each event places an equivalent physiological stress on the athletes' bodies (52). In light of recent research shortcomings, there is an increasing requirement for automated algorithm detection to improve quantification of unique Rugby Union contact events, providing enhanced understanding of the physical demands (9,13,52).

To address this, the study purpose was to use data derived from player-worn microtechnology to develop and validate an algorithm capable of identifying tackle and ruck events in Rugby Union match-play scenarios. It was hypothesised that using the accelerometer, magnetometer and gyroscope data provided, an algorithm could be developed to automate detection of tackles and rucks in Rugby Union.

#### 7.2 Methods

Twelve elite male Rugby Union players (mean  $\pm$  SD age; 26.6  $\pm$  3.3 yrs; forwards n=7, backs n=5) were recruited to develop and validate a tackle and ruck detection algorithm. At the time of testing, all participants were free of injury and had no known medical conditions that would compromise their participation or influence the recorded outcomes. All participants received a clear explanation of the study's requirements and provided written informed consent prior to their involvement. The study's experimental procedures were reviewed and approved by the Institution's Human Research Ethics Committee (Approval #2014-135Q).

Participants were required to wear a single Catapult S5 Optimeye device (Melbourne, Victoria, Australia) positioned between the shoulder blades in a purpose-built vest to assist initial algorithm development. Devices contained tri-axial accelerometers, gyroscopes and magnetometers that captured data at 100 Hz. A total of 40 (n=19 Forwards; n=21 Backs) data files were captured across a series of elite international Rugby Union matches (n=6) using the aforementioned cohort. Using television broadcast footage of each match, ruck and tackle events were also manually identified by a single assessor on two separate occasions that were separated by at least 10 weeks. Statistical comparison of the two assessments indicated excellent intra-rater reliability for the visual identification of tackles (ICC: 0.998; 95% CI: 0.995 to 0.998) and rucks (ICC: 0.997; 95% CI: 0.995 to 0.998). Tackle criteria were set as one-on-one tackles completed by defenders, where an opposing attacking player was taken to ground as a result, using varied tackling techniques and varying points of impact. Due to oneon-one tackling being the most common tackle type, any assisting tackle events were excluded (105). Assisted or double-tackle events were classified as when two or more players were required to take an attacking player to ground and this was determined using video data. Ruck events were selected based on the criteria that a player had taken part in a ruck and was involved in a physical competition for possession with an opposing player in attack or defence. Events that did not require a competition with an opposing player were not included.

A total of 250 tackle (n=125) and ruck (n=125) events were manually identified from the video using the defined criteria, only using tackles requiring one player from either team from the selected sub-group. Microtechnology and video data were then synchronised in order to construct 20-second video clips of each identified ruck/tackle instance (10-seconds before and after the frame of impact in each selected ruck/tackle instance). The corresponding 20-seconds of data from the microtechnology device was then extracted at 100 Hz. In addition to the ruck/tackle event data gathered from match-play, a further 29 microtechnology data files were collected from training sessions completed by the aforementioned cohort. These supplementary training files did not include any ruck, tackle or contact events, but rather were used within the investigation and categorised as 'other movements'. Each of the 'other movement' files were at least 1-hour long, with 20 second windows across the files randomly extracted to assist algorithm differentiation between 'contact' and 'non-contact' events. An initial two-second sliding window was designed to develop a descriptive feature set for tackle and ruck movements (110). For individual movement identification in isolated windows (activityspecific recordings) accelerometer and gyroscope data (X, Y, and Z axes) were utilised to effectively develop a descriptive feature set for the required movements (tackle, ruck and 'other movement') over each of the 50% overlap of sliding window (s\*) regions (Figure 7.1). Features were extracted from within all of these regions for each of the relevant sensor outputs, with the feature set containing both temporal and spatial features of each contact type.

Identify initial ruck and tackle movements from match play for testing set data.

Export microsensor data (100 Hz) for 40 players (21 Backs, 19 Forwards) collected over 6 matches.

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Synchronise video and microsensor sources and extract 20-second windows of data corresponding with 250 collision-based events (125 rucks, 125 tackles) for algorithm training. Add a further 29 data files containing other movements (non-contact), also exported at 100 Hz.

Create 2-second sliding window (s\*) for all files and calculate relevant variables and descriptive feature sets to characterise rucks, tackles and other movements.

Identify key temporal and spatial features for the relevant variables:

- Maximum
  - Minimum
- Mean
- Variance
- Kurtosis
- Skewness
- Spectral Bandwidth
- Spectral Centroid
- Magnitude

Train and optimise random forest classification algorithm for ruck and tackle events using 166 data files from the original 250 training set data files.

Internal validation of random forest classification algorithm for rucks and tackles using the remaining 84 data files from the original 250 training set data files.

Use a further 177 unique data files exported at 100 Hz from match-play (testing set) to validate the algorithm against manually-coded video instances of rucks (n=979) and tackles (n=781).

Figure 7.1 Schematic overview of methodology

Once temporal and spatial features were identified, these signals were applied to a random forest classification model using 166 (two thirds) randomly selected files from the total 250 tackle and ruck files to train the algorithm. Resultant magnitude of accelerometer data was identified using  $\sqrt{x^2 + y^2 + z^2}$ , where *x*, *y*, and *z* represent data from each of the individual accelerometer axes. These were then smoothed using a low-pass 4<sup>th</sup> order Butterworth filter with a 25 Hz cut-off frequency. Movement profiles were clustered using Gaussian Mixture Models (GMM)(111) over one-second windows and classified using Dynamic Time Warping (DTW)(112) methods. Random forest models were optimised using the original 166 files using the identified variables for detection (Figure 7.2). This process was repeated 10 times to achieve a 10-fold cross-validation, after which the means and standard deviations were calculated. The remaining 84 files from initial ruck and tackle events were subsequently used to validate the algorithm's capability to detect both ruck and tackle events.



Importance of Input Variables to Random Forest

Figure 7.2 Relative importance of each input variables derived from the player-worn Catapult S5 Optimeye device. The figure depicts the decrease in predictive accuracy for the algorithm when each of the predictor variables was excluded. Variables with a larger mean decrease in accuracy were of greater importance for event classification.

Following development and optimisation of the ruck and tackle classification algorithm, we sought to validate the algorithm using an additional 177 microtechnology data files with synchronised video data, collected from the same cohort during eight international matches. Video data recorded during these matches were initially manually coded by an experienced sports scientist who recorded all rucks (979 total) and tackles (781 total) completed in these matches and their timings for the video and microtechnology datasets. The 177 data files collected were processed in the R statistical software package (<u>http://www.r-project.org/</u>) using the developed tackle- and ruck-detecting algorithm.

To effectively process continuous match-play data to identify the incidence of rucks and tackles, the algorithm sequentially processed the time-series of the three-dimensional accelerations and orientations from the microtechnology units within consecutive 2-second windows with a 0.5 second overlap for event identification. For each 2-second window, the algorithm generated a series of decision trees from the random forest using recognised variables that collectively determined whether the data within the window represented; i) a tackle; ii) a ruck; or iii) another movement; providing a confidence score based on each outcome (sum of probabilities within each window equalled 100%). For example, within a 2-second window, the proportion of decision trees agreeing that the data represented a ruck might have been 60%, while 25% might have indicated a tackle and 15% may have indicated another movement.

The proportion of decision trees agreeing data within each 2-second window represented a tackle, a ruck, or another movement was exported to Excel, where these data were compared with visually identified events derived from synchronised video data. This process involved

determining the optimal proportion of decision trees that were required to be in agreement to maximise the likelihood of correctly identifying that a specific movement had occurred. To facilitate this, the criteria of true positives, true negatives, false positives and false negatives were determined, with the optimal cut-off considered to be the proportion of agreeing decision trees that generated the least number of false positives and false negatives.

To evaluate the performance of the ruck and tackle algorithm, results were provided as a percentage of random forest decisions that agreed with video-based determination of ruck, tackle or other movement events. In the first instance, the movement that corresponded with the highest proportion of agreeing decision trees was recorded as the event that was occurring during each 2-second window. Using this approach resulted in a high number of false positives being recorded (e.g. a tackle or a ruck being recorded when one did not exist); hence the greatest number of agreeing decision trees was sought to maximise the algorithm's predictive capacity of the validation data set.

Means and standard deviations were calculated for the entire cohort and each positional subgroup (forwards, backs) using all ruck and tackle results. Normative distributions of the data were also derived to gain a better understanding of any outliers and overall spread of the results. Finally, the data were also evaluated to determine whether the performance of the algorithm was frequency dependent; that is, if algorithm performance was influenced by the number of rucks or tackles performed by a specific player.

# 7.3 Results

For the entire cohort, the results of this process indicated that rucks were accurately predicted by the algorithm when an average of 79.4  $\pm$ 9.2% of the decision trees agreed that a ruck event had occurred (Figure 7.3). Importantly, this value was not influenced by the players' sub-group, with the respective cut-offs for forwards and backs being 79.8 $\pm$ 9.8% and 79.1 $\pm$ 8.5%. With respect to the algorithm's capacity to predict tackles, it was shown that events were correctly identified when an average of 81.0 $\pm$ 9.3% of the decision trees agreed that a tackle had taken place. Sub-analysis of the positional groups indicated that the optimal cut-off for tackles experienced by forwards (77.7 $\pm$ 12.2%) was significantly lower than the cut-off for tackles experienced by backs (85.3 $\pm$ 7.2%). The proportion of agreeing decision trees required to optimise the algorithm's ability to predict rucks (79.4 $\pm$ 9.2%) and tackles (81.0 $\pm$ 9.3%) was not influenced by the number of actual rucks and tackles performed by each of the players.



Figure 7.3 Study outcomes showing the; A) distribution of rucks completed by players and lowest returned average algorithm percentage; B) distribution of tackles completed by players and lowest returned average algorithm percentage; C) variation amongst the cohort, with respect to the number of rucks completed during match play (x-axis) and the corresponding optimal algorithm cut-off (y-axis); and D) variation amongst the cohort, with respect to the number of tackles completed during match play (x-axis) and the corresponding optimal algorithm cut-off (y-axis). Note: The optimal cut-off refers to the percentage of decisions trees within the random forest classification algorithm that produced the greatest level of agreement between the algorithm's predictions and the video-based appraisal of the collision events.

## 7.4 Discussion

This is the first study to investigate the use of microtechnology and associated algorithms to automatically detect ruck and tackle events in elite Rugby Union. Results demonstrate that ruck and tackle events can be correctly detected when applying a specifically designed algorithm to microtechnology data during international matchplay. The algorithm was developed and trained to return a number reflecting the algorithm's confidence that a time-series of data represented a ruck, tackle or 'other' event (e.g. a locomotor activity, such as running). To minimise the risk of over- or under-reporting the number of rucks and tackles, the optimum confidence cut-off was determined via validation of the algorithm's outcomes against traditional video coding techniques. Results showed that using an algorithm confidence cut-off of 80% for both rucks and tackles would provide practitioners with the best ability to characterise a large proportion of commonly occurring contact-related demands of Rugby Union during training and match-play.

Overall, the results revealed similar optimal algorithm confidence cut-offs for rucks involving the whole cohort and the forwards (79.7%) and backs (79.1%), separately. Furthermore, optimal cut-offs for both groups had low standard deviations, which can likely be attributed to the homogeneity of the ruck movement, regardless of playing position. In contrast, the optimal cut-off for tackles completed by the backs (85.3%) was marginally higher than reported for the forwards (77.7%). Although tackle techniques are similar, there are likely to be a number of potential variations that occur due to differences in the speeds and points of contact made between the athletes involved in one-on-one tackles. This study focused on tackles that required the ball carrier to be taken to ground; however, there are other one-on-one tackle situations that

do not require the attacking player to go to ground, but still impede the ball carrier's progress (108). Therefore, a limitation of this study was that only one-on-one tackles resulting in the ball carrier being taken to ground were validated. In contrast, the algorithm's predictions of ruck events were possibly more consistent due to the body position required to best compete for possession after a completed tackle.

To determine whether the predictive capability of the algorithm was influenced by the number of collision events that a specific player was involved in, the optimal algorithm cut-offs were analysed separately for players who completed few rucks/tackles and those who completed many. On the basis of this analysis, it was shown that the algorithm's predictive ability was not affected by the frequency of either collision event; returning similar optimal cut-offs for players who performed one tackle and/or ruck and those who completed many (up to 21 tackles and 31 rucks). These results demonstrated that the algorithm is capable of providing a consistent account of a player's contact events, irrespective of the number of contacts they perform during training or match-play.

Results of this study complement those of a recently published paper that describes the use of microtechnology data to quantify the number and timing of scrum events completed by Rugby Union players during training and match-play (113). Furthermore, this study adds to growing literature that has highlighted the overwhelming potential of the time-series data that is available from athlete-worn microtechnology (52). Application of these specifically designed algorithms have already been highlighted. However, it is important to recognise that many of the algorithms developed using microtechnology data are highly specific to the sports for

which they were developed, which likely influences their transferability to sports that share some similarities. For example, previously highlighted research in Rugby League, demonstrates the performance decrement of an tackle detection algorithm when applied to Rugby Union and Australian Rules football (9,41,53,54). The reduced performance of the Rugby League-specific algorithm in other codes of football is likely explained by the distinct variations that exist in the tackling techniques of the different sports (96). Furthermore, each of these sports involves unique collision events that may elicit similar patterns in the microtechnology data, but are considered quite different to tackles in the context of the game (e.g. hip and shoulder in Australian Rules football). Collectively, these data suggest that it is important to implement collision-detecting algorithms that have been developed and validated using data derived from athletes that are intended to be examined (52-54).

During rugby training and match-play, coaches and analysts count tackles and rucks using labour-intensive and time-consuming video notational analysis. To date research highlights microtechnology's limitations in Rugby Union and inability to detect and distinguish between collisions, as research identifies all contacts as 'collisions' or 'static exertions' (52). This research has found a practical method to automate collection and differentiation of such events and builds on earlier work in this area (9,113,114). Collectively, these results provide practitioners with novel and time-efficient means for discriminating between the different types of contact events in Rugby Union, which will ultimately facilitate better interpretation of an individual's physical load in training and match-play situations(52).

Although results of this study suggest that the presented algorithm may provide sports scientists with an efficient and objective means of understanding the contact demands of training and match-play in Rugby Union, there are a number of potential limitations that should be considered. First, this algorithm was developed and validated using data collected during match-play for one International Rugby Union team. Although it could be argued that tackles and rucks would not differ considerably between other elite level squads, at lower levels of competition subtle differences may exist, where techniques may vary. As such, future research is needed to determine the suitability of the presented algorithm for use in different Rugby Union populations. Second, although this algorithm has been shown to accurately detect ruck and tackle events, it is not capable of providing insight into the nature of the forces experienced by the players during such events. As such, the presented algorithm is limited by the assumption that all tackles and rucks involve equal force; emphasising the need for future developments that are capable of providing insight into the specific physical demands of each collision to further quantify total training and match loads. As previously stated, the algorithm was trained using one-on-one tackles, thereby disregarding the contact load required during tackle assists. Despite the advancements in detecting contact demands in Rugby Union there is still a possibility that there is an underestimation of a player's contact demands.

# 7.5 Conclusion

Current research has focused on the running demands of Rugby Union and more recently scrum demands. This study provides sport scientists with a valid method of quantifying the contact and collision demands of Rugby Union by counting ruck and tackle events. This research enhances the ability to improve preparation and injury prevention of Rugby Union players. Automated detection of ruck and tackle events provides a time-efficient alternative to traditional time-consuming and labour-intensive methods requiring video-based analyses. Furthermore, it complements existing research that has described microtechnology-based algorithms to quantify the running demands and scrum incidence in Rugby Union athletes. Further research investigating forces within these contact movements is advocated.

#### 7.6 Practical Applications

- Results demonstrate the competencies of microtechnology, demonstrating the ability to detect ruck and tackle events in Rugby Union when applying a specifically designed algorithm. In addition with recent research, providing sport scientists the capability to detect and quantify the most frequent collisions in Rugby Union using microtechnology devices.
- This current study provides practitioners with a time efficient and validated method to detect and monitor rucks and tackles events during match-play and training to assist with player preparation and injury prevention. This provides more objective results than previous labour-intensive methods that are potentially error prone.

• This research will provide sport scientists with a more in-depth understanding of a player's demands by allowing different contact types, in this instance rucks and tackles, to be independently classified.

# Chapter 8 – Microtechnology-based Locomotor and Collision Profiles of

## Winning and Losing Elite Rugby Union Teams

This study has been submitted for publication following peer-review to the *International Journal of Sports Physiology and Performance*. Full reference details of the published manuscript are:

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Studies 2 and 3 of this thesis developed and validated the first Rugby Union-specific algorithms for automatically identifying scrums, one-on-one tackles and ruck events using player-worn microsensor data. By combining these novel outcomes with the measures of running-based workloads that are more traditionally reported, it is possible to gain a more complete understanding of the physical demands placed on elite Rugby Union players.

To extend upon the findings of existing research, the final study of this thesis aimed to use wearable microsensor data collected from four elite Rugby Union teams to evaluate differences in running demands and collision events between positional playing groups (Forwards vs. Backs) and winning and losing teams.

#### **8.1 Introduction**

Rugby Union is a team sport that requires players to perform repeated high-intensity locomotor efforts (running, sprinting and accelerations) and collisions (20,113). These events are interspersed with low-intensity aerobic activity (walking and jogging) or rest (6,18). The game is also characterised by distinct collisions that include scrums, rucks, tackles and mauls (113). The match demands of Rugby Union have been quantified using commercially available microtechnology devices containing global positioning systems (GPS), accelerometers, magnetometers and gyroscopes (13,52). These devices provide real-time and retrospective feedback of match-play and training distances, high-speed running, accelerations and collisions (52,113). Research has predominantly quantified locomotor activity profiles using GPS to describe whole match or per half demands (12,115). Contact demands have been represented in the literature by the total number of collisions or impacts using microsensor data (6,9) or manually-coded video data during match-play (12,22). However, such research has characterised collisions as 'static-exertions', while the manual coding of video data is labour-intensive and a potentially more erroneous method (52).

Although the contact demands of Rugby Union have previously been quantified using microtechnology-based algorithms (6,9), the validity of these methods was not assessed and/or their procedures were not specific to Rugby Union (e.g. they were designed for Rugby League). A previous systematic review highlighted that microsensors have been extensively used to detect sport-specific movements in individual and team sports, but emphasised that sport-specific algorithms should be used for the purpose they were developed (52). Therefore, finding that an algorithm developed to detect tackles in Rugby League was unsuitable for use in Rugby Union was unsurprising and suggests

that existing research that has used non-specific algorithms for impact detection may have inaccurately reported the contact demands (9,52). Furthermore, given Rugby Union is characterised by a number of different and often unique collision types (e.g. scrums, rucks, tackles, mauls), methods for evaluating the collision-based demands of this sport should seek to delineate these collision types to allow the physical costs of each event to be determined (52,113).

Until recently, no specifically designed algorithms existed for use in Rugby Union; however, newly validated scrum, ruck and tackle algorithms have now made it possible to differentiate between the different contact events in Rugby Union (52,113,116). By incorporating such algorithms into day-to-day practice, sport scientists are now able to more accurately and efficiently quantify the demands of training and match-play. Quantification of these demands provides a more holistic appreciation of players' activity profiles, which might ultimately assist physical preparation and prevention of injury for these athletes.

To ensure players are adequately prepared for the most critical moments of play, it is important to identify the most demanding phases of competition. Rugby Union researchers have used microtechnology to document the locomotor and collision-based demands of each ball-in-play period of a match (from ball entering play until a stoppage in play) in order to identify the most demanding passages of play (also referred to as the 'worst case scenario') (6,17). However, the algorithms used in this research were not validated and were not capable of differentiating the different types of rugbyspecific collisions, which potentially limits the application of this research (52). A separate study analysed the running demands of match-play by separating the game data into a consecutive series of five-minute segments (115). Although this type of analysis provides insight into the intermittent demands of the sport, it reportedly underestimates actual relative demands in comparison to ball-in-play analysis, which may have important implications for athlete preparation (17). Furthermore, this type of analysis does not consider the game time or score (6). Dissecting data into predetermined epochs can account for score differences and would potentially highlight differences between winning and losing teams over the course of a match if both sets of data were available. Research involving athletes from soccer (117,118) and Rugby League (119,120) have investigated the differences in activity profiles between winning and losing teams. Studies in Rugby League highlighted that although losing teams generally have higher locomotor demands and more repeated high-intensity bouts, winning teams performed more collisions (119,120). Similarly, in soccer, losing teams were more likely to have greater total distance and high-intensity running demands (117,118). To date, no research has concurrently investigated locomotor and contact demands and match outcome in Rugby Union match-play.

This research first sought to apply specifically designed algorithms to match-play data to develop a greater understanding of the contact demands of elite Rugby Union (113). Secondly, this study aimed to compare running-based and collision-based data for opposing teams to provide a unique perspective of the key differences between winning and losing teams. To establish the effects of score and match-time on these activity profiles, data were analysed as complete matches and in consecutive five-minute periods throughout the match. It was hypothesised that losing teams would perform higher locomotor demands than winning teams. Additionally, it was hypothesised that teams that won would perform more collision events than those who lost (24). Losing teams were expected to perform more tackles, as percentage of possession is reported to have an effect on success (121). It was also anticipated that ruck events would be similar between winning and losing teams as these events happen regardless of team possession.

#### 8.2 Methods

A total of 185 elite Rugby Union players (forwards n=107, backs n=78) were recruited from four elite-level Pro 12 Rugby Union teams. During competitive matches, players wore a single Catapult S5 Optimeye device (Catapult Sports, Melbourne, Victoria, Australia) positioned between the shoulder blades in a purpose-built vest. Devices contained GPS sampling at 10 Hz and tri-axial accelerometers, gyroscopes and magnetometers that captured data at 100 Hz. During a season, the four selected teams played one another twice (once home and once away); therefore, providing 12 matches for which data could be obtained for both teams. Over the 12 matches, 518 microtechnology data files were analysed. Data were collected from the 2016/17 season; matches were selected based on the availability of microtechnology data for both teams involved. Players were classified into positional sub-groups, which included forwards or backs. The study's experimental procedures were reviewed and approved by the Australian Catholic University's Human Research Ethics Committee (Approval #2014-135Q).

In order to obtain locomotor and collision profiles, all raw data files were analysed postmatch using commercially available software (Openfield version 1.17.0 Build #30874, Catapult Sports, Melbourne, Victoria, Australia). Specifically, this software was used to calculate total match locomotor demands using GPS data and scrum incidence, using a validated scrum algorithm integrated within the software (113). To determine the number of rucks and tackles performed, microsensor data (from accelerometers, magnetometers and gyroscopes) were exported at 100 Hz for each player data file. These player data files were imported into the R statistical software package (<u>http://www.r-project.org/</u>) and processed using a validated ruck and tackle algorithm, which quantified the number and timing of these events for each match (116). The locomotor demands and contact events were then separated into five-minute periods (113). The outcomes of both algorithms were combined with several more traditional locomotor-based variables using Microsoft Excel (Microsoft Corporation, USA). Specifically, locomotor variables included total distances covered at low  $(0.5-2.8 \text{ m}\cdot\text{s}^{-1})$ , moderate (2.8-5.6m·s<sup>-1</sup>), high (5.6-7.5m·s<sup>-1</sup>) and sprinting speed (>7.5m·s<sup>-1</sup>) and accelerations (>2.79m·s<sup>-2</sup>) (122). Total distance and high-speed distance (HSD) were also quantified relative to game time (m.min<sup>-1</sup>). Collision-based variables included the frequency of rucks, tackles and scrums. Data from the four teams were collated and classified into winning and losing teams. Players were further dichotomised into players who contributed to whole games (i.e. players who started the match and played for a minimum of 60 minutes) (6), and substituted players (i.e. players who did not start on the field, but played at least 5 minutes). Of the available data, a total of 57 player files (11%) did not meet the criteria for inclusion (i.e. starting player not playing enough minutes, substitute not playing more than five minutes or playing longer than 60 minutes) and, therefore, were removed.

Primary analyses calculated means and standard deviations (SD) for forwards and backs, whole game and substituted players, and winning and losing teams. For single comparisons between means, the distribution of all data was verified as normal using a Shapiro-Wilk test and independent *t* tests were used throughout. To provide real world

applicability to findings, effect sizes were calculated using the standardised difference between winning and losing teams for each of the measured variables. Effect sizes were interpreted as: <0.20, trivial; 0.20-0.59, small; 0.60-1.19, moderate; 1.20-1.99, large; >2.00, very large (90,123,124). All data were reported as mean  $\pm$  *SD*, difference in effect size with  $\pm$ 90% CI. All statistical analyses were conducted in the Statistical Package for the Social Sciences (SPSS v24).

The secondary analyses involved only the data collected for starting players due to the varying introduction of substitutes throughout a match. Specifically, the mean locomotor (distance per minute, high-speed per minute and low-speed per minute) and contact (scrums per minute, tackles per minute and rucks per minute) data for the starting players were divided to represent consecutive 5-minute periods (115). Data collected during injury or stoppage time were not included in the analysis, as the contribution of these time periods to the overall match duration are highly variable. To ensure that the player workloads were not inadvertently biased by extended stoppage periods, only the data derived from the minimum game time of 80 minutes were used.

#### 8.3 Results

Table 8.1 shows the results of the primary analyses and includes the physical demands of winning and losing teams in elite Rugby Union for starting players and substitutes. For starting players (>60 min), winning forwards covered less total distance than losing forwards (ES 0.38; *small*). This difference was primarily as a result of reduced distance at moderate (ES 0.38; *small*) and high speed (ES 0.43; *small*) with a *trivial* difference at low speed (ES 0.12). For starting backs these differences were *trivial*. Accordingly, relative locomotor variables (M.min<sup>-1</sup>; high speed M.min<sup>-1</sup>) were lower for starting forwards (ES 0.37; *small*; ES 0.39; *small*, respectively) while this difference was *trivial* for starting backs (both ES < 0.2). Winning forwards also performed fewer tackles than losing forwards (ES 0.48; *small*).

Substitutes performed fewer contacts and had lower locomotor activity than starting players for all reported variables. Total distance and distances covered at low, moderate, high and sprint speeds varied substantially due to total game time. A large proportion of these variables were found to have a *trivial* difference between the two groups. Total distance covered by substitute forwards and backs was found to have *small* differences, with losing teams completing greater work. Substitute forwards were found to have *small* differences for moderate speed running and sprint speed running respectively. Backs substitutes showed *small* differences in high speed and sprint speed distance although high speed per minute was *trivial*. Contact variables were again lower for substitutes in comparison to starters due to total game time. However, tackles performed by substitute backs and rucks by substitute forwards were found to have *small* differences between winning and losing teams.

		Starting Players (>60 mins)					Substituted Players (<60 mins)			
Metric	Position	Winning	Losing	Effect Size ±90%, CI	Inference Classification	Winning	Losing	Effect Size ±90%, CI	Inference	
Distance (m)	Forward	5449 (±997)	5814 (±947)	0.38 (0.19 to 0.56)	Small	1426 (±808)	1739 (±859)	0.38 (0.13 to 0.63)	Small	
	Back	6347 (±954)	6470 (±913)	0.13 (-0.05 to 0.32)	Trivial	1727 (±885)	2165 (±1101)	0.44 (0.19 to 0.69)	Small	
Low Speed Distance (m)	Forward	2556 (±790)	2657 (±916)	0.12 (-0.07 to 0.3)	Trivial	892 (±408)	969 (±478)	0.17 (-0.08 to 0.42)	Trivial	
	Back	2920 (±1004)	2969 (±1033)	0.05 (-0.14 to 0.23)	Trivial	1073 (±578)	1151 (±609)	0.13 (-0.12 to 0.38)	Trivial	
Moderate Speed Distance (m)	Forward	1390 (±480)	1582 (±529)	0.38 (0.19 to 0.57)	Small	470 (±268)	553 (±309)	0.29 (0.04 to 0.54)	Small	
	Back	1575 (±599)	1600 (±574)	0.04 (-0.14 to 0.23)	Trivial	588 (±393)	590 (±330)	0.01 (-0.24 to 0.26)	Trivial	
High Speed Distance (m)	Forward	102 (±72)	135 (±82)	0.43 (0.24 to 0.61)	Small	23.3 (±29.2)	25.0 (±26.0)	0.06 (-0.19 to 0.31)	Trivial	
	Back	389 (±143)	412 (±150)	0.16 (-0.03 to 0.34)	Trivial	90.0 (±62.0)	111.0 (±83.4)	0.29 (0.04 to 0.54)	Small	
High Speed Efforts	Forward	7.8 (±5.3)	10.4 (±5.9)	0.46 (0.27 to 0.65)	Small	1.9 (±2.2)	2.0 (±2.1)	0.05 (-0.2 to 0.3)	Trivial	
	Back	29.2 (±10.4)	30.7 (±11.7)	0.14 (-0.05 to 0.32)	Trivial	6.3 (±3.8)	8.6 (±5.7)	0.47 (0.22 to 0.72)	Small	
Sprint Speed Distance (m)	Forward	2.5 (±6.74)	4.0 (±11.28)	0.16 (-0.02 to 0.35)	Trivial	0.75 (±2.5)	0.86 (±3.9)	0.31 (0.06 to 0.56)	Small	
	Back	54.5 (±54.72)	59.3 (±52.38)	0.09 (-0.1 to 0.27)	Trivial	5.2 (±9.5)	11.4 (±19.4)	0.41 (0.16 to 0.66)	Small	
Sprint Efforts	Forward	0.2 (±0.39)	0.6 (2.38)	0.23 (0.05 to 0.42)	Small	0.1 (±0.1)	0.1 (±0.2)	0.71 (0.46 to 0.96)	Moderate	
	Back	3.0 (±2.5)	3.6 (±2.7)	0.23 (0.04 to 0.42)	Small	0.4 (±0.7)	0.6 (±1.0)	0.23 (-0.02 to 0.48)	Small	
M.min <sup>-1</sup>	Forward	63.7 (±8.5)	66.6 (±7.3)	0.37 (0.18 to 0.55)	Small	68.2 (±13.7)	69.6 (±16.4)	0.09 (-0.16 to 0.34)	Trivial	
	Back	71.8 (±8.0)	72.3 (±7.2)	0.07 (-0.12 to 0.25)	Trivial	75.1 (±10.4)	73.0 (±12.5)	0.18 (-0.07 to 0.43)	Trivial	
High speed distance m.min <sup>-1</sup>	Forward	1.2 (±0.80)	1.5 (±0.87)	0.39 (0.21 to 0.58)	Small	1.2 (±1.5)	1.0 (±1.0)	0.16 (-0.09 to 0.41)	Trivial	
	Back	4.4 (±1.55)	4.6 (±1.59)	0.13 (-0.06 to 0.31)	Trivial	4.1 (±2.4)	3.8 (±2.7)	0.12 (-0.13 to 0.37)	Trivial	

Table 8.1 Average locomotor and contact demands of winning and losing forwards and backs and effect.

		Starting Players (>60 mins)					Substituted Players (<60 mins)			
Metric	Position	Winning	Losing	Effect Size ±90%, CI	Inference Classification	Winning	Losing	Effect Size ±90%, CI	Inference	
Accelerations	Forward	35.8 (±31.7)	38.4 (±35.8)	0.08 (-0.11 to 0.26)	Trivial	9.9 (±10.2)	10.9 (±12.5)	0.09 (-0.16 to 0.34)	Trivial	
(m.s <sup>-2</sup> )	Back	45.8 (±40.8)	49.4 (±44.1)	0.08 (-0.1 to 0.27)	Trivial	14.6 (±17.8)	15.7 (±16.4)	0.06 (-0.19 to 0.31)	Trivial	
Forw <b>Tackles</b> Back	Forward	7.5 (±3.7)	9.7 (±5.3)	0.48 (0.29 to 0.67)	Small	2.7 (±2.4)	2.7 (±2.2)	0 (-0.25 to 0.25)	Trivial	
	Back	4.6 (±3.1)	5.0 (±3.7)	0.12 (-0.07 to 0.3)	Trivial	1.8 (±1.9)	1.3 (±1.3)	0.31 (0.06 to 0.56)	Small	
Ducks	Forward	13.3 (±8.7)	13.8 (±6.6)	0.06 (-0.12 to 0.25)	Trivial	3.8 (±3.7)	5.0 (±3.9)	0.32 (0.07 to 0.57)	Small	
RUCKS	Back	4.1 (±3.6)	3.4 (±2.8)	0.22 (0.03 to 0.4)	Small	1.1 (±1.3)	1.3 (±1.4)	0.15 (-0.1 to 0.4)	Trivial	
Scrums	Forward	12.7 (±4.3)	13.3 (±3.6)	0.15 (-0.04 to 0.34)	Trivial	5.3 (±2.6)	4.7 (±2.8)	0.22 (-0.8 to 0.52)	Small	
	Back	-	-	-	-	-	-	-	-	
The secondary analysis of the sixteen 5-minute intervals that compared starting forwards and backs from winning and losing teams identified the peak demands for each 5-minute period of match play and variability between each epoch. Specifically, the locomotor (m.min<sup>-1</sup>, low-speed distance m.min<sup>-1</sup> and high-speed distance m.min<sup>-1</sup>) and contact (rucks.min<sup>-1</sup>, tackles.min<sup>-1</sup> and scrums.min<sup>-1</sup>) demands were determined for each group to facilitate comparison (Figure 8.1). The peak demands across all intervals for losing forwards involved 93.0 m.min<sup>-1</sup> with 58.2 m.min<sup>-1</sup> at low speed and 4.6 m.min<sup>-1</sup> at high speed. Additionally, the contact demands for these athletes included 0.8 tackles.min<sup>-1</sup> and 1.3 rucks.min<sup>-1</sup>. In contrast, winning forwards had lower peak demands, performing 91.5 m.min<sup>-1</sup> with 55.4 m.min<sup>-1</sup> at low speed and 3.4 m.min<sup>-1</sup> at high speed. Similarly, their contact demands were lower and included 0.6 tackles and 1.1 rucks.min<sup>-1</sup>. Scrum demands throughout each match were understandably equal for both winning and losing teams, with a peak of 1.4 scrums per minute. The highest demands of winning backs were 94.5 m.min<sup>-1</sup>, with players completing 56.9 m.min<sup>-1</sup> at low speed and 7.3 m.min<sup>-1</sup> at high speed. The contact demands for these athletes included 0.4 tackles.min<sup>-1</sup> and 0.4 rucks.min<sup>-1</sup>. In contrast, peak demands for losing backs included distances of 92.9 m.min<sup>-1</sup>, with 59.5 m.min<sup>-1</sup> at low speed and 8.8 m.min<sup>-1</sup> <sup>1</sup> at high speed. Contact demands for losing backs were similar to winning backs and included 0.3 rucks.min<sup>-1</sup>. With respect to the locomotor demands, losing forwards and backs generally exhibited higher values for a greater proportion of the 5-minute match intervals.

The secondary analysis of the sixteen 5-minute intervals that compared starting forwards and backs from winning and losing teams identified the peak and variability of demands for each of 5-minute period of match play. Specifically, the locomotor

(m.min<sup>-1</sup>, low speed distance m.min<sup>-1</sup> and high-speed distance m.min<sup>-1</sup>) and contact (rucks.min<sup>-1</sup>, tackles.min<sup>-1</sup> and scrums.min<sup>-1</sup>) demands were determined for each group to facilitate comparison (Figure 8.1). The peak demands across all intervals for losing forwards involved 93.0 m.min<sup>-1</sup> with 58.2 m.min<sup>-1</sup> at low speed and 4.6 m.min<sup>-1</sup> at high speed. Additionally, the contact demands for these athletes included 0.8 tackles.min<sup>-1</sup> and 1.3 rucks.min<sup>-1</sup>. In contrast, winning forwards had lower peak demands, performing 91.5 m.min<sup>-1</sup> with 55.4 m.min<sup>-1</sup> at low speed and 3.4 m.min<sup>-1</sup> at high speed. Similarly, their contact demands were lower and included 0.6 tackles and 1.1 rucks.min<sup>-1</sup>. Scrum demands throughout each match were understandably equal for both winning and losing teams, with a peak of 1.4 scrums per minute. The highest demands of winning backs was 94.5 m.min<sup>-1</sup> with players completing 56.9 m.min<sup>-1</sup> at low speed and 7.3 m.min<sup>-1</sup> at high speed. The peak contact demands for winning backs included 0.4 tackles.min<sup>-1</sup> and 0.4 rucks.min<sup>-1</sup>. In contrast, peak demands for losing backs included distances of 92.9 m.min<sup>-1</sup>, with 59.5 m.min<sup>-1</sup> at low speed and 8.8 m.min<sup>-1</sup> at high speed. Contact demands for losing backs were similar to winning backs and included 0.3 rucks.min<sup>-1</sup> and 0.4 tackles.min<sup>-1</sup>. With respect to the locomotor demands, losing forwards and backs generally exhibited higher values for a greater proportion of the 5minute match intervals.



WF – Winning Starting Forwards; LF – Losing Starting Forwards; WB – Winning Starting Backs; LB – Losing Starting Backs

Figure 8.1 – The changes in physical demands across 80 minutes of match-play segmented into 5-minute intervals. A) M/min of playing groups, B) Low speed running demands of playing groups, C) High speed running demands of playing groups, D) Tackles per minute of playing groups, E) Rucks per minute of playing groups, F) Scrums per minute for forwards only.

### **8.4 Discussion**

This study is the first to use microtechnology and specifically designed validated algorithms to quantify the locomotor and contact demands of elite Rugby Union matchplay. In a first for the sport, validated scrum, tackle and ruck algorithms were applied to data distinguishing between contact events (52,113). Additionally, a novel aspect of this research was the comparison of the physical demands of winning and losing Rugby Union teams competing in the same domestic league.

As hypothesised, there were differences between winning and losing teams with respect to the running-based demands of the game. The results showed losing teams perform greater locomotor activity than that of winning teams. These findings are in accordance with other research from Rugby League (120,125,126) and soccer (117,118), where losing teams performed greater locomotor activity than winning teams. Although *trivial* differences were observed for absolute locomotor variables for starting backs the reported relative data was higher than starting backs reported in other publications (6).

Observed findings demonstrate that losing starting forwards are subjected to a greater locomotor workload particularly in moderate and high-speed running. Although these differences were found to be *small*, it is possibly due to less team possession and greater time spent defending. Given the differences occurring at moderate and high-speeds, Rugby League research has hypothesised that this is due to missed tackles or poor defence requiring higher intensity exertion from the defence to scramble (127). Furthermore, given that losing team forwards also perform more tackles (*small*), combined with increased locomotor demands may decrease the technical and tactical capabilities of losing starting forwards. Other observations of starting players included

winning backs completing more rucks (*small*), this may be advantageous in order to retain possession and improve speed of ball, or alternatively slow opposition speed of ball.

Total distance and sprint distance for substitute forwards and backs were found to have *small* differences between both groups, with losing teams performing greater activity. Differences were acknowledged between substitute backs with losing substitute backs performing a greater number of high speed and sprint efforts (both *small*), while winning substitute backs performed more tackles (*small*). Although some differences can be attributed to total time played, it is evident that the locomotor and contact demands required of substitutes may also differ between sub-groups based on the tactical requirements of these players. For example, the demands placed on substituted players may be dependent on the score margin at the time they enter the match or by the specific role and/or strengths and weaknesses of the individual. Given the lack of differences in relative locomotor variables for substitute forwards and backs, these findings suggest that losing teams make substitutions earlier in the match particularly forwards, as mean losing substitute forwards distance is higher than winning substitute backs.

The finding that match outcome was associated with very few variables supports the notion that match outcomes are multifactorial and depend on physical attributes, as well as technical and tactical effectiveness. For example, it has been documented that more successful teams kick more frequently (121), perform more line breaks and have better ball carrying abilities than less successful teams (128). Therefore, more dominant teams

may manipulate their possession, thereby forcing the opposition to run more and perform more contact events, in particular tackles of forwards.

Winning the collision is frequently associated with a positive match outcome (24); yet, in this research, losing teams performed a greater total number of contacts than winning teams. Tackle events were higher for losing teams for both starting forwards and backs and substitute forwards, which is likely due to winning teams having greater possession requiring losing teams to tackle more. However, substituted backs from winning teams performed more tackles than from losing teams (*small*), such differences could require further investigation to account for these differences in activity profiles.

Ruck events for starting forwards were only found to be different between winning or losing substitute backs, with the differences observed between substituted forwards from winning and losing sides found to be only *trivial*. Such results may be attributed to technical and physical limitations of losing teams. However, we did not consider forces measured by the microsensors which would influence tackle, ruck and scrum dominance. Future research quantifying the quality and/or intensity (forces) associated with each contact type may be warranted to better understand the stresses experienced by players and the overall influence of these factors on match outcome.

Although there were very few differences in the total locomotor and contact demands of winning and losing forwards and backs, a player's capability to prepare adequately for the peak match demands would likely have positive effects on their technical and tactical effectiveness. This is potentially reflected in the analysis of sixteen 5-minute intervals (Figure 8.1), which shows the fluctuations of match demands throughout the 80-minutes of match play. Of the reported variables, there were no observations that distinguished either winning or losing teams to have an advantage over the 16 epochs. However, it should be noted that the first interval had the highest combined locomotor and contact demands. There was another spike in demands shortly after half-time which could be due to the rest period of half-time and possible introduction of substitutes. Dividing the match into consecutive 5-minute periods provided insight into possible differences in the physical demands of winning and losing teams. The general lack of differences between locomotor and contact demands of winning and losing teams may be attributable, at least in part, to the limitations of this method, as some studies have suggested that it may underestimate peak locomotor demands by up to 25% (6,45). Further analyses investigating the rolling average demands or ball-in-play demands of winning and losing teams may be warranted (21).

This research provides novel insight into the physical demands of elite Rugby Union and describes their association with differences in activity profiles between winning and losing teams. As this research only uses data from microtechnology, it would be beneficial to include subjective match performance indicators to further understand match demands and variables associated with success. Future research investigating peak ball-in-play periods (6), rolling average demands (21), and additional physiological measures, such as heart rate, would likely extend the findings of this research by providing further insight into the total match demands and the effect of intense match periods.

# **8.5** Conclusion

This study is the first to quantify the locomotor and specific contact demands (rucks, tackles and scrums) of Rugby Union match-play using validated sport-specific microtechnology-based algorithms. Combining locomotor and contact demands provides a more complete and objective measure of the physical demands associated with elite Rugby Union. Losing forwards (starters and substitutes) do have higher activity profiles than those of winning forwards, although fewer differences were observed between backs. Given the difference in physical demands of losing forwards, it may prove beneficial to increase recovery protocols during the season. Although this research presents novel methods for objectively quantifying the locomotor demands and contact events of rucks, scrums, and one-on-one tackles, it does not identify other collision events, such as mauls, tackles involving more than 2 players, and attacking collisions, such as the ball carrier being tackled nor the effectiveness of these events.

### **8.6 Practical Applications**

- The use of microtechnology to quantify match demands can provide practitioners with useful information to improve player preparation. Differences in demands may help with specific conditioning of starters and substitutes.
- Application of these algorithms to quantify training methods is beneficial to ensure that teams adequately prepare for elite match-play. Exposing players to rugby-specific drills in training that elicit positional peak and average locomotor and contact demands could potentially benefit team preparation.
- Although few physical variables were associated with match outcome, other technical and/or tactical aspects will influence whether a team wins or loses.

Therefore, it is recommended that future work consider physical activity profiles with other contextualised technical and tactical information.

• Due to locomotor and contact demands being greater for losing team forwards, this might impact recovery between matches. Losing teams may benefit from increased exposure to recovery modalities in order to facilitate greater recovery between matches.

# **Chapter 9 – General Discussion and Conclusions**

## 9.1 Overview

The aim of this program of research was to provide an overview of the current usage of microtechnology and to validate specifically designed algorithms to differentiate and quantify the contact and match-play demands of elite Rugby Union match-play using player-worn microtechnology. The research first identified existing methods to quantify sport-specific movements. The use of wearable technology was then explored, developing a reliable and valid measure to identify and monitor scrums, rucks and one-on-one tackles in Rugby Union. To improve our understanding of the contact demands experienced in Rugby Union, observational data were also collected across both physical preparation and competition periods (Table 9.1).

Table 9.1 Study outlines, aims, and experimental hypotheses

Chapter in Thesis	Study Outline	Aims	Experimental Hypotheses
Chapter 4	Investigate the uses of microsensors to	Systematically review previous literature and	Existing research would provide evidence for
-	quantify sport-specific movements.	their methods to examine the effectiveness of	the use of microsensors to analyse sport-
		athlete-worn microsensors (accelerometers,	specific movements in individual sports, team
		gyroscopes and magnetometers) to detect	sports, snow sports and water sports.
		sport specific movements in a wide variety of	
		sports.	

Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. Sports Medicine. 2015 Jul 1;45(7):1065-81.

Chapter 6	Create a specifically designed algorithm to	Design and validate scrum specific algorithm	Wearable microtechnology will be both
	detect scrum events in elite Rugby Union	using events from training and match-play.	sensitive and specific in the detection of
	training and match-play.		scrum events during training and match-play.

Chambers RM, Gabbett TJ, Cole MH. Validity of a microsensor-based algorithm for detecting scrum events in Rugby Union. International Journal of Sports Physiology and Performance. 2019 Feb 1;14(2):176-82.

Chapter 7	Create a specifically designed algorithm to	Design and validate an algorithm for one-on-	Wearable microtechnology will be capable of
	detect ruck and one-on-one tackle events in	one tackle and ruck detection using events	detecting one-on-one tackle and ruck events
	elite Rugby Union match-play.	from match-play.	during match-play using a specifically
			designed algorithm.

Chambers RM, Gabbett TJ, Gupta R, Josman C, Bown R, Stridgeon P, Cole MH. Automatic detection of one-on-one tackles and ruck events using microtechnology in Rugby Union. *Journal of Science and Medicine in Sport.* 2019 Jan 6;22(7):827-832.

Chapter 8	Profile the collision and locomotor demands	Quantify locomotor and contact demands of	Losing teams would perform more collision	
	of winning and losing match-play demands	rugby union using GPS and specifically	events and have higher locomotor demands	
	of elite Rugby Union teams using	designed algorithms and determine	than winning teams.	
	microtechnology.	differences between winning and losing		
		teams.		
Chambers RM, Gabbett TJ, Miller C, Bown R, Stridgeon P, Cole MH. Microtechnology-based locomotor and collision profiles of winning and losing elite Rugby Union teams.				
International Journal of Sports Physiology and Performance. 2020; Submitted January 2020.				

# 9.2 Summary of Findings

Table 9.1 summarises the study outlines, aims and hypotheses of each experimental chapter. Expanding on this summary:

- (i) Chapter 4 hypothesised that research would have extensively used microsensors to analyse sport-specific movements in individual sports, team sports, snow sports and water sports. Microsensors are becoming an increasingly more popular method to quantify and analyse sport-specific movements. Chapter 4 summarised findings from a range of individual and team sports and identified that although there was evidence of an existing Rugby Union tackle algorithm, there were no current applications of microsensors to identify other contact movements such as rucks, scrums and mauls.
- (ii) In Chapter 6 it was hypothesised that wearable microtechnology would be both sensitive and specific for the detection of scrum events during training and matchplay. Using player-worn microtechnology devices in elite Rugby Union matchplay and training, this study showed that a specifically designed algorithm could be created and validated. High sensitivities (91%) and specificities (91%) demonstrated the capabilities of microsensors for detecting scrum events when using this specifically designed algorithm. The experimental hypothesis was strongly supported by the results of this study.
- (iii) Chapter 7 hypothesised that wearable microtechnology would be capable of detecting one-on-one tackle and ruck events during match-play using a specifically designed algorithm. Specific microsensor signal patterns were identified by combining 100 Hz sensor data with video to create an algorithm training set of ruck

and tackle data. When the algorithm was applied to match-play data, rucks and one-on-one tackles were correctly identified by the specifically designed algorithm. Thus, the results of the experimental study strongly support the hypothesis.

(iv) Chapter 8 hypothesised that losing Rugby Union teams would perform higher locomotor and contact demands than winning teams. Using microtechnology devices containing GPS and microsensors with the application of scrum, ruck and one-on-one tackle algorithms provided greater insight into the physical demands, than has previously been available for elite Rugby Union match-play. Additionally, using data from four teams, further analysis was carried out to determine differences between workload metrics for winning and losing teams. Results showed that starting forwards from losing teams performed a higher frequency of locomotor and contact demands, while substitute backs from winning teams performed more tackles. However, it is important to note that most variables returned a *trivial* difference between winning and losing starting and substitute forwards and backs. Therefore, the results of this study predominantly support the experimental hypotheses.

## 9.3 Points of Difference

The points of difference provided by this program of research are:

(i) The systematic review in this thesis identified current applications of athlete-worn microsensors to detect and quantify sport-specific movements in individual sports, swimming, snow sports and team sports. Thus, the systematic review provided a summary of how athlete-worn devices are currently used to monitor non-locomotor movements. Additionally, this review identified gaps in the current literature, particularly around the identification and discrimination of common contact and collision events in Rugby Union, such as rucks, mauls and scrums.

- (ii) The results from Studies 2 (chapter 6) and 3 (chapter 7) provide valid automated detection solutions for ruck, one-on-one tackle and scrum events. The developed algorithms provide practitioners with a means to better understand the non-locomotor demands of elite Rugby Union training and match-play. Previous investigations required researchers to manually code and count collisions, which is both time consuming and labour intensive. Additionally, due to the physical difference in each contact type, such algorithms can improve understanding of player demands, as existing research did not delineate between contact events. Such algorithms can provide an improved understanding of athlete workload, benefitting player preparation and injury prevention efforts by understanding daily contact load more thoroughly.
- (iii) Study 4 (chapter 8) profiled elite Rugby Union demands using the contact algorithms developed in Studies 2 and 3, in combination with locomotor measurements provided by the player-centred GPS data. Firstly, the research provides a novel overview of locomotor and non-locomotor demands by position (forwards and backs). Secondly, this research examined differences in locomotor and collision variables between winning and losing teams using effect sizes, providing 'real world' applicability for practitioners. Finally, analysis of the data in rolling 5-minute intervals across the match also indicated intense periods of match-play and potential "worst-case scenarios" when combining contact and

locomotor demands. Overall this investigation provides practitioners with an improved insight into the physical demands of elite Rugby Union, which may potentially have benefits for player preparation.

# 9.4 Strengths

The strengths of this program of research are summarised as:

- (i) Advancing current knowledge of the application of athlete-worn microtechnology, specifically microsensors, to quantify the demands of sport-specific movements across a variety of sports.
- (ii) Validation of innovative algorithms to detect specific contact events in Rugby Union. Algorithms applied to microsensor-based data can reliably differentiate between scrums, rucks and one-on-one tackles.
- (*iii*) Analysing the locomotor and contact demands of elite Rugby Union match-play using microtechnology. This research provides an in-depth analysis of the locomotor and contact demands of forwards and backs and the differences in microtechnology variables between winning and losing teams. In turn, this provides sport scientists, coaches and conditioners with a better understanding of the peak contact and locomotor demands of each sub-group during match-play.

# 9.5 Limitations

The sample of players used in the design of the contact-specific algorithms could be considered a limitation of the research due to the forces in men's elite Rugby Union. Such algorithms may not be valid or reliable in other variations of the game such as junior or women's rugby where the forces may not meet the criteria required by the algorithms. Similarly, the profiles of match-demands of elite men's Rugby Union detailed in Study 4 (Chapter 8) may also differ from amateur club or international levels and may not be applicable for other forms of Rugby Union.

Although this research is the first to examine the contact demands of elite Rugby Union using microtechnology it could be considered a limitation that these algorithms only detect contact events and do not specifically consider the magnitude of force associated with each of these collisions. Furthermore, in their current form, the presented algorithms have no capacity to characterise the effectiveness of the movement (e.g. if the tackle was successful or not) without the use of complementary video-based methods.

A critical limitation of this research is that although it presents novel methods for objectively quantifying the contact events of rucks, scrums, and one-on-one tackles, it does not identify other collision events, such as mauls, tackles involving more than 2 players and attacking collisions such as the ball carrier being tackled.

# 9.6 Future Directions

The advancements in contact detection in elite Rugby Union using microsensors have presented an opportunity to explore physical demands in greater detail. Future research should:

- (i) Explore the forces of these contact events in order to examine the "load" for each contact event. This may require additional sensors or devices to be used and would improve understanding of each contact event.
- *(ii)* Explore the application of these contact events to identify acute and chronic loads for individuals and their impact on contact injury, fatigue, and performance. Many

sports have explored the effect of acute and chronic loading on athletes (49,129-131), but only used subjective training loads or locomotor loads. As contact injuries in Rugby Union cause a large proportion of athlete time loss, it would be beneficial to investigate these possible applications.

*(iii)* Combine contact-specific algorithms with subjective match data and effectiveness of contact events and individual performance. As these algorithms only determine whether an action has been performed (e.g. a scrum has taken place) and not whether the outcome of the movements was successful or effective (e.g. if a tackle event was successful or not), including relevant qualitative data would complement the objective outcomes provided by microsensor technology.

### 9.7 Practical Applications

This thesis significantly advances our understanding of the contact demands in elite Rugby Union and has the potential to impact the monitoring of physical demands of elite Rugby Union players. Previous investigations have used microtechnology to quantify the locomotor demands of match-play; these specifically designed algorithms will complement existing research by also quantifying the contact demands on players.

Previously, Rugby Union match-play and training contact loads has been difficult to objectively quantify due to the labour-intensive and time-consuming collection methods. Furthermore, such techniques may only quantify events that are effective and miss those that aren't effective (i.e. a collapsed scrum or missed tackle) and may not give a real contact load. The use of microtechnology to quantify contact events is not only time effective and less erroneous but can provide a more realistic view of the total contact demands of a player in match or training. Additional applications for the results presented in this thesis include the capacity for Sports Scientists to better quantify the training demands of players. Currently, matchplay contact events are coded and analysed by independent statistics companies (e.g. OptaSports), although no such service is available during training. Manual coding of training events is also labour intensive and time consuming. The use of microtechnology and these contact algorithms provides practitioners with an efficient and immediate system to more objectively quantify the contact demands of training. Furthermore, the appropriate application of these algorithms to training situations will ensure that player preparedness is optimal This can assist session design by understanding the contact load of particular drills to ensure they replicate match demands to prepare players for match-play. Longitudinal monitoring of scrum, ruck and tackle events can provide practitioners with an improved understanding of the acute and chronic contact loads of players.

These algorithms provide a valid method of quantifying contact events in training to understand an individual's contact loads. Study 4 (Chapter 8) presents the first attempt to practically quantify the locomotor and collision-based demands of elite Rugby Union match-play using wearable microtechnology and validated algorithms.

Understanding the contact demands of Rugby Union match-play can provide a greater insight into the overall demands of each position as well as the most physically demanding passages of play. Understanding the demands of training and match-play should result in training sessions being more specific and applicable to the game.

# 9.8 Conclusion

The results presented in this thesis make a significant contribution to the applied sports science discipline by presenting and validating two novel collision-detecting algorithms that have the capacity to automatically monitor contact demands in elite Rugby Union. Monitoring elite players using these validated algorithms provides insight into the demands of Rugby Union training and match-play, benefitting player preparation by improving training to replicate the demands of the game. Such monitoring strategies will help players returning from injury, thereby assisting rehabilitation and injury prevention efforts. Furthermore, these algorithms provide an objective and time efficient process to quantify ruck, scrum, and one-on-one tackle events.

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Appendices
### Appendix A – Ethics Approval ID 2014 135Q

Dear Applicant,

Dr Timothy Gabbett
Mr Ryan Chambers
2014 135Q
Validation of Contact and Collision in Rugby Union
using Microtechnology
Low Risk
13/05/2014
31/12/2016

This email is to advise that your application has been reviewed by the Australian Catholic University's Human Research Ethics Committee and confirmed as meeting the requirements of the National Statement on Ethical Conduct in Human Research subject to the following conditions:

Written permissions required from appropriate personnel within selected rugby union clubs.

This project has been awarded ethical clearance until 31/12/2016. In order to comply with the National Statement on Ethical Conduct in Human Research, progress reports are to be submitted on an annual basis. If an extension of time is required researchers must submit a progress report.

Whilst the data collection of your project has received ethical clearance, the decision and authority to commence may be dependent on factors beyond the remit of the ethics review process. The Chief Investigator is responsible for ensuring that appropriate permission letters are obtained, if relevant, and a copy forwarded to ACU HREC before any data collection can occur at the specified organisation. Failure to provide permission letters to ACU HREC before data collection commences is in breach of the National Statement on Ethical Conduct in Human Research and the Australian Code for the Responsible Conduct of Research. Further, this approval is only valid as long as approved procedures are followed.

If you require a formal approval certificate, please respond via reply email and one will be issued.

Decisions related to low risk ethical review are subject to ratification at the next available Committee meeting. You will be contacted should the Committee raises any additional questions or concerns.

Researchers who fail to submit a progress report may have their ethical clearance revoked and/or the ethical clearances of other projects suspended. When your project has been completed please complete and submit a progress/final report form and advise us by email at your earliest convenience. The information researchers provide on the security of records, compliance with approval consent procedures and documentation and responses to special conditions is reported to the NHMRC on an annual basis. In accordance with NHMRC the ACU HREC may undertake annual audits of any projects considered to be of more than low risk.

It is the Principal Investigators / Supervisors responsibility to ensure that:

- 1. All serious and unexpected adverse events should be reported to the HREC with 72 hours.
- 2. Any changes to the protocol must be approved by the HREC by submitting a Modification Form prior to the research commencing or continuing.
- 3. All research participants are to be provided with a Participant Information Letter and consent form, unless otherwise agreed by the Committee.

For progress and/or final reports, please complete and submit a Progress / Final Report form:

http://www.acu.edu.au/research/support\_for\_researchers/human\_ethics/forms

For modifications to your project, please complete and submit a Modification form: <u>http://www.acu.edu.au/research/support\_for\_researchers/human\_ethics/forms</u>

Researchers must immediately report to HREC any matter that might affect the ethical acceptability of the protocol e.g.: changes to protocols or unforeseen circumstances or adverse effects on participants.

Please do not hesitate to contact the office if you have any queries.

Kind regards,

Kylie Pashley

on behalf of

ACU HREC Chair, Dr Nadia Crittenden

Ethics Officer | Research Services Office of the Deputy Vice Chancellor (Research) Australian Catholic University

### Appendix B – Participant Information Letter

# **PARTICIPANT INFORMATION LETTER**

# **PROJECT TITLE:** Validation of Contact and Collision in Rugby Union using Microtechnology

## PRINCIPAL INVESTIGATOR: Tim Gabbett

Dear Participant,

You are invited to participate in the research project described below.

#### What is the project about?

The research project is investigating collision and contact within rugby union using microtechnology.

#### Who is undertaking the project?

This project is being conducted by Ryan Chambers and will form the basis for his PhD at Australian Catholic University under the supervision of Tim Gabbett.

#### Are there any risks associated with participating in this project?

There are no foreseeable risks with this project, as you are familiar with the microtechnology unit and you will not be asked to carry out any extra training or physical load based on this study. You will only be required to carry out your normal training demands.

#### What will I be asked to do?

- You will be required to wear a microtechnology (GPS) unit at every rugby session
- You will only need to perform what is required of you in training and nothing else.
- Consent for all sessions and games where you are wearing the unit will be required. We will use these files to assist in the analysis and development of an algorithm to detect contacts and collisions, but this will be de-identified. You will only be categorised by position.
- Consent to film all training sessions and games will also be required to assist in the validation of the contacts and collisions.

#### How much time will the project take?

All data collection will take place during training or matches. You will not be required to participate in any extra activities outside of training.

The study is to be completed by 31/12/2016

#### What are the benefits of the research project?

This study will assist in the physical preparation and load monitoring of yourself by understanding in greater detail the demands of elite rugby union.

#### Can I withdraw from the study?

Participation in this study is completely voluntary. You are not under any obligation to participate. If you agree to participate, you can withdraw from the study at any time without adverse consequences.

#### Will anyone else know the results of the project?

All data will be de-identified and be only referred to by position.

#### Will I be able to find out the results of the project?

Yes, upon validation of contact and collision in rugby union your personal data will be available to you.

#### Who do I contact if I have questions about the project?

Ryan Chambers e-mail: <u>rchambers@wru.co.uk</u> Mobile: 07584 488264

#### What if I have a complaint or any concerns?

The study has been approved by the Human Research Ethics Committee at Australian Catholic University (approval number 2014 135Q). If you have any complaints or concerns about the conduct of the project, you may write to the Chair of the Human Research Ethics Committee care of the Office of the Deputy Vice Chancellor (Research).

Chair, HREC c/o Office of the Deputy Vice Chancellor (Research) Australian Catholic University Melbourne Campus Locked Bag 4115 FITZROY, VIC, 3065 Ph: 03 9953 3150 Fax: 03 9953 3315 Email: <u>res.ethics@acu.edu.au</u>

Any complaint or concern will be treated in confidence and fully investigated. You will be informed of the outcome.

#### I want to participate! How do I sign up?

*I*\_\_\_\_\_\_ understand the proposed study and risks involved and, understand my data collected will contribute to the validation of collision and contact in rugby union using microtechnology and therefore would like to participate in the study from

\_\_\_\_/ \_\_\_ until the 31/12/16.

Signed\_\_\_\_\_

Date\_\_\_\_\_

Yours sincerely,

**Ryan Chambers** 

#### **Appendix C – Participant Consent Form**

### CONSENT FORM Copy for Participant to Keep

TITLE OF PROJECT: Validation of Contact and Collision in Rugby Union using Microtechnology

PRINCIPAL INVESTIGATOR: Tim Gabbett

STUDENT RESEARCHER: Ryan Chambers

I ...... (the participant) have read and understood the information provided in the Letter to Participants. Any questions I have asked have been answered to my satisfaction. I agree to participate in this study, which involves the validation of contact and collision using microtechnology in rugby union. I understand that I will be required to wear a microtechnology (GPS) unit at every rugby session.

I understand that I can withdraw my consent at any time without comment or penalty or affect upon my future relationship with the researchers or the team. I agree that research data collected for the study may be published or may be provided to other researchers in a form that does not identify me in any way.

NAME OF PARTICIPANT:	
SIGNATURE	DATE
SIGNATURE OF PRINCIPAL INVESTIGATOR (or SUPE	RVISOR):
	DATE
(and, if applicable)	
SIGNATURE OF STUDENT RESEARCHER:	
	DATE

#### Appendix D – Proof of publication (Study 1) – Systematic review: The use of

#### wearable microsensors to quantify sport-specific movements

Sports Med DOI 10.1007/s40279-015-0332-9

SYSTEMATIC REVIEW

# The Use of Wearable Microsensors to Quantify Sport-Specific Movements

Ryan Chambers<sup>1,2</sup> · Tim J. Gabbett<sup>2,3</sup> · Michael H. Cole<sup>2</sup> · Adam Beard<sup>4</sup>

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#### Abstract

*Background* Microtechnology has allowed sport scientists to understand the locomotor demands of various sports. While wearable global positioning technology has been used to quantify the locomotor demands of sporting activities, microsensors (i.e. accelerometers, gyroscopes and magnetometers) embedded within the units also have the capability to detect sport-specific movements.

*Objective* The objective of this study was to determine the extent to which microsensors (also referred to as inertial measurement units and microelectromechanical sensors) have been utilised in quantifying sport-specific movements.

Methods A systematic review of the use of microsensors and associated terms to evaluate sport-specific movements was conducted; permutations of the terms used included alternate names of the various technologies used, their applications and different applied environments. Studies for this review were published between 2008 and 2014 and were identified through a systematic search of six electronic databases: Academic Search Complete, CINAHL, PsycINFO, PubMed, SPORTDiscus, and Web of Science. Articles were required to have used athlete-mounted sensors to detect sport-specific movements (e.g. rugby union

Tim J. Gabbett tim gabbett@yahoo.com.au

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tackle) rather than sensors mounted to equipment and monitoring generic movement patterns.

Results A total of 2395 studies were initially retrieved from the six databases and 737 results were removed as they were duplicates, review articles or conference abstracts. After screening titles and abstracts of the remaining papers, the full text of 47 papers was reviewed, resulting in the inclusion of 28 articles that met the set criteria around the application of microsensors for detecting sport-specific movements. Eight articles addressed the use of microsensors within individual sports, team sports provided seven results, water sports provided eight articles, and five articles addressed the use of microsensors in snow sports. All articles provided evidence of the ability of microsensors to detect sport-specific movements. Results demonstrated varying purposes for the use of microsensors, encompassing the detection of movement and movement frequency. the identification of movement errors and the assessment of forces during collisions

*Conclusion* This systematic review has highlighted the use of microsensors to detect sport-specific movements across a wide range of individual and team sports. The ability of microsensors to capture sport-specific movements emphasises the capability of this technology to provide further detail on athlete demands and performance. However, there was mixed evidence on the ability of microsensors to quantify some movements (e.g. tackling within rugby union, rugby league and Australian rules football). Given these contrasting results, further research is required to validate the ability of wearable microsensors containing accelerometers, gyroscopes and magnetometers to detect tackles in collision sports, as well as other contact events such as the ruck, maul and scrum in rugby union.

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<sup>&</sup>lt;sup>1</sup> Welsh Rugby Union, Westgate Street, Cardiff, Wales

<sup>&</sup>lt;sup>2</sup> School of Exercise Science, Australian Catholic University, 1100 Nudgee Road, Brisbane, QLD 4014, Australia

<sup>&</sup>lt;sup>3</sup> School of Human Movement Studies, The University of Queensland, Brisbane, QLD, Australia

<sup>4</sup> University of Lausanne, Lausanne, Switzerland

#### Appendix E – Proof of publication (Study 2) – Validity of a microsensor-based

#### algorithm for detecting scrum events in Rugby Union

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#### Validity of a Microsensor-Based Algorithm for Detecting Scrum Events in Rugby Union

Ryan M. Chambers, Tim J. Gabbett, and Michael H. Cole

**Purpose:** Commercially available microtechnology devices containing accelerometers, gyroscopes, magnetometers, and global positioning technology have been widely used to quantify the demands of rugby union. This study investigated whether data derived from wearable microsensors can be used to develop an algorithm that automatically detects scrum events in rugby union training and match play. **Methods:** Data were collected from 30 elite rugby players wearing a Catapult OptimEye S5 (Catapult Sports, Melbourne, Australia) microtechnology device during a series of competitive matches (n = 46) and training sessions (n = 51). A total of 97 files were required to "train" an algorithm to automatically detect scrum events using random forest machine learning. A further 310 files from training (n = 167) and match-play (n = 143) sessions were used to validate the algorithm's performance. **Results:** Across all positions (front row, second row, and back row), the algorithm demonstrated good sensitivity (91%) for training an match-play events (93.6%) than for training events (87.6%). **Conclusions:** The scrum algorithm was able to accurately detect scrum events for front-row, second-row, and back-row positions. However, for optimal results, practitioners are advised to use the recommended confidence level for each position to limit false positives. Scrum algorithm detection was better with scrums involving  $\geq$  5 players and is therefore unlikely to be suitable for scrums involving 3 players (eg, rugby sevens). Additional contact- and collision-detection algorithms are required to fully quartify rugby union demands.

Keywords: microtechnology, team sport, machine learning, contact detection

Commercially available microtechnology devices containing global positioning systems (GPSs) and microsensors (accelerometers, gyroscopes, and magnetometers) are commonly used to quantify the physical demands of rugby union.<sup>1</sup> During match play and training, players are divided into subgroups of forwards and backs and are required to perform repeated bouts of high-intensity locomotor activity (sprinting, running, and accelerations) separated by low-intensity activity (standing, walking, and jogging).<sup>1–6</sup> In addition to the locomotor demands of match play, players are frequently involved in high-intensity physical contact and collisions, such as mauls, tackles, and rucks, with forwards also required to compete in scrums.<sup>1–8</sup> Scrums are used to restart play after a minor infringement and involve all 8 forwards from each team forming 3 interconnected rows of players. While facing each other, the players forming the front row for each team lock heads and shoulders with the opposition forwards and attempt to produce a greater force than their opponents to gain possession of the ball.<sup>9</sup>

Despite researchers accurately quantifying the locomotor demands of elite rugby union, contact events such as scrums, rucks, mauls, and tackles are usually combined and defined as "impacts" when using microtechnology.<sup>14,7</sup> Similarly, research evaluating contact events by video-based time-motion analysis has typically categorized these incidents as "high-intensity efforts"<sup>3</sup> or "static exertions."<sup>5,6,8</sup> Success in rugby union frequently depends on the players' ability to tolerate contact events.<sup>10</sup> However, research summarizing the physical contribution of contact events (scrums, tackles, rucks, and mauls) during match play provides a count of the total number of contact events, a rating of the force involved,<sup>1</sup> or the total time attributable to collisions.<sup>8</sup> To date, no research has differentiated among scrums, rucks, mauls, and tackles, which inadvertently implies that each form of contact poses an equal physiologic stress to the players.<sup>11</sup> Classification of each contact type would contribute to an improved understanding of the unique stresses associated with each, in turn potentially helping improve player preparation and reduce the risk of injury and reinjury during training and competition.

Microsensors have been used to quantify the demands of sportspecific movements in team sports, snow sports, individual sports, and water sports.<sup>11</sup> Validated algorithms have been applied to microsensor data to automate the collection of sport-specific move ments, such as fast bowling in cricket,<sup>12</sup> pitching in baseball,<sup>13</sup> and tackling in rugby <sup>11,14,15</sup> To date, researchers have used microsensors to quantify only tackling in rugby union,16 with scrums, rucks, and mauls neglected.<sup>11</sup> Researchers have highlighted the injury risk associated with scrums,<sup>17</sup> predominantly in match play.<sup>18</sup> Currently, no other valid method for quantifying scrum workload during training or match play exists apart from using video-based time-motion analysis, which is a labor-intensive process.11 Many researchers have highlighted the need to further investigate contact movements in rugby union because they generally require the body to endure very high forces that are imparted over a relatively short time period. However, despite the relatively short duration of each contact event, the repeated collisions involved in a typical training or match-play scenario contribute significantly to the players' total workload. Of the contact movements performed during regular match play, scrum events occur approximately 25 times per game; in contrast, depending on playing position, each player will complete approximately 30 rucks and tackles per match.<sup>5,11,19–21</sup>

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Chambers is with Welsh Rugby Union, Cardiff, United Kingdom. Chambers and Cole are with the School of Exercise Science, Australian Catholic University, Brisbane, QLD, Australia. Gabbett is with Gabbett Performance Solutions, Brisbane, QLD, Australia, and the Inst for Resilient Regions, University of Southern Queensland, Ipswich, QLD, Australia. Chambers (ryanchambers 13@gmail.com) is corresponding author.

#### Appendix F - Proof of publication (Study 3) - Automatic detection of one-on-one

#### tackles and ruck events using microtechnology in Rugby Union

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Automatic detec microtechnology	tion of one-on-one tackles and ruck events using v in rugby union	
Ryan M. Chambers <sup>a,b</sup> Paul Stridgeon <sup>a</sup> , Mich	<sup>,*</sup> , Tim J. Gabbett <sup>c,d</sup> , Ritu Gupta <sup>e</sup> , Casey Josman <sup>e</sup> , Rhodri Bown <sup>.</sup> nael H. Cole <sup>b</sup>	a ,
<sup>a</sup> Welsh Rugby Union, United Kingdo <sup>b</sup> School of Exercise Science, Australic <sup>c</sup> Gabbett Performance Solutions, Aus <sup>d</sup> University of Southern Queensland, <sup>e</sup> Curtin University, Australia	m ın Catholic University, Australia stralia Institute for Resilient Regions, Australia	
ARTICLE INFO	АВЅТКАСТ	
Article history: Received 23 June 2018 Received in revised form 12 November 2018 Accepted 1 January 2019 Available online xxx	Objectives: To automate the detection of ruck and tackle events in rugby designed algorithm based on microsensor data. Design: Cross-sectional study. Methods: Elite rugby union players wore microtechnology devices (Catapult (n = 125) and tackle (n = 125) event data was synchronised with video foo tional nucley union match-play ruck and tackle events. A specifically-design	y union using a specifically- ,S5) during match-play. Ruck tage compiled from interna- ned algorithm to detect tuck
Keywords: Algorithm Microtechnology Team sport Ruck Tackle	and tackle events was developed using a random forset classification movel validated using 8 additional international match-play datasets and video tackle manually coded and verified if the event was correctly identified by <i>Results</i> : The classification algorithm's results indicated that all rucks and tac during match-play when 79.4 $\pm$ 9.2% and 81.0 $\pm$ 9.3% of the random forest d video-based determination of these events. Sub-group analyses of backs?	del. This algorithm was then footage, with each ruck and the algorithm. kles were correctly identified ecision trees agreed with the and forwards yielded similar
	optimal confidence percentages of 79.7% and 79.1% respectively for rucks. $(85.3 \pm 7.2\%)$ produced a higher algorithm cut-off for tackles than forwards <i>Conclusions</i> : The specifically-designed algorithm was able to detect rucks involved. For optimal results, it is recommended that practitioners use the to limit false positives for match-play and training. Although this algorithm into the number and two of collisions in which ruley players generge this	Sub-analysis revealed backs ( $77.7 \pm 12.2\%$ ). and tackles for all positions recommended cut-off ( $80\%$ ) provides an improved insight saleorithm does not provide

impact forces of these events. © 2019 Published by Elsevier Ltd on behalf of Sports Medicine Australia.

#### Practical implications

- Results demonstrate the competencies of microtechnology, demonstrating the ability to detect ruck and tackle events in rugby union when applying a specifically designed algorithm. In collaboration with recent research, providing sport scientists the capability to detect and quantify the most frequent collisions in rugby union using microtechnology devices.
- This current study provides practitioners with a time efficient and validated method to detect and monitor rucks and tackles events

\* Corresponding author at: Welsh Rugby Union, Westgate Street, Cardiff, UK. E-mail address: ryanchambers13@gmail.com (R.M. Chambers).

https://doi.org/10.1016/j.jsams.2019.01.001 1440-2440/© 2019 Published by Elsevier Ltd on behalf of Sports Medicine Australia. during match-play and training to assist with player preparation and injury prevention. Providing more objective results than previous labour-intensive methods that are potentially error prone. This research will provide sport scientists with a more in-depth understanding of a player's demands by allowing different con-

 Inis research win provide sport scientists with a more in-depin understanding of a player's demands by allowing different contact types, in this instance rucks and tackles, to be independently classified.

#### 1. Introduction

Commercially-available microtechnology devices containing global positioning systems (GPS) and microsensors (accelerometers, magnetometers and gyroscopes) are extensively used to quantify the activity demands of various sports, including

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