Accelerometer Validity to Measure and Classify Movement in Team Sports

by

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List of Publications and Presentations

Studies 1, 2, 3 and 4 have been published or accepted for publication. The details of these are as follows:


Conference paper:

Abstract

Introduction: Accelerometers contained within wearable tracking devices have become an established method for objective workload measurement in team sports. Raw accelerometer data are recorded and expressed in either peak impact acceleration bands or used to calculate arbitrary “load” metrics based on accumulated accelerations throughout a training session or game. However, information pertaining to the validity of these outputs is lacking. This information is important to determine whether accelerometry provides an accurate means to measure and classify different human movements typically performed by athletes in team sports. Therefore, the overall purpose of this thesis was to evaluate the validity of an accelerometer contained within a wearable tracking device to measure and classify movements in team sports.

Method: Participants in this thesis included healthy, recreationally active (Study 1: 28 males, 11 females; Studies 3–5: 76 males) and semi-elite (Study 2: 25 males) team sport players. In Studies 1–3, the concurrent validity of the 100 Hz triaxial accelerometer contained within the MinimaxX S4 wearable tracking device (Catapult Innovations, Australia) to assess resultant peak accelerations was compared against a multi-camera motion analysis system (Raptor-E, Motion Analysis Corporation, USA). Validity was examined whilst participants performed: walking, jogging and running on a treadmill (Study 1); tackling and bumping on a rugby field (Study 2); and, a simulated team sport circuit in a laboratory setting (Studies 3–5). The raw accelerometer data were filtered between 6–30 Hz to determine the most optimal cut-off frequency. A number of statistics were applied including agreement, precision and error measures, as well as statistical hypothesis tests. In Studies 4–5, participants wore an accelerometer while completing a simulated team sport circuit, to examine whether
accelerometer data could be used to classify eight team sport movements. A number of classifiers (logistic model tree [LMT], support vector machine and random forest), movement capture durations (0.5, 1.0, and 1.5 s) and feature selection scenarios (ANOVA, Lasso regression) were examined.

Results: Across Studies 1–3, the accelerometer data typically overestimated peak accelerations during team sport movements, irrespective of the type and intensity of movement performed. Filtering reduced or removed this overestimation, however excessively low cut-off frequencies resulted in underestimated peak accelerations. During walking, jogging, and running tasks, the accelerometer was able to accurately record peak accelerations when filtered at a 10-Hz cut-off frequency (Study 1). However, for tackling and bumping, the optimal cut-off frequency was higher (20 Hz; Study 2). When these and other common movements (change of direction and jumping) were combined into a simulated team sport circuit, 12 Hz was deemed the most optimal cut-off frequency (Study 3). Results also indicated that different movement types could be classified based solely on the accelerometer data (88% accuracy), or by combining accelerometer and gyroscope data (90% accuracy), using a LMT classifier combined with a 1.0 s movement capture duration (Study 4). The processing time was also dramatically reduced when only the accelerometer was used (Studies 4 and 5).

Conclusion: This thesis demonstrates that accelerometer data were accurate for measuring peak accelerations when filtered at an appropriate cut-off frequency, however raw data appeared to consistently overestimate team sport movement peak accelerations. With appropriate filtering, accelerometer data are suitable for workload
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List of Abbreviations

A1 or Z; Antero-posterior accelerometer axis
A2 or X; Medio-lateral accelerometer axis
A3 or Y; Vertical accelerometer axis
ADJ; Adjustables
ANOVA; Analysis of variance
Centroid; Spectral centroid
cm; Centimetres
CMJ; Countermovement jump
COD; Change of direction
CV; Coefficient of variation
DL; Double leg
EnergyAcc; Energy calculated from the accelerometer
$g$; Gravitational acceleration
GPS; Global positioning system
HR; Heart rate
HU; Hit up forwards
Hz; Hertz
IQR; Interquartile range
kg; Kilograms
LMT; Logistic model tree
m; Meters
MA; Motion analysis
MaxAmp; Maximum amplitude
MCD; Movement capture duration
MeanAmp; Mean amplitude
MEMS; Micro-electrical-mechanical systems
MinAmp; Minimum amplitude
mm; Millimetres
m/s\(^1\); Meters per second
n; Number
OB; Outside backs
RPE; Rating of perceived exertion
Q25; The 25\(^{\text{th}}\) quartile
Q75; The 75\(^{\text{th}}\) quartile
r; Correlation coefficient
s; Second
SD; Standard deviation
SL; Single leg
RMSEP; Root mean square error of prediction
VarAmp; Variance of amplitude
yr; Years
95\% LoA; Ninety-five percent limits of agreement
Chapter 1.

1 General Introduction
1.1 General Introduction

The development of accelerometers can be traced back to the early 1920s, when McCollum and Peters first developed sensors to measure accelerations in dynamometers, aircraft, and bridges (1). Since then, the advancement of accelerometer technology has increased dramatically, enabling its application to a variety of settings including engineering (2), medical technology (3), consumer electronics (4), physical activity research (5), and more recently, team sports (6). In team sports, accelerometers offer a new method of measuring workloads (7-9) and potentially provide many benefits to the player, team, and coach. However, information about accelerometer validity in this context is lacking.

Prior to commencement of this doctoral investigation, only a single validation study regarding an accelerometer contained within a wearable tracking device had been published (10). This study suggested that accelerometers have poor validity, and found that peak accelerations during jumping and landing movements were overestimated (coefficient of variation [CV] = 16.8 to 30.8%). Overestimations remained despite efforts to improve the signal using a filter (CV = 10.9 to 22.2%). Despite these results, four studies had already been published using accelerometers for workload monitoring in team sports (6, 11-13). Therefore, validation research on accelerometers is still in its infancy and requires further investigation. Little is currently known about the utility of the raw accelerometer signal, the effect different filtering cut-off frequencies have on the validity of the accelerometer, and the accuracy of accelerometer data for assessing a range of team-sport movements. It has also been documented that accelerometer data may be used to classify specific player movements, including tackling in contact sports and bowling in cricket (9, 14). However, it is unclear whether
multiple team sport movements (e.g., walking, running, sprinting, and tackling, etc.) can be classified from accelerometer data and what classification technique should be used to do so. With the increased application and usage of accelerometers in team sports, a clearer understanding of the device’s validity is imperative. The ability to accurately measure team sport movements would assist in understanding the intensity of movements players typically complete. Furthermore, the ability to accurately classify team sport movements would also assist in understanding the type and number of movements players perform. Combining this data has the potential to inform training and game-play interventions such as optimal workloads for improved player performance, or injury prevention in team sports. For accelerometers to be used with confidence for these and similar purposes the accuracy of the data must be determined. As a result, two overarching questions emerged. Specifically, can accelerometers be used to accurately monitor the physical demands during a variety of activities in team sports? And can the type of activity undertaken be accurately identified using accelerometers?

The purpose of this thesis was to examine the validity of the accelerometer contained within a wearable tracking device to measure and classify movements in team sports. Three studies were undertaken to bridge the gap in the current knowledge regarding accelerometer concurrent validity (attempting to answer the first overarching research question). A further two additional studies were conducted to assess the accelerometer’s ability to classify team sport movements (attempting to answer the second overarching research question).
1.2 Thesis Aims

The aim of this thesis was to evaluate the validity of the accelerometer contained within a wearable tracking device to measure and classify movements in team sports. The specific aims and research questions of each study in this thesis are as follows:

1.2.1 Study 1

The aims of Study 1 were: i) to compare peak accelerations from an accelerometer with a concurrent measure, while assessing walking, jogging, and running activities; ii) to investigate the effect of different filtering cut-off frequencies on accelerometer validity, and; iii) to examine whether the magnitude of acceleration recorded influences accelerometer validity. The following questions were posed:

1. Is an accelerometer worn on the upper back valid for measuring peak accelerations during walking, jogging and running, when compared to a traditional laboratory-based method?

2. If there are inaccuracies, can filtering improve accelerometer validity?

3. Does the magnitude of acceleration recorded influence accelerometer validity?

1.2.2 Study 2

The aims of Study 2 were: i) to compare peak accelerations from an accelerometer with a concurrent measure, while assessing tackling and bumping movements; ii) to investigate the effect of different filtering cut-off frequencies on accelerometer validity, and; iii) to examine whether the magnitude of acceleration recorded influences accelerometer validity. The following questions were posed:
1. Is an accelerometer worn on the upper back valid for measuring peak accelerations during tackling and bumping, when compared to a traditional laboratory-based method?
2. If there are inaccuracies, can filtering improve accelerometer validity?
3. Does the magnitude of acceleration recorded influence accelerometer validity?

1.2.3 Study 3

The primary aim of Study 3 was to compare peak accelerations from an accelerometer with a concurrent MA system, while participants performed a combination of seven common team sport movements in a simulated team sport circuit. Study 3 also investigated the effect that different filtering cut-off frequencies may have on accelerometer validity. The following questions were posed:

1. Is an accelerometer worn on the upper back valid for measuring peak accelerations during a simulated team sport circuit, when compared to a traditional laboratory-based method?
2. If there are inaccuracies, can filtering improve accelerometer validity and what is the single most optimal cut-off frequency across all movements?

1.2.4 Study 4

The primary aim of Study 4 was to determine whether data obtained from an accelerometer and gyroscope can be used to classify team sport movements. In this study, different classification algorithms and movement capture durations in order to classify movements in team sports were investigated. The computational and data collection burdens associated with all methods were also considered. The study posed the questions:
1. Can data obtained from wearable tracking device inputs (specifically, an accelerometer and a gyroscope) be used to classify team sport-related movements?

2. Which classification algorithm (LMT, random forest, or support vector machines) and movement capture duration (0.5, 1.0, or 1.5 s) for feature extraction is optimal for classifying movements in team sports?

3. What are the processing time and data collection burdens associated with these methods, and can they be minimised while maintaining classification accuracy?

1.2.5 Study 5

The primary aim of Study 5 was to determine the ability of an accelerometer to classify eight common team sport movements using a single machine learning classifier. The following questions were posed:

1. Can the accelerometer contained within wearable tracking devices obtain valid data for accurately classifying team sport movements?

2. What are the most important accelerometer features required to classify team sport movements and can less relevant features be removed to improve computational time?

3. What team sport movements are difficult to classify using accelerometer data and why?
1.3 General Overview of the Thesis

The above aims were addressed by conducting a series of five studies. Firstly, it has been reported that accelerometers overestimate peak foot-strike accelerations during jumping and landing movements (10). Walking, jogging and, to a lesser degree, running are the most commonly performed movements in team sports (15, 16), thus providing a strong foundation to assess accelerometer validity. However, it is unknown how accurate the accelerometer is to measure upper trunk peak accelerations and what (if any) filtering is needed to improve validity. Thus, Study 1 investigated the validity of accelerometers to measure walking, jogging and running peak accelerations when compared to a MA system capable of measuring upper trunk accelerations. Further to this, tackling and bumping are commonly performed in contact sports (16), impose large peak accelerations on the body of athletes and have been linked to an increased risk of injury compared to other team sport movements (17). The validity of the accelerometer to quantify these higher intensity impacts is unknown and Study 2 addressed this gap in the literature.

To date, previous validation work has focused on the accelerometer during a single movement type, while applying one to five generic filtering cut-off frequencies to the raw data (10, 18). However, identifying and filtering the movements performed in team sports may pose a substantial burden on practitioners and manufacturers. Further, a single, universal cut-off frequency for all movements would be highly desirable. Therefore, Study 3 investigated the validity of accelerometers to measure walking, jogging, running, COD, jumping and tackling movements in a simulated team sport circuit. In total, 13 filtering cut-off frequencies ranging from 6 to 25 Hz were examined providing insight into a single, optimal filtering frequency to accurately measure these
team sport movements. Further, the ability of accelerometer peak accelerations to discriminate between these movements was also examined.

The last two studies detailed in Chapters 5 and 6 built on the results obtained in Study 3. The literature has purported that accelerometers data can be used to classify activities of daily living (19) and some basic sporting movements accurately (9, 14, 20). However, there is no direct research assessing an accelerometer contained within a wearable tracking device to accurately classify more than a single sporting movement type (e.g., tackling or cricket bowling). Given that the movement construct of most team sports generally entails walking, jogging, running, jumping and COD movements during game-play, the accelerometer’s ability to classify these movements should be assessed. Therefore, Study 4 reported on the use of a method to classify team sport movements. Lastly, the ability of the method to classify eight common team sport movements was tested and evaluated in Study 5. A flow diagram of the studies conducted in this thesis is shown in Figure 1-1.
Figure 1-1. Overview and flow of thesis studies.
1.4 Thesis Structure: A Note for Readers

This thesis presents a series of studies that have been published (Studies 1-3) or accepted for publication (Study 4), or have been drafted for publication (Study 5). Furthermore, Studies 1–4 are presented as they appear in press. Some common methods were used in multiple studies, e.g., the concurrent measure (Studies 1–3), accelerometer (Studies 1–5), and classification technique (Studies 4 and 5). Consequently, some duplication exists in the description of methods and abbreviations in Studies 2–5. In addition, due to minor discrepancies in journal submission guidelines, some abbreviations differ slightly between chapters. Apart from these discrepancies, the thesis has been produced with consistent text formatting, referencing style, and language throughout all chapters, with a single reference list compiled at the end of the thesis.
Chapter 2.

2 Literature Review
2.1 Introduction

Objective measurement and analysis of movement is essential for understanding sports performance (21). This form of analysis is also important for evaluating the effectiveness of training programs designed to increase performance, prevent injury or optimise rehabilitation of athletes from injury (22). Fundamental to furthering this understanding is the need to accurately measure specific information relating to the type, intensity, and frequency of movements performed (23). As a result, wearable technologies (e.g., accelerometers) are now considered integral to player monitoring in team sports. To provide a theoretical framework and background for this thesis, an understanding of team sports and workload monitoring techniques used to measure team sport movements is required. Accelerometer technology will be explored in general, followed by an introduction to wearable tracking devices. Following this, the review will concentrate specifically on accelerometers contained within wearable tracking devices, focusing on its reliability, validity, and application to team sports. Finally, areas requiring scientific investigation will be highlighted and a series of experimental studies proposed.

2.2 Team Sports

2.2.1 Definition and Movement Construct of Team Sports

A team sport is easily distinguished as a sport or game played by a group of individuals in a playing field of specific dimensions (24). Currently, six team sports are globally recognised by their inclusion in the Olympic Games. These include netball, field hockey, football (soccer), basketball, handball, and rugby. Additionally, countries such
as America (gridiron) and Australia (Australian football) have indigenous team sports played by a substantial number of the country’s population (25). Team sports can be played by teams comprising as few as five (basketball) or as many as 18 players (Australian football) (25). Field hockey, soccer, and basketball are non-contact sports, whereas rugby, gridiron, and Australian football are contact sports.

When the movement construct of team sports are examined, a number of similar movement patterns can be clearly identified (Figure 2-1). These include standing, walking and jogging (26), striding and sprinting (27), lateral movements or changes of direction (COD) (28), jumping, and physical collisions, including tackling and bumping in contact sports (25, 29). Due to the large number of player’s on a field at any one time, many of these movements are performed without possession of the ball.

![Figure 2-1. Deterministic model of common team sport movements.](image)

These movements are generally executed in an intermittent pattern, where high intensity passages of play involving one or more movements (sprinting, jumping, and tackling) are interspersed with low intensity recovery periods (e.g., standing, walking, and jogging) (25). There are, however, notable differences in the amount of time players spend in each movement category. For example, in field hockey, players spend approximately 53.9% of time standing and walking, 44.6% jogging and striding, and 1.5% sprinting (15). Whereas in soccer, players spend approximately 61.3% of time
standing and walking, 37.3% jogging and striding, and 1.4% sprinting (30). Furthermore, differences in the amount of time players spend in each movement category may differ depending on the position played (16, 28) and the level of competition (30, 31). For example, in rugby, hit-up forwards spend more time standing and tackling, but less time walking, jogging, and striding than adjustables and outside back positional players (Figure 2-2 (16)).

**Figure 2-2.** The percentage (%) of time spent in different movement categories by three positional groups (outside backs [OB], adjustables [ADJ] and hit-up forwards [HU]). Retrieved from King, Jenkins and Gabbett (16).

As demonstrated in Figure 2-2, high intensity movements only represent a small proportion of a player’s time in team sports (15, 30). However, these movements usually occur at crucial time periods and contribute directly to the desired performance outcome, such as winning possession of the ball and scoring (27, 32). High intensity movements have also been linked with an increased risk of injury (17, 33-35). For example, Gabbett and Ullah (36) found that injury risk is 2.7 times higher when sprinting in rugby compared to other movements. Furthermore, in contact sports the majority of injuries occur during physical collisions (e.g., tackling (17, 33)).
appears to be related to the speed at which players are capable of moving (i.e. faster players generate greater impulse resulting in higher impact forces during physical collisions, which may increase contact injury rates (17, 35)).

Different movements appear to impose different physiological strains on the bodies of players as they train and compete. However; with a need to maximise adaptations whilst avoiding negative outcomes, including fatigue, over-reaching, over-training, and injury, optimal workload prescription can be challenging (37-41). This is further confounded by individual differences (e.g., due to a players training status or injury history), where the optimal workload imposed on one player will vary when compared to another in the same team (42). These differences can then lead to errors in workload prescription for more physically fit players, compared to their less fit teammates if a generalised whole team approach is prescribed (43). In addition, competition games can be scheduled twice or more in a single week; a common occurrence in soccer and basketball. This then has the potential to further increase the workloads placed on players, while providing little time to recover between games (44). Therefore, there is a need to capture, analyse, and evaluate the movements performed and the workloads experienced by team sport players (45). This information is important for understanding the physical and technical demands related to sports performance. It is also vital for assisting coaches and sports scientists with the design of training programs to minimise injury risk (46) and improve performance (21, 47).

2.3 Monitoring Workloads in Team Sports

Player workloads during training and game-play in team sports can be extremely difficult to measure directly (45). Instead, indirect methods of measurement such as
notational analysis (e.g., questionnaires, diaries, direct observation), physiological analysis (e.g., HR monitoring, perceived exertion scales, oxygen consumption tests) (48), and video analysis (49) are commonly employed. However, measuring workloads indirectly is limited. For example, the time required to complete the analysis may be lengthy (e.g., direct observation and video analysis), some methods lack reliability and accuracy, and others are prone to subjective errors (e.g., direct observation, questionnaires and diaries) (48). The most accurate methodologies for measuring human movement are typically laboratory-based, such as force plates (50) and three-dimensional motion analysis (MA) systems. These technologies may be considered the gold standard for human movement analysis, and along with video analysis, will be described in more detail in the next sub-sections.

2.3.1 Video Analysis

Video analysis is one of the most popular human movement analysis techniques available (51, 52). Video cameras record and store captured images of the movement of interest. These images are then replayed for qualitative or quantitative analysis (53). Video cameras are low cost, flexible (can be used in almost any environment), offer little performer interference, and can be used to provide visual feedback to players that most other techniques cannot (52). However, video analysis has several shortcomings. Firstly, for detailed analyses, video analysis has enormous time requirements (54), which may not be conducive to providing timely feedback to athletes (20). Secondly, there are difficulties in tracking multiple players in team sports, especially during periods of player congestion (54). Thirdly, the validity and reliability of video analysis can vary. For example, errors can occur when manually digitising specific anatomical locations on images (55). Lastly, the experience of the person performing the analysis
and the quality of the video captured, including inappropriate image rate (52) or viewing angle (54) can all influence the quality of the data captured and subsequently analysed.

### 2.3.2 Force Plate Analysis

A technique often employed in laboratories is kinetic analysis via a force plate. Force plates measure the ground reaction forces acting on the body (51), and researchers commonly use these to quantify the kinetic parameters of balance and gait (55). Force plate data are also used to initiate calculation of other biomechanical parameters (e.g., internal forces and torques generated at each joint (53)). Force plates are inherently stable, accurate, reliable, relatively robust, easy to use and may be preferred as a criterion instrument when a new measurement technique is proposed (e.g., (56)). However, force plates are also expensive to purchase (57), heavy and typically restricted to laboratory settings, as they are built into the floor (50). Portable systems are available, however these lack the precision of built-in plates (51). There are potential difficulties with participants consciously targeting the surface of the force plate and altering the way they move (51). Furthermore, the types of movements assessed are limited (e.g., body contact between athletes cannot be measured using a force plate) and only one participant may be assessed at a time. They are also difficult to calibrate dynamically (52). It is, therefore, difficult to replicate in-field environmental conditions in a laboratory setting using force plate analysis (58, 59).

### 2.3.3 Three-Dimensional Motion Analysis

Three dimensional motion analysis (MA) utilises a system of cameras that measure the three-dimensional position and orientation of a participant’s body in space. Motion
analysis data may be used to measure kinematic quantities of interest, such as changes in linear and angular position (and the time derivatives of velocity and acceleration). Motion analysis is used in a variety of fields including; sports, robotics, military, medical, and entertainment (e.g., filmmaking and video game development) settings. Specific strengths of MA include its accuracy, reliability, flexibility (of camera positioning), ability to capture multiple movements, and high sampling rate (52). Furthermore, some systems can now automatically identify markers in real-time.

However, MA has several weaknesses. First, it is generally limited to laboratory settings (52, 55), although outdoor capture is now possible with newer systems (e.g., Raptor-E cameras, Motion Analysis Corporation, USA). Second, each reflective marker attached to the body must be recorded by a minimum of two cameras for three-dimensional spatial coordinate reconstruction (53). Therefore, MA systems cannot capture data when markers are occluded and are unreliable when markers are placed too close together (i.e., only one marker will be shown). Third, movement of the skin may introduce a discrepancy between the specific anatomical location under investigation and the location of the marker on the skin (52). Fourth, MA is expensive to purchase, time consuming to set-up, and data analysis can be lengthy (52, 55). Lastly, the desired capture volume affects the resolution of the system (52). As a result, the accuracy with which a MA system calculates the position of reflective marker(s) may be reduced if the volume is increased to accommodate movements requiring larger volumes. For example, the capture volume required for use during training and game-play in team sports is too large for current systems to measure.
In summary, team sport movements have traditionally been measured in laboratory settings using large immobile devices such as force plates or MA systems. These approaches, although valid and reliable (52, 56), limit the in-field understanding of movement workloads players are exposed to during training and game-play. Subjective in-field workload monitoring techniques have also been proposed such as perceived exertion scales, however, these lack the validity and reliability of their laboratory based counterparts (48). Therefore, it is difficult to obtain valid and reliable in-field measures of movement workloads in field settings using these techniques. Examination of alternative techniques capable of measuring individual and team workloads during both training and game-play are needed. For example, it has been proposed that measuring human movement using accelerometers may be possible as acceleration is proportional to external force and may more accurately reflect the frequency and intensity of the movements performed (60).
2.3.4 Accelerometer Technology

2.3.4.1 History

A thorough history of accelerometer technology including the development, applications, and types of accelerometers can be found in reviews by Walter (1, 61) and is summarised in Figure 2-3. The accelerometer was first developed in the early 1920s by McCollum and Peters (1, 61). It weighed nearly 0.5 kg, was approximately 0.22 × 0.05 × 0.02 m in size, could measure acceleration up to 100 g, was quite expensive and had application in dynamometers, aircraft, and bridges (61). In the 1950s, accelerometers found application in laboratory-based human movement assessment. For example, Ryker and Bartholomew (62) used Statham Linear (type AP and C) uniaxial accelerometers sampling at 30 Hz (range ±2.3 g) to obtain shank accelerations while walking. Saunders, Inman, and Eberhart (63) used ‘electrical accelerometers’ to compare the displacement of the lower extremities with laboratory-based techniques (e.g., force platforms and motion picture time-displacement data [grapho-numerical differentiation]). These early accelerometers were not suited to field-based human movement research as they were considered bulky, expensive and unreliable (64). In the 1960s, the sampling rate and range of accelerometers increased, although they were still primarily limited to laboratory-based settings. For example, Stapp and Taylor (65) used Statham strain gauge triaxial accelerometers sampling at 300 Hz and ±50 g to measure impact forces in simulated space cabin landings.

A major breakthrough occurred in the 1990s with the development of micro-electrical-mechanical systems (MEMS) technology (1, 61, 66). This technology enabled accelerometers to dramatically decrease in size (e.g., 0.005 m²) (1), cost (may be as little as $20) (67), and power consumption, whilst also improving in accuracy (66),
and speed of manufacturing (68). Furthermore, combining MEMS technology with an on-board flash memory and a higher sampling rate made accelerometers an attractive instrument for in-field measurement of human movement (66). Since 2009, accelerometers have been used in team sports for movement analysis (6, 12). For example, Cunniffe and colleagues (6) used the accelerometer contained within wearable tracking devices (SPI Pro, GSPorts Pty Ltd, Australia) to measure the number and intensity of physical collisions rugby athletes experienced during gameplay.
Figure 2-3. The history of the accelerometer. Adapted from Walter (1, 61).
2.3.4.2 Description of Accelerometry

An accelerometer is an electrical device that directly measures the applied acceleration acting along a sensitive axis (53, 55, 69). Acceleration can be defined as a change of velocity with respect to time (acceleration = meters per second per second [m/s²]) and is measured in gravitational acceleration units (g; 1 g = 9.81 m/s²) (51, 70, 71). Accelerometer data are bi-directional when first produced, meaning the sensors can monitor acceleration in both directions along the sensitive axis. Most accelerometers are uniaxial and sensitive to movement in one axis (72). Accelerometers may also be biaxial or triaxial, thus sensitive to movement in two or three orthogonal axes (55). As triaxial accelerometers measure accelerations in three axes, they are seen as more accurate for measuring human movement than uniaxial and biaxial accelerometers (70, 71). Triaxial accelerometer data can also be combined into a single summarised outcome parameter, termed acceleration magnitude or resultant vector (73):

\[ \text{Resultant vector} = \sqrt{x^2 + y^2 + z^2} \]

Equation 1. Resultant vector.

where: Z, antero-posterior acceleration; X, medio-lateral acceleration; Y, vertical acceleration.

The total acceleration measured by an accelerometer is a product of gravity, change in linear motion (linear acceleration) and forces related to rotational motions of an object to which the accelerometer is attached (74, 75). For example, when an object is stationary the acceleration of the object will be closer to -1.0 g when the axis is perpendicular to gravity, and 1.0 g when inverted (76). In this type of accelerometer,
when movement occurs, both the linear and rotational components will be combined with gravitational components in the acceleration signal (Figure 2-4 (69)). It is possible, although difficult (76) to separate the two components. Algorithms based on accelerometer tilt, gyroscope data (77) and/or filtering algorithms (78, 79) may be used to achieve this separation. For example, when an object is stationary the acceleration of the object will be zero in accelerometers that do not respond to gravity (70). Therefore, accelerometers can be divided into those that respond to the acceleration due to gravity and those that do not as a result of a form of correction in the software (69).

![Figure 2-4](image-url)

Figure 2-4. The net acceleration acting along the sensitive axis as measured by an accelerometer. Retrieved from Mathie and colleagues (69).

There are many different types of accelerometers including; electrostatic, magnetic reluctance, inductive, potentiometric, variable capacitance, servo force balance and motion balance, piezoelectric, piezoresistive (69), MEMS (80), and strain gauge (53). The most common types of accelerometers in human movement studies are
piezoresistive, variable capacitance (81), MEMS (66), or piezoelectric accelerometers (82). A thorough explanation of the design of most can be found in Meydan (83) or Mathie and colleagues (69). Although each uses different mechanisms, designs, and manufacturing techniques, in theory, all are variations of the spring mass system shown in Figure 2-5 (69).

![Figure 2-5. A simple spring mass model. Retrieved from Mathie and colleagues (69).](image)

In a spring mass system, a suspended mass is connected by a beam to the accelerometer frame. The suspended mass can be represented by a damped spring (84). When acceleration is applied to the accelerometer, the mass attached to the spring responds by applying force to the spring, causing it to compress or stretch (69). The applied acceleration can then be calculated by measuring the displacement of the spring, which is proportional to the applied force (69, 76). Accelerometers specifically operate under the principles of Hook's law (Equation 2) and Newton's second law of motion (Equation 3 (76)). Given that the stiffness of the spring, and mass can be controlled, the resultant acceleration of the mass can be determined from characteristics of its displacement (Equation 4 (76)). As acceleration is directly proportional to the net external force imposed on the object, measuring human movement with accelerometers is possible (70).
\[ F = kx \]

**Equation 2.** Hooks law.

\[ F = ma \]

**Equation 3.** Newton’s second law.

\[ F = kx = ma, \text{ thus } a = kx / m \]

**Equation 4.** Hooks and Newton’s second law combined.

where \( F \) = force, \( k \) = spring constant, and \( x \) = spring displacement, \( m \) = mass, and \( a \) = acceleration.

### 2.3.4.3 Monitoring Human Movement with an Accelerometer

The location of the accelerometer is important in human movement research (69). The accelerometer is typically attached to the object or body segment of interest (51) and aligned with the anatomical axes of the body, such as displayed in Figure 2-6 when positioned at the hypothetical centre of mass. Accelerometers have been attached to the chest (85), legs and feet (86), waist (87), shin (88), ankle, thigh (89), lower back (5), wrist, hip (19), upper back (90), or even placed in an object carried by a participant, such as a rucksack (91). As a result, single or multiple accelerometers may be positioned in a variety of locations on the body. For example, to correctly identify the type of movement performed, Mitchell, Monaghan, and Connor (90) attached two different smartphones (Google Nexus One, HTC Corporation, Taiwan; HTC Desire, HTC Corporation, Taiwan) to the upper back, both of which contained a single triaxial accelerometer sampling at 16-25 Hz. Whereas Leutheuser, Schulhaus and Eskofier (19) attached multiple SHIMMER sensor nodes (Shimmer 2R, Shimmer Technology,
USA) to the wrist, chest, hip and ankle, which contained a triaxial accelerometer (among other sensors) sampling at 204.8 Hz (range ±6 g). Both studies correctly classified the type of movement performed >80% of the time.

**Figure 2-6.** The directions of the vertical, medio-lateral, and antero-posterior axes with respect to the body. Retrieved from Mathie and colleagues (69).

The accelerations generated during human movement vary across the body and depend on not only the location of the accelerometer (69, 92), type (69), and speed of movement performed (93), but also the stride length and frequency (94), joint orientation (95), surface gradient (96), and footwear (97). These factors will determine the change in momentum of the foot and leg at foot-strike and thus the magnitude of acceleration experienced (94, 95). Furthermore, these external impact forces cause internal loading of the lower extremities and the impact shock to travel up through the body (98-100). This shock is presumably absorbed by the muscles and comes at the cost of increased oxygen consumption demands (101). Thus, during human locomotion the measured accelerations will be largest at the feet and smallest at the head (92). For example, peak accelerations at the feet may be as large as ±12.0 g and
may be reduced to approximately ±4.0 g at the head (92, 98). In addition, the amplitude of acceleration is also typically largest in the vertical direction and smallest in the medio-lateral due to the movement performed (98). To ensure that these movements are captured correctly, the accelerometer must have a frequency range that fulfils the Nyquist criterion (53). This specifies that the sampled frequency must be greater than twice as high as the highest frequency range of the movement assessed (102). The frequency range of most movements is relatively low (76), with most movements below 8 Hz when measured at the centre of mass (103). However, the sampling frequency may be as high as 25 Hz in specific arm movements (70) and 60 Hz when measured at the foot (102). In general, a sampling frequency 5-10 times the highest frequency of the movement performed is used (53). For example, Abel and colleagues (104) used accelerometers with a low sampling frequency (30 to 32 Hz) and range (0.05 to 2.00 g) to estimate step count and energy expenditure during walking and running. Whereas, Rowson and colleagues (105) used uniaxial accelerometers with a higher sampling frequency (10000 Hz) and range (±250 g) to record head impact acceleration data in collegiate football players during game-play. Therefore, this demonstrates that accelerometers can have broad amplitude and frequency ranges in human movement research (76).

The application of accelerometry is diverse and ever expanding, extending to multiple fields including medical, industry, engineering, biology, navigation, transport, consumer electronics, physical activity, and sports. For example, accelerometers are used in; cars to deploy airbags (106), animals to identify movement patterns (107), and structures to monitor dynamic loads (108). In regards to sports specifically, accelerometry has found utility in protective equipment design (109), performance
monitoring (7), injury risk prediction, rehabilitation (34, 110), and movement classification (90). Furthermore, this technology has been used in team sport to measure fatigue (111), energy expenditure (112), and identify the level of game-play (8). For example, Wixted and colleagues (112) used MEMS dual axis accelerometers sampling at 150 Hz (range ±2 g) to establish a method for estimating energy expenditure in athletes during training and game-play. In addition, as acceleration is the time derivative of velocity and velocity is the time derivative of position (67), accelerometers have the potential to measure speed and distance using integration of position data with respect to time (67, 70). However, accelerometers are unable to accurately assess non-ambulatory movements, such as cycling, especially with hip or superiorly positioned devices (113).

In summary, accelerometers offer a practical and low cost method of objectively measuring human movement in the field, thus highlighting the devices applicability to monitor workload in team sports. In this setting, however, the use of the accelerometer contained within wearable tracking devices is in its infancy. The following section will specifically explore technology including its validity, reliability, and application. However, before doing so a brief description of the wearable tracking device and other sensors contained within will be provided.

2.3.5 Wearable Tracking Devices

In 2001 the Australian Cooperative Research Centre for Micro Technology, under Project 2.5 “Interface Technologies for Athlete Monitoring”, began work to develop unique and unobtrusive real-time athlete monitoring equipment (114). Recent years have witnessed further development and the introduction of wearable tracking device
technology to team sports with a view of providing objective and possibly real-time workload monitoring during training and game-play. Wearable tracking devices often contain multiple sensors (Figure 2-7) in a small, lightweight unit worn by players on their upper (dorsal) body (e.g., the MinimaxX S4 wearable tracking device is 0.088 × 0.050 × 0.019 m in dimension weighs 67 grams). These devices may include global positioning system (GPS), accelerometer, heart rate (HR), gyroscope, and magnetometer sensors. Thus, time, position, distance, velocity, acceleration, heart rate, angular velocity and orientation can be synchronously recorded.

![Figure 2-7. The five sensors contained within a typical wearable tracking device.](image)

The GPS component of the wearable tracking device records information in regards to time, distance, position, direction, and velocity. Specifically, the GPS receiver within the device works off a network of satellites to triangulate its position (115). However, signals from the satellites to the GPS can be influenced by the atmosphere, deviations off various local obstructions (e.g., stadiums), and the number of satellites available to the receiver (four set as a minimum to triangulate the position and altitude of the unit). Therefore, GPS data cannot be collected indoors (116) and are less accurate in enclosed stadiums where team sports are commonly played. Although, newer models have the capability of working off fixed nodes within enclosed stadiums to enable the indoor capture of GPS data (e.g., Optimeye T5, Catapult Innovations, Australia), these
units have only recently been released (end of 2014) and have not been validated. In addition, GPS data cannot be used to quantify the workloads imposed on athletes during low velocity, high intensity movements, such as tackling and bumping in contact sports.

The HR component provides a non-invasive method of measuring HR in team sports (117) and is one of the most commonly used methods to indicate the intensity of exercise (118). Although accurate in the field (119), HR may be influenced by a number of factors including environmental conditions (temperature, humidity, ambient air), hydration status, altitude (118), state of training, exercise duration, and medication (120).

The application of gyroscopes to human movement analysis is still developing (84). In team sports, the gyroscope provides information about angular velocity or rotation of a player’s body (75). As human movement consists of mainly limb rotations around joints (84), gyroscopes are extensively used in gait analysis (75). However, in team sports the wearable tracking device is positioned on the upper body and this may limit its full potential. Gyroscopes are more commonly used in navigation and automotive fields (e.g., by integrating the rate of angular velocity, change in orientation, and direction from the initial reference orientation, direction can be obtained (121)), as well as in consumer products (e.g., anti-jitter compensation in cameras (122)).

A magnetometer measures the direction and strength of a magnetic field (75). This data is then used to detect the direction of travel (123). However, local disturbances in the magnetic field caused by electric currents, close permanent magnetic interference,
and large iron bodies can significantly affect its measurements (74). These can also affect the magnetic field angle of inclination (the angle of the earth’s magnetic field with respect to the surface of the earth) that is different at various locations around the world (74). As a result, this sensor is predominantly not used in team sports. Although, research has shown that a combination of technologies such as accelerometers, gyroscopes and magnetometers can improve the accuracy and performance of either technology alone (124). For instance, accelerometers can compensate the drift of the gyroscope about the axes of the horizontal plane, while magnetometers can do the same for the vertical plane (74).

The most relevant sensor to this thesis is the accelerometer. The accelerometer contained within wearable tracking devices is typically triaxial, samples at 100 Hz and has a range anywhere between ±6.0 to 12.0 g (Figure 2-8). For example, the MinimaxX S4 wearable tracking device contains a triaxial accelerometer (KXD94, Konix, USA) with a sampling frequency of 100 Hz and a range of ±10.0 g.

![Figure 2-8](image)

**Figure 2-8.** An accelerometer (left), MinimaxX S4 wearable tracking device (middle), and example sports vest (right).
2.4 Validity and Reliability of the Measuring Devices

2.4.1 Validity and Reliability Definition

Validity may be described as the ability of the measurement device to indicate what it is designed to measure and reliability is described as the repeatability of measurements (i.e., the absence of measurement error) (125). The validity of a measurement device also depends on its reliability (126). Reliability testing is used to evaluate the consistency (test-retest reliability) with which a measurement device can be used (126), both within devices (intra-instrument) and across devices (inter-instrument). It is important to assess reliability to ensure that new methods are sensitive enough to detect any changes in player performance (125).

In elite sport settings, coaches and sport scientists are constantly trying to find new ways to measure player performance in order to gain an advantage over their competition (49). However, quantifying performance can be extremely difficult or impossible to measure directly, leaving the true value of performance unknown (45). Instead coaches and sport scientists have turned to indirect methods of measurement (e.g., accelerometers), and when these new methods are proposed assessment of their value can only occur by comparison with other established techniques (127). Established techniques should be accepted as a measure of the concept of interest (i.e., acceleration) and are sometimes referred to as the ‘gold standard’ or ‘criterion measure’ (125-127). However, this does not imply that it is without measurement error (127).

If the accelerometer is reliable, it will measure the same value every time the same movement is performed (providing that all conditions and procedures are the same).
However, if the accelerometer is unreliable, then the measured value may vary from recording to recording and the measurement error would be above that deemed acceptable (125). Furthermore, for the accelerometer to be valid and reliable, it has to measure the same value every time, as well as measuring the actual or true value every time. For example, if a player gets tackled five times and the true peak acceleration value for each tackle is 5 \text{g}, then for the accelerometer to be valid and reliable it should measure 5 \text{g} five times. However, if the accelerometer measures 10 \text{g} five times it is reliable, but not valid. Alternatively, if the accelerometer measures five different values (e.g., 2 \text{g}, 4 \text{g}, 6 \text{g}, 8 \text{g}, and 10 \text{g}), then the accelerometer is neither reliable or valid. In either situation, a player may subsequently stop training too soon or too late based on the accelerometer and has been exposed to an incorrect workload required to ensure that training adaptations occur. This may then lead to a decreased ability for the player to perform at their fullest in subsequent training sessions or during game-play. Therefore, it is extremely important to make sure that the accelerometer contained within the wearable tracking device is both valid and reliable.

### 2.4.2 Accelerometer Reliability and Validity in Team Sports

There is limited scientific literature that examines the reliability and/or validity of accelerometers contained within wearable tracking devices (Table 2-1). Currently only six validity (10, 11, 18, 128-130) and three reliability (128, 130, 131) studies have been published. Two additional studies used a manufacturer calculated metric (PlayerLoad\textsuperscript{TM}; Equation 5) derived from accelerometer data, which assessed the validity and/or reliability of session RPE- and HR-derived workloads (132, 133).
\[
\text{PlayerLoad}_{t=n} = \sum_{t=0}^{t=n} \sqrt{((Z_{t=i+1} - Z_{t=i})^2 + (X_{t=i+1} - X_{t=i})^2 + (Y_{t=i+1} - Y_{t=i})^2}
\]

**Equation 5.** Example of PlayerLoad\textsuperscript{TM} accumulated used in team sports.

Where: \( Z \), antero-posterior acceleration; \( X \), medio-lateral acceleration; \( Y \), vertical acceleration; \( t \), time; \( n \), number.

### 2.4.2.1 Accelerometer Reliability

Boyd, Ball, and Aughey (131) assessed the inter- and intra-device reliability of eight MinimaxX accelerometers (Catapult Innovations, Australia) both statically (calibration drift tests) and dynamically (attached to a hydraulic shaker, and shaken at 0.5 g and 3.0 g) during a sport specific scenario. They found high intra- (CV = 0.91 to 1.01%) and inter-device (CV = 1.02 to 1.10%) reliability during both the static and dynamic trials. The inter device reliability was also high (CV = 1.94%). The authors concluded that the accelerometer contained within the MinimaxX wearable tracking device was reliable and capable of detecting workload differences in team sports. In a more recent study, Kelly and colleagues (130) also assessed the inter- and intra-device reliability of four SPI Pro X accelerometers (GP Sports Pty Ltd, Australia) to repeatedly measure peak accelerations. They found no differences, and high inter- and intra-device reliability (CV = 1.87 to 2.21%). Furthermore, Barrett, Midgley, and Lovell (128) assessed MinimaxX PlayerLoad\textsuperscript{TM} test-retest reliability at two locations (centre of mass and a novel scapulae position). They found no differences and moderate test-retest reliability (CV = 5.2 to 5.9%), which was not effected by device location. As a result of this, the authors concluded that the upper back location was appropriate for use in team sports.
2.4.2.2 Accelerometer Validity

Tran and colleagues (10) assessed the criterion validity of a single SPI Pro accelerometer to measure peak accelerations (converted to peak forces) during jumping and landing tasks. They found poor validity between accelerometer-derived peak forces and those obtained via force plate (CV = 16.8 to 30.8%). When the raw accelerometer data were filtered with a 20 Hz cut-off frequency, the validity of the accelerometer was slightly improved (CV = 10.9 to 22.2%). The authors concluded that additional research is needed to assess alternate locations and methods of securing the devices to the body. Similarly, Wundersitz and colleagues (18) assessed the criterion validity of a single SPI Pro X accelerometer to measure peak accelerations (converted to peak forces) during running and three COD movements. They also found poor validity between accelerometer-derived peak forces and those obtained via force plate (CV = 16.4 to 23.0%). When the raw accelerometer data were filtered at multiple cut-off frequencies (10, 15, 20, and 25 Hz), the validity of the data generally improved as the cut-off frequency reduced (except for the 180° COD). For example, the 10 Hz cut-off frequency produced a relative error of 11.7 to 17.2% (0 to 90°) and 23.9% (180°). The authors concluded that accelerometer data should be filtered at a 10 Hz cut-off frequency. These studies suggest that these errors may be a result of the distance between the accelerometer and force plate and that further consideration of alternative validation techniques to assess validity at the site the device is located is warranted. Kelly and colleagues (130) recently assessed the concurrent validity of the 100 Hz (±8.0 g) SPI Pro X II accelerometer in comparison to a reference accelerometer with the same frequency and range outputs (ADXL345, Analog Devices, Australia). Significant differences and large errors (CV = 27.5 to 30.5%) were found over a range
of mechanical shaking frequencies from 5 to 15 Hz. The authors concluded that static and dynamic validity was poor and they recommended caution when measuring peak accelerations in team sports, particularly for high intensity movements. However, it is important to note that they did not attempt to filter accelerometer data which may have improved the validity.

Gabbett, Jenkins, and Abernathy (11) assessed the concurrent validity of rugby player physical collisions coded as mild, moderate and heavy from video-replay to those recorded by the MinimaxX accelerometer. They found strong correlations ($r = 0.89$ to $0.99$), and concluded that the accelerometer is a valid method for quantifying impact workloads in team sports. However, in this study the comparison of intensity from video replay was subjective. Furthermore, correlations do not assess the precision, accuracy, agreement, and relative error between devices, they simply show that they are related. Barrett, Midgley, and Lovell (128) assessed the between- and within-subject convergent validity of the accelerometer when compared against HR and oxygen consumption data. They found trivial between subject correlations ($r = -0.03$ to $-0.20$) and strong within subject correlations ($r = 0.96$ to $0.98$). They advised caution when comparing between-player workloads in team sports. In addition, two similar studies compared session RPE and/or HR to PlayerLoadTM as the established technique (132, 133). Both studies found strong correlations ($r > 0.70$) between methods and suggested that PlayerLoadTM should be used in team sports to monitor workloads.

The accelerometer contained within wearable tracking devices have also been validated for applications in water sports (134, 135). Beanland and colleagues (134) assessed the criterion validity of the accelerometer positioned on the head to record
stroke counts for butterfly, breaststroke, and freestyle swimming styles. They found that
the accelerometer was valid for stroke count quantification in breaststroke and
butterfly (r > 0.98), and supported the application of accelerometry to swimming.
Janssen and Sachlikidis (135) assessed the validity and reliability accelerometers
attached to the kayak to measure intra-stroke velocity and acceleration. The
accelerometer’s reliability and validity was strong for intra-stroke velocity
measurements (r ≥ 0.95), however the validity was only moderate for intra-stroke
acceleration (r = 0.37 to 0.45). In addition, both velocity and acceleration were
underestimated. The authors suggested that sport specific validity and reliability
studies are needed to ensure the accuracy of the data. As these studies did not assess
team sports movements and utilised novel locations of the accelerometer (head and
kayak), the ability to generalise the findings to team sport movements and workload
monitoring is limited.
Table 2-1. Validity and reliability of accelerometers contained within wearable tracking devices in team sports.

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Device</th>
<th>Movement or Sport</th>
<th>Measure</th>
<th>Comparison measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barrett and colleagues (128)</td>
<td>2014</td>
<td>MinimaxX S4</td>
<td>Treadmill locomotion</td>
<td>Convergent validity, test-retest reliability</td>
<td>Accelerometer, oxygen consumption, HR</td>
</tr>
<tr>
<td>Beanland and colleagues (134)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>Swimming</td>
<td>Criterion validity</td>
<td>Video replay</td>
</tr>
<tr>
<td>Boyd, Ball, and Aughey (131)</td>
<td>2011</td>
<td>MinimaxX</td>
<td>AF</td>
<td>Test-retest reliability</td>
<td>Hydraulic shaker</td>
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<td>Casamichana and colleagues (132)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>Football</td>
<td>Convergent validity</td>
<td>Session RPE, HR</td>
</tr>
<tr>
<td>Gabbett, Jenkins, and Abernethy (11)</td>
<td>2010</td>
<td>MinimaxX</td>
<td>Tackling</td>
<td>Concurrent validity</td>
<td>Video replay</td>
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<td>2013</td>
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<td>Video replay</td>
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<td>MinimaxX</td>
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<td>Kelly and colleagues (20)</td>
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<td>Rugby Union</td>
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<td>Video replay</td>
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<td>Kelly and colleagues (130)</td>
<td>2014</td>
<td>SPI Pro X II</td>
<td>Mechanical testing</td>
<td>Concurrent validity, test-retest reliability</td>
<td>Accelerometer</td>
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<td>McNamara and colleagues (14)</td>
<td>2014</td>
<td>MinimaxX</td>
<td>Cricket</td>
<td>Concurrent validity</td>
<td>Manual counts</td>
</tr>
<tr>
<td>Scott and colleagues (133)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>AF</td>
<td>Convergent validity</td>
<td>Session RPE, HR</td>
</tr>
<tr>
<td>Tran and colleagues (10)</td>
<td>2010</td>
<td>SPI Pro</td>
<td>Jumping, landing</td>
<td>Criterion validity</td>
<td>Force platform</td>
</tr>
<tr>
<td>Wundersitz and colleagues (18)</td>
<td>2013</td>
<td>SPI Pro X</td>
<td>Running, COD</td>
<td>Criterion validity</td>
<td>Force platform</td>
</tr>
</tbody>
</table>

Note: Boldface indicates studies published prior to the commencement of this thesis. AF, Australian football; HR, heart rate; RPE, rating of perceived exertion.
Studies have begun to examine the accelerometer’s ability to classify team sport movements. McNamara and colleagues (14) tested a cricket bowling detection algorithm on 12 highly skilled cricket fast bowlers. The participants performed bowling, non-bowling, and competition events, with the algorithm correctly classifying bowling events 98.1% of the time during training and 74.0% of the time during competition. Similarly, Gastin and colleagues (129) assessed the concurrent validity of a tackle detection algorithm, which was compared against video-replay that was subjectively coded into three intensity categories (light, moderate, and heavy) during game-play. They found a mean accuracy of 78%, with tackled players more accurately detected. In addition, 76% of the tackles were correctly placed in the right intensity category. However, during game-play the algorithm was only able to correctly identify tackles 18% of the time. The authors concluded that the algorithm was unable to accurately detect tackles in Australian football, and suggested more advanced sport and movement specific algorithms are required.

In another study, Kelly and colleagues (20) applied machine learning algorithms (support vector machine and hidden conditional random field) to accelerometer data in order to classify tackling in rugby. Their tackling algorithm was able to consistently classify collisions, with a maximum accuracy of 95% found when both algorithms were combined. The authors supported the use of accelerometers in team sports, and suggested that they can be used to provide reliable and objective collision measurements in real-time. However, none of the abovementioned studies examined the accelerometer’s ability to classify multiple team sport movements (e.g., walking,
running, tackling etc.). Furthermore, classification is more difficult when movements are complex or similar to each other (136).

Mitchell, Monaghan, and Connor (90) attached two different smartphones (Google Nexus One, HTC Corporation, Taiwan; HTC Desire, HTC Corporation, Taiwan) in a customised harness on the upper back. They examined a number of accelerometer features, movement capture durations, and machine learning algorithms in order to classify field hockey and football specific activities. Similar to Kelly and colleagues (20), they found that a combination of machine learning algorithms was most appropriate for classifying multiple movements, with a maximum accuracy of 87%. However, their recordings were made using smartphones which are currently not permitted in team sports and have a low sampling rate (16 to 25 Hz). Furthermore, the techniques developed were not tested on jumping and changing direction (COD) movements, or combined with tackling movements, which are a part of many team sports. Readers interested in a more detailed explanation of these and other classifiers are directed towards the work of Zaki and Meira (137).

2.4.3 Accelerometer Applications

The recent development of wearable tracking device technology has permitted the wider application of accelerometers in team sports, with 15 publications produced since 2009 (Table 2-2). The majority of these publications are descriptive in nature and focus on accelerometer peak accelerations or accumulated accelerations expressed as an arbitrary metric (PlayerLoad™). Furthermore, the number of impacts players experience may be split into intensity categories; light impact (5.0 to 6.0 g), light-
moderate impact (6.0 to 6.5 g), moderate-heavy (6.5 to 7.0 g), heavy (7.0 to 8.0 g),
very heavy (8.0 to 10.0 g), and severe (10.0+ g), as recommended by device
manufacturers (6). In addition, accelerometer values may be expressed in other ways,
such as impacts per minute, PlayerLoad™ per minute, PlayerLoad™ slow etc. Of the
15 papers published, the majority used Catapult Sports wearable tracking devices,
were conducted in Australian football or rugby (league/ union), and reported primarily
peak accelerations (Table 2-2).

Cunniffe and colleagues (6) reported that rugby players are exposed to a large number
of peak accelerations above 5 g (n = 798 to 1274), with forwards subjected to greater
number, intensity, and PlayerLoad™ per minute values than backs. The authors
concluded that detailed analysis of accelerometer data may help evaluate player
workloads outside of traditional locomotor activity. Similarly, Venter and colleagues
(13) found back row forwards had the highest (n = 683) and outside backs the least (n
= 474) number of impacts in rugby. Although, inside backs experienced the most
number of severe impacts. The authors concluded that different positions have unique
physical requirements and accelerometer technology was able to offer valuable insight
into the severity of impacts. Gabbett, Jenkins, and Abernathy (11) also found that
rugby players were exposed to more than 57000 training impacts in a season and for
every 10000 impacts, more than six injuries occurred. The authors concluded that
substantial collision workloads are imposed on players during training and game-play,
and that the application of accelerometers (and other sensors) has allowed collisions
to be recorded.
Boyd, Ball, and Aughey (7) found that PlayerLoad™ values differed between playing positions, training and game-play, as well as elite and sub-elite standards of Australian football competition. Interestingly, only one training drill (small sided games) exposed players to similar PlayerLoad™ values as actual game-play. The authors concluded that accelerometers are useful tools for differentiating workloads in training and game-play. Colby and colleagues (34) recently found that pre-season PlayerLoad™ values were substantially higher than in-season values in Australian football. In addition, Montgomery, Payne, and Minahan (12) found that PlayerLoad™ values were significantly higher during game-play than training in basketball. The authors concluded that accelerometer data are useful for determining workloads in basketball. Colby and colleagues (34) also found that PlayerLoad™ values greater than 5,397 arbitrary units (averaged over three weeks) increased injury risk by 2.5 times in an Australian football season. The authors concluded that PlayerLoad™ significantly relates to injury risk and accelerometer variables should be considered, when monitoring or modifying player’s weekly workloads, to reduce injury risk.
Table 2-2. Application of accelerometers contained within wearable tracking device in team sports.

<table>
<thead>
<tr>
<th>Author and colleagues</th>
<th>Year</th>
<th>Device</th>
<th>Sport</th>
<th>Measure</th>
<th>Accelerometer Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abade and colleagues (138)</td>
<td>2014</td>
<td>SPI Pro X II</td>
<td>Football</td>
<td>Training workloads</td>
<td>Impacts, number per minute</td>
</tr>
<tr>
<td>Boyd, Ball, and Aughey (7)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>AF</td>
<td>Training &amp; game workloads</td>
<td>PlayerLoad™</td>
</tr>
<tr>
<td>Colby and colleagues (34)</td>
<td>2014</td>
<td>SPI Pro X</td>
<td>AF</td>
<td>Training &amp; game workloads, injury</td>
<td>PlayerLoad™</td>
</tr>
<tr>
<td>Cormack and colleagues (111)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>AF</td>
<td>Training &amp; game workloads, Fatigue</td>
<td>PlayerLoad™ per minute</td>
</tr>
<tr>
<td>Cormack and colleagues (8)</td>
<td>2014</td>
<td>MinimaxX S4</td>
<td>Netball</td>
<td>Game workloads, standards of PlayerLoad™</td>
<td>PlayerLoad™ per minute</td>
</tr>
<tr>
<td>Cunniffe and colleagues (6)</td>
<td>2009</td>
<td>SPI Elite</td>
<td>Rugby Union</td>
<td>Training workloads</td>
<td>Impacts, PlayerLoad™ per minute</td>
</tr>
<tr>
<td>Gabbett, Jenkins, and Abernethy (11)</td>
<td>2010</td>
<td>MinimaxX</td>
<td>Rugby Union</td>
<td>Training &amp; game workloads, injury, validity</td>
<td>Impacts</td>
</tr>
<tr>
<td>Gabbett, Jenkins, and Abernethy (139)</td>
<td>2012</td>
<td>MinimaxX</td>
<td>Rugby League</td>
<td>Training &amp; game workloads</td>
<td>Impacts, number per minute</td>
</tr>
<tr>
<td>Gabbett and Seibold (140)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>Rugby League</td>
<td>Game workloads</td>
<td>Impacts, PlayerLoad™</td>
</tr>
<tr>
<td>Gastin and colleagues (9)</td>
<td>2014</td>
<td>MinimaxX S4</td>
<td>AF</td>
<td>Game workloads</td>
<td>PlayerLoad™</td>
</tr>
<tr>
<td>McLellan and Lovell (141)</td>
<td>2012</td>
<td>SPI Pro</td>
<td>Rugby League</td>
<td>Game workloads, neuromuscular response</td>
<td>Impacts</td>
</tr>
<tr>
<td>Montgomery and colleagues (12)</td>
<td>2010</td>
<td>MinimaxX</td>
<td>Basketball</td>
<td>Training &amp; game workloads</td>
<td>PlayerLoad™</td>
</tr>
<tr>
<td>Mooney and colleagues (142)</td>
<td>2013</td>
<td>MinimaxX S4</td>
<td>AF</td>
<td>Game workloads, fatigue</td>
<td>PlayerLoad™ per minute</td>
</tr>
<tr>
<td>Suárez-Arrones and colleagues (47)</td>
<td>2012</td>
<td>SPI Elite</td>
<td>Football</td>
<td>Game workloads</td>
<td>Impacts</td>
</tr>
<tr>
<td>Venter and colleagues (13)</td>
<td>2011</td>
<td>SPI Pro</td>
<td>Rugby Union</td>
<td>Game workloads</td>
<td>Impacts</td>
</tr>
</tbody>
</table>

Note boldface indicates studies published prior to the commencement of this thesis. AF, Australian football.
2.5 Summary

There are many methods available to capture, analyse, and evaluate information about player movements in team sports. The most accurate methods are generally expensive and restricted to laboratory settings. Accelerometers offer a new method for measuring movements and workloads in team sports, providing many potential benefits to the player, team, and coach. In the field, the use of accelerometers for workload monitoring in team sports continues to grow. However, well-controlled studies investigating the validity of this technology are lacking. At the start of this doctoral research, no studies had been conducted to validate the accelerometer at the position worn on the upper back, or during movements of different types and intensities that are typically performed in team sports. The validity of the accelerometer may be improved by filtering the raw data, however, there has been little published research to substantiate this claim. While it has been documented that accelerometers may be used to classify single team sport movements, it is unknown whether multiple team sport movements can be classified when performed sequentially. Furthermore, there is a lack of evidence on appropriate methodology to do so.

Given these gaps in the available literature, more robust studies are required to obtain conclusive evidence regarding the validity of an accelerometer contained within a wearable tracking device, to measure and classify movement in team sports.
Chapter 3.

3 Study 1. Validity of a Trunk Mounted Accelerometer to Assess Peak Accelerations during Walking, Jogging and Running.
3.1 Abstract

The purpose of this study was to validate peak acceleration data from an accelerometer contained within a wearable tracking device while walking, jogging, and running. Thirty-nine participants walked, jogged, and ran on a treadmill while 10 peak accelerations per movement were obtained (n = 390). A single triaxial accelerometer measured resultant acceleration during all movements. To provide a criterion measure of acceleration, a 12-camera motion analysis (MA) system tracked the position of a retro-reflective marker affixed to the wearable tracking device. Peak raw acceleration recorded by the accelerometer significantly overestimated peak MA acceleration ($P <0.01$). Filtering accelerometer data improved the relationship with the MA system ($P <0.01$). However, only the 10 Hz and 8 Hz cut-off frequencies significantly reduced the errors found. The walk movement demonstrated the highest accuracy, agreement, and precision, and the lowest relative errors. Linear increases in error were observed for jog compared with walk and for run compared to both other movements. As the magnitude of acceleration increased, the strength of the relationship between the accelerometer and criterion measure decreased. These results indicate that filtered accelerometer data provides an acceptable means of assessing peak accelerations, in particular for walking and jogging.

Keywords: 3D analysis, acceleration, technology, methodology, game analysis.
3.2 Introduction

Direct observation, physical activity questionnaires, and body-mounted motion sensors are common techniques used to assess human movement (78). Accelerometers, were first developed in the 1920’s (61) and specifically designed in the 1950’s to measure human movement accelerations (63). In field-based settings, measuring human movement using accelerometers is preferred as acceleration is proportional to external force and therefore reflects the frequency and intensity of the movements performed (60). A commercially available wearable tracking device (MinimaxX S4, Catapult Innovations, Australia) contains a triaxial accelerometer and is currently employed in a variety of settings, in particular for sports performance monitoring in field team sports (129, 131, 143). Typically, the accelerations recorded during sports performance are converted into a metric (e.g., athlete load or accumulated number of peak impacts per acceleration band) and used alone or in combination with global positioning system (GPS) metrics to monitor athletic performance (6, 129, 143). However, fundamental to the usefulness of this technology to measure peak accelerations in sport is the underlying accuracy of the raw accelerometer data.

Force plates (10, 18), video-recordings (11, 129), and mechanical set-ups (131) have all been used to assess the validity and reliability of accelerometers contained within wearable tracking devices, generally reporting strong correlations and small to large relative errors. However, only two of these studies (10, 18) assessed the accelerometer’s ability to measure acceleration against a criterion measure of acceleration (ground reaction force), with relative errors between 16.4% and 30.8% found. Filtering of the raw acceleration data, however, reduced the errors noted
between the accelerometer and force plate (relative error 11.7% to 22.2% (10, 18)). A possible explanation for this are additive errors or noise present in the raw accelerometer signal (100). Noise refers to components within the raw signal that are not a result of human movement and add characteristics (e.g., frequency content) to the true signal (53, 55). A common method of reducing noise is filtering techniques, which require the choice of an optimal cut-off frequency to be applied to the data (53, 55). However, despite some studies utilising multiple cut-off frequencies (25 to 10 Hz) to filter the raw data (10, 18), an optimal cut-off frequency has not been ascertained.

Based on previous research (10, 18), a possible explanation for the errors found may be due to the distance between the accelerometer worn on the upper trunk and the criterion measure chosen, such as a force plate located on the ground. An alternative criterion measure is a motion analysis (MA) system, which is capable of measuring acceleration from the upper trunk and may be more appropriate than one restricted to the ground (18). A MA system captures the position of one or more retro-reflective markers located anywhere on the body (80) and through filtering and numerical differentiation (of a retro-reflective marker’s position data), high-quality estimates of time derivatives (velocity and acceleration) can be obtained (144, 145). Such technology has been used previously to validate GPS derived position and velocity data (146, 147).

No study to date has validated the accelerometer during walking, jogging, and running. This is despite a large percentage of an athlete’s time spent performing such movements (15, 28, 148). Furthermore, these movements are commonly performed in both clinical (98, 149) and physical activity (150-152) settings.


3.3 Purpose

The aim of this study was to compare peak acceleration data from an accelerometer contained within a wearable tracking device with a criterion measure, derived from a MA system, while walking, jogging, and running. This study also investigated the effect different filtering cut-off frequencies have on accelerometer accuracy, agreement, precision, and relative error.

3.4 Methods

Thirty-nine recreationally active participants (28 males and 11 females: age 24.2, 2.5 years; height 1.79, 0.09 m; mass 71.6, 12.0 kg; mean value, s) were recruited. Ethics approval for the study protocol was given and written informed consent was provided prior to participating.

Familiarisation with all equipment and procedures, as well as a standardised warm-up on a calibrated motorised treadmill (Quinton Q65, Quinton Instrument Company, USA) was performed prior to data collection. A single, wearable tracking device (Minimax S4, Catapult Innovations, Australia), which contained a 100 Hz triaxial accelerometer, was worn by each participant in a tightly fitted manufacturer supplied harness, similar to a compression sports top (18). The device weighed 67 grams and was 0.088 × 0.050 × 0.019 m in dimension, and records accelerations up to ±12 g in each axis. To assess the criterion validity of the accelerometer, a single five gram, 0.013 m retro-reflective marker was attached to the wearable tracking device and its position was determined using a calibrated 12-camera, MA system (Raptor-E, Motion

51
Analysis Corporation, USA) operating at 200 Hz. The system was calibrated immediately before each session. Dynamic calibration (with a 0.5 m wand) was 0.50003 ± 0.00024 (mean ± SD) with a relative error of 0.004%.

Prior to completing each trial, participants stood next to the treadmill, inside the capture volume of the MA system and performed three countermovement jumps. This was done to synchronise the accelerometer and MA system when data analysis occurred. Following the countermovement jumps, participants were instructed to mount the treadmill, which was already operating at the set walk velocity (1.5 m s⁻¹). After 30 s, the velocity was increased linearly until the desired jog velocity (3.3 m s⁻¹) was reached. Again after 30 s, this velocity was increased to the final run velocity (5.0 [female] to 5.9 [male] m s⁻¹) with participants running for 30 s before the treadmill was stopped. Within the 30 s, a sequence of 10 foot-strikes were chosen for analysis. Velocity ranges were based on standardised ranges developed by previous work for field team sport athletes (153).

Resultant data, defined as a single vector representing the combined effects of the X, Y and Z axes, for both the MA system and accelerometer were analysed through the manufacturer-supplied software (MA: Cortex, version 3.6.1.1315, Motion Analysis Corporation, USA; accelerometer: Logan Plus, version 5.0.9.2, Catapult Sports, Australia). Accelerometer accelerations, which were corrected for gravity (Inertial Movement Analysis proprietary software; Catapult Sports, Australia), as well as MA position data were then exported to Excel for further analysis (Microsoft Office Excel, version 14.0.6112.500, Microsoft Corporation, USA). The MA position data in the walk, jog, and run movements were spectrally analysed using a fast Fourier
transformation (FFT). Visual inspection of FFT outputs suggested that irrespective of
the movement performed, 6 Hz was the optimal cut-off frequency. To investigate the
effect different filtering cut off frequencies had on accelerometer accuracy, the raw
accelerometer data were filtered at multiple cut-off frequencies (20, 15, 10, 8, and 6
Hz) and compared against the MA data filtered at 6 Hz. The 20, 15, and 10 Hz cut-off
frequencies were chosen to match previous validation research (10, 18). The 8 Hz cut-
off frequency was chosen as previous validation research has not filtered below 10 Hz,
while the 6 Hz cut-off frequency was also chosen to match the criterion cut-off
frequency.

A customised MatLab program (R2012a, version 7.14.0.739, MathWorks Inc., USA)
was used to smooth and synchronize the recorded MA and accelerometer signals, as
well as detect the 10 sequential peak foot-strike accelerations per movement (i.e., walk,
jog, run; \( n = 390 \)). Specifically, to smooth accelerometer acceleration and MA position
data a low-pass, zero-lag, 4\(^{th}\) order Butterworth digital filter was applied. The MA
smoothed X, Y, and Z position data were then differentiated twice to calculate
acceleration (80). The resultant vector was then calculated in multiples of gravity or \( g \).
To synchronise the two devices and ensure the same peak resultant accelerations were
analysed at the correct time-point, the accelerations captured during three
countermovement jumps performed immediately prior to mounting the treadmill were
used to find the offset between both devices using MatLab’s built in cross correlation
function \( xcorr \). Subsequently, the offset between devices was subtracted from the time
domain of the MA data and peaks were identified, based on previously labelled events
(i.e., start and end of foot-strike), in the original frequency of the captured
accelerations. The alignment was also visually inspected to ensure the synchronisation of both signals was correct, prior to peak identification.

Prior to undertaking the statistical analyses the data were tested for its distribution (Kolmogorov-Smirnov test). The criterion and raw accelerometer data displayed a non-Gaussian distribution and heteroscedasticity \((P < 0.05)\) and were log-transformed to the power of 10. To determine whether differences were apparent between Gender (male and female) and Trial (1 to 10), independent sample Kruskal-Wallis tests were undertaken on the mean bias calculated between the raw accelerometer data and criterion measure. No differences for Gender and Trial were noted, as such both were pooled for all subsequent analyses. As these analyses were exploratory in nature, the alpha level was set at 0.05.

To determine the ability of the accelerometer to quantify peak accelerations, a number of measurement indices were obtained. The level of agreement, accuracy, precision, and relative error for the accelerometer and criterion accelerations were obtained by calculating the 95% limits of agreement \((95\% \text{ LoA } (125))\), mean bias, root mean square error of prediction \((\text{RMSEP } (154))\), and coefficient of variation \((\text{CV}\% (155))\) respectively. The details of these measures are given in equations 6-9:

\[
\text{Mean bias} = \text{mean} \ (\text{predicted} - \text{actual})
\]

\textbf{Equation 6.} Mean bias.

\[
95\% \text{ LoA} = \text{mean} \pm (\text{standard deviation} \times 1.96)
\]

\textbf{Equation 7.} 95% LoA.
\[ \text{RMSEP} = \sqrt{\frac{(\text{predicted} - \text{actual})^2}{\text{number of observations}}} \]

**Equation 8.** RMSEP.

\[ CV = 100 \left( e^{\text{standard error}} - 1 \right) \]

**Equation 9.** CV.

These measurement indices were calculated for i) each accelerometer variable (accelerometer accelerations analysed as raw and filtered at 20, 15, 10, 8 and 6 Hz), ii) each movement performed (walk, jog, and run) and iii) each acceleration band (the magnitude of acceleration split into five 0.5 g categories: 0.0 g to 0.5 g, >0.5 g to 1.0 g, >1.0 g to 1.5 g, >1.5 g to 2.0 g, and >2.0 g). Secondly, to determine if peak (log transformed) acceleration values recorded by the accelerometer were different from the MA system, a one way (variable) ANOVA was performed. Bonferroni corrected pairwise comparisons were used to identify the source of any differences, with the significant alpha level for the ANOVA’s adjusted to 0.007 via the Bonferroni procedure (156). The most optimal accelerometer variable was the one whose mean bias was closest to zero and was then used for all subsequent analyses. To investigate whether differences in mean bias were evident for the optimal accelerometer variable and the MA system, one way ANOVA’s were conducted between the three movements performed and the five acceleration bands. Bonferroni corrected pairwise comparisons were used to identify the source of any differences, with the alpha level for the ANOVA’s adjusted to 0.02 (movement performed) and 0.01 (acceleration band).
Bland-Altman plots were also used to examine the data visually (157) by plotting the raw and optimal accelerometer filter for each movement performed (walk, jog, run).

The ANOVA and exploratory analyses were conducted using SPSS (version 21.0, IBM Corporation, USA). The mean bias, 95% LoA, RMSEP, and CV% were calculated using Microsoft Excel™, whereas the Bland-Altman plots were obtained using Prism software (GraphPad, version 6, USA).

3.5 Results
Indices of accuracy, agreement, precision and relative error have been presented between each accelerometer variable and the MA system (Table 3-1). Peak raw accelerometer acceleration was shown to significantly overestimate peak MA acceleration ($P < 0.01$). All filter cut-off frequencies improved the relationship between the accelerometer and the MA system, when compared to the raw accelerometer data. Generally, the lower the cut-off frequency, the smaller the relative error found, with the higher frequency cut-offs typically resulting in significant overestimations (20 Hz and 15 Hz) and the lower cut-off (6 Hz) resulting in significantly underestimated MA accelerations ($P < 0.01$; Figure 3-1). The 10 Hz cut-off frequency displayed the best accuracy with the MA system and was deemed optimal for all subsequent comparisons (Table 3-2 and 3-3). Bland-Altman plots have been shown in Figure 3-1, and these highlight the lack of agreement for the raw accelerometer data and the improved agreement with lower filtering cut-off frequencies.
Table 3-1. Data relating to accuracy, agreement, precision, and relative error for each accelerometer variable assessed (n = 1170).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean Bias ± s (g)</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>0.85 ± 0.74*</td>
<td>-0.59 to 2.30</td>
<td>1.13</td>
<td>15.8</td>
</tr>
<tr>
<td>20 Hz</td>
<td>0.61 ± 0.53*</td>
<td>-0.43 to 1.65</td>
<td>0.81</td>
<td>13.8</td>
</tr>
<tr>
<td>15 Hz</td>
<td>0.33 ± 0.32*</td>
<td>-0.29 to 0.95</td>
<td>0.46</td>
<td>11.5</td>
</tr>
<tr>
<td>10 Hz</td>
<td>0.04 ± 0.14</td>
<td>-0.24 to 0.32</td>
<td>0.15</td>
<td>8.9</td>
</tr>
<tr>
<td>8 Hz</td>
<td>-0.08 ± 0.12</td>
<td>-0.31 to 0.16</td>
<td>0.14</td>
<td>8.2</td>
</tr>
<tr>
<td>6 Hz</td>
<td>-0.20 ± 0.14*</td>
<td>-0.48 to 0.08</td>
<td>0.24</td>
<td>8.2</td>
</tr>
</tbody>
</table>

*The mean difference (accelerometer vs. RM-Unit) is significant at the 0.007 level (log transformed data).

s – standard deviation; 95% LoA – 95% limits of agreement; RMSEP – root mean square error of prediction; CV – coefficient of variation.
Figure 3-1. Bland-Altman plots showing the relationship between the mean and difference values calculated by the accelerometer and criterion measure. The comparisons are; raw accelerometer acceleration – criterion acceleration (A), filtered accelerometer acceleration at 20 Hz – criterion acceleration (B), filtered accelerometer acceleration at 15 Hz – criterion acceleration (C), filtered accelerometer acceleration at 10 Hz – criterion acceleration (D), filtered accelerometer acceleration at 8 Hz – criterion acceleration (E), and filtered accelerometer acceleration at 6 Hz – criterion acceleration (F). Dotted line: mean bias; dashed lines: 95% LoA.
Filtering accelerometer data using a cut-off frequency of 10 Hz demonstrated significant differences ($P < 0.01$) in mean bias values for the run movement when compared to the walk and jog movements (Table 3-2). The accuracy, agreement, precision and relative error were strongest for the walk condition, with linear increases in indices noted for the jog compared with walk and for run compared to both lower intensity movements (Table 3-2). Significant differences ($P < 0.01$) were noted in mean bias values for the 1.5 to 2.0 g and >2.0 g acceleration bands when compared to each preceding acceleration band (Table 3-3). The strongest relationships were noted for the smallest (0.0 to 0.5 g) acceleration band and linear increases in error were found as the magnitude of acceleration increased.
Table 3-2. Data relating to accuracy, agreement, precision, and relative error for each movement performed for the 10 Hz filtered accelerometer data.

<table>
<thead>
<tr>
<th>Movement</th>
<th>Peak acceleration ± s (g)</th>
<th>Mean Bias ± s (g)</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk (n = 390)</td>
<td>0.44 ± 0.07</td>
<td>0.00 ± 0.03</td>
<td>-0.06 to 0.05</td>
<td>0.03</td>
<td>6.5</td>
</tr>
<tr>
<td>Jog (n = 390)</td>
<td>1.43 ± 0.24</td>
<td>0.00 ± 0.11</td>
<td>-0.22 to 0.22</td>
<td>0.11</td>
<td>7.5</td>
</tr>
<tr>
<td>Run (n = 390)</td>
<td>1.76 ± 0.35</td>
<td>0.18 ± 0.19*</td>
<td>-0.24 to 0.50</td>
<td>0.23</td>
<td>9.3</td>
</tr>
</tbody>
</table>

Peak acceleration values are the back transformed mean ± s.

* The mean difference is significantly higher ($P < 0.017$) when compared to each preceding movement.

s – standard deviation; 95% LoA – 95% limits of agreement; RMSEP – root mean square error of prediction; CV – coefficient of variation.
Table 3-3. Data relating to accuracy, agreement, precision, and relative error at each acceleration band for the 10 Hz filtered accelerometer data.

<table>
<thead>
<tr>
<th>Acceleration Band (g)</th>
<th>Mean Bias ± s (g)</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 to 0.5 (n = 310)</td>
<td>-0.01 ± 0.03</td>
<td>-0.06 to 0.05</td>
<td>0.03</td>
<td>6.8</td>
</tr>
<tr>
<td>0.5 to 1.0 (n = 87)</td>
<td>-0.01 ± 0.04</td>
<td>-0.08 to 0.07</td>
<td>0.04</td>
<td>4.9</td>
</tr>
<tr>
<td>1.0 to 1.5 (n = 282)</td>
<td>-0.01 ± 0.10</td>
<td>-0.21 to 0.18</td>
<td>0.10</td>
<td>7.0</td>
</tr>
<tr>
<td>1.5 to 2.0 (n = 400)</td>
<td>0.07 ± 0.15*</td>
<td>-0.21 to 0.36</td>
<td>0.16</td>
<td>9.0</td>
</tr>
<tr>
<td>&gt;2.0 (n = 91)</td>
<td>0.27 ± 0.24*</td>
<td>-0.19 to 0.73</td>
<td>0.36</td>
<td>10.6</td>
</tr>
</tbody>
</table>

* The mean difference is significantly higher ($P <0.01$) when compared to every other acceleration band.

s – standard deviation; 95% LoA – 95% limits of agreement; RMSEP – root mean square error of prediction; CV – coefficient of variation.
3.6 Discussion

The purpose of this study was to validate peak acceleration data from an accelerometer contained within a wearable tracking device with a criterion measure of acceleration, derived from a MA system, during walking, jogging and running movements. Filtering accelerometer data using a cut-off frequency of 10 Hz demonstrated the best accuracy with the MA system. Further, both the movement performed (Table 3-2) and the magnitude of acceleration recorded (Table 3-3) significantly affected the relationship found between the accelerometer and MA system.

The current study was the first to incorporate a criterion measure capable of recording peak accelerations at the location the wearable tracking device was worn, through the use of a MA system. The accelerometer was found to overestimate MA peak accelerations (mean bias 0.85 g) when all movement intensities were pooled together (Table 3-1; Figure 3-1). However, filtering the accelerometer signal reduced this overestimation (Figure 3-1). Further, it was evident that as the cut-off frequency applied to the raw data reduced (e.g., 20 Hz versus 15 Hz etc.), the overestimation decreased. With reference to the agreement, precision and relative errors found, all filtering frequencies improved the relationship noted with the MA system when compared to the raw accelerometer data alone. The validity of the accelerometer to measure peak accelerations, therefore, appears to be affected by additive errors or noise recorded within the raw signal. It was apparent that the accelerometer was most accurate when a 10 Hz cut-off frequency was applied to the data (mean bias 0.04 g). This is consistent with previous accelerometer validation research investigating peak acceleration measurements (18). The overall validity of the accelerometer data was
acceptable, with smaller relative errors noted than previous research using a different criterion measure (10, 18). These findings could be expected given that separation of the wearable tracking device from the criterion measure (i.e., force plate) may introduce or amplify errors between devices (18). Therefore, the lower relative errors (4.9 to 10.6%) found in this study may simply be the result of the criterion measure chosen, rather than an improved ability of the accelerometer to record peak accelerations.

A second major finding of this study was that the accelerometer’s validity varied between the movements performed and magnitude of acceleration recorded, evidenced by the differences found in accuracy, agreement, precision and relative error (Table 3-2 and 3-3). Specifically, as the magnitude of acceleration recorded increased, the validity of the accelerometer decreased. Gait (158, 159) and physical activity (104, 160) research using accelerometers have also demonstrated decreased accuracy during higher velocity movements, such as running. Furthermore, validation work with other sensors (GPS) that are housed within the wearable tracking device have shown similar errors (161). The inability of the mounting technique (harness) to hold the accelerometer to the body as the velocity of movement increases, may cause the wearable tracking device (and accelerometer) to be whipped, vibrated or hit against the body during movement (10, 18, 158), contributing to the errors found in the present investigation.

Some amount of error will always be present when comparing different technologies (125, 157). A relative error value of 5% for reliability (131) and 20% for validity (10, 18) has previously been suggested as an analytical goal for the acceptable use of this
technology in the field. Based on these values the accelerometer might then be considered acceptable as the largest relative error found (when a cut-off frequency of 10 Hz was applied) was 10.6% in the current study. However, it may be more appropriate to assess validity using multiple statistical approaches (as performed in the current study), rather than a single statistical approach, such as the CV% statistic that does not describe 32% of the variability between the accelerometer and MA system (125). With this in mind, the accuracy, agreement, precision, and relative error statistics combined support the use of the accelerometer for in-field monitoring of peak accelerations during walking, jogging (up to a magnitude of 1.5 $g$), and to a lesser degree running (for magnitudes greater than 1.5 $g$). Practically, to enhance the accuracy of the accelerometer data produced, wearable tracking device manufacturers should consider incorporating a 10 Hz filtering algorithm within the device’s software. Alternatively, practitioners could export raw accelerometer data and, prior to interpretation, apply a 10 Hz filter to this data. Furthermore, as can be seen in Figure 3-1A and 3-1D, the magnitude of acceleration is reduced with filtering (e.g., a 3.0 $g$ peak acceleration when filtered at 10 Hz may become a 2.5 $g$ peak acceleration). Practitioners should be aware of this, especially when comparing to previously recorded metrics obtained from raw accelerometer data. Further research is required to assess other movements, such as tackling and bumping, which impose peak accelerations greater than those recorded in the current study (i.e., greater than 5 $g$ as is common in contact sports (6, 129)).

This study has shown that the accelerometer contained within the MinimaxX S4 wearable tracking device can accurately measure walking, jogging, and to a lesser degree running peak accelerations when filtered at a 10 Hz cut-off frequency. Accurate
assessment of walking, jogging, and running is important considering that field team sports athletes spend most of their time in these movement categories (15, 28, 148). For example, in Soccer athletes spend 14.2%, 28.1%, and 11.1% of their time walking, jogging, and running respectively (28). Accelerometers may, therefore, be used accurately to evaluate the effectiveness of training programs designed to increase sports performance, and the prevention and rehabilitation of athletes from injury. Further, researchers have used accelerometers to evaluate different standards of gameplay (8), exercise induced muscle damage (162), fatigue (142), injury risk (163), the overall physical demands of sport performance, including the frequency and intensity of physical collisions (129). Our findings suggest that the accelerometer may have found greater levels of accuracy than shown in these studies if the raw data were filtered.

The current investigation has several strengths and limitations. A strength of the study was that human trials were conducted to validate the accelerometer as compared to validation in a mechanical setting. The choice of criterion measure also ensured that the accelerometer was validated at the location it is worn. Additionally, both raw and multiple data processing (i.e., filtering) techniques were investigated, thus providing practitioners with alternatives to improve accelerometer accuracy beyond the use of raw data. In terms of weaknesses, the treadmill-based protocol limits the scope of the study to replicate field team sport movement patterns (164). Hong and colleagues (165) found that treadmill running increased ground contact time and decreased peak plantar forces at foot-strike. As a result, it may be possible that the peak accelerations recorded in the current investigation are smaller than those recorded in the field. The fastest velocity participants ran at was 5.9 m s⁻¹, while elite team sport athletes
routinely attain higher velocities (e.g., 8.3 m s\(^{-1}\) in Australian football (166)). Although a single cut-off was chosen for all movements, it may be that the 6 Hz (MA) and 10 Hz (accelerometer) cut-offs were most appropriate for walking, and less so for jogging and running. However, as the FFT supported a single cut-off for all movements and multiple movements are performed in a data set, a single cut-off that can be applied to a data set has more practical use for practitioners.

3.7 Conclusion

The findings of this study show that the accelerometer contained within a wearable tracking device is capable of accurately measuring peak accelerations, in particular for walking and jogging. The current use of raw accelerometer data in the technology likely leads to an overestimation of peak accelerations, while the application of appropriate filtering cut-off frequencies enable the accelerometer to measure peak accelerations with greater accuracy. As a result, wearable tracking device manufacturers should consider incorporating a 10 Hz filtering algorithm within the device’s software. Further, it appears that the accuracy of the accelerometer may be reduced as the movement velocity and magnitude of acceleration recorded increases. Future research should consider assessing the performance of accelerometers in measuring other movements, especially those that result in larger peak accelerations.
Chapter 4.

Study 2. Validity of a Trunk Mounted Accelerometer to Measure Physical Collisions in Contact Sports.
4.1 Abstract

Accelerometer peak impact accelerations are being used to measure player physical demands in contact sports. However, their accuracy to do so has not been ascertained. The purpose of this study was to compare peak impact acceleration data from an accelerometer contained within a wearable tracking device with a three dimensional motion analysis (MA) system during tackling and bumping. Twenty-five semi-elite rugby athletes wore a tracking device containing a 100 Hz triaxial accelerometer (MinimaxX S4, Catapult Innovations, Australia). A single retro-reflective marker was attached to the device with its position recorded by a 12-camera MA system during three physical collision movements (tackle bag, bump pad, and tackle drill; n = 625). The accuracy, effect size, agreement, precision, and relative errors for each comparison were obtained as measures of accelerometer validity. Physical collision peak impact accelerations recorded by the accelerometer overestimated (mean bias 0.60 g) those recorded by the MA system ($P < 0.01$). Filtering the raw data at a 20 Hz cut-off improved the accelerometer’s relationship with MA data (mean bias 0.01 g; $P > 0.05$). When considering the data in nine magnitude bands, the strongest relationship with the MA system was found in the 3.0 g or less band and the precision of the accelerometer tended to reduce as the magnitude of impact acceleration increased. Of the three movements performed, the tackle bag movement displayed the greatest validity with MA. The findings indicate that the MinimaxX S4 accelerometer can accurately measure physical collision peak impact accelerations when data were filtered at a 20 Hz cut-off frequency. As a result, accelerometers may be useful to measure physical collisions in contact sports.

**Keywords:** Acceleration, motion analysis, impact, load, intensity.
4.2 Introduction

Physical collisions form a major component of contact team sports and include movements such as tackling, bumping, and landing on the ground (9, 167). These physical collisions have been shown to expose athletes to an increased risk of contact related injury (167, 168). Further, the intensity of the collision may contribute to the incidence of injury (17, 168). Historically, collisions have been identified retrospectively using video replay (169, 170). However, this approach is limited largely due to test-retest reliability issues (54), and the considerable time required to collect and analyse the data (49).

Commercially-available wearable tracking devices have been developed for field team sports (e.g., MinimaxX S4, Catapult Innovations, Australia) and are worn by athletes on their upper back in a sports vest (20). Such devices typically contain global positioning system (GPS), gyroscope, and magnetometer sensors (143). They also contain an accelerometer, making it possible to measure the accelerations associated with sporting movements, including physical collisions in contact sports (11, 20, 129). As acceleration is directly proportional to external force (60), accelerometers can therefore be used to reflect the intensity of collisions that athletes experience.

Previous research has shown that accelerometers can be used to describe physical collisions during game-play (9, 20). Additionally, research assessing the intensity of collisions have found strong relationships between accelerometer data and subjective categorisation from video observation (11, 129). These studies show accelerometers have the potential to quantify physical collisions in contact sports, however in order
for accelerometers to be used with confidence for these purposes, the data output should be both reliable and valid.

To this end, Boyd, Ball, and Aughey (131) assessed the reliability of the MinimaxX S4 accelerometer and found a good level of within- and between-device reliability (0.9% to 1.9%). The concurrent-validity (a type of criterion-related validity where a new instrument [i.e., accelerometer] is compared to an alternative form of measurement previously validated (171)) of an accelerometer (SPI Pro, GPSports Pty Ltd., Australia) during jumping, landing (10), running, and change of direction movements (18, 172) has also been assessed. In both studies, raw accelerometer data overestimated force plate-derived ground reaction force, although the application of a low-pass filter improved the validity of the data. A more recent investigation assessed the concurrent validity of another accelerometer (MinimaxX S4, Catapult Innovations, Australia) using a three-dimensional motion analysis (MA) system during treadmill walking, jogging, and running (172). Similarly, the raw accelerometer data overestimated the concurrent measure and filtering improved the validity of the data.

As seen from this previous research, two accelerometer types have been assessed, targeting lower intensity movements and displaying consistent overestimations of movement intensity. In contact sports, high intensity collisions are of more interest to coaches than low intensity collisions due to the additional physical demand these larger collisions place on the body (11, 17). However, no study has validated the MinimaxX S4 accelerometer at intensities similar to those experienced in contact sports (e.g., >5.0 g (6, 129)). The aim of this study was to concurrently validate peak impact acceleration
data from an accelerometer contained within a MinimaxX S4 wearable tracking device with a MA system during tackling and bumping.

4.3 Purpose
The aim of this study was to concurrently validate peak impact acceleration data from an accelerometer contained within a MinimaxX S4 wearable tracking device with a MA system during tackling and bumping.

4.4 Methods
Twenty-five males (age 23.3 ± 4.3 years; height 1.80 ± 0.06 m; mass 96.5 ± 18.1 kg; mean ± SD) competing in the Victorian Rugby Union Premier Division were recruited for participation in the study. Ethics approval for the study was provided by the relevant human research ethics committee, with written informed consent obtained from all participants prior to testing. This study evaluated the concurrent validity of peak impact acceleration data collected from an accelerometer against a MA system during physical collisions movements. Raw accelerometer data as well as data filtered at several cut-off frequencies were compared.

Participants wore a single, wearable tracking device (MinimaxX S4, Catapult Innovations, Australia) in a sports vest, which contained a 100 Hz triaxial accelerometer (20). The device weighed 67 grams and was 88 × 50 × 19 mm in dimension. To assess the concurrent validity of the accelerometer, a single five gram, 13 mm retro-reflective marker was affixed with medical tape to the wearable tracking device and its position was tracked using a 12-camera, MA system (Raptor-E, Motion
Analysis Corporation, USA) operating at 500 Hz. The MA system was calibrated both statically (L-frame) and dynamically (0.5 m wand; to 0.50004 ± 0.0005 m [mean ± SD] and a precision of 0.00006 m). In clinical gait analysis, MA systems are the gold standard measure used to accurately describe the kinematics of motion (173). Recently, MA systems have been used in sports laboratories to assess the concurrent validity of wearable tracking device sensors (e.g., (146, 147, 172)).

Familiarisation with all equipment and procedures, as well as a standardised warm-up was performed prior to commencing data collection. Participants then performed three physical collision tasks outdoors on a rugby field, during which time acceleration and three-dimensional kinematic data were collected. The cameras comprising the MA system contain new proprietary image processing software that enables outdoor (in direct sunlight) and indoor capture. The three physical collision tasks were broken down into those that involved ground contact (tackle bag) and those that involved body contact, as either the ball carrier being tackled (tackle drill) or the defender tackling the ball carrier (bump pad). The run up velocity (prior to collision) was self-selected with instruction given to run as fast as possible and perform each physical collision as is typical during game-play.

In the tackle bag task, participants started 5 m away from a stationary upright padded tackle bag (1.53 × 0.46 m, Senior Tackle Dummy, Madison Sport, Australia) and ran and tackled the tackle bag to the ground. In the bump pad task, participants performed the same running movement, however a second participant was standing stationary six meters away and prior to contact was instructed to forcefully step into the approaching participant while holding a padded hit shield (0.76 × 0.51 m, Large Hit Shield,
Lastly, in the tackle drill task, both participants started 10 m apart and ran at each other, with the first designated as the defender and the second designated as the ball carrier (peak impact acceleration of interest). The defending participant was instructed to tackle the first participant around their centre of gravity (i.e., aiming for shoulder contact around the midriff area). Participants were matched for mass and after five trials, swapped roles. Participants were required to perform 10 trials of the bump pad (n = 250) and tackle bag tasks (n = 250), and five trials of the tackle drill task (n = 125), in the same order as mentioned above (this order was chosen to expose participants to the two tasks that involved some form of padding prior to the tackle drill task which did not). A one minute break was given between each trial with an additional five minutes recovery given between each task. The trial was excluded if a trial was performed unsuccessfully (e.g., missed or broke through a tackle too easily etc.), and the participants were reminded of correct technique (see Gabbett (174)) and asked to repeat the trial. In addition, no direction was given in regards to the footwear worn (either football boots or cross-trainers) during testing.

Resultant data, defined as a single vector representing the combined effects of the X, Y and Z axes, for both the MA system and accelerometer were analysed through the manufacturer-supplied software (MA: Cortex, version 3.6.1.1315, Motion Analysis Corporation, USA; accelerometer: Logan Plus, version 5.0.9.2, Catapult Sports, Australia). Accelerometer-derived accelerations, which were corrected for gravity (Inertial Movement Analysis proprietary software, Catapult Sports, Australia), along with MA position data were then exported to Microsoft Excel™ for further analysis (version 14.0.6112.500, Microsoft Corporation, USA).
Three-dimensional kinematic data are subject to high-frequency noise not the result of human movement (175, 176). For example, even in static conditions, reconstructed marker data are not stationary (175). As a result, when estimating time derivatives, noise within the raw signal may be amplified (55, 144). For these and other reasons, marker position data are low-pass filtered (176), to remove high-frequency noise and obtain accurate derivative estimates (144, 145). To choose the optimal cut-off frequency, a residual analysis of the difference between the unfiltered and filtered MA signals over a range of cut-off frequencies was performed for each movement, with the decision made via visual inspection (55). As a result of the residual analysis, MA data for all movements were filtered at a 10 Hz cut-off frequency. The MA smoothed X, Y, and Z position data were then differentiated twice to calculate acceleration (80). The resultant vector was then calculated in multiples of gravity or $g$. To investigate the effect different filtering cut-off frequencies had on accelerometer accuracy, the raw accelerometer data were filtered at multiple cut-off frequencies (30 Hz, 25 Hz, 20 Hz, 15 Hz, 10 Hz, 8 Hz, and 6 Hz) and compared against the MA system. To filter both the MA and accelerometer data, a low-pass, zero-lag, 4th order Butterworth digital filter was applied in a customised Labview program (version 7.1, National Instruments, USA).

To synchronise the accelerometer and MA system, at the beginning of each trial the participant stood within the capture volume of the MA system and the wearable tracking device was hit from the side while being filmed by a digital video recorder (GZ-MG330HAA, JVC, Japan) operating at 50 Hz. The data were subsequently imported into video analysis software (Team Pro version 7, Dartfish Ltd, Switzerland) and the hit peak acceleration was used to synchronise the two devices. Thus, the time-
point at which the physical collision occurred at was recorded and the peak impact acceleration value manually retrieved for each trial.

The accelerometer was examined across a broad range of peak impact accelerations from 2.2 - 14.5 g. Prior to undertaking the main statistical analyses, a Kruskal-Wallis test was performed to determine whether differences in mean bias values between the raw accelerometer data and concurrent measure existed between the 25 trials. As this analysis was exploratory in nature, the critical alpha level was set at 0.05. No differences for trial were noted, as such all data were pooled for all subsequent analyses.

In order to determine the ability of the accelerometer to quantify peak accelerations, multiple measurement indices of validity were obtained. The level of accuracy, effect size, agreement, precision, and relative error for the accelerometer and MA accelerations were obtained by calculating the mean bias (154), Cohen’s d, 95% limits of agreement (95% LoA (125)), RMSEP (154), and coefficient of variation (CV%) respectively.

Analysis of variance (ANOVA) was performed on four occasions, each analysing the data reported in different formats. To determine if peak acceleration values recorded by the accelerometer (eight levels: raw, filtered at 30 Hz, 25 Hz, 20 Hz, 15 Hz, 10 Hz, 8 Hz, and 6 Hz) differed from the MA system, a one-way ANOVA was performed. Filtered accelerometer values displaying high levels of accuracy, agreement, and precision with the MA system (e.g., mean bias and RMSEP values close to 0.0 g) were then used for all subsequent analyses. A second one-way ANOVA was performed in
order to investigate whether differences in mean bias existed between the accelerometer and MA system when peak impact accelerations were compared across multiple magnitude bands (nine levels: <3.0 g, 3.0 g to 3.99 g, 4.0 g to 4.99 g, 5.0 g, 5.0 g to 5.99 g, 6.0 g to 6.99 g, 7.0 g to 7.99 g, 8.0 g to 9.99 g, and 10.0 g or greater). These magnitude bands were modified from scaling categories previously reported in the literature (6, 129). A third one-way ANOVA was performed in order to investigate whether differences in mean bias existed between the accelerometer and MA system across the different movements undertaken (three levels: tackle bag, bump pad, and tackle drill). Lastly, a fourth one-way ANOVA was performed in order to investigate whether peak impact accelerations could be used as a feature to distinguish between the three physical collisions performed (three levels: tackle bag, bump pad, and tackle drill).

Bonferroni corrected pairwise comparisons for the four ANOVAs were used to identify the source of any differences, with the alpha level adjusted to 0.006, 0.006, 0.02, and 0.02 respectively via the Bonferroni procedure (156). The exploratory analysis and ANOVAs were conducted using SPSS (version 21.0, IBM Corporation, USA). The mean bias, effect size, 95% LoA, RMSEP, and CV were calculated using Microsoft Excel™.

4.5 Results

Indices of accuracy, effect size, agreement, precision, and relative error between raw and filtered accelerometer data and the MA system are presented in Table 4-1. Raw and 30 Hz filtered accelerometer data significantly overestimated MA data ($P < 0.006$,
mean bias = 0.34 to 0.60 g, Cohen’s $d$ = 0.16 to 0.28). Filtering raw accelerometer data at 25 Hz ($P = 0.41$, Cohen’s $d$ = 0.10), 20 Hz ($P = 1.00$, Cohen’s $d$ = 0.01) and 15 Hz ($P = 0.06$, Cohen’s $d$ = -0.15) cut-offs displayed better validity when compared with MA data (mean bias = 0.21 to -0.31 g). However, the lowest cut-offs (10, 8 and 6 Hz) significantly underestimated MA data ($P < 0.006$, mean bias = -0.92 to -1.87 g, Cohen’s $d$ = -0.47 to -1.03). Filtering raw accelerometer data using a 20 Hz cut-off frequency demonstrated the best accuracy, agreement and precision values. Therefore, raw accelerometer data filtered at the 20 Hz cut-off frequency was used for all subsequent analyses.
Table 4-1. Data relating to accuracy, effect size, agreement, precision and relative error for each accelerometer variable assessed (n = 625).

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean ± SD (g)</th>
<th>Cohen’s d</th>
<th>Mean Bias ± SD (g)</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA</td>
<td>6.00 ± 2.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raw</td>
<td>6.60 ± 2.10*</td>
<td>0.28</td>
<td>0.60 ± 1.09</td>
<td>-1.53 to 2.73</td>
<td>1.24</td>
<td>15.1</td>
</tr>
<tr>
<td>30 Hz</td>
<td>6.34 ± 2.05</td>
<td>0.16</td>
<td>0.34 ± 0.88</td>
<td>-1.38 to 2.06</td>
<td>0.94</td>
<td>12.0</td>
</tr>
<tr>
<td>25 Hz</td>
<td>6.21 ± 2.04</td>
<td>0.10</td>
<td>0.21 ± 0.82</td>
<td>-1.40 to 1.81</td>
<td>0.84</td>
<td>10.8</td>
</tr>
<tr>
<td>20 Hz</td>
<td>6.01 ± 2.01</td>
<td>0.01</td>
<td>0.01 ± 0.75</td>
<td>-1.46 to 1.48</td>
<td>0.75</td>
<td>9.6</td>
</tr>
<tr>
<td>15 Hz</td>
<td>5.69 ± 1.95</td>
<td>-0.15</td>
<td>-0.31 ± 0.70</td>
<td>-1.69 to 1.07</td>
<td>0.77</td>
<td>9.5</td>
</tr>
<tr>
<td>10 Hz</td>
<td>5.08 ± 1.72*</td>
<td>-0.47</td>
<td>-0.92 ± 0.82</td>
<td>-2.53 to 0.68</td>
<td>1.23</td>
<td>14.5</td>
</tr>
<tr>
<td>8 Hz</td>
<td>4.67 ± 1.55*</td>
<td>-0.69</td>
<td>-1.33 ± 0.95</td>
<td>-3.19 to 0.53</td>
<td>1.63</td>
<td>19.3</td>
</tr>
<tr>
<td>6 Hz</td>
<td>4.13 ± 1.29*</td>
<td>-1.03</td>
<td>-1.87 ± 1.14</td>
<td>-4.14 to 0.37</td>
<td>2.19</td>
<td>26.9</td>
</tr>
</tbody>
</table>

* The mean difference (accelerometer vs. MA) is significant at the 0.008 level;

CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.
Table 4-2 shows the relationship between the accelerometer data filtered at a 20 Hz cut-off frequency and the MA system for each magnitude band. The mean bias values calculated in the 9.0 to 9.99 \( g \) magnitude band significantly underestimated those calculated in the \(<5.0 \ g\) and 6.0 to 7.0 \( g \) magnitude bands \((P < 0.006)\). The precision of the accelerometer tended to reduce as the magnitude of impact acceleration increased. The mean bias values calculated for the tackle bag movement significantly underestimated those calculated for the bump pad and tackle drill movements \((P < 0.02; \text{Table 4-3})\). There was only a minor difference in mean bias between the tackle drill and bump pad movements. The tackle bag movement displayed the strongest agreement and precision, while the bump pad movement displayed the strongest accuracy with the MA system. The tackle bag peak accelerations were significantly greater than the tackle drill, with peak accelerations for both movements higher than the bump pad.
Table 4-2. Data relating to accuracy, effect size, agreement, precision and relative error at each acceleration band, MA versus 20 Hz filtered acceleration data.

<table>
<thead>
<tr>
<th>Acceleration band (g)</th>
<th>Mean Bias ± SD (g)</th>
<th>Cohen’s d</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;3.0 (n = 25)</td>
<td>0.08 ± 0.42</td>
<td>-0.20</td>
<td>-0.90 to 0.74</td>
<td>0.42</td>
<td>10.8</td>
</tr>
<tr>
<td>3.0 to 3.99 (n = 85)</td>
<td>-0.04 ± 0.53</td>
<td>-0.09</td>
<td>-1.07 to 0.99</td>
<td>0.53</td>
<td>9.9</td>
</tr>
<tr>
<td>4.0 to 4.99 (n = 101)</td>
<td>0.20 ± 0.62*</td>
<td>0.42</td>
<td>-1.03 to 1.42</td>
<td>0.58</td>
<td>11.7</td>
</tr>
<tr>
<td>5.0 to 5.99 (n = 123)</td>
<td>0.08 ± 0.73*</td>
<td>0.14</td>
<td>-1.35 to 1.51</td>
<td>0.73</td>
<td>9.8</td>
</tr>
<tr>
<td>6.0 to 6.99 (n = 107)</td>
<td>0.09 ± 0.74*</td>
<td>0.16</td>
<td>-1.37 to 1.55</td>
<td>0.75</td>
<td>8.9</td>
</tr>
<tr>
<td>7.0 to 7.99 (n = 74)</td>
<td>0.04 ± 0.86</td>
<td>0.06</td>
<td>-1.64 to 1.72</td>
<td>0.85</td>
<td>8.7</td>
</tr>
<tr>
<td>8.0 to 8.99 (n = 57)</td>
<td>-0.21 ± 0.92</td>
<td>-0.30</td>
<td>-2.02 to 1.60</td>
<td>0.94</td>
<td>8.8</td>
</tr>
<tr>
<td>9 to 9.99 (n = 35)</td>
<td>-0.47 ± 0.90</td>
<td>-0.28</td>
<td>-2.22 to 1.29</td>
<td>1.00</td>
<td>7.0</td>
</tr>
<tr>
<td>10.0+ (n = 19)</td>
<td>-0.17 ± 1.02</td>
<td>-0.14</td>
<td>-2.16 to 1.82</td>
<td>1.00</td>
<td>6.6</td>
</tr>
</tbody>
</table>

* The mean difference (accelerometer vs. MA) is significant at the 0.01 level when compared to the 9.0-9.99 g acceleration band;

CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.
Table 4-3. Data relating to accuracy, effect size, agreement, precision and relative error for each movement performed, MA versus 20 Hz filtered acceleration data.

<table>
<thead>
<tr>
<th>Movement</th>
<th>Mean ± SD (g)</th>
<th>Mean Bias ± SD (g)</th>
<th>Cohen’s d</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tackle bag (n = 250)</td>
<td>7.24 ± 1.65</td>
<td>-0.28 ± 0.64</td>
<td>-0.16</td>
<td>-1.52 to 0.97</td>
<td>0.69</td>
<td>6.5</td>
</tr>
<tr>
<td>Bump pad (n = 250)</td>
<td>4.79 ± 1.58</td>
<td>0.20 ± 0.74</td>
<td>0.13</td>
<td>-1.24 to 1.64</td>
<td>0.76</td>
<td>11.3</td>
</tr>
<tr>
<td>Tackle drill (n = 125)</td>
<td>6.00 ± 1.93</td>
<td>0.21 ± 0.82</td>
<td>0.10</td>
<td>-1.39 to 1.81</td>
<td>0.84</td>
<td>11.2</td>
</tr>
</tbody>
</table>

* The mean difference (accelerometer vs. MA) is significant at the 0.01 level when compared to bump pad and tackle drill movements;

b The mean difference (movement) is significant at the 0.01 level;

CV – coefficient of variation; RMSEP - root mean square error of prediction; SD - standard deviation; 95% LoA – 95% limits of agreement.
4.6 Discussion

The aim of this study was to concurrently validate peak impact acceleration data from an accelerometer with a MA system during three physical collision movements. When filtered at 20 Hz the accelerometer displayed the strongest relationship with the MA system (i.e., accuracy, agreement, precision etc.). However, raw and 30 Hz filtered accelerometer data overestimated, and 10 Hz, 8 Hz, and 6 Hz accelerometer data underestimated, physical collision peak impact accelerations. Further, both the intensity of acceleration recorded and the type of physical collision performed influenced accelerometer validity. Collectively, these results highlight that accelerometers can be used to accurately quantify the intensity of physical collisions experienced in contact sports, provided that the raw data is filtered using an appropriate cut-off frequency (e.g., 20 Hz).

The raw accelerometer data overestimated physical collision peak impact accelerations (mean bias = 0.60 g), and displayed poor agreement and precision with MA peak accelerations. This finding is supported by previous research which has shown that the accelerometer contained within wearable tracking devices can overestimate concurrent methods by 15.6% to 30.8% (10, 18, 172). For example, a physical collision with a true peak impact acceleration value of 6.0 g if recorded by the accelerometer will have an error of 1.24 g under or over the actual value when raw data are used.

The poor accuracy of these devices for assessing peak impact accelerations may be due to noise present in the raw accelerometer signal (100). Noise refers to elements within the raw signal that are not a result of human movement and add characteristics
Filtering of a raw signal is commonly used to reduce noise (53, 55). Although the raw accelerometer data overestimated physical collision peak accelerations, when filtered at 30 Hz, 25 Hz, 20 Hz, and 15 Hz cut-off frequencies, the validity with the MA system was improved (e.g., mean bias = -0.31 to 0.34 g, RMSEP = 0.75 to 0.94 g). The concurrent validity of the 20 Hz cut-off frequency was equal or superior to all other cut-offs assessed. Indeed, the accuracy (0.01 g), effect size (0.005), agreement (-1.46 to 1.48 g), and precision (0.75 g) values were superior to all other accelerometer cut-off frequencies trialled. However, the concurrent validity of the 10 Hz, 8 Hz and 6 Hz cut-off frequencies were equal or poorer to the raw data (e.g., RMSEP 1.23 2.19 g). When physical collision peak accelerations are filtered with a cut-off frequency at or below 15 Hz, the accelerometer data may be over-filtered, thereby underestimating the intensity of the collisions. While this was the case for the lower cut-off frequencies, the 20 Hz cut-off frequency appeared optimal, displaying the strongest concurrent validity with the MA system.

The findings of the current study are similar to previous research (10, 18, 172). However, the optimal cut-off frequency was different, with two of the aforementioned studies suggesting a 10 Hz filter as optimal (18, 172). The difference in the optimal cut-off frequency between this study (20 Hz) and previous research may be due to the different movements performed, the wearable tracking devices assessed and/or concurrent measure chosen (including differences in sampling rates). For instance, previous research suggests that the dominant frequencies of human movement increase with movement intensity (177, 178). Therefore, physical collisions may have higher frequency content characteristics than other contact sport movements (e.g. walking,
running etc.) assessed by previous validation work. Caution is advised if filtering accelerometer accelerations below 20 Hz as this may underestimate physical collision peak impact accelerations, which are used to quantify the physical demands of sports performance(6).

When the 20 Hz filtered accelerometer data were split into nine magnitude bands and three activities, results showed strong concurrent validity between the accelerometer and MA system, with mean bias values not differing by more than 0.47 g and RMSEP not exceeding 1.0 g. Thus, considering the movements performed and the broad range of peak accelerations assessed, including those considerably larger than previously evaluated (range 0.3-6.0 g (10, 18, 172)), the results of this study support the accelerometer’s ability to accurately measure the intensity of physical collisions in contact sports.

In addition, the peak accelerations recorded were different between the three activities performed. To this end, the detailed analysis of accelerometer peak impact accelerations, as a discriminatory feature, may be used to identify the type of physical collision performed (9, 20). Future research should consider the accuracy of the peak impact acceleration feature to identify and discriminate between contact sport movements (e.g., tackling, running, jumping etc.).

This study has shown that the accelerometer can be confidently applied to measure the intensity of physical collisions when filtered at 20 Hz. As a result, accelerometers may be useful to measure physical collisions in contact sports. Given the limitations of other sensors within wearable tracking devices to measure physical collisions,
accelerometers may provide a valuable tool for the regular monitoring of physical workloads during training and game-play. The detailed analysis of accelerometer data (e.g., individual and accumulated collisions) may help devise individual-specific training and recovery programs to improve performance and reduce injury risks. There is also the possibility that accelerometer peak accelerations may help classify the type of movement performed. However, this requires further investigation.

A limitation of this study was that the physical collisions assessed were simulated to represent game-play. Although in-game validation would be preferred, current validity measures are not suited to such analyses (158). As a result, the peak accelerations recorded may be different than those recorded during game-play, which should be acknowledged. Another potential source of error is the moment arm of the reflective marker. As the reflective marker must be visible at all times the moment arm of the marker and accelerometer may be different.

4.7 Conclusion

The results of this study suggest that the accelerometer sensor contained within MinimaxX S4 wearable tracking device technology can accurately measure physical collision peak accelerations when data are filtered at a 20 Hz cut-off frequency. With appropriate filtering, the accelerometer can be considered an acceptable objective method to quantify physical collisions in contact sports. Caution is advised, however when interpreting raw data, with the accelerometer output likely to overestimate the intensity of the physical collision. Detailed analysis of accelerometer data alone or in combination with other wearable sensor data may help practitioners better understand
the physical demands imposed on athletes. Future research should continue to assess the validity of the accelerometer in-game or in simulated scenarios where multiple sporting movements are performed.
Chapter 5.

5 Study 3. Validation of a Trunk Mounted Accelerometer to Measure Peak Impacts during Team Sport Movements.
5.1 Abstract

This study assessed the validity of an accelerometer to measure impacts in team sports. Seventy-six participants completed a team sport circuit. Accelerations were collected concurrently at 100 Hz using an accelerometer and a 36-camera motion analysis system. The largest peak acceleration per movement were compared in two ways: i) pooled together and filtered at 13 different cut off frequencies (range 6 to 25 Hz) to identify the optimal filtering frequency, and ii) the optimal cut off frequency split into the seven movements performed (n = 532). Raw and 20 to 16 Hz filtering frequencies significantly overestimated and 6 Hz underestimated motion analysis peak accelerations (P < 0.007). The 12 Hz filtered accelerometer data revealed the strongest relationship with motion analysis data (accuracy -0.01 ± 0.27 g, effect size -0.01, agreement -0.55 to 0.53 g, precision 0.27 g, and relative error 5.5%; P = 1.00). The accelerometer underestimated peak accelerations during tackling and jumping, and overestimated during walking, jogging, sprinting, and change of direction. Lower agreement and reduced precision were associated with sprinting, jumping, and tackling. The accelerometer demonstrated an acceptable level of concurrent validity compared to a motion analysis system when filtered at a cut off frequency of 12 Hz. The results advocate the use of accelerometers to measure movements in team sport.

Keywords: Filtering, workloads, reproducibility of results, wearable technology.
5.2 Introduction

Human movement analysis can provide valuable information to better understand the physical demands of sporting competition (179). This information can be used to provide feedback to athletes (45), design training programs to improve performance (21, 47), and reduce injury risk (46). The emergence of accelerometer technology has allowed quantification of movement accelerations in team sports, thereby facilitating more sophisticated analysis of the physical demands imposed on athletes (8, 9, 12). For example, Cormack and colleagues (8) used accelerometer-derived load to determine differences in netball standards of game-play, with players of higher standards experiencing greater load values. In order for accelerometers to be used with confidence for these and similar purposes, the data output should be both reliable and valid. Accelerometers have demonstrated excellent reliability in both mechanical and field settings (130, 131). However, recent research has questioned the validity of accelerometers to accurately assess peak impacts in team sports, with accelerometers overestimating concurrently-obtained measures (10, 18, 130, 172).

It is well established that measures of human movement can be contaminated with noise (180), contributing to the inaccuracies found. Noise refers to any unwanted portion of a signal that is typically in a frequency range different from that of the true signal (53). The general technique used to remove noise from kinematic measures of human movement is to apply a low-pass filter with an appropriate cut off frequency (176, 180). However, if too high a cut off frequency is used, the signal will maintain high levels of noise; conversely if too low a cut off frequency is applied, the filter may eliminate important characteristics of the signal (180). Furthermore, the frequency content of a signal may change with different movements (55). A single cut off
frequency that can be applied to the accelerometer signal to accurately measure team
sport movement peak impacts would be highly desirable. However, there is no cut off
frequency currently validated to do so. Therefore, the aim of this study was to assess
the validity of an accelerometer to measure peak impacts undertaken during a
simulated team sport circuit. Multiple filtering cut off frequencies were examined and
presented.

5.3 Purpose
The aim of this study was to assess the validity of an accelerometer to measure peak
impacts undertaken during a simulated team sport circuit. Multiple filtering cut off
frequencies were examined and presented.

5.4 Methods
Seventy-six recreationally active, healthy, male participants (age, 24.4 ± 3.3 years;
height, 181.8 ± 7.5 m; mass, 77.4 ± 11.6 kg; mean ± SD) competing in one or more
team sport competitions per week were recruited. The study protocol was approved by
the relevant University Human Ethics Advisory Group (HEAG-H 135_2013). All
participants gave informed consent following full disclosure of the study protocol and
procedures.

This was a concurrent validation study in which an accelerometer was compared
against a three dimensional motion analysis (MA) system, whilst participants
performed a simulated team sport circuit. During each trial participants wore a
wearable tracking device (Minimax S4, Catapult Innovations, Australia) in a sports
vest (20), which contained a 100 Hz triaxial accelerometer. A single five gram, 0.013 m retro-reflective marker was also affixed to the wearable tracking device and its position was determined using a calibrated (root mean square error of prediction [RMSEP] = 0.000042 m) 36-camera, MA system (Raptor-E, Motion Analysis Corporation, USA) operating at 100 Hz. In clinical gait laboratories, MA systems are the gold standard measure used to accurately describe the kinematics of motion (173). Recently, MA systems have been used in sports laboratories to assess the concurrent validity of wearable tracking device sensors (e.g., accelerometer acceleration (147, 172), and GPS position and velocity data (146, 147)).

The simulated team sport circuit used in this study involved a modified version of the circuit developed by Singh and colleagues (181). Each circuit included the following movements (in order); three double-leg (DL) jumps, a jog, three changes of direction (COD), two single-leg (SL) jumps for distance, a sprint, a walk, and a tackle bag to be taken to ground with maximum force (Figure 5-1). Each movement finished with the participant standing stationary for one second before commencing the next movement. A full circuit took approximately 40 s to complete, allowing 20 s to rest before the next with six trials completed in total. All participants performed an active warm-up prior to commencing the full protocol, which involved five minutes of jogging followed by six laps of the circuit.
Figure 5-1. Modified simulated team sport circuit developed by Singh and colleagues (181).

Accelerometer data were downloaded with manufacturer supplied software (LoganPlus version 5.0.1, Catapult Innovations, Australia) and corrected for gravity (Inertial Movement Analysis proprietary software; Catapult Sports, Australia). Resultant acceleration data, defined as a single vector representing the combined effects of the X, Y and Z axes, were then exported to Microsoft Excel (Excel, Microsoft Office Professional Plus 2013, Microsoft, USA) for further analysis. The MA displacement data were pre-processed with manufacturer supplied software (Cortex version 3.6.1.1315, Motion Analysis Corporation, USA) and also exported to Excel for further analysis.
To synchronise the MA and accelerometer data, a data analysis program was developed in LabVIEW 2013 (National Instruments Corporation, Texas, USA). Each X, Y and Z component of the raw, doubly-differentiated MA displacement data was cross-correlated with the corresponding component of the raw accelerometer data. The peak from the component that displayed the most significant cross-correlation peak was chosen and the lag of MA data relative to accelerometer data (in samples) was determined. A warning system was in-built to the program to determine if the cross-correlation was poor (<0.8), however, in all cases, the cross-correlation was excellent (>0.9). Once the signals were synchronised, the data was partitioned into each activity automatically (based on the 1 s stationary pauses participants performed), with manual adjustment. From the partitioned data, the largest peak acceleration for each movement was obtained. The MA acceleration data were filtered and displayed time-synchronised with the accelerometer acceleration data and the user manually located the peaks in the MA data using a peripheral input device (computer mouse). The software assisted the user in locating the exact peak by pinpointing the peak of the data within four pixels of the mouse click. The time point of each peak acceleration identified was stored in the program ready for further analysis.

Three-dimensional kinematic data are subject to high-frequency noise not the result of human movement (175, 176). For example, even in static conditions, reconstructed marker data are not stationary (175). As a result, when estimating time derivatives, noise within the raw signal may be amplified (55, 144). For these and other reasons, marker position data are low-pass filtered (176), to remove high-frequency noise and obtain accurate derivative estimates (144, 145). To choose the optimal cut-off frequency, a residual analysis of the difference between the unfiltered and filtered MA
signals over a range of cut-off frequencies was performed for each movement, and each axes, with the decision made via visual inspection (55). As a result of the residual analysis, MA data for all movements were filtered at a 10 Hz cut-off frequency. The filtered displacement data were then differentiated twice to calculate acceleration (80) (in multiples of gravity or $g$) and the resultant vector was calculated. Accelerometer acceleration data were filtered at 13 different cut off frequencies (range 6 to 25 Hz). The identified time point of the peak acceleration of each activity was then used to output (to Microsoft Excel™) peak filtered MA acceleration, and peak raw and filtered accelerometer acceleration. Both MA and accelerometer accelerations were filtered in LabVIEW using a zero-lag, low pass Butterworth filter.

Data utilised in the statistical analyses were based upon a total of 532 peak accelerations measured across the seven movements performed during the third trial of the circuit. The accelerometer was examined across a broad range of peak impact accelerations from 0.4 to 11.1 g. In order to determine the ability of the accelerometer to quantify peak accelerations, multiple measurement indices of validity were obtained. The level of agreement, accuracy, precision, and relative error for the accelerometer and MA accelerations were acquired by calculating the 95% limits of agreement (95% LoA (125)), mean bias, RMSEP (154), and coefficient of variation (CV (155)) respectively.

One way analysis of variance (ANOVA) was performed to determine whether peak acceleration values recorded by the accelerometer (14 levels: raw and filtered at 13 cut off frequencies from 6 to 25 Hz) differed from those obtained by MA. The cut off frequency displaying the best level of accuracy (e.g., mean bias values closest to 0.0
agreement (e.g., closest 95% LoA values), precision (e.g., RMSEP values closest
to 0.0 g), and relative error (e.g., CV values closest to 0.0%) was used for all
subsequent analyses. A second one-way ANOVA was performed to investigate
whether differences in mean bias were present between the accelerometer and MA
system across the different movements undertaken (seven levels: DL jump, jog, COD,
SL jump, sprint, walk, and tackle). A third one-way ANOVA was performed to
investigate whether differences in peak acceleration values were present between the
seven movements performed. Bonferroni-corrected post hoc pairwise comparisons for
the three ANOVA performed were used to identify the source of any differences, with
the alpha level adjusted to 0.003, 0.007, and 0.007 respectively (156). In addition,
Bland-Altman plots were used to examine the raw and best performing accelerometer
cut off frequency visually (157).

The exploratory analysis and ANOVA’s were conducted using SPSS (version 21.0,
IBM Corporation, USA). The mean bias, Cohen’s $d$, 95% LoA, RMSEP, and CV were
calculated using Microsoft Excel™, whereas the Bland-Altman plots were developed
using Prism software (GraphPad, version 6, USA).

5.5 Results

The mean ± SD for the MA system across all activities was 3.30 ± 1.78 g. Figure 5-2a
shows that the raw, 25, 20, 19, 18, and 17 Hz filtered accelerometer data significantly
overestimated (Cohen’s $d$ 0.22 to 0.56; $P < 0.007$), and the 6 Hz filtered accelerometer
data significantly underestimated MA peak accelerations (Cohen’s $d$ -0.51; $P < 0.007$).
All other cut off frequencies (16 to 10 Hz) displayed no differences with MA peak
accelerations (Cohen’s $d = -0.14 \text{ to } 0.18$; $P = 0.29-1.00$). The raw accelerometer data revealed the weakest relationship with MA data (mean bias $1.13 \pm 0.83 \text{ g}$, Cohen’s $d 0.56$, 95% LoA -0.51 to 2.76 g, RMSEP 1.40 g, CV 23.4%), while the 12 Hz filtered accelerometer data revealed the strongest relationship (mean bias $-0.01 \pm 0.27 \text{ g}$, Cohen’s $d -0.01$, 95% LoA -0.55 to 0.53 g, RMSEP 0.27 g, CV 5.5%; Figure 4-2b and Figure 4-2c). The accuracy and agreement of the 12 Hz compared to raw accelerometer data are illustrated in Figure 5-3a and Figure 5-3b, respectively.
Figure 5-2. (A) Mean bias (95% LoA; g), (B) RMSEP (g), and (C) CV (%) of peak accelerations from 14 accelerometer variables when compared against the MA system.
Figure 5-3. Bland-Altman plots showing the relationship between the mean and difference values calculated by the accelerometer and MA system. The comparisons are; raw accelerometer acceleration – MA acceleration (A), and filtered accelerometer acceleration at 12 Hz – MA acceleration (B). Dotted line denotes mean bias value of 0.0 g and straight line denotes 95% LoA (±2 SD).
The concurrent validity of the 12 Hz filtered accelerometer data for multiple movements is presented in Table 5-1. The accelerometer underestimated MA peak accelerations during tackling, DL and SL jumping (mean bias -0.06 to -0.18 g, Cohen’s $d = -0.06$ to -0.20), and overestimated MA peak accelerations during jogging, COD, sprinting and walking (mean bias 0.03 to 0.14 g, Cohen’s $d = 0.05$ to 0.24). Weaker limits of agreement and precision were associated with sprinting, jumping and tackling. CV values ranged from 3.7% (jogging) to 6.9% (sprinting). Of the 21 movement comparisons assessed, the average peak acceleration values for jog and COD, and DL jump and sprint were not different from each other ($P = 1.00$). All other movement peak accelerations were significantly different from each other ($P < 0.007$).
Table 5-1. Accelerometer data filtered at 12 Hz compared to MA data of seven different team sport movements (n = 76).

<table>
<thead>
<tr>
<th>Movement</th>
<th>Mean ± SD (g)</th>
<th>Mean Bias ± SD (g)</th>
<th>Cohen’s $d$</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DL jump</td>
<td>3.51 ± 0.89$^{a,de}$</td>
<td>-0.18 ± 0.14$^{bf}$</td>
<td>-0.20</td>
<td>-0.45 to 0.10</td>
<td>0.23</td>
<td>4.6</td>
</tr>
<tr>
<td>Jog</td>
<td>2.59 ± 0.69$^{a}$</td>
<td>0.03 ± 0.13$^{c}$</td>
<td>0.05</td>
<td>-0.22 to 0.28</td>
<td>0.13</td>
<td>3.7</td>
</tr>
<tr>
<td>COD</td>
<td>2.77 ± 0.64$^{a,de}$</td>
<td>0.11 ± 0.20$^{d,ij}$</td>
<td>0.18</td>
<td>-0.27 to 0.50</td>
<td>0.23</td>
<td>6.2</td>
</tr>
<tr>
<td>SL Jump</td>
<td>4.21 ± 0.89$^{a}$</td>
<td>-0.06 ± 0.31$^{b}$</td>
<td>-0.06</td>
<td>-0.66 to 0.55</td>
<td>0.31</td>
<td>5.3</td>
</tr>
<tr>
<td>Sprint</td>
<td>3.41 ± 0.67$^{c,de}$</td>
<td>0.14 ± 0.28$^{ij}$</td>
<td>0.20</td>
<td>-0.40 to 0.69</td>
<td>0.31</td>
<td>6.9</td>
</tr>
<tr>
<td>Walk</td>
<td>0.62 ± 0.13$^{a}$</td>
<td>0.03 ± 0.04$^{ij}$</td>
<td>0.24</td>
<td>-0.04 to 0.11</td>
<td>0.05</td>
<td>6.3</td>
</tr>
<tr>
<td>Tackle</td>
<td>5.88 ± 1.22$^{a}$</td>
<td>-0.18 ± 0.43$^{hl,ik}$</td>
<td>-0.14</td>
<td>-1.02 to 0.67</td>
<td>1.95</td>
<td>4.8</td>
</tr>
<tr>
<td>All (n = 532)</td>
<td>3.28 ± 1.69</td>
<td>-0.01 ± 0.27</td>
<td>-0.01</td>
<td>-0.55 to 0.53</td>
<td>0.28</td>
<td>5.6</td>
</tr>
</tbody>
</table>

* The mean difference is significant at the 0.007 level when compared to all other movements;
The mean difference is significant at the 0.007 level when compared to the: $^a$DL jump, $^c$Jog, $^d$COD, and $^e$Sprint;
The mean bias is significant at the 0.007 level when compared to the: $^b$DL jump, $^f$Jog, $^g$COD, $^h$SL Jump, $^i$Sprint, $^j$Walk, and $^k$Tackle;
COD – change of direction; CV – coefficient of variation; DL – double-leg; RMSEP – root mean square error of prediction; SD – standard deviation; SL – single-leg; 95% LoA – 95% limits of agreement.
5.7 Discussion

This study examined the validity of an accelerometer to measure peak impacts for multiple movements undertaken during a simulated team sport circuit. Our findings indicate that the accelerometer contained within the wearable tracking device shows acceptable validity when filtered at a cut off frequency of 12 Hz. However, the type of movement performed appeared to influence validity.

The current study confirmed that different team sport movements have different peak acceleration profiles, with only the jog and COD, and DL jump and sprint not significantly different from one another. The walk displayed the best, and the tackle the worst, validity of all movements assessed. For example, an error of 0.05 g (walk) or 1.95 g (tackle) under or over the actual value recorded by the accelerometer would be expected for each movement. In addition, the three movements with the largest peak acceleration profiles (DL jump, SL jump, and tackle) were underestimated (mean bias -0.06 to -0.18 g). The chosen cut off frequency possibly attenuated higher frequency characteristics within the accelerometer signal. Thus, a higher cut-off may be more appropriate for team sports that impose larger peak impacts on players (e.g., contact sports such as rugby). Future research should consider improving the measurement of team sport movements through extracting more sophisticated information from the accelerometer data. For example, whether combining peak accelerations with other features of the accelerometer signal (such as mean, minimum and variance in amplitude (19)) increases the ability to measure and classify team sport movements.

The current study also confirmed that raw accelerometer data significantly overestimated MA data (mean bias 1.13 g). It appears that metrics derived from the
raw accelerometer signal, such as the number of peak accelerations in specific impact zones (e.g., (6)) or through accumulated accelerations over time (expressed as Player Load (131)), should be interpreted with caution.

Filtering improved accelerometer validity, with the 12 Hz cut off frequency displaying the best accuracy, precision, and relative errors of all cut-offs assessed. This finding is in line with previous accelerometer validation research (10, 18, 172). However, the choice of optimal cut off frequency differed from previous and methodological differences between the current study and other investigations can explain this. For example, all previous work has focused on a single movement type and only assessed a limited number of cut off frequencies. Additionally, two previous studies used a force plate as a concurrent validity measure (10, 18) and evaluated a different accelerometer (SPI Pro, GPSports Pty Ltd, Australia). Further, previous work was unrepresentative of team sport movements (e.g., in one study all movements were performed on a treadmill (172)), whereas this study was more generalizable to those movements performed during game-play. One or more of these factors may have resulted in the different cut off frequency and better validity than previously found (10, 18, 172).

The results of the current study advocate the use of accelerometers to measure movements in team sport, provided that the data were filtered at 12 Hz. The different movements together and the number of filtering frequencies examined were strengths of the current study. However, some limitations must be acknowledged. Although the MA system has been considered as the gold standard for measuring position (53), it does not measure acceleration directly. Furthermore, the movements were performed in a laboratory setting and therefore cannot be considered completely representative of
team sport activity in actual competition. Further work is required to examine accelerometer validity in dynamic team sport environments.

5.8 Conclusion

The accelerometer contained within a wearable tracking device demonstrated an acceptable level of concurrent validity compared to a MA system when filtered at a cut off frequency of 12 Hz. This result advocates the use of accelerometers to measure peak impacts in team sports. Furthermore, caution is advised when interpreting raw accelerometer data, with the output likely to overestimate movement intensity. Detailed analysis of accelerometer data may help practitioners better understand the physical demands imposed on athletes. Future research should consider the validity of accelerometers to identify and discriminate between team sport movements.
Chapter 6.

6 Study 4. Classification of Team Sport Activities using a Single Wearable Tracking Device.
6.1 Abstract

Wearable tracking devices incorporating accelerometers and gyroscopes are increasingly being used for activity analysis in sports. However, minimal research exists relating to their ability to classify common activities. The purpose of this study was to determine whether data obtained from a single wearable tracking device can be used to classify team sport-related activities. Seventy-six non-elite sporting participants were tested during a simulated team sport circuit (involving stationary, walking, jogging, running, changing direction, counter-movement jumping, jumping for distance, and tackling activities). A MinimaxX S4 wearable tracking device was worn below the neck, in-line and dorsal to the first to fifth thoracic vertebrae of the spine, with tri-axial accelerometer and gyroscope data collected at 100 Hz. Multiple time domain, frequency domain and custom features were extracted from each sensor using 0.5, 1.0, and 1.5 s movement capture durations. Features were further screened using a combination of ANOVA and Lasso methods. Relevant features were used to classify the eight activities performed using the random forest (RF), support vector machine (SVM), and logistic model tree (LMT) algorithms. The LMT (79-92% classification accuracy) outperformed RF (32-43%) and SVM algorithms (27-40%), obtaining strongest performance using the full model (accelerometer and gyroscope inputs). Processing time was reduced through feature selection methods (range 1.5-30.2%), however a trade-off exists between classification accuracy and processing time. Movement capture duration also had little impact on classification accuracy or processing time. In sporting scenarios where wearable tracking devices are employed, it is both possible and feasible to accurately classify team sport-related activities.

**Keywords:** Accelerometer, gyroscope, random forest, logistic model tree, support vector machines.
6.2 Introduction

Objective measurement of sports activities is essential for understanding the physical and technical demands related to sports performance (21). It is also important in evaluating the effectiveness of training programs designed to increase performance as well as those targeting both the prevention and rehabilitation of injury (22). Fundamental to furthering these understandings is the need to accurately collect specific information relating to the type, intensity, and frequency of activities performed (23). Consequently, attempts to improve the techniques related to activity analysis in sports have been made in recent years.

At least partially responsible for these improvements are the considerable developments that have occurred in commercially available wearable tracking device technology. Wearable tracking devices typically integrate multiple sensors (e.g., global positioning system [GPS], accelerometer, and gyroscope) into a single, versatile unit often worn on the upper back in a sports vest (20). To date, the majority of research has focused on the GPS sensor contained within these devices to obtain basic descriptors of sports activities, such as speed, distance travelled, and the number of high-intensity efforts performed (182). However, evidence suggests that more detailed analysis can be obtained using the accelerometer sensor (85). Specifically, different activity types can be classified based on the features of the accelerometer signal.

McNamara and colleagues (14) developed a bowling detection algorithm for cricket. The researchers found that the algorithm was able to classify cricket bowling more effectively in training than game-play, with a maximum accuracy of 98.1% (training). Kelly and colleagues (20) applied support vector machine (SVM) and hidden
conditional random field algorithms to automatically detect tackling in rugby. The algorithm was able to consistently classify collisions, with a maximum accuracy of 95%. Similarly, Gastin and colleagues (129) assessed the concurrent validity of a manufacturer-developed tackle detection algorithm (Catapult Sports), which was compared against video-replay and coded into three intensity categories. The researchers found a maximum classification accuracy of 78%, with tackled players more accurately detected than the players initiating the tackle. However, during gameplay the algorithm was only able to correctly detect tackles 18% of the time. Although these findings are promising, more sophisticated and generalisable sport and activity specific algorithms are required (9).

Mitchell, Monaghan, and O’Connor (90) recently proposed a method using a single accelerometer contained within a smartphone worn on the upper-back, with the aim of identifying seven different sporting activities (stationary, walking, jogging, sprinting, hitting a ball, standing tackle, and dribbling a ball). An overall activity classification success rate of 75% was achieved using classification approaches that included SVM, logistic model tree (LMT), and a range of neural network/optimization type classifiers. With the aim of achieving higher classification accuracy, multiple sensors (i.e., both accelerometer and gyroscope) have also been considered in the literature, rather than a single accelerometer sensor alone (e.g. (19, 177)). Gyroscopes are insensitive to linear accelerations and gravity, and provide essential information pertaining to the rotational motions of the body during human activity (75). As a gyroscope sensor is typically contained within most wearable tracking devices, this would appear to be a feasible approach to aid in the ability to classify of sporting activities.
Another important methodological consideration in the classification literature relates to the duration over which the activity is measured (movement capture duration) for a given classification algorithm (183). The optimal duration will ideally be long enough to capture the entire activity as it occurs, while also being short enough to not include any additional activities (90). Previous work classifying activity type has extracted features in accelerometer data from movement capture durations as short as 0.1 s (184) or as long as 60 s (183). In team sports, however, most activities (sprinting, jumping, tackling etc.) can be performed over much shorter durations. For example, the lowest intensity movement (walking) occurs approximately 1.4-2.2 times per second (e.g. (185)). Therefore, much shorter movement capture durations (e.g. 1.5 s or less) may be required to capture activities in team sports. Further, this may improve classification accuracy of these activities, as more periods are available for training (186).

6.3 Purpose

The aims of this study were threefold. First, to determine whether data obtained from wearable tracking device inputs (specifically, gyroscope and accelerometer sensors) alone or in combination can be used to classify team sport-related activities. Second, to determine the ability of three classification algorithms (LMT, random forest [RF], and SVM) and movement capture durations (0.5, 1.0, and 1.5 s) for feature extraction to classify activities in team sports. Third, to consider the processing time and data collection burdens associated with these methods and identify the best option for practitioners.
6.4 Methods

Seventy-six recreationally active, healthy male participants (age 24.4 ± 3.3 years; height 181.8 ± 7.5 m; mass 77.4 ± 11.6 kg; mean ± SD) were recruited for participation in the study. All participants were regular competitors in one or more contact-based team sport events per week at the time of testing. The study protocol was approved by the relevant University Human Ethics Advisory Group (HEAG-H 135_2013); all procedures followed ethical guidelines for human research and participants provided written informed consent prior to participating.

The simulated team sport circuit involved a modified version of a circuit developed by Singh and colleagues (187) and reported in Wundersitz and colleagues (188). Each circuit included three counter-movement jumps, an eight metre jog, an eight metre change of direction agility section (COD), two jumps for distance, a 10 m sprint, seven metres of walking, and a tackle bag to be taken to ground with maximum force. After the completion of each activity, the participant stood in a stationary position for approximately one second before commencing the next (i.e., three counter-movement jumps were performed in a row then a one second pause occurred). Stationary pauses ensure that there is no bias in data accumulation (e.g., influence of previous activity (189)). Each individual circuit took approximately 45 s to complete, allowing the participant 15 s of rest before completing the next circuit (on 1 minute). Each participant completed the circuit six times. During testing, each participant wore a single, wearable tracking device (MinimaxX S4, Catapult Innovations, Australia), which contained (among other sensors not utilised for this study) a 100 Hz tri-axial accelerometer and gyroscope. The device was worn in a tightly fitted manufacturer
supplied sports vest and located below the neck (on the upper trunk), in-line and dorsal to the first to fifth thoracic vertebrae of the spine.

The data collected comprised of accelerometer (X, Y, Z axes \( n_1 = 3 \)) and the resultant vector \( n_2 = 1 \)) and gyroscope (X, Y, Z axes \( n_3 = 3 \)) inputs for the duration of the circuit (seven total inputs; \( n_1+n_2+n_3 = 7 \)). For each of the eight activities of interest (stationary pause, counter movement jump, jog, COD, run and jump, sprint, walk, and tackle), the corresponding data was extracted and processed to generate features of interest.

Features were extracted from the data using three different movement capture durations of 0.5, 1.0, and 1.5 s respectively, each with a 50% overlap (89). These were chosen in such a way as to be long enough to capture the descriptive segment of each activity, but short enough to avoid overlap of the information. The feature set consisted of seven time domain features calculated for each of the seven inputs (minimum amplitude, maximum amplitude, mean amplitude, variance of amplitude, 25th percentile, 75th percentile, and interquartile range; \( m_1 = 49 \)). In addition, two frequency domain features were calculated with one spectral centroid for each of the seven inputs and a single bandwidth feature for the set of inputs as a whole (i.e., one bandwidth feature for the four accelerometer and three gyroscope inputs; \( m_2 = 8 \)). Lastly, one custom energy feature was calculated for each sensor (\( m_3 = 2 \)). The energy feature is defined as (19):
where $a_i$ are the sum of the squared values for axes $i$ ($i = X, Y, Z$) corresponding to either the accelerometer or gyroscope and $p$ is the number of observations per axis.

Thus, for each activity a total of 59 accelerometer and gyroscope features were calculated ($m_1 + m_2 + m_3 = 59$). The amplitude and percentile features provided important descriptors of the time domain of each input, while the percentiles also deliver a more representative measure of statistical dispersion (190). The spectral density and bandwidth features provided important descriptors relating to central mass and the frequency domain (obtained via fast Fourier transformation). The energy feature can be used to distinguish between sedentary and high intensity movements (191).

In classification problems, it is common to compare the performance of different algorithms in order to determine which addresses the relevant problem most effectively. Classification algorithms are now typically preferred to traditional analysis approaches when assessing potentially non-linear data, due to their often improved overall classification performance (192, 193). To classify the eight activities of interest, three classification algorithms (LMT, RF, and SVM) were employed. These were chosen for implementation based on their prevalence in the previous literature investigating similar problems. The LMT is a commonly used classification algorithm, which performs competitively with other machine learning classifiers and has the

\[
E = \frac{\left(\sum_{i=1}^{3} a_i\right)^{\frac{3}{2}}}{p}
\]

**Equation 10.** Energy feature.
additional advantage of being easy to interpret (194). It combines two complementary classification techniques: tree induction and linear regression (195). Random forest is another classification algorithm, which in its application grows multiple classification trees and builds upon them until each tree is at its largest (196). The mean classification performance of the trees is then taken, which further assists in protecting against model overfitting (196). Overfitting refers to the development of a model so specific to a particular training set that the findings are not generalizable when validated on a new test set of data (193, 197). Additionally, RF is considered to have various useful features including high efficiency with large data sets and built-in ensemble classifiers (196). Support vector machine differs slightly from the previous two algorithms, in that it attempts to find the best separating vector between two groups within a set of descriptors (198). In this study a radial kernel was used and both gamma ($\gamma \in [10^{-6}, 10^{-1}]$) and cost ($c \in [0.1, 10]$) values were tuned (199). For classification of data with more than two groups (as seen here), the original problem is split into multiple binary problems which are then classified and compared. The problem receiving the most votes per instance is then assigned as the classifier. Readers interested in a more detailed explanation of these and other classifiers are directed towards the work of Zaki and Meira (137).

However as both classification accuracy and processing time was assessed, the analysis was conducted in two phases. First, the aim of phase one was to ascertain the data collection burden to achieve the desired classification accuracy. Specifically, the accuracy of each classification algorithm was investigated in four different ways for each of the three moment capture durations. These were, i) all 59 features from accelerometer, resultant vector and gyroscope, ii) only the accelerometer and resultant
vector features (m = 33), iii) only the accelerometer features (m = 26), and iv) only the gyroscope features (m = 26).

Phase two aimed to investigate novel feature selection methodology in three different ways for the full set of inputs (n1+n2+n3=7). This was undertaken as a large number of features do not always assist in obtaining better classification accuracy. Irrelevant features may introduce ‘noise’ leading to a loss in accuracy and over-fitting. Furthermore, the resulting model may take longer to implement and be more difficult to interpret (200). In addition to processing time, comparisons of accuracies across each feature selection method, movement capture duration and classifier were also investigated. These were, i) all 59 features were considered (no feature selection used), ii) only features with significant results (p<0.05) for one-way analysis of variance (ANOVA) across classification groups were selected (201), with each feature examined for possible significance individually (202), and iii) all features that were selected though ANOVA (m = 42) were passed for screening under Lasso regression simultaneously (203) and further reduced (m = 37 [0.5 s] and 38 [1.0 and 1.5 s]). Under this screening a feature was retained if it was contained in all of the three the feature sets produced by Lasso model based on the criterion of Mallow’s Cp ( \( \min_{p=1,2,...,m} (C_p - p) \)) (204), residual sum of squares ( \( \min_{p=1,2,...,m} (RSS) \)) (205), and coefficient of determination (205). In this instance m, was the number of features included in the model as determined by the feature selection methodology (no feature selection, ANOVA feature selection, ANOVA and lasso feature selection).
The computed set of feature data were split into a training and testing data set in accordance with a leave-one-out cross-validation methodology. The classification model was developed on the training set and its accuracy was ascertained on the testing data set. A single activity was randomly chosen (with equivalent probability) for each participant and assigned to the validation set (76 activities). From this validation set, a training set of 75 activities and a testing set of 1 activity not included in the training set are assigned. The leave-one-out cross-validation was repeated 76 times validating on each possible training and testing set combination. This process was repeated a further 10 times with the validation set being randomly re-sampled. The classification accuracy, defined as percent of correctly classified cases, was computed for each repeat, resulting in a hybrid 10-fold leave-one-out cross validation (192). The three algorithms were compared for mean classification accuracy across 10-fold cross validation. Figure 6-1 below gives an overview of both the feature extraction and classification process.
Figure 6-1. Overview of the feature extraction and classification process. IQR, interquartile range; MCD, movement capture duration.
All analyses were conducted on a 64-bit Windows operating system computer with Intel® Core™ i7-2670QM CPU and 8 GB RAM. All statistical analyses were conducted using R (version 3.0.1, R Core Team, Australia), which makes use of the following packages: e1071 (199), lars (203), RF (206), and RWeka (195).

6.5 Results

The accuracy of classifiers per input variation and movement capture duration are presented in Table 6-1. Throughout all classification iterations LMT greatly outperformed both RF and SVM classifiers, obtaining classification rates 79% or above. As the number of input variables increased from three to seven, the accuracy of the classifiers generally remained the same or increased. The SVM and RF classifiers generally exhibited the strongest accuracy with a 1.5 s movement capture duration, while the LMT was generally strongest with a 1.0 s movement capture duration.

Table 6-2 presents the processing times for the accelerometer X, Y, Z, resultant vector, and gyroscope inputs for all classifiers and movement duration combinations. The processing time (for both extraction and classification) was reduced (range 1.5-30.2%) using ANOVA or ANOVA and Lasso feature selection methods. The ANOVA and Lasso feature selection method was generally slower than the pure ANOVA method. The reduction in processing time had little effect on LMT (0-3%) and RF (0-5%) classifier accuracy, and a larger effect on SVM classifier accuracy (0-15%).
Table 6-1. Accuracy (Mean ± SD %) of classifiers per input variation and movement capture duration after 10-fold leave-one-out cross-validation.

<table>
<thead>
<tr>
<th>Input description</th>
<th>Classifier</th>
<th>Movement capture duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Accelerometer, resultant vector, and gyroscope (n1+n2+n3 = 7, m = 59)</td>
<td>RF</td>
<td>0.39 ± 0.14</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.92 ± 0.04</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.37 ± 0.16</td>
</tr>
<tr>
<td>Accelerometer and resultant vector (n1+n2 = 4, m = 33)</td>
<td>RF</td>
<td>0.32 ± 0.12</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.89 ± 0.04</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.33 ± 0.15</td>
</tr>
<tr>
<td>Accelerometer only (n1 = 3, m = 26)</td>
<td>RF</td>
<td>0.29 ± 0.16</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.88 ± 0.05</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.29 ± 0.13</td>
</tr>
<tr>
<td>Gyroscope Only (n=3, m=26)</td>
<td>RF</td>
<td>0.41 ± 0.10</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.80 ± 0.05</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.32 ± 0.10</td>
</tr>
</tbody>
</table>

LMT, logistic model tree; m, total number of observations; n1-3, number of inputs; RF, random forest; SD, standard deviation; SVM, support vector machine.
Figure 6-2 presents the full models (n = 7, m = 59) activity-specific classification accuracies on the basis of 0.5, 1.0, and 1.5 s movement capture durations. For all three movement capture durations, classification accuracy exceeded 86%. Walking (98-99%) and stationary (95-98%) were best classified, whereas tackling (86-91%) and run and jump (89-90%) showed lower classification rates in the 1.0 (tackling) and 1.5 (tackling, run and jump) movement capture durations. Differences in movement capture duration classification accuracy ranged from 0% (COD/ jog [0.5 versus 1.5 s] and sprint/ walk [0.5 versus 1.0 s]) to 8% (run and jump [1.0 versus 1.5 s]).
Table 6-2. Accuracy (Mean ± SD %) and processing time (s) of classifiers and model selection variations for the movement capture durations after 10-fold leave-one-out cross-validation. All comparisons are from accelerometer, resultant vector, and gyroscope inputs \((n_1+n_2+n_3 = 7, m = 59)\) of differing feature selection methodology.

<table>
<thead>
<tr>
<th>Feature selection</th>
<th>Classifier</th>
<th>Movement capture duration and [processing time] (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5 [236.25]</td>
</tr>
<tr>
<td>Full model (m = 59)</td>
<td>RF</td>
<td>0.39 ± 0.14 [7.5]</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.92 ± 0.04 [53.5]</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.37 ± 0.16 [104.6]</td>
</tr>
<tr>
<td>ANOVA feature selection (m = 41/42)</td>
<td>RF</td>
<td>0.36 ± 0.13 [6.6]</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.91 ± 0.04 [42.5]</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.23 ± 0.07 [77.1]</td>
</tr>
<tr>
<td>ANOVA and Lasso feature selection (m = 37/38)</td>
<td>RF</td>
<td>0.36 ± 0.16 [7.0]</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.91 ± 0.05 [44.2]</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.24 ± 0.06 [77.6]</td>
</tr>
</tbody>
</table>

LMT, logistic model tree; m, total number of observations; \(n_1, n_2, n_3\), number of inputs; RF, random forest; SD, standard deviation; SVM, support vector machine. Note that features were reduced to 37 (0.5 s movement capture duration) and 38 (1.0 and 1.5 s movement capture duration) using a combination of ANOVA and lasso regression. Note that the processing times reported in the column sub-
heading refers to the amount of time it took to extract the relevant features, and the processing times reported in the table refer to the amount of time it took to classify all activities.
Figure 6-2. Full model \((n = 7, m = 59)\) activity classification accuracies (expressed as a ratio) for each movement capture duration. CMJ, countermovement jump; COD, change of direction.
6.6 Discussion

The results of this study demonstrate that accurate activity classification using accelerometer and gyroscope inputs is achievable in a team-sport simulated circuit. Specifically, results showed that the highest performing algorithm for this purpose was LMT with an overall mean classification rate ranging from 79% to 92%. Further, the highest classification rate was achieved by combining all seven inputs from the accelerometer and gyroscope. Notably, the classification rate was substantially lower in the RF and SVM than those obtained using the LMT approach.

The findings of the current study are somewhat comparable to previous accelerometer input classification work (90). Mitchell, Monaghan, and O’Connor (90) found that LMT (74%) outperformed SVM (55%) for activity classification in football (soccer), however, no differences were noted between classifiers when field hockey-specific activities were performed. Similar classification performance with the current study was found when multiple classifiers were combined. The stronger individual classifier results in the current study may be due to differences in experimental methodology. Specifically, Mitchell, Monaghan, and O’Connor (90) did not assess gyroscope inputs, used lower frequency sampled accelerometer data (16-25 Hz), and also assessed activities such as dribbling (soccer) and hitting (field hockey) the ball (not assessed in this study). As the higher sample rate in the current study (100 Hz) may have contributed to the increased comparative classification performance, it may be that further increases in sample rate (> 100 Hz) could aid classification performance. However, this may have a negative effect on processing time.
When all seven accelerometer and gyroscope inputs were combined, highest rates of activity classification were achieved (e.g., mean classification accuracy of 92%). This was not surprising however, given that there was more information available for algorithm training. For example, previous research has shown that by combining both accelerometer and gyroscope inputs the classification rate during daily living and tennis-specific activities can be improved by as much as 14% (184). Interestingly, classification performance was only improved by 2-3% when the three gyroscope inputs were included with accelerometer inputs in the current study, meaning this sensor contributed less to activity classification in these contexts (e.g. 8-10% decrease in classification accuracy compared to accelerometer inputs). This study made one of the first attempts to evaluate the effect of gyroscope inputs alone in classifying sporting activities. Generally lower rates of activity classification for the gyroscope inputs may be due to the upper back being predominantly exposed to linear motions, as compared to rotational motion that a gyroscope measures (84). Gyroscopes placed on the limbs (e.g. wrist and ankle) may be better able to aid classification, as limb motion is essentially a rotation around the corresponding joint (75). Therefore, consideration of the location of the device and the activities performed may be important in deciding on the number of inputs included in future classification assessments. Furthermore, no study has assessed the validity and reliability of the gyroscope contained within the wearable tracking device, whereas a number of studies have been published in regards to the accelerometer (e.g. (131, 172)).

This investigation also analysed how movement capture durations of 0.5, 1.0, and 1.5 s affect the classification accuracy across different input and activity variations. There was no clear influence of movement capture duration on classification accuracy.
Comparatively, Bulling, Blanke, and Schiele (184) assessed durations ranging from 0.1 to 9.0 s during daily living and tennis-specific activities. The researchers found classification accuracy peaked at 1.0 s and dramatically decreased thereafter. Mitchell, Monaghan, and O’Connor (90) also assessed durations from 1.0 to 9.0 s and found classification accuracy was maintained for all movement capture durations during field hockey, however soccer-based activity classification accuracy decreased past 3.0 s. Larger movement capture durations have also been used in lifestyle activity classification settings (e.g. (91, 183, 186)), however, the frequency of sporting activities may result in two or more activities occurring in longer movement capture durations (e.g., greater than 1.0 s), dramatically increasing classification difficulty (90, 186). Team sport activities, therefore, may benefit from shorter movement capture durations than are typically employed in the lifestyle activity classification literature.

It should also be acknowledged that inter- and intra-participant variations and set movement capture durations as used in the current study may have contributed to the lower than expected classification rates. Future work may consider alternative approaches, such as a sliding window approach, where a capture duration with a time length of T is slid across the data and if an activity is detected within the window it is flagged.

A further practical consideration relates to the effect different model selection variations had on processing time and classification accuracy. The number of features included in the analysis (range 37 to 59) tended to improve classification accuracy, but this was generally at the cost of increased processing time. The classifier chosen also appeared to affect this relationship. For example, the processing burden was shortest for RF (6.6 to 7.7 s) and longest for SVM (76.7 to 106.0 s), with the LMT falling in
the middle (42.5 to 56.7 s). However, movement capture duration had minimal impact on processing time in the current study.

Removing low-level contributing features from the training process can have a positive effect on classification performance, with ANOVA feature selection reducing processing time by approximately 15%. For reduced processing time, using ANOVA or ANOVA and Lasso feature selection, the classification accuracy only decreased by 5% and 4% respectively. Such a model would require approximately 230 s of time for feature extraction to occur and a further 45 to 54 s for classification of the activities performed using LMT. Comparable results are reported in literature with much larger volumes of data accumulation and smaller number of classification groups. Nathan and colleagues (207) using accelerometer and GPS data, gathered over 750,000 measurements and achieved accuracy of over 84% for RF and SVM classifiers. Leutheuser, Schuldhaus, and Eskofier (19) also using a large dataset and pre-clustering of the activities, achieved an accuracy of 87% for SMV method. Mitchell, Monaghan, and O’Connor (90) reported a similar trend in classification accuracy with LMT method, on a much smaller dataset. To this end, the similar between classification rates to previous studies using a reduced number of measurement features is encouraging. This is especially important where real-time classification (e.g., during training and game-play) may be a future aim. Based on these findings, presently the LMT algorithm combined with accelerometer inputs alone, provided the best trade-off between classification accuracy and processing time for use in this context.
6.7 Conclusion

In conclusion, a variety of classification algorithms, movement capture durations and feature selection methods were compared to determine the most parsimonious approach to classify multiple simulated team sport-related activities. The LMT was shown to be highly accurate using data obtained from a single accelerometer and gyroscope sensor contained within wearable tracking device technology. Consequently, in sporting scenarios where wearable tracking devices are employed, it is both possible and feasible to use accelerometer and gyroscope data to accurately classify sporting activities. Furthermore, the processing time can be reduced through feature selection models, however a trade-off exists between classification accuracy and processing time. With this in mind, accelerometer inputs alone appear to be the most parsimonious approach from this location. Further development and validation of algorithms in sports is required. Once developed, the ability of these algorithms to classify team sport activities during game-play should be performed. Further exploration of accelerometer and gyroscope features, and feature reduction is needed to provide real-time classification in the future.
Chapter 7.

7 Study 5. Classification of Sporting Activities using a Single Triaxial Accelerometer.
7.1 Abstract

Accelerometers contained within wearable tracking devices have become popular for monitoring workloads in team sports. Data obtained from these devices may be used to classify the types of activities performed, thereby potentially informing training prescription. The purpose of this study was to determine the ability of data features obtained from a single accelerometer sensor to classify eight activities commonly undertaken in team sports. A simulated circuit (including stationary pauses, walking, jogging, running, changing direction, counter-movement jumping, jumping for distance, and tackling activities) was implemented in a laboratory setting. Seventy-six non-elite sporting participants completed this circuit while wearing an accelerometer contained within a MinimaxX S4 wearable tracking device on the upper back. A logistic model tree (LMT) classifier was trained on time domain, frequency domain and custom features \((n = 26)\) from accelerometer data which was obtained using 1.0 s movement capture durations. Feature efficacy was evaluated by using a combination of ANOVA and Lasso regression. Overall activity classification accuracy was 88.4%. Feature extraction and training took 101.8 s to perform, with a further 7.7 s required to classify activities using all 26 features. Classification accuracy was highest (93.8 to 100.0%) for stationary pauses, walking, and sprinting whereas single-leg jumping and tackling showed lower classification accuracies (68.8 to 73.9%). Using reduced feature sets \((n = 19, n = 16)\) decreased processing time by 16.7 to 17.1%, but classification accuracy was concurrently reduced by 5.6 to 8.7%. Single accelerometer sensor data can be used to accurately classify team sport-related activities using the LMT algorithm.

**Keywords:** Sport movement classification, tri-axial accelerometer, feature extraction.
7.2 Introduction

Accelerometers contained within wearable tracking devices are widely used for training and game-play analysis in many team sports, such as Australian football (7) and rugby (6). Data are conventionally used to generate basic descriptions of player activity, such as the number of impacts in multiple intensity zones or the accumulated accelerations expressed as a single arbitrary value (e.g., PlayerLoad\textsuperscript{TM} (7, 129)). Although useful, these descriptors alone are unable to be used to classify the types of activity performed in such contexts. Obtaining these classifications is important for improved specificity of workload monitoring, injury prevention and rehabilitation in team sports (46). For example, coaches may be able to link training intensity to the type of activity performed. Currently, the majority of activity classification literature uses video analysis, which is often time-consuming to perform and limited to a single player (208). Therefore, technology that has the capability to accurately classify team sport activities in a timely manner is needed.

In the past decade, machine learning approaches have been used extensively to classify specific activities of interest in many fields, including physical activity (5) and animal behaviour (207) research. More recently, similar approaches have been used in team sports (9, 14, 20). These analysis techniques allow computers to learn from raw data by recognising complex, potentially non-linear, patterns in the data and make intelligent classification decisions (5). To date, three studies have classified single sporting activities from accelerometers contained within wearable tracking devices (9, 14, 20), reporting classification accuracies ranging from 15% to 96%. Partial explanation for these varying results may be that classification becomes more difficult
when multiple activities are performed, or when activities are more complex or similar to each other (136).

To the authors’ knowledge, to date only one study has used accelerometer data to classify multiple team sport activities (stationary, walking, jogging, sprinting, hitting a ball, standing tackle, and dribbling a ball) (90). This example revealed specific activity classification accuracies ranging from 10 to 100%. However, this work used smartphone-based accelerometers, which are not permitted in team sports and also have lower sampling rates (16 to 25 Hz) than those contained within dedicated wearable tracking devices (e.g., 100 Hz) (7). Lower sampling rates may not accurately portray acceleration features of the body as measured by the accelerometer in the time domain; potentially missing peaks in amplitude (53). Furthermore, jumping, COD, and tackling activities, which are common to many team sports, are also yet to be classified.

It is not known which features of the accelerometer signal contribute most to classification accuracy in these contexts. Features commonly used to describe an accelerometer signal include amplitude (i.e., minimum, maximum, mean, and variance), spectral centroid, and bandwidth (19). Removal of those features which do not contribute to classification accuracy may minimise memory requirements and, improve computer processing time (184), as less information needs to be extracted from the accelerometer signal.
7.3 Purpose

The aim of the current study was to determine the ability of data obtained from a 100 Hz accelerometer contained within a MinimaxX S4 wearable tracking device to classify eight common team sport activities using a common classifier algorithm.

7.4 Methods

Seventy-six recreationally active males participated in this study (age 24.4 ± 3.3 y; height 181.8 ± 7.5 m; mass 77.4 ± 11.6 kg; mean ± SD), which was approved by the Deakin University Human Advisory Group (HEAG-H 135_2013). All procedures followed ethical guidelines for human research and written informed consent was obtained from all participants prior to testing.

Following a standardised warm up, participants completed a simulated team sport circuit modified from Singh and colleagues (181) The circuit included: three counter-movement jumps (DL jump), a jog, a change of direction agility section (COD), two single-leg jumps performed for distance landing on one leg (SL jump), a sprint (i.e., participants were instructed to maximally accelerate for 6 m and decelerate for 4 m), a walk, and a tackle bag to be taken to ground with maximum force. After the completion of each activity, the participant stood in a stationary position for approximately 1.0 s before commencing the next activity (i.e., three DL jumps were performed in a row then a 1.0 s stationary pause occurred; Figure 7-1). The circuit took approximately 40 s to complete, and finished with the participant lying stationary on or beside the tackle bag.
Figure 7.1. Example participant acceleration measured in the antero-posterior axis (A1), medio-lateral axis (A2) and vertical (A3) axis during the experimental protocol. Arrows highlight the signal measured during the circuit: DL jumping (A); stationary pause (B1-6); jog (C); COD (D); SL jump (E); sprint (F); walk (G); tackle (H). Note: black dotted line denotes A1, dark grey dashed line denotes A2 and light grey solid line denotes A3.

During testing, each participant wore a single, wearable tracking device (MinimaxX S4, Catapult Innovations, Australia), which contained a 100 Hz tri-axial accelerometer with a recording range of ±12.0 g (1.0 g = 9.81 m s⁻²). The device was worn in a tightly fitted manufacturer supplied sports vest located below the neck, in-line with the spine on the upper back. Raw acceleration data, corrected for gravity (Inertial movement analysis proprietary software), were exported from manufacturer software (LoganPlus Version 5.0.9.2, Catapult Innovations, Australia) into Microsoft Excel™ (Version 14.0.6112.500, Microsoft Corporation, USA) for further analysis. All activities were
also recorded using a 30 Hz high-definition network camera (SNCCH140, Sony Electronics Inc., Japan). Acceleration data and video recordings were synchronised using video analysis software (Dartfish Team Pro Version 7, Dartfish Ltd, Switzerland) and the eight activities and six stationary periods were labelled manually in the original data set. For the activity trial, all 40 s of data were used for analysis. Since the 76 participants performed the activities with data captured at 100 Hz, there were a total of 76 participants * 40 s * 100 Hz * 1 trial = 300400 data points available for algorithm training.

The data processing was performed in 1.0 s movement capture durations (184, 209) and a 50% overlap (89, 210). For each movement capture duration, tri-axial accelerometer data (antero-posterior [A1], medio-lateral [A2], and vertical [A3] axes) were extracted and processed to generate features of interest (n = 26). A similar feature-set as described by Leutheuser, Schuldhaus, and Eskofier (19) was used. These included the minimum amplitude (MinAmp), maximum amplitude (MaxAmp), mean amplitude (MeanAmp), variance of amplitude (VarAmp), spectral centroid (Centroid), bandwidth, and energy (EnergyAcc). The 25th (Q25), 75th (Q75), and interquartile range (IQR) were also extracted to deliver a more representative measure of statistical dispersion (190). The logistic model tree (LMT) algorithm was used to classify the eight movements of interest. This algorithm combines two complementary classification techniques: tree induction and linear regression (211). Further, the LMT has an advantage of being easier to interpret than some other algorithms (194) and has been shown to be effective in previous human activity classification work using accelerometer data (90).
In order to consider both the classification performance and processing time of the LMT, the analysis was conducted by extracting features using three different scenarios. For scenario 1, all 26 features were considered. In scenario 2, only features with significant results \((p < 0.05)\) for one-way analysis of variance (ANOVA) across classification groups were selected \((201)\), with each feature examined for possible significance individually \((202)\). For scenario 3, all features that were selected though ANOVA \((n = 19)\) were passed for screening under Lasso regression simultaneously \((203)\) and further reduced \((n = 16)\). Under this scenario a feature was retained if it was contained in all of the three feature sets produced by Lasso model based on the criterion of Mallow’s \(C_p\) \((204)\), residual sum of squares \((205)\), and coefficient of determination \((205)\).

The computed set of feature data were split into a training and testing data set. The classification model was developed on the training set and its accuracy was ascertained on the testing data set. A single activity was randomly chosen (with equivalent probability) for each participant and assigned to the training set \((76\text{ activities})\). A random sample (with equivalent probability) of 32 activities was then taken from the remaining set of feature data and assigned to the testing set. The above process was repeated 10 times, selecting a random training and testing data set. A classification model was then developed from the training data set and this model was used to classify the activity in the testing set. The classification accuracy, defined as percent of correctly classified cases, was computed for each repeat, resulting in 10-fold cross-validation \((192)\). The algorithm was compared for mean classification accuracy across 10-fold cross-validation. In addition, sampling was done in such a manner that the same activity from a participant used in the training data set was not used in the testing
data set. A confusion matrix was used to present results for each classification and evaluated in terms of accuracy (precision and recall) (184, 212).

All analyses were conducted on a 64-bit Windows operating system computer with Intel® Core™ i7-2670QM CPU and 8 GB RAM. All statistical analyses were conducted using R (Version 3.0.1, R Core Team, Australia), which made use of the RWeka package for the LMT algorithm (195).
7.5 Results

The highest overall classification accuracy was achieved in scenario 1 where all acceleration features \((n = 26)\) were included in the LMT training process \((88.4 \pm 13.2\%)\) over the 10 iterations). In this scenario, the LMT required 101.8 s for feature extraction and training to occur, and a further 7.69 \pm 0.07 s for classification of the performed activities. In scenario 2 \((n = 19)\), the features MinA1Amp, MaxA1Amp, MaxA2Amp, VarA1Amp, CentroidA3, Bandwidth and Q75A1 were removed from the full model as they did not provide a statistically significant \((P > 0.05)\) contribution to classification. In this scenario, classification accuracy \((82.8 \pm 14.1\%)\) decreased by 5.6% when compared to scenario 1, however classification of the performed activities improved \((6.50 \pm 0.07\) s). In scenario 3 \((n = 16)\), EnergyAccS1, Q25A2 and Q25A3 features were removed. Classification accuracy \((79.7 \pm 15.4\%)\) decreased by 8.7%, with classification of the performed activities similar to scenario 2 \((6.48 \pm 0.07\) s). Overall, the feature contributing most to classification for the three scenarios was MeanA3Amp, with the lowest contribution coming from the three MinAmp features (Figure 7-2).

Table 7-1 presents the full model confusion matrix for the eight team sport activities performed. Stationary, walking, and sprinting activities were best classified \((93.8\) to 100.0\%)\), whereas SL jumping and tackling activities showed lower classification accuracies \((68.8\) to 73.9\%). Confusion and misclassification of SL jumping occurred mostly with DL jumping and jogging, and of tackling occurred mostly with COD and SL jumping.
Figure 7-2. Full model column graph showing each accelerometer feature’s power for classification (n = 26). Information gain provides an estimate of feature importance to activity classification (212), with higher information gain indicating increased power for classification. Note: A1, antero-posterior axis; A2, medio-lateral axis; A3, vertical axis; Amp, amplitude; IQR, interquartile range; Q, quartile; and Var, variation.
Table 7-1. Full model confusion matrix testing accuracy (n = 26).

<table>
<thead>
<tr>
<th>Activity</th>
<th>DL Jump</th>
<th>COD</th>
<th>Jog</th>
<th>SL Jump</th>
<th>Sprint</th>
<th>Stationary</th>
<th>Tackle</th>
<th>Walk</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DL Jump</td>
<td>24</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>88.9</td>
</tr>
<tr>
<td>COD</td>
<td>0</td>
<td>40</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>90.9</td>
</tr>
<tr>
<td>Jog</td>
<td>1</td>
<td>0</td>
<td>21</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>91.1</td>
</tr>
<tr>
<td>SL Jump</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>68.8</td>
</tr>
<tr>
<td>Sprint</td>
<td>0</td>
<td>3</td>
<td>45</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>93.8</td>
</tr>
<tr>
<td>Stationary</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>38</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>97.4</td>
</tr>
<tr>
<td>Tackle</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>73.9</td>
</tr>
<tr>
<td>Walk</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>39</td>
<td>0</td>
<td>0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Precision (%) 80.0 85.1 85.4 75.9 88.2 100.0 91.9 97.5 88.4

Note: A confusion matrix summarises the number of times the different activities were misclassified. Rows show the number of actual instances, whereas columns show the number of predicted instances for each activity type (184). Values shaded indicate the number (absolute value) of times the activity was correctly classified. Value in boldface indicates the overall classification accuracy.
7.6 Discussion

The aim of the current study was to determine the ability of data obtained from the accelerometer contained within a wearable tracking device to classify eight common team sport activities using the LMT classifier. The findings indicate that the LMT combined with a 1.0 s movement capture duration showed very good overall accuracy (88.4%) for classifying team sport activity type from accelerometer data.

The accelerometer feature shown to contribute most to classification was MeanA3Amp; i.e., the average acceleration in the vertical axis (Figure 7-2). This was not unexpected, given that the largest acceleration values are usually obtained in the vertical axis (e.g., during walking, jogging, and running (78)). The second, third, and fourth most contributing features were the Q75A2, MaxA2Amp, and MeanA2Amp, i.e., three quarters of the medio-lateral accelerations less than or equal to the 75th percentile, the peak medio-lateral accelerations, and the mean medio-lateral accelerations. Of the 10 best contributing features, nine related to the medio-lateral or vertical axes. These results clearly indicate that time-domain features derived from the medio-lateral and vertical axes have increased contribution power for classification in this context compared to the antero-posterior axis.

The results from this study relating to processing time also have ramifications relating to use in the field. For example, in many team sports up to 40 players may be utilising a wearable tracking device concurrently. As such the classification process should be as time efficient as possible. In the current study, the most time-consuming aspect of the analysis was feature extraction, which took 102 s to perform. The LMT training
process (scenario’s 1-3) was substantially faster; specifically scenario 1 took 7.7 s to classify the activities performed. Removing low-level contributing features from the training process (scenario 2 and 3) had a positive effect on processing time, with reductions of 1.19 to 1.21 s noted respectively. The ANOVA feature selection (scenario 2) was able to successfully identify and remove the four least important features, which contributed little to classification performance (e.g., MinAmp in all three axes and Bandwidth). However, it was the removal of the 6th (Q75A1; scenario 2), 8th (Q25A3; scenario 3) and 12th (VarA1Amp; scenario 2) most important features that likely contributed to the decreased accuracy found. Therefore, the trade-off between classification accuracy and processing time was evident in the current study, and scenario 2 could be considered as most appropriate for use in the field.

The ability to automatically classify the activities of 76 participants’ in such a short amount of time (approximately 110 s to classify 40 s of activity) suggests that conventional classification techniques such as using video replay may be considerably less efficient comparably. Under these conditions, two human operators may be required for video-analysis, with one watching the video and calling out the activity changes of a single player and the second manually keying the activities into a computer (15). Automatic classification of team sport activities with accelerometer data has potential, with the number of wearable tracking devices a team owns and the processing power of these devices appearing to be the main limitations at present. Further, there may be substantial costs associated with video classification and coding of game-play (operator, video, analysis, etc.), which may be mitigated or removed completely using accelerometer activity classification.
The overall classification accuracy for the LMT was higher than that reported in a recently published study testing a smartphone accelerometer placed on the upper back during team sport activities (88.4% compared with approximately 71.8 to 74.6%) (90). The average classification rates reported by Mitchell, Monaghan, and Connor (90) were likely reduced by the inclusion of three sport specific activities (dribbling the ball, hitting the ball, and standing tackle), which resulted in similar acceleration signals. Whereas the LMT used in this study was trained to classify COD, jumping, and tackling activities, which result in distinct acceleration signals (see Figure 7-1).

Complex high-intensity activities such as SL jumping and tackling introduced classification difficulties in the current study. SL jumping was classified correctly 68.9% of the time and was most misclassified with DL jumping. This lower level of classification accuracy is likely due to similar acceleration signals between jumping activities (Figure 7-1). SL and DL jumping are common activities in team sports and landing on a SL rather than a DL may increase an athlete’s injury risk (213). However, little work to date has classified SL or DL jumping against other movements, especially at intensities similar to sports. Preece and colleagues (89) assessed SL hopping on both the left or right leg and DL jumping, and found the classification rates to be 82.8%, 76.8%, and 62.8% respectively. DL jumping was often confused with a number of other activities, including SL hopping. However, when DL jumping was removed from the analysis, overall classification accuracy increased by 3% to 97% (89). Other research has combined similar activities into a single classification group (19). If SL and DL jumping was considered as a single activity group in the current study, classification accuracy may have improved. However, this was not performed in the current study because they represent different actions in most team sports.
Tackling was classified correctly 73.9% of the time, and most confused with COD and SL jumping. This finding is surprising considering that this is the only activity that required participants to move from an upright to a prone position on the ground. This action would presumably uniquely change the acceleration signal, generating larger values in the antero-posterior and medio-lateral axes (Figure 7-1). This activity also exposes participants to the highest MaxAmp (e.g., values greater than 10.0 \( g \) are common in elite competition (6)).

All other activities (stationary, walking, jogging, running, and COD) were classified correctly most of the time (>90%). Further, the classification accuracy was comparable to that obtained in other studies where these activities were measured using multiple accelerometers placed on different parts of the body (85, 210). The similar accuracies with only a single accelerometer are promising. To our knowledge this work represents the first study to classify multiple team sport activities using a commercially available wearable tracking device specifically used in an elite team sport environment. However, our data were obtained from controlled activity trials, which do not perfectly replicate the non-laboratory behaviour exhibited during sports training and game-play. Consequently, additional research is needed to evaluate the validity of the methodology employed here in a field setting.

7.7 Conclusion

The LMT machine learning algorithm can be used to predict team sport-related activity type based on data obtained from a single upper back-mounted accelerometer
contained within the MinimaxX S4 wearable tracking device. The LMT algorithm
performed efficiently in this context and could be implemented with little processing
time required (approximately 110 s to classify 40 s of team sport activities performed
by 76 participants). Processing of accelerometer data using machine learning
techniques may complement or replace video-based activity classification in the future
to inform training and game-play interventions, such as optimal workloads for
improved performance. Future studies are needed to validate the algorithm in elite
team sport athletes during training and game-play.
Chapter 8.

8 General Discussion and Conclusion
8.1 General Discussion

The aim of this thesis was to evaluate the validity of the accelerometer contained within a wearable tracking device to measure and classify movements in team sports. The primary focus was on the validity of accelerometer peak accelerations during a variety of team sport movements (Studies 1–3), while the accuracy and utility of accelerometer data for classifying team sport activities was also investigated (Studies 4 and 5).

As demonstrated by the literature, accelerometers are increasingly being used to monitor workloads in team sports (7, 12, 34). The benefits of using accelerometry in this context are that the accelerations measured are proportional to external force, and thus should reflect the type, frequency, and intensity of movement performed. However, to date, few studies have been conducted that specifically examine the validity of accelerometers for measuring, and classifying team sport movements. Other researchers have assessed the accelerometer’s ability to measure acceleration against a concurrent measure of acceleration (force plate ground reaction force (10, 18)), but the distance of the accelerometer from the force plate and unwanted movements of the device within its harness may have influenced these findings. Therefore, Study 1 examined the validity of the accelerometer to measure peak accelerations against a MA system during walking, jogging and running. The MA system was chosen due to the system’s ability to derive acceleration from the same position where the wearable tracking device is worn, without interfering with the movements of participants. The accelerometer overestimated MA-derived acceleration, but filtering the raw data improved the accelerometer’s validity. A possible explanation for this is that the accelerometer signal could be contaminated by high-frequency noise. This may inflate
the acceleration values recorded during movement and lead to overestimation. By employing a number of filtering cut-off frequencies to the raw accelerometer data, high frequency noise within the raw signal was reduced, improving concurrent validity with the MA system. Furthermore, it appeared that the magnitude of error was related to the intensity of movement performed; higher intensity movements (jogging and running) producing larger peak accelerations and measurement error when compared to walking. It should be noted that the range of accelerations examined were low, and thus were unlikely to encompass the typical ranges that team sport athletes are exposed to during training and game-play (e.g., (6, 129)). As it was unclear whether the magnitude of measurement error may be related to the magnitude of acceleration recorded, Study 2 investigated the validity of the accelerometer during tackling and bumping movements, which impose greater accelerations on the body. Consistent with Study 1, the accelerometer overestimated MA-derived acceleration and again, filtering improved validity. Furthermore, Study 2 showed that the magnitude of acceleration recorded did influence accelerometer validity, with measurement error increasing as the magnitude of acceleration increased.

Choosing the optimal filtering cut-off frequency to remove errors from raw accelerometer data is complicated by the variety of movements typically performed by team sport athletes. This has resulted in recommended filtering cut-off values ranging from 10 Hz (18) to 20 Hz (10). Study 1 addressed the issue of optimal cut-off frequency during walking, jogging, and running (10 Hz was recommended), while Study 2 provided further insight into this question during tackling and bumping (20 Hz was recommended). It appears that the type and intensity of the movement performed dictates the most appropriate filtering frequency. However, no study has investigated
the application of a single cut-off frequency to accurately measure a range of team sport movements. Therefore, Study 3 considered the validity of accelerometer peak accelerations during a simulated circuit encompassing seven common team sport movements. Again, raw accelerometer data overestimated MA-derived acceleration and filtering improved accelerometer validity, with a 12 Hz cut-off frequency found to be optimal. Some error was apparent when a single cut-off frequency was applied to filter accelerometer data across all movements. For example, at 12 Hz walking, jogging, running and COD were overestimated, and SL jumping, DL jumping and tackling were underestimated. In summary, Studies 1–3 suggest that the workloads imposed upon players in team sports may be overestimated by raw accelerometer data (e.g., the number of peak accelerations in specific impact zones) and by metrics drawn from the accumulation of raw accelerations over time (PlayerLoad™). The results also suggest that the raw data must be filtered to accurately measure impacts in team sports, with a 12 Hz cut-off deemed optimal. However, if practitioners were to use filtered accelerometer data, this could create problems when compared to previously collected unfiltered data (i.e. The preceding seasons data). Years’ worth of this old accelerometer data may be less useful as a result. For example, the overall arbitrary PlayerLoad™ values would likely be lower, the number of impacts in intensity zones would be reduced and a larger number would likely occur in lower intensity zones. Therefore, if this new filtered data were compared against old unfiltered data, it may appear that the athlete is working at a lower intensity or has done less overall. Furthermore, prescription of workloads, if based off old unfiltered established/expected values, may result in team sport athletes being pushed too hard to achieve these levels, hence increasing the likelihood of injury. The benefit of the filtered data
are that once understood, a more realistic understanding of the physical demands imposed on team sport athletes should be obtained.

Recent literature demonstrates that different movement types in team sports can be classified based on the features of the accelerometer signal (9, 14, 20). Furthermore, the study detailed in Chapter 5 showed that accelerometer peak accelerations may have application towards classification of multiple movements, with differences found between peak accelerations of different movements. However, previous research has not attempted to classify movements that are most relevant to team sports. Therefore, the final studies in this thesis investigated the ability of the accelerometer to classify team sport movements. The accelerometer data captured in Study 3 was used to examine the classification techniques tested in subsequent studies. Therefore, Study 4 examined the ability of the accelerometer and gyroscope sensors, contained within a wearable tracking device, to classify team sport movements. Accurate classification was achieved by combining accelerometer and gyroscope data using the LMT classifier and 1.0 s movement capture duration (92% accuracy). Furthermore, when the gyroscope was removed from the analysis and only accelerometer data were used, processing time was nearly halved and classification accuracy was similar (89% accuracy). Therefore, the most time-efficient approach was to use accelerometer data alone to classify team sport movements. With this in mind, Study 5 investigated the movement-specific classification accuracies, the importance of each feature to classification, and feature-reduction strategies to improve processing time. Apart from tackling and SL jumping, all movements were classified correctly ≥89% of the time. The removal of low-level accelerometer features had a large positive effect on processing time (i.e. decreasing processing time), which was noticeably improved
from Study 4. However, the removal of features resulted in a moderate negative reduction in classification accuracy. As such, there appears to be a trade-off between classification accuracy and processing time.
8.2 Conclusions

A number of specific aims and research questions were identified to investigate the validity of the accelerometer to measure and classify team sport movements (see Chapter 1) and under the conditions of the studies contained in this thesis, the following conclusions were formed:

1. Is an accelerometer worn on the upper back valid for measuring peak accelerations during a variety of activities in team sports, when compared to a traditional laboratory-based method? If there are inaccuracies, can filtering improve accelerometer validity? The accelerometer is not as accurate as traditional laboratory-based methods. The raw data consistently overestimated peak accelerations irrespective of the type or intensity of movement performed (Studies 1–3). When all movements were pooled together, the mean bias ranged between 0.60 g to 1.13 g. This amount of error is not acceptable. By filtering the raw accelerometer data, it was possible to reduce the amount of error to obtain accurate peak acceleration values. A cut-off frequency of 12 Hz was required to accurately measure multiple team sport movement peak accelerations (e.g., the mean bias ranged between -0.18 g to 0.11 g; Study 3). For contact sports, where higher magnitude peak accelerations are often of primary interest, it is recommended that the cut-off frequency be increased to 20 Hz. However, a validity trade-off exists between contact events (mean bias 0.01 g; Study 2) and other team sport movements such as walking, jogging and running (mean bias 0.61 g; Study 1) when this frequency is chosen. Therefore, when the nature of the movement is known, selection of the optimal cut-off frequency is not a problem. However, when various movements are mixed such as those seen in team sport competitions and performed in Study 3, the use of a...
single cut-off frequency can present problems. This is particularly true when
the physical demand has to be assessed relatively accurately, as a single cut-off
frequency can distort the acceleration signal from the true value for each
movement type.
2. *Does the magnitude of acceleration recorded influence accelerometer validity?* The magnitude of error in accelerometer data increased as the magnitude of acceleration recorded increased. For example, the precision of the accelerometer was 0.03 g for the 0.0 to 0.5 g acceleration band (Study 1) and increased linearly to 1.0 g for the 10+ g acceleration band (Study 2). Therefore, the larger the peak acceleration, the larger the error will be, and conversely the smaller the peak acceleration the smaller the error will be.

Can data obtained from wearable tracking device inputs (specifically, an accelerometer and a gyroscope) be used to classify team sport movements? If so, then what are the optimal input, classifier, movement capture duration and features? It was possible to accurately classify 69 to 100% of the movements performed during a simulated team sport circuit by using the accelerometer data alone, or by using a combination of accelerometer and gyroscope data (Study 4 and 5). Although the gyroscope and accelerometer together was the most accurate means of classifying the movements performed, using the accelerometer data alone was noticeably quicker and only slightly inferior in terms of classification accuracy (90% compared with 88%). Time-domain features in the vertical and medio-lateral axes contributed most to classification accuracy. The exclusion of less relevant features improved processing time, however a trade-off exists between classification accuracy and processing time. With this in mind, accelerometer inputs used in isolation appear to be the most parsimonious approach.

In summary, this thesis demonstrated that accelerometer data were accurate when filtered at an appropriate cut-off frequency, however raw data appears to consistently
overestimate team sport movement peak accelerations. It was concluded that, when filtered at appropriate frequencies, accelerometer data are suitable for workload monitoring and movement classification of typical team sport movements.
8.3 Limitations of the Research

The conduct of this research presented a number of methodological and practical issues which should be acknowledged as potential limitations and considered when interpreting the findings of the thesis. A limitation of this thesis was that MA-derived acceleration was used as the concurrent measure to examine peak accelerations during different team sport movements. With the desire to compare accelerations from the upper body using a different technology to the accelerometer, MA was deemed suitable for this task. MA has been considered as the gold standard for measuring position (53), and is receiving increasing attention as a concurrent measure (e.g., (146, 147)) of derived data in the literature. While errors are common in the raw data, specific data processing and analysis techniques justify this choice and are described in more detail elsewhere in this thesis (see the methods sections of Studies 1-3).

Ideally, the validity of the accelerometer should be assessed in the field under game conditions, but it is important to examine any measure in controlled conditions first. If a measure is sufficiently accurate in laboratory-based conditions, then progression to more open/less controlled conditions may occur. As accelerometer validation research is in its infancy, data collection was undertaken in controlled conditions. However, data collection was undertaken in less controlled conditions as the thesis progressed. Furthermore, the selection of recreationally active (Studies 1, 3–5) or semi-elite (Study 2) participants may limit the application of findings to elite sport. In addition, only a single wearable tracking device was examined. Inter-device reliability studies are required to determine whether the findings are generalizable across multiple devices produced by the same manufacturer. In addition, these findings may not be applicable to wearable tracking devices currently utilised in team sports and developed by other
manufacturers, such as the SPI HPU (GPSports, Canberra, Australia). However, Catapult Sports is arguably one of the world-leaders in player tracking in team sports, as they currently service at least 515 sporting teams worldwide (214). On this basis, the focus on a Catapult device in this research is warranted.

A possible limitation of this thesis is that stationary pauses were introduced between movements. This perhaps helps achieve a more accurate classification of the activities based on the acceleration patterns. In real life situations, various activities are not well separated, but rather performed continuously at various intensities and for various durations. However, the stationary pauses were implemented in order to define clear commencement and completion times for each task. This then enabled the algorithm to be trained and evaluated for the entirety of each activity. Furthermore, there is no reason to suggest that the pauses altered each participant’s activity pattern associated with each evaluation task as all participants were instructed to perform each activity normally. Another limitation relates to the number of activities chosen to be classified. Different team sports incorporate activities that are indigenous to each, such as handballing in AF, bowling in cricket, and dribbling in field hockey. Therefore, the algorithm developed will be incapable of identifying these activities and if employed in team sports will miss-classify these additional activities. Furthermore, activities that are common between sports may still be performed in a completely different manner (e.g., kicking in AF versus football). This may also decrease the classification performance of any generically developed classification algorithm.
8.4 Recommendations for Future Research

The evaluation of player workloads remains a difficult task. The accelerometer sensor contained within a wearable tracking device has yet to become the gold standard for the field-based measurement of workloads in team sports. While it may well have the potential to do so, and is appealing for its utility in both indoor and outdoor settings, further critical analysis of this method is required. Specifically, further work is required to explore how filtered accelerometer data affects subsequently derived workload metrics. It would also be desirable to perform more research across a broader range of team sports and to recruit participants at higher competitive levels within these sports. In addition, manufacturers regularly release new and updated devices, and the validity of these new devices will need to be verified. Future work should also consider validating the accelerometer against a combination of methods used to assess team sport movements, such as force plates, MA systems and other wearable sensors.

Currently, the algorithm developed in Studies 4 and 5 can only classify generic team sport movements. This limits its application to those sports where unique sport-specific movements are performed, such as kicking, hitting, and throwing an object. Further development and validation of algorithms in sport-specific scenarios is required. Once developed, the ability of the accelerometer to classify team sport movements during game-play should be examined. Further exploration of accelerometer features and feature reduction is needed to determine whether real-time classification is achievable.

In summary, accelerometers are becoming increasingly integrated into routine workload monitoring strategies in team sports. Such strategies must be founded upon
well-established evidence of the device’s validity. This thesis contributes to this need and provides a foundation for future validation work towards meeting the desired outcome of an in-field, real-time gold standard of workload monitoring in team sports. The major contributions of this thesis included: the validation of the accelerometer at the position worn on the upper back; its validity across eight common team sport movements and a range of movement intensities; the identification of one or more optimal filtering cut-off frequencies; and the demonstrated capacity to use accelerometer data to classify team sport movements.
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Appendix A

STUDY 1

Journal Article

Conference Paper

Informed Consent
European Journal of Sport Science

Validation of a trunk-mounted accelerometer to assess peak accelerations during walking, jogging and running

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Validity of a trunk-mounted accelerometer to assess peak accelerations during walking, jogging and running

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Abstract

The purpose of this study was to validate peak acceleration data from an accelerometer mounted within a wearable tracking device while walking, jogging and running. Thirty-nine participants walked, jogged and ran on a treadmill while 10 peak accelerations per movement were obtained (n = 390). A single trunk-mounted accelerometer measured resultant acceleration during all movements. To provide a criterion measure of acceleration, a 12-camera motion analysis (MA) system tracked the position of a retroreflective marker affixed to the wearable tracking device. Peak raw acceleration recorded by the accelerometer significantly overestimated peak MA acceleration (P < 0.01). Filtering accelerometer data improved the relationship with the MA system (P < 0.01). However, only the 10 Hz and 0 Hz cut-off frequencies significantly reduced the errors found. The walk-jog movement demonstrated the highest accuracy, agreement and precision and the lowest relative errors. Linear increases in error were observed for jog compared with walk and for run compared to both other movements. As the magnitudes of acceleration increased, the strength of the relationship between the accelerometer and the criterion measure decreased. These results indicate that filtered accelerometer data provides an acceptable means of assessing peak accelerations, in particular for walking and jogging.

Keywords: 3D analysis, acceleration, technology, methodology, gait analysis

Introduction

Direct observation, physical activity questionnaires and body-mounted motion sensors are common techniques used to assess human movement (Bouten, Koole, Verhees, Keddie, & Jansen, 1997). Accelerometers were first developed in the 1920s (Walter, 1999) and specifically designed in the 1990s to measure human movement accelerations (Saunders, Hamman, & Elbert, 1993). In field-based settings, measuring human movement using accelerometers is preferred as acceleration is proportional to external force and therefore reflects the frequency and intensity of the movements performed (Yang & Hsu, 2010). A commercially available wearable tracking device (MinimaxX S4, Catapult Innovations, Australia) contains a triaxial accelerometer and is currently employed in a variety of settings, in particular for sports performance monitoring in field team sports (Daly, Ball, & Ageley, 2011; Cummins, Orr, O’Connor, & West, 2013; Gustin, McLean, Spears, & Breen, 2013). Typically, the accelerations recorded during sports performance are converted into a metric (e.g., athlete load or accumulated number of peak impacts per acceleration band) and used alone or in combination with global positioning system (GPS) metrics to monitor athletic performance (Cummins et al., 2013; Cunniffe, Proctor, Baker, & Davies, 2009; Gustin et al., 2013). However, fundamental to the usefulness of this technology to measure peak accelerations in sport is the underlying accuracy of the raw accelerometer data.

Force plates (Tram, Netto, Aisbett, & Gustin, 2018; Wundersitz, Netto, Aisbett, & Gastin, 2013), video-recordings (Gustin, Jenkins, & Abernethy, 2013) and accelerometry have been used to determine the dynamic 

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and mechanical set-ups (Boyd et al., 2011) have all been used to assess the validity and reliability of accelerometers contained within wearable tracking devices, generally reporting somewhat spurious results and small to large relative errors. However, only two of these studies (Tran et al., 2010; Wundersitz et al., 2013) assessed the accelerometer’s ability to measure acceleration against a criterion measure of acceleration (ground reaction force), with relative errors between 10.4% and 30.8% found. Filtering of the raw acceleration data, however, reduced the errors noted between the accelerometer and force plate (relative error 11.7–22.2%) (Tran et al., 2010; Wundersitz et al., 2013). A possible explanation for this is additive errors or noise present in the raw accelerometer signal (Shorten & Winklowski, 1992). Noise refers to components within the raw signal that are not a result of human movement and add characteristics (e.g., frequency content) to the true signal (Robertson, Caldwell, Hamill, & Whitley, 2004; Winter, 2005). A common method of reducing noise is filtering techniques, which require the choice of an optimal cut-off frequency to be applied to the data (Robertson et al., 2004; Winter, 2005). However, despite some studies utilising multiple cut-off frequencies (25–100 Hz) to filter the raw data (Tran et al., 2010; Wundersitz et al., 2013), an optimal cut-off frequency has not been ascertained.

Based on previous research (Tran et al., 2010; Wundersitz et al., 2013), a possible explanation for the errors found may be due to the distance between the accelerometer worn on the upper trunk and the criterion measure chosen, such as a force plate located on the ground. An alternative criterion measure is a motion analysis (MA) system. A MA system captures the position of one or more retro-reflective markers located anywhere on the body (Ladin & Wn, 1991) and through filtering and numerical differentiation (of a retro-reflective marker’s position data), high-quality estimates of time derivatives (velocity and acceleration) can be obtained (Ladin, Pauwels, & Mesner, 1989; Pezzack, Norman, & Winter, 1977). Such technology has been used previously to validate GPS-derived position and velocity data (Duffield, Reid, Bate, & Sprattford, 2009; Severson et al., 2014).

No study to date has validated the accelerometer during walking, jogging and running. This is despite a large percentage of an athlete’s time spent performing such movements (Bicorne, Poiani, & O’Donoghue, 2007; Butter, Fyfe, & Hooper, 2007; Spencer et al., 2004). Furthermore, these movements are commonly performed in both clinical (Beyer & Nigg, 2000; Lafontaine, 1991) and physical activity (Cooper et al., 2010; Pidgeon et al., 2007; Leenders, Sherman, & Nagaraja, 2000) settings. Therefore, the aim of this study was to compare peak acceleration data from an accelerometer contained within a wearable tracking device with a criterion measure of acceleration, derived from a MA system, while walking, jogging and running. This study also investigated the effect different filtering cut-off frequencies have on accelerometer accuracy, agreement, precision and relative error.

Methods

Thirty-nine recreationally active participants (28 males and 11 females: age 24.2 ± 1.9 years; height 1.79 ± 0.09 m; mass 71.6 ± 12.0 kg; mean value, standard deviation) were recruited. Ethics approved for the study protocol was given and written informed consent was provided prior to participating.

Perturbation with all equipment and procedures, as well as a standardised warm-up on a calibrated motorised treadmill (Quinton Q55, Quinton Instrument Company, USA), was performed prior to data collection. A single, wearable tracking device (MiniMaxx SA; Catapult Innovations, Australia), which contained a 100-Hz triaxial accelerometer, was worn by each participant in a tightly fitted manufacturer-supplied harness, similar to a compression sports top (Wundersitz et al., 2013). The device weighed 0.7 g and was 88 mm × 50 mm × 19 mm in dimension. To assess the criterion validity of the accelerometer, a single 5-g, 15-mm retro-reflective marker was attached to the wearable tracking device and its position was determined using a calibrated 12-camera, MA system (Raptor-E, Motion Analysis Corporation, USA) operating at 200 Hz. The system was calibrated immediately before each session. Dynamic calibration (with a 0.5 m s⁻¹) was 0.50003 ± 0.00004 (mean ± SD) with a relative error of 0.004%.

Prior to completing each trial, participants stood next to the treadmill, inside the capture volume of the MA system and performed three countermovement jumps. This was done to synchronise the accelerometer and MA system when data analysis occurred. Following the countermovement jumps, participants were instructed to mount the treadmill, which was already operating at the set walk velocity (1.5 m s⁻¹). After 30 seconds, the velocity was increased linearly until the desired jog velocity (3.3 m s⁻¹) was reached. Again after 30 seconds, this velocity was increased to the final run velocity (5.0 m s⁻¹) with participants running for 30 seconds before the treadmill was stopped. Within the 30 seconds, a sequence of 10 foot-strikes were chosen for analysis. Velocity ranges
were based on standardized ranges developed by previous work for field sport athleticism (Dwyer & Gabbert, 2012).

Resultant data, defined as a single vector representing the combined effect of the X, Y, and Z axes, for both the MA system and accelerometer were analysed through the manufacturer-supplied software (MA: Cortex, version 3.6.1.315, Motion Analysis Corporation, USA; accelerometer: Logan Plus, version 5.0.0.2, Catapult Sports, Australia), as well as MA and accelerometer position data were then exported to Excel for further analysis (Microsoft Office Excel, version 14.0.6122.500, Microsoft Corporation, USA). The MA position data in the walk, jog and run movements were specifically analysed using a fast Fourier transformation (FFT). Visual inspection of FFT outputs suggested that irrespective of the movement performed, 6 Hz was the optimal cut-off frequency. To investigate the effect different filtering cut-off frequencies had on accelerometer accuracy, the raw accelerometer data were filtered at multiple cut-off frequencies (20 Hz, 15 Hz, 10 Hz, 8 Hz and 6 Hz) and compared against the MA data filtered at 6 Hz. The 20 Hz, 15 Hz and 10 Hz cut-off frequencies were chosen to match previous validation research (Tran et al., 2016; Wundervis et al., 2013). The 6 Hz cut-off frequency was chosen as previous validation research has not filtered below 6 Hz, while the 6 Hz cut-off frequency was also chosen to match the criterion cut-off frequency.

A customised Matlab program (R2012a, version 7.14.0.739, MathWorks Inc., USA) was used to smooth and synchronise the recorded MA and accelerometer signals, as well as to detect the 10 sequential peak foot-strike accelerations per movement (i.e., walk, jog and run). Specifically, to smooth accelerometer acceleration and MA position data a low-pass, zero-lag, fourth order Butterworth digital filter was applied. The MA smoothed X, Y and Z position data were then differentiated twice to calculate acceleration (Ladin & Wu, 2004). The resultant vector was then calculated in multiples of gravity or g. To synchronise the two devices and ensure the same peak resultant accelerations were analysed at the correct time-point, the accelerations captured during three countermovement jumps performed immediately prior to mounting the treadmill were used to find the offset between both devices using Matlab’s built-in cross correlation function xcorr. Subsequently, the offset between devices was subtracted from the time domain of the MA data and peaks were identified, based on previously labelled events (i.e., start and end of foot-strike), in the original frequency of the captured accelerations.

The alignment was also visually inspected to ensure that the synchronisation of both signals was correct, prior to peak identification.

Prior to undertaking the statistical analyses, the data were tested for its distribution (Kolmogorov-Smirnov test). The criterion and raw accelerometer data displayed a non-Gaussian distribution and heteroscedasticity (P < 0.05) and were log-transformed to the power of 10. To determine whether differences were apparent between gender (male and female) and trial (1–10), independent-sample Kruskal-Wallis tests were undertaken on the mean bias calculated between the raw accelerometer data and criterion measure. No differences for gender and trial were noted, as such both were pooled for all subsequent analyses. As these analyses were exploratory in nature, the alpha level was set at 0.05.

To determine the ability of the accelerometer to quantify peak accelerations, a number of measurement indices were obtained. The level of agreement, accuracy, precision and relative error for the accelerometer and criterion accelerations were obtained by calculating the 95% limits of agreement (95% LoA; Atkinson & Nevill, 1998), mean bias, root mean square error of prediction (RMSEP; Gomes, Meyer, Castro, Saran Netto, & Rodrigues, 2012) and coefficient of variation (CV; Hopkins, 2000), respectively. The details of these measures are given in equations 1–4:

\[
\text{Mean bias} = \text{mean (predicted − actual)} \quad (1)
\]

\[
95\% \text{ LoA} = \text{mean difference ± (standard deviation} \times 1.96) \quad (2)
\]

\[
\text{RMSEP} = \sqrt{\frac{\text{predicted} - \text{actual}}{\text{number of observations}}} \quad (3)
\]

\[
\text{CV} = \frac{\text{standard deviation}}{\text{mean}} \quad (4)
\]

These measurement indices were calculated for (1) each accelerometer variable (accelerometer accelerations analysed as raw and filtered at 20, 15, 10, 8 and 6 Hz), (2) each movement performed (walk, jog, and run) and (3) each acceleration band (the magnitude of acceleration split into five 0.5 G categories: 0–0.5 G, >0.5 G to 1.0 G, >1.0 G to 1.5 G, >1.5 G to 2.0 G and >2.0 G). Second, to determine if peak (log-transformed) acceleration values recorded by the accelerometer were different from the MA system, a one-way (variable) analysis of variance (ANOVA) was performed. Bonferroni-corrected pairwise comparisons were used to identify the
source of any differences with the significant alpha level for the ANOVA's adjusted to 0.007 via the Bonferroni procedure (Westfall, Johnson, & Utts, 1997). The most optimal accelerometer variable was the one whose mean bias was closest to zero and was then used for all subsequent analyses. To investigate whether differences in mean bias were evident for the optimal accelerometer variable and the MA system, one-way ANOVAs were conducted between the three movements performed and the five acceleration bands. Bonferroni-corrected pairwise comparisons were used to identify the source of any differences, with the alpha level for the ANOVAs adjusted to 0.02 (movement performed) and 0.01 (acceleration band). Bland–Altman plots were also used to examine the data visually (Bland & Altman, 1986) by plotting each accelerometer variable against the MA system.

The ANOVA and exploratory analyses were conducted using SPSS (version 21.0, IBM Corporation, USA). The mean bias, 95% LOA, RMSEP, and CV% were calculated using Microsoft Excel™, whereas the Bland–Altman plots were obtained using Prism software (GraphPad, version 6, USA).

Results

Indices of accuracy, agreement, precision, and relative error have been presented between each accelerometer variable and the MA system (Table I). Peak raw accelerometer acceleration was shown to significantly overestimate peak MA acceleration (P < 0.01). All filter cut-off frequencies improved the relationship between the accelerometer and the MA system, when compared to the raw accelerometer data. Generally, the lower the cut-off frequency, the smaller the relative error found, with the higher frequency cut-off typically resulting in significant overestimations (20 Hz and 15 Hz) and the lower frequency cut-off (6 Hz) resulting in significant

underestimation of MA accelerations (P < 0.01; Figure 1A–F). The 10 Hz cut-off frequency displayed the best accuracy with the MA system and was deemed optimal for all subsequent comparisons (Tables II and III). Bland–Altman plots have been shown in Figure 1, and these highlight the lack of agreement for the raw accelerometer data and the improved agreement with lower filtering cut-off frequencies.

Filtering accelerometer data using a cut-off frequency of 10 Hz demonstrated significant differences (P < 0.01) in mean bias values for the run movement when compared to the walk and jog movements (Table II). The accuracy, agreement, precision, and relative error were strongest for the walk condition, with linear increases in indices noted for the jog compared with walk and for run compared to both lower intensity movements (Table II).

Significant differences (P < 0.01) were noted in mean bias values for the 1.5–2.0 G and 2.0–2.5 G acceleration bands when compared to each preceding acceleration band (Table III). The strongest relationships were noted for the smallest (0.5–0.6 G) acceleration band and linear increases in error were found as the magnitude of acceleration increased.

Discussion

The purpose of this study was to validate peak acceleration data from an accelerometer contained within a wearable tracking device with a criterion measure of acceleration, derived from a MA system, during walking, jogging, and running movements. Filtering accelerometer data using a cut-off frequency of 10 Hz demonstrated the best accuracy with the MA system. Further, both the movement performed and the magnitude of acceleration recorded significantly affected the relationship found between the accelerometer and the MA system.

The current study was the first to incorporate a criterion measure capable of ranking peak accelerations in the location the wearable tracking device was worn, through the use of a MA system. The accelerometer was found to overestimate MA peak accelerations (mean bias = 0.85 G) when all movement intensities were pooled together. However, filtering the accelerometer signal reduced this overestimation. Further, it was evident that as the cut-off frequency applied to the raw data reduced (e.g., 20 Hz versus 15 Hz etc.), the overestimation decreased. With reference to the agreement, precision, and relative error found, all filtering frequencies improved the relationship noted with the MA system when compared to the raw accelerometer data alone. The validity of the accelerometer to measure peak accelerations, therefore, appears to be affected by

| Table I: Data relating to accuracy, agreement, precision and relative error for each accelerometer variable assessed (n= 1170) |
|-------------|----------------|----------------|----------------|
| Variable    | Mean bias     | 95% LoA (%)    | RMSEP (%)      | CV (%)         |
| Raw         | 0.95 ± 0.75*  | -0.68 to 2.30  | 1.13           | 15.0           |
| 20 Hz       | 0.61 ± 0.53*  | -0.43 to 1.66  | 0.61           | 13.0           |
| 15 Hz       | 0.33 ± 0.22*  | -0.29 to 0.95  | 0.46           | 11.6           |
| 10 Hz       | 0.04 ± 0.14*  | -0.24 to 0.32  | 0.25           | 8.9            |
| 8 Hz        | 0.08 ± 0.12    | -0.33 to 0.46  | 0.14           | 8.2            |
| 6 Hz        | 0.20 ± 0.15*   | -0.48 to 0.58  | 0.24           | 8.2            |

*The mean difference (accelerometer vs. MA unit) is significant at the 0.007 level (log-transformed data),

**Standard deviation, 95% LoA, 95% limits of agreement, RMSEP, root mean square error of prediction, CV, coefficient of variation.
additive errors or noise recorded within the raw signal. It was apparent that the accelerometer was most accurate when a 10 Hz cut-off frequency was applied to the data (mean bias 0.04 G). This is consistent with previous accelerometer validation research investigating peak acceleration measurement (Wundersitz et al., 2013). The overall validity of the accelerometer data was acceptable, with smaller relative errors noted than previous research using a different criterion measure (Tran et al., 2010; Wundersitz et al., 2013). These findings could be expected given that separation of the wearable tracking device from the criterion measure (i.e., force plate) may introduce or amplify errors between devices (Wundersitz et al., 2013). Therefore, the lower relative errors (4.9-10.6%) found in this study may simply be the result of the criterion measure chosen, rather than the result of the criterion measure chosen, with the relative errors noted than previous research using a different criterion measure (Tran et al., 2010; Wundersitz et al., 2013) contributing to the errors found in the present investigation.

Some amount of error will always be present when comparing different technologies (Atkinson & Nevill, 1998; Bland & Altman, 1986). A relative error value of 5% for reliability (Boyd et al., 2011) and 20% for validity (Tran et al., 2010; Wundersitz et al., 2013) has previously been suggested as an analytical goal for the acceptable use of this technology in the field. Based on these values the accelerometer might then be considered acceptable as the largest relative error found (when a cut-off frequency of 10 Hz was applied) was 10.6% in the current study. However, it may be more appropriate to assess validity using multiple statistical approaches (as performed in the current study), rather than a single statistical approach, such as the CV% statistic that does not describe 32% of the variability between the accelerometer and MA system (Atkinson & Nevill, 1998). With this in mind, the accuracy, agreement, precision and relative error statistics combined support the use of the accelerometer for in-field monitoring of peak accelerations during walking, jogging (up to a magnitude of 1.4 G) and to a lesser degree running (for magnitudes greater than 1.5 G). Practically, to enhance the accuracy of the accelerometer data produced, wearable tracking device manufacturers should consider incorporating a 10 Hz filtering algorithm within the device's software. Alternatively, practitioners could export raw accelerometer data and, if necessary, apply a 10 Hz filter to this data. Furthermore, as can

Table III. Data relating to accuracy, agreement, precision and relative error at each accelerometer band for the 10 Hz filtered accelerometer data

<table>
<thead>
<tr>
<th>Acceleration</th>
<th>Mean bias ± s (G)</th>
<th>95% LoA (G)</th>
<th>RMSEP (G)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0-0.5 (n = 113)</td>
<td>-0.01 ± 0.03</td>
<td>-0.06 to 0.03</td>
<td>0.03</td>
<td>8.8</td>
</tr>
<tr>
<td>0.5-1.0 (n = 87)</td>
<td>-0.02 ± 0.04</td>
<td>-0.08 to 0.02</td>
<td>0.01</td>
<td>9.0</td>
</tr>
<tr>
<td>1.0-1.5 (n = 282)</td>
<td>0.01 ± 0.03</td>
<td>-0.21 to 0.23</td>
<td>0.10</td>
<td>7.0</td>
</tr>
<tr>
<td>1.5-2.0 (n = 408)</td>
<td>0.07 ± 0.10</td>
<td>-0.17 to 0.35</td>
<td>0.16</td>
<td>9.0</td>
</tr>
<tr>
<td>2.0-4.9 (n = 91)</td>
<td>0.27 ± 0.24</td>
<td>-0.19 to 0.73</td>
<td>0.36</td>
<td>16.6</td>
</tr>
</tbody>
</table>

*The mean difference is significantly higher (P < 0.01) when compared to each preceding acceleration band.*
be seen in Figure 1A–D, the magnitude of acceleration is reduced with filtering (e.g., a 3.0 G peak acceleration when filtered at 10 Hz may become a 2.5 G peak acceleration). Practitioners should be aware of this, especially when comparing previously recorded metrics obtained from raw accelerometer data. Further research is required to assess other movements, such as edging and bumping, which impose peak accelerations greater than those recorded in the current study (i.e., greater than 5 G as is common in contact sports; Cunniffe et al., 2009; Gistrin et al., 2013).

This study has shown that the accelerometer contained within the MinimamX S4 wearable tracking device can accurately measure walking, jogging and to a lesser degree running peak accelerations when filtered at a 10 Hz cut-off frequency. Accurate assessment of walking, jogging and running is important considering that field team sport athletes spend most of their time in these movement categories (Bloomfield et al., 2007; Duthie et al., 2005; Spencer et al., 2004). For example, in Soccer athletes spend 14.2%, 58.1% and 11.1% of their time in walking, jogging and running, respectively (Bloomfield et al., 2007). Accelerometers may, therefore, be used accurately to evaluate the effectiveness of training programmes designed to increase sports performance and the prevention and rehabilitation of athletes from injury. Further, researchers have used accelerometers to evaluate different
standards of game-play (Cornack, Smith, Mooney, Young, & O’Brien, 2014), exercise-induced muscle damage (McLellan, Lovell, & Giss, 2011), fatigue (Mooney, Cornack, O’Brien, Morgan, & McGuigan, 2013), injury risk (Kogias, Dawson, Hearse, & Gabbert, 2013), the overall physical demands of sport performance, including the frequency and intensity of physical collisions (Guskin et al., 2013), as well as the automatic detection of physical collisions (Kelly, Coughlan, Green, & Coullfield, 2012). Our findings suggest that the accelerometer may have found greater levels of accuracy than shown in these studies if the raw data were filtered.

The current investigation has several strengths and limitations. A strength of the study was that human trials were conducted to validate the accelerometer as compared to validation in a mechanical setting. The choice of criterion measure also ensured that the accelerometer was validated at the location it is worn. Additionally, both raw and pre-processed data (i.e., filtering) techniques were investigated, thus providing practitioners with alternatives to improve accelerometer accuracy beyond the use of raw data. In terms of weaknesses, the treadmill-based protocol limits the scope of the study to replicate field team sport movement patterns (Gray, 2009; Hong, Wang, Li, and Zhou (2012) found that treadmill running increased ground contact time and decreased peak plantar forces at foot-strike. As a result, it may be possible that the peak accelerations recorded in the current investigation are smaller than those recorded in the field. The fastest velocity participants ran at was 5.9 m/s, while elite team sport athletes routinely attain higher velocities (e.g., 8.3 m/s in Australian football, Wiles, Montgomerie, Price, & Rathey, 2010). Although a single cut-off was chosen for all movements, it may be that 10 Hz (MA) and 10 Hz (accelerometer) cut-offs were most appropriate for walking and, less so for jogging and running. However, the FTTI supported a single cut-off for all movements and multiple movements are performed in a data set, a single cut-off can be applied to a data set has more practical use for practitioners.

Conclusion

The findings of this study show that the accelerometer contained within a wearable tracking device is capable of accurately measuring peak accelerations in particular for walking and jogging. The current use of raw accelerometer data in the technology likely leads to an overestimation of peak accelerations, while the application of appropriate filtering cut-off frequencies enables the accelerometer to measure peak accelerations with greater accuracy. As a result, wearable tracking device manufacturers should consider incorporating a 10 Hz filtering algorithm within the device’s software. Further, it appears that the accuracy of the accelerometer may be reduced as the movement velocity and magnitude of acceleration recorded increases. Future research should consider assessing the performance of accelerometers in measuring movement, especially those that result in larger peak accelerations.

References


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VALIDITY OF WEARABLE TECHNOLOGY TO MEASURE PEAK IMPACT DURING HIGH-INTENSITY TREADMILL RUNNING

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The purpose of this study was to identify the validity of an upper-body mounted accelerometer to measure peak acceleration during high-intensity treadmill running. A twelve camera motion analysis (MA) system was used as the criterion measure with markers placed on and close to the accelerometer. Ten peak impacts per participant were compared (n = 390). All accelerometer values were significantly different between the MA unit and T6 reflective marker’s acceleration data. Smoothing accelerometer data at 8 and 6 Hz provides an acceptable indirect measure of peak impact acceleration performed during high-intensity running. Consequently, smoothing algorithms should be incorporated into the commercially available software that the devices are supplied with.

KEY WORDS: Motion analysis, accelerometer, acceleration, collision.

INTRODUCTION: In field team sports, impacts typically occur as a result of running foot-strikes, landings and player contact (Young, Hepner & Robbins 2012). Historically, impacts from running foot-strikes are measured in a laboratory setting, using large, expensive and immobile devices, such as force plates (Besser et al., 2001b; Keller et al., 1996). This situation limits the understanding of the ‘in field’ demands imposed on athletes. More recently, field team sports have adopted accelerometer’s integrated within commercially available wearable tracking devices to quantify whole body load. These devices are worn on the upper-body, and are used to quantify discrete and accumulated (over time) accelerations recorded by the tri-axial accelerometer. Research has shown these devices can automatically detect (Kelly et al., 2012) and quantify (number and intensity) collisions in rugby (Gabbett, Jenkins & Abernethy, 2010). They can also quantify the physical demands imposed during basketball (Montgomery, Pyne & Minahan, 2010) and Australian football (Young, Hepner & Robbins, 2012). Excellent reliability of these devices has been shown in mechanical testing (CV = 0.91 to 1.9%; Boyd, Bail & Aughey, 2011), while poorer results (CV = 10.0 – 30.8%) were reported during jumping and landing when using ground reaction force as the criterion measure (Tran et al., 2010). The investigation of Tran et al. (2010) also showed filtering the raw accelerometer data at 20 Hz improved the relationship with the criterion measure. Tran et al.’s (2010) choice of cut-off frequency was derived from previous counter-movement jump research (Bisseling & Hof, 2006) with no attention to the actual frequency content of the acceleration time histories. Of further concern, the harness used to mount the tracking device on the participants was suggested to influence the accelerometer’s accuracy. No studies have sought to identify, the most optimal smoothing frequency, the influence of the harness mount and the validity of an upper-body mounted accelerometer integrated within wearable tracking devices to measure impact accelerations during high-intensity running. To gain confidence in the data produced by this technology and to enhance the understanding of the whole body physical demands imposed on athletes during high-intensity movements, the accuracy of the accelerometer output must be ascertained. The primary aim of this study was to examine the criterion validity of peak resultant acceleration values recorded by an accelerometer worn on the upper-body, against peak resultant acceleration values concurrently measured by a motion analysis (MA) system during high-intensity treadmill running.
running. The secondary aim was to identify the most optimal smoothing frequency and any influence of the harness mount for an accelerometer worn on the upper-body.

**METHODS:** Thirty-nine recreationally active participants (twenty-eight males and eleven females; age 24.2 ± 2.5 years; height 1.79 ± 0.09 m; mass 71.6 ± 12.0 kg; mean ± SD) were recruited. The study protocol was approved by the Deakin University Ethics Committee and written informed consent was obtained from all participants prior to testing. A single commercially available wearable tracking device (minimaxS4, Catapult Innovations, Australia) containing a tri-axial accelerometer (Konix, USA) was utilised in this study. The sampling frequency of the accelerometer was 100 Hz and the full-scale output range was ±10 G in each axis. The device was worn in a manufacturer supplied harness (Catapult, Australia) which located the device firmly in the centre of the upper-back at the level of T2. All testing was performed indoors with the GPS functionality of the device disabled. Three-dimensional (3D) positional data were collected at 200 Hz using a 12-camera MA system (Raptor-E, Motion Analysis Corporation, USA). Eleven reflective markers were attached to the body. A marker located on the lateral malleolus of each foot was used to identify foot-strike. A marker located on the unit itself and at T6 level was used to assess criterion validity. The T6 marker location was chosen to allow comparison without any harness influence on the marker, while being close enough to ascertain a reasonable comparison. All trials were completed on a calibrated motorised treadmill (Quinton Q65, Quinton Instrument Company, Washington, USA). Following familiarisation with all equipment, procedures, and the exercise protocol, participants were asked to run at a high-intensity (females 5 m/s; males 5.83 m/s) on a treadmill for 30 seconds. Acceleration (from the accelerometer) and positional data off each reflective marker were recorded simultaneously. In total, 390 comparisons were made per marker. Raw accelerometer recordings were corrected for gravity using the manufacturer supplied algorithms so that the accelerometer displayed 0 G while stationary. This data along with the raw position data from the MA system were spectrally analysed using a customised Fast Fourier transform (FFT) in Microsoft Excel (version 14.0.8112.5000). This program displayed the spectra of the signal and provided the researcher with a visual means to choose an optimal cut-off frequency for smoothing. A 4th order, dual pass, digital Butterworth filter was applied to smooth the accelerometer acceleration and MA position data. The MA smoothed position data were then differentiated twice to calculate acceleration. To aid in synchronising the device signals, participants performed three countermovement jumps prior to testing, while standing within the 3D space. A customised MATLAB program (R2012a 7.14.0.739, USA) was used to synchronize the captured signals and to detect peak values during previously labelled steps. The accelerations captured during the countermovement jumps were used to find the offset between the devices, using cross correlation. Subsequently, the offset between the devices was subtracted from the time domain of the MA data and peaks were identified, based on previously labelled time stamps, in the original frequency of the captured accelerations. All data were log transformed as the data were not normally distributed and displayed heteroscedasticity. Non-parametric Spearman’s Rho correlation coefficients (r) and typical error of the estimate expressed as a percentage (CV%) were subsequently used. Our operational definition for the CV% was small (CV% < 5), moderate (CV% > 5 and < 20) and large (CV% ≥ 20). A one way (Device) ANOVA was used to determine if peak impact values recorded by each measurement device for each movement were significantly different from each other. If significant interactions existed, multiple pairwise comparisons (with Bonferroni correction) were used to identify where the significant differences lay.

**RESULTS:** Visual inspection of the FFT outputs suggested the optimal cut off frequency to be 6 Hz for the MA data and between 6 and 10 Hz for the accelerometer data. Additionally, a 20 Hz cut off was analysed to make the current results comparable to previous work. There was a significant main effect of device on impact acceleration (p < 0.01). All accelerometer
variables were significantly different (p < 0.01) from both MA measures (Table 1a and 1b). The 6, 8 and 10 Hz accelerometer measures showed the strongest correlations (r = 0.6) and moderate measurement errors (CV% = 10) compared to the MA marker on the unit. All accelerometer measures showed weaker conformity when compared to the MA marker located at T6 (Table 1b). Both MA measures were significantly different from each other, but displayed a strong correlation (r = 0.75) and moderate measurement error (CV% = 11.3). Smoothing positively influenced the accuracy of the accelerometer data.

### Table 1a and 1b

Measurement results for accelerometer (raw, smoothed 2C, 10, 8 and 6) and MA reflective marker acceleration during high-intensity treadmill running (n = 390). Table 1a compares the means from the accelerometer to the mean of the MA reflective marker located on the accelerometer unit itself. Table 1b compares the means from the same accelerometer data to the mean of the MA reflective marker located below the accelerometer (on the skin) at the level of T6.

<table>
<thead>
<tr>
<th>Device</th>
<th>Mean ± SD</th>
<th>r</th>
<th>CV%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA Unit</td>
<td>1.06 ± 0.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raw</td>
<td>3.16 ± 0.82</td>
<td>0.62</td>
<td>13.4</td>
</tr>
<tr>
<td>20 Hz</td>
<td>2.74 ± 0.66</td>
<td>0.73</td>
<td>11.6</td>
</tr>
<tr>
<td>10 Hz</td>
<td>1.80 ± 0.36</td>
<td>0.83</td>
<td>9.3</td>
</tr>
<tr>
<td>6 Hz</td>
<td>1.31 ± 0.30</td>
<td>0.84</td>
<td>9.1</td>
</tr>
<tr>
<td>1.41 ± 0.23</td>
<td>0.85</td>
<td>9.1</td>
<td></td>
</tr>
<tr>
<td>Accelerometer</td>
<td>MA T6</td>
<td>1.47 ± 0.22</td>
<td></td>
</tr>
<tr>
<td>Raw</td>
<td>3.16 ± 0.82</td>
<td>0.45</td>
<td>14.4</td>
</tr>
<tr>
<td>20 Hz</td>
<td>2.74 ± 0.66</td>
<td>0.50</td>
<td>13.9</td>
</tr>
<tr>
<td>10 Hz</td>
<td>1.80 ± 0.36</td>
<td>0.56</td>
<td>13.2</td>
</tr>
<tr>
<td>6 Hz</td>
<td>1.01 ± 0.30</td>
<td>0.59</td>
<td>13.0</td>
</tr>
<tr>
<td>1.41 ± 0.23</td>
<td>0.61</td>
<td>12.9</td>
<td></td>
</tr>
</tbody>
</table>

* The mean difference (Accelerometer vs. MA marker) is significant at the 0.01 level (based on the log transformed data); The correlation is significant at the 0.01 level. MA, motion analysis; SD, standard deviation; T6, thoracic vertebrae six reflective marker; r, Spearman Rho correlation coefficient; CV%, typical error of the estimate presented as a percentage.

**DISCUSSION:** In field team sports, the use of wearable tracking devices is widespread and continues to grow. The accuracy of accelerometer’s integrated within this technology for quantifying high-intensity movements is largely unknown. In this study, peak impact accelerations in an upper-body mounted accelerometer were examined against a MA system during high-intensity treadmill running. Multiple cut-off frequencies were also assessed to identify optimal smoothing parameters. On the criterion validity of the unit, significant differences (p < 0.01), strong correlations (r = 0.64) and moderate measurement errors (CV% = 9.1) suggest the 8 Hz accelerometer measure were the best gauge of impact acceleration. On the global whole body impact load (compared to the T6 marker’s acceleration), smoothing at 6 Hz appears more appropriate. The FFT suggested that the majority of MA signal power was contained in the lower 7 harmonics; any harmonic power above the 10th harmonic was negligible (Winter, 2008). As such, multiple frequencies (6, 8 and 10) were analysed. The current investigation suggests that raw accelerometer data and a 20 Hz (previously validated (Tran et al., 2010)) cut-off frequency are both unacceptable to measure peak impact acceleration. This data are nearly double the actual peak recorded by the MA system (Table 1a). Smoothing improved the relationship with the criterion measure and reduced the measurement error found (Table 1a). For example, the 8 Hz cut-off frequency resulted in a ±0.06 G difference with the unit MA measure. The harness used to attach the accelerometer to the wearer was suggested as a possible cause of the error in previous research (Tran et al., 2010). In the present study, significant overestimation of impact.
acceleration from the unit measure compared to the T6 measure support this observation. These results suggest that the harness causes excessive movement of the unit outside of that experienced by the body (i.e. whipping movement of the unit increases the impact acceleration recorded). Therefore, comparison of validity should be against that of the T6 measure to remove the influence of the harness. As such, a 6 Hz cut-off frequency appears to be most appropriate (Table 1b). The ability to use accelerometers to accurately quantify impact loads in the field (over the laboratory) gives practitioners a unique insight into the impact load imposed on the musculoskeletal system during training and competition. This has implications for the prescription of training loads, injury management programs and recovery practices.

CONCLUSION: In field team sports, the accurate quantification of peak foot-strike impact accelerations will aid sports scientists and coaches to understand the physical demands imposed on athletes during training and competition. The findings of the present investigation support the use of accelerometer data to quantify high-intensity running impacts, if the data is smoothed. Cut-off frequencies within 6-8 Hz should be incorporated into the commercially available software that the units are supplied with. Further research is required to assess the validity of these devices during different movements and the devices ability to measure load in multiple movement that simulate field team sport.

REFERENCES:
1. **Your Consent**
   You have been invited to take part in this valuable research project, which has received approval from Deakin University.
   This Plain Language Statement contains detailed information about the research project. Its purpose is to explain to you as openly and clearly as possible all the procedures involved in this project so that you can make a fully informed decision whether you are going to participate. Please read this Plain Language Statement carefully. Feel free to ask questions about any information in the document. Once you understand what the project is about you will be required to sign the Consent Form. By signing the Consent Form, you indicate that you understand the information and that you give your consent to participate in the research project. You will be sent a copy of the Plain Language Statement and Consent Form to keep as a record.

2. **Purpose and Background**
   The application of accelerometry in sport is widely reported and continues to grow rapidly, as it provides an objective measure of accelerations associated with player movements in training and competitive game environments. However, research investigating the validity of these devices to measure such movements is scarce. The aim of this study is to assess the validity of accelerometer data for quantifying team-sport related movements. The data recorded by the accelerometers will be compared statistically with acceleration measurements, collected using a calibrated 6-camera Motion Analysis system, to establish the criterion validity of the accelerometer devices.

3. **Procedures**
   You will be required to complete a familiarisation session prior to testing to experience the requirements of the study, where they will be encouraged to ask any questions that may arise, and reminded that they may withdraw from the study at any time. You will be required to complete one four movement tasks (walking, jogging,
striding and running) that have been selected to represent common player movements performed in team sports. You will be required to complete three trials in total while wearing three commercially available global positioning units (GPS; Catapult and GPSports 100Hz & GPSports 200Hz, Australia).
While completing each task, you will be required to wear one small matchbox-sized accelerometer, integrated within a Global Positioning System (GPS) device, which will be securely attached to you in a custom-made pouch on your upper back.
Further, four additional accelerometers will be worn while completing each trial. These will be located on both wrists (similar to a wrist watch) and on the waist in a custom belt.
Acceleration data will be collected from the accelerometers, and compared to the MA system (Gold standard measure). For this to occur reflective markers will be placed on each accelerometer and on your ankles, knees, hips, lower spine and neck (these are non-invasive and weigh five grams).
A standard 10 minute warm-up will be performed on the treadmill slowly increasing in intensity to match the maximum speed required of participants during the trials. Each trial will last for approximately two minutes. Once the trial has been completed, the GPS unit and harness will be swapped and five minutes recovery will be given. In total three trials will be performed per participant (three GPS units to be tested).
4. **Possible Benefits**
The project seeks to provide information regarding the validity of accelerometer devices for measuring athlete movements typically found in field-based, team sports. While you may not personally receive any benefits from this project, it will allow sports scientists to more confidently use accelerometers to better quantify player movements and loads during competition and training.
5. **Possible Risks**
There are no foreseeable risks. You will be guided through an appropriate warm up and warm down to prevent the risk of any injuries occurring whilst completing the tasks. You are under no obligation to participate and if you give consent to participate in the study, you are free to withdraw at any time.
6. **Privacy, Confidentiality and Disclosure of Information**
All information provided will remain strictly confidential. Any identifying information, such as your name, and data, will be kept separately from the written copy of the results. These will be identified only by a number. All information will be stored at Deakin University in a locked filing cabinet and will be retained for a period of six years after the study finishes. The information gathered during this study may be published in scientific literature and presented at conferences. However, only pooled anonymous data would be presented, with no information included that would allow any individual to be identified.
7. **Participation is Voluntary**
Participation in any research project is voluntary. If you do not wish to take part you are not obliged to. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. Any information obtained from the participants to date will not be used and will be destroyed.
8. **Complaints**
If you have any complaints about any aspect of the project, the way it is being conducted or any questions about your rights as a research participant, then you may contact:
9. **Reimbursement for your costs**
You will not be paid for your involvement in this project.

10. **Further Information, Queries or Any Problems**
If you require further information, wish to withdraw your participation or if you have any problems concerning this project, you can contact either of the principal researchers.

**Principal Researchers**

Dr. Kevin Netto  
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Burwood VIC 3125  
9244 5013  
dwunder@deakin.edu.au
PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

<table>
<thead>
<tr>
<th>Consent Form</th>
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<tbody>
<tr>
<td><strong>Date:</strong></td>
</tr>
<tr>
<td><strong>Full Project Title:</strong> What effect does the harness mount of wearable technology (WT) have on peak impacts during treadmill running at different speeds?</td>
</tr>
<tr>
<td><strong>Reference Number:</strong> HEAG-H 64-2011</td>
</tr>
</tbody>
</table>

I have read, and I understand the attached Plain Language Statement. I freely agree to participate in this project according to the conditions in the Plain Language Statement. I have been given a copy of the Plain Language Statement and Consent Form to keep. The researcher has agreed not to reveal my identity and personal details, including where information about this project is published, or presented in any public form. I acknowledge that I am free to withdraw from at any time.

Participant’s Name (printed)

..........................................................
Signature ..................................................  Date

........................................
Revocation of Consent Form

(To be used for participants who wish to withdraw from the project)

Date:

Full Project Title: What effect does the harness mount of wearable technology (WT) have on peak impacts during treadmill running at different speeds?

Reference Number: HEAG-H 64-2011

I hereby wish to WITHDRAW my consent to participate in the above research project and understand that such withdrawal WILL NOT jeopardise my relationship with Deakin University.

Participant’s Name (printed) ……………………………………………………………

Signature ………………………………………………………………………………… Date

……………………

Please mail or fax this form to:

Dr. Kevin Netto
School of Exercise and Nutrition Sciences
Deakin University
221 Burwood Highway
Burwood VIC 3125
Fax: 9244 6017
kevin.netto@deakin.edu.au
Appendix B

STUDY 2

Journal Article

Informed Consent
Validity of a Trunk-Mounted Accelerometer to Measure Physical Collisions in Contact Sports

Daniel W.T. Wunderitz, Paul B. Gaust, Samuel J. Robertson, and Kevin J. Netto

Context: Accelerometer peak impact accelerations are being used to measure player physical demands in contact sports. However, their accuracy to do so has not been ascertained. Purpose: To compare peak-impact-acceleration data from an accelerometer contained in a wearable tracking device with a 3-dimensional motion-analysis (MA) system during tackling and bumping. Methods: Twenty-five semiflute rugby athletes wore a tracking device containing a 100-Hz triaxial accelerometer (MiniMaxX S4, Catapult Innovations, Australia). A single reflective marker was attached to the device, with its position recorded by a 12-camera MA system during 3 physical-collision tasks (tackle bag, bump pad, and tackle drill). The accuracy, effect size, agreement, precision, and relative errors for each comparison were obtained as measures of accelerometer validity. Results: Physical-collision peak impact accelerations recorded by the accelerometer overestimated (mean bias 0.60 g) those recorded by the MA system (P < 0.01). Filtering the raw data at a 20-Hz cutoff improved the accelerometer’s relationship with MA data (mean bias 0.01 g, P > 0.05). When considering the data in 9 magnitude bands, the strongest relationship with the MA system was found in the 3.0-g or less band, and the precision of the accelerometer tended to reduce as the magnitude of impact acceleration increased. Of the 3 movements performed, the tackle bag task displayed the greatest validity with MA. Conclusions: The findings indicate that the MiniMaxX S4 accelerometer can accurately measure physical-collision peak impact accelerations when data are filtered at a 20-Hz cutoff frequency. As a result, accelerometers may be useful to measure physical collisions in contact sports.

Keywords: acceleration, motion analysis, impact, load, intensity

Physical collisions form a major component of contact team sports and include movements such as tackling, bumping, and landing on the ground.1–4 These physical collisions have been shown to expose athletes to an increased risk of contact-related injury.1–2 Furthermore, the intensity of the collision may contribute to the incidence of injury.3–4 Historically, collisions have been identified retrospectively using video replay.5–6 However, this approach is limited largely due to test–retest reliability issues7 and the considerable time required to collect and analyze the data.8

Commercially available wearable tracking devices (eg, MiniMaxX S4, Catapult Innovations, Australia) have been developed for field team sports and are worn by athletes on their upper back in a sports vest.9 Such devices typically contain a global positioning system (GPS), gyroscope, and magnetometer sensors.10 They also contain an accelerometer, making it possible to measure the accelerations associated with sporting movements including physical collisions in contact sports.9,11–13 As acceleration is directly proportional to external force,13 accelerometers can therefore be used to reflect the intensity of collisions that athletes experience.

Previous research has shown that accelerometers can be used to describe physical collisions during game play.14 In addition, research assessing the intensity of collisions has found strong relationships between accelerometer data and subjective categorization from video observation.15–17 These studies show that accelerometers have the potential to quantify physical collisions in contact sports; however, in order for accelerometers to be used with confidence for these purposes, the data output should be both reliable and valid.

To this end, Boyd et al.14 assessed the reliability of the MiniMaxX S4 accelerometer and found a good level of within- and between-devices reliability (0.9–1.9%). The concurrent validity (a type of criterion-related validity where a new instrument [eg, accelerometer] is compared with a previously validated alternative form of measurement) of an accelerometer (SPI Pro, GPSports Pty Ltd, Australia) during jumping, landing,15 running, and change of direction movements15,16 has also been assessed. In both studies, raw accelerometer data overestimated force plate–derived ground-reaction force, although the application of a low-pass filter improved the validity of the data. A more recent investigation assessed the concurrent validity of another accelerometer (MiniMaxX S4, Catapult Innovations, Australia) using a 3-dimensional motion-analysis (MA) system during treadmill walking, jogging, and running.18 Similarly, the raw accelerometer data overestimated the concurrent measure, and filtering improved the validity of the data.

As seen from this previous research, 2 accelerometer types have been assessed; targeting lower-intensity movements and displaying consistent overestimations of movement intensity. In contact sports, high-intensity collisions are of more interest to coaches than low-intensity collisions due to the additional physical demand these larger collisions place on the body.19 However, no study has validated the MiniMaxX S4 accelerometer at intensities similar to those experienced in contact sports (eg, >5.0 g).15,19 The aim of this study was to concurrently validate peak-impact-acceleration data from an accelerometer contained in a MiniMaxX S4 wearable tracking device with an MA system during tackling and bumping.

Wunderitz, Gaust, and Robertson are with the Centre for Exercise and Sport Science, Deakin University, Melbourne, Australia. Netto is with the School of Physiotherapy and Exercise Science, Curtin University, Perth, Australia. Address author correspondence to Daniel Wunderitz at dwunder@deakin.edu.au.
Methods

Subjects
Twenty-five male athletes (mean ± SD age 23.3 ± 4.3 years, height 1.80 ± 0.06 m, mass 96.5 ± 18.1 kg) competing in the Victorian Rugby Union Premier Division were recruited for participation in the study. Ethics approval for the study was provided by the relevant human research ethics committee, with written informed consent obtained from all participants prior to testing.

Design
This study evaluated the concurrent validity of peak-impact-acceleration data collected from an accelerometer integrated in an MA system during physical-collision tasks. Raw accelerometer data and data filtered at several cutoff frequencies were compared.

Methodology

Participants
Participants were a single, wearable tracking device (MiniMax X5, Catapult Innovations, Australia) in a sports vest, which contained a 100-Hz triaxial accelerometer. The device weighed 67 g and was 88 × 50 × 19 mm in dimension. To assess the concurrent validity of the accelerometer, a single 5-g, 13-mm retroreflective marker was affixed with medical tape to the wearable tracking device, and its position was tracked using a 12-camera MA system (Raptor-X, Motion Analysis Corp., USA) operating at 500 Hz. The MA system was calibrated both statically (L-frame) and dynamically (0.2-m wand, ± 0.0004 m, ± 0.0005 m (mean ± SD) and at a precision of 0.000000 m). In clinical gait analysis, MA systems are the gold-standard measure used to accurately determine the dynamics of motion. Recently, MA systems have been used in sports laboratories to assess the concurrent validity of wearable tracking-device sensors (eg, references 18, 21, and 22).

Familiarization with all equipment and procedures, as well as a standardized warm-up, was performed before commencing data collection. Participants then performed 3 physical-collision tasks outdoors on a rugby field, during which time acceleration and 3-dimensional kinematic data were collected. The camera of the MA system contains new proprietary image-processing software that enables outdoor (in direct sunlight) and indoor capture. The 3 physical-collision tasks were broken down into those that involved ground contact (tackle bag) and those that involved body contact, as either the ball carrier being tackled (tackle drill) or the defender tackling the ball carrier (tackle bag). The run-up velocity (before collision) was self-selected with instruction given to run as fast as possible and perform each physical collision as is typical during game play.

In the tackle bag task, participants started 5 m away from a stationary upright padded tackle bag (1.53 × 0.46 m, Senior tackle dummy, Madison Sport, Australia) and ran and tackled the tackle bag to the ground. In the bulb pad task, participants performed the same running movement; however, a second participant was standing stationary 6 m away and was instructed to run forwards as the approaching participant while holding a padded hit shield (0.76 × 0.51 m, Large Hit Shield, Madison Sport, Australia). In the tackle drill task, both participants started 10 m apart and ran at each other, with the first designated as the defender and the second designated as the ball carrier (peak impact acceleration of interest). The defending participant was instructed to tackle the first participant around his center of gravity (ie, aiming for shoulder contact around the midfoot area). Participants were matched for mass, and after 5 trials they swapped roles. Participants were required to perform 10 trials of the bulb pad task (n = 250) and tackle-bag tasks (n = 250) and 5 trials of the tackle-drill task (n = 125), in the same order as mentioned previously (this order was chosen to expose participants to the 2 tasks that involved some form of tackling before the tackle-drill task, which did not). A 1-minute break was given between trials, with an additional 5 minutes recovery given between tasks. A trial was excluded if it was performed unsuccessfully (eg, missed or broke through a tackle too easily, etc.) and the participant was reminded of correct technique (see Gabbett23) and asked to repeat the trial. In addition, no direction was given in regard to the footwear worn (either football boots or cross-trainers) during testing.

Resultant data, defined as a single vector representing the combined effects of the x, y, and z axes for both the MA system and accelerometer, were analyzed through the manufacturers-supplied software (MA: Cortex, version 1.6.1.1315, Motion Analysis Corp., USA: accelerometer: Logan Plus, version 5.0.9.2, Catapult Sports, Australia). Accelerometer-derived accelerations, which were corrected for gravity (Inertial Movement Analysis proprietary software, Catapult Sports, Australia), along with MA position data, were then exported to Microsoft Excel (version 14.0.6121.500, Microsoft Corp., Redmond, WA, USA) for further analysis.

Three dimensional kinematic data are subject to high-frequency noise not the result of human movement.24 For example, even in static conditions, reconstructed marker data are not stationary.24 As a result, when estimating time derivatives, noise within the raw signal may be amplified.22 For these and other reasons, marker position data are low-pass filtered22 to remove high-frequency noise and obtain accurate derivative estimates.22 To choose the optimal cutoff frequency, a residual analysis of the difference between the unfiltered and filtered MA signals over a range of cutoff frequencies was performed for each movement, with the decision made via visual inspection.22 As a result of the residual analysis, MA data for all movements were filtered at a 10-Hz cutoff frequency. The MA smoothing x, y, and z position data were then used to calculate acceleration.29 The resultant vector was then calculated in multiples of gravity, or g. To investigate the effect different filtering cutoff frequencies had on accelerometer accuracy, the raw accelerometer data were filtered at multiple cutoff frequencies (30, 25, 20, 15, 10, 8, and 6 Hz) and compared against the MA system. To filter both the MA and accelerometer data, a low-pass, zero-lag, fourth-order Butterworth digital filter was applied in a customized Labview program (version 7.1, National Instruments, USA).

To synchronize the accelerometer and MA system, at the beginning of each trial the participant stood within the capture volume of the MA system, and the wearable tracking device was hit from the side while being filmed by a digital video recorder (GZ-MG5300HVA, JVC, Japan) operating at 50 Hz. The data were subsequently imported into video-analysis software (Team Pro version 7, Dartfish Ltd., Switzerland), and the hit peak acceleration was used to synchronize the 2 devices. Thus, the time point at which the physical collision occurred was recorded and the peak impact acceleration value manually retrieved for each trial.

Statistical Analysis
The accelerometer was examined across a broad range of peak impact accelerations from 2.2 to 14.5 g. Before undertaking the
main statistical analyses, a Kruskal-Wallis test was performed to determine whether differences in mean bias values between the raw accelerometer data and concurrent measures existed between the 23 trials. This was exploratory in nature, and the critical alpha level was set at .05. No differences for trial were noted, so all data were pooled for all subsequent analyses.

To determine the ability of the accelerometer to quantify peak accelerations, multiple measurement indices of validity were obtained. The level of accuracy, effect size, agreement, precision, and relative error for the accelerometer and MA accelerations were obtained by calculating the mean bias, Cohen’s d, 95% limits of agreement (LoA), root mean square error of prediction (RMSE), and coefficient of variation (CV), respectively.

Analysis of variance (ANOVA) was performed on 4 occasions, each analyzing the data reported in different formats. To determine if peak acceleration values recorded by the accelerometer (8 levels: raw and filtered at 30, 20, 15, 10, 8, and 6 Hz) differed from those of the MA system, a 1-way ANOVA was performed. Filtered accelerometer values displayed high levels of accuracy, agreement, and precision with the MA system (e.g., mean bias and RMSEP values close to 0.0 g) were then used for all subsequent analyses. A second 1-way ANOVA was performed to investigate whether differences in mean bias existed between the accelerometer and MA system when peak impact accelerations were compared across multiple magnitude bands (9 levels: <2.0 g, 2.0-3.99 g, 4.0-4.99 g, 5.0-5.99 g, 6.0-6.99 g, 7.0-7.99 g, 8.0-9.99 g, and 10.0 g or greater). These magnitude bands were modified from scaling categories previously reported in the literature.34 A third 1-way ANOVA was performed to investigate whether differences in mean bias existed between the accelerometer and MA system across the different movements undertaken (3 levels: tackle bag, bump pad, and tackle drill). Finally, a fourth 1-way ANOVA was performed to investigate whether peak impact accelerations could be used as a feature to distinguish between the 3 physical collisions performed (3 levels: tackle bag, bump pad, and tackle drill).

Bonferroni-corrected pairwise comparisons for the 4 ANOVA were used to identify the source of any differences, with the alpha level adjusted to .006, .006, .02, and .02 respectively, via the Bonferroni procedure.33 The exploratory analysis and ANOVAs were conducted using SPSS (version 21.0, IBM Corp., Armonk, NY, USA). The mean bias, effect size, 95% LoA, RMSEP, and CV were calculated using Microsoft Excel.

Results

Indices of accuracy, effect size, agreement, precision, and relative error between raw and filtered accelerometer data and the MA system are presented in Table 1. Raw and 20-Hz filtered accelerometer data significantly underestimated MA data (P < .006, mean bias = 0.34 – 0.60 g, Cohen’s d = 0.16 – 0.28). Filtering raw accelerometer data at 25–Hz (P = .01, Cohen d = 0.10), 20–Hz (P = .06, Cohen d = 0.01), and 15–Hz (P = .06, Cohen d = 0.01) cutoffs displayed better validity than MA data (mean bias = 0.10 – 0.31). However, the lowest cutoffs (10, 8, and 6 Hz) significantly underestimated MA data (P < .006, mean bias = 0.92 – 1.87 g, Cohen d = 0.47 to 1.03). Filtering raw accelerometer data using a 20-Hz cutoff frequency demonstrated the best accuracy, agreement, and precision values. Therefore, raw accelerometer data filtered at the 20-Hz cutoff frequency were used for all subsequent analyses.

Table 1: Data Relating to Accuracy, Effect Size, Agreement, Precision, and Relative Error for Each Accelerometer Variable Assessed (N = 625)

<table>
<thead>
<tr>
<th>Measure</th>
<th>Cohen d</th>
<th>Bias, mean ± SD (g)</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motion analysis</td>
<td>6.00 ± 2.22</td>
<td>0.28</td>
<td>0.60 ± 0.89</td>
<td>-1.53 ± 2.73</td>
<td>1.24</td>
</tr>
<tr>
<td>Raw</td>
<td>6.00 ± 2.30*</td>
<td>0.28</td>
<td>0.60 ± 0.89</td>
<td>-1.53 ± 2.73</td>
<td>1.24</td>
</tr>
<tr>
<td>20 Hz</td>
<td>6.34 ± 2.05</td>
<td>0.16</td>
<td>0.24 ± 0.88</td>
<td>-1.38 ± 2.06</td>
<td>0.94</td>
</tr>
<tr>
<td>25 Hz</td>
<td>6.21 ± 2.04</td>
<td>0.10</td>
<td>0.21 ± 0.82</td>
<td>-1.40 ± 1.81</td>
<td>0.84</td>
</tr>
<tr>
<td>30 Hz</td>
<td>6.01 ± 2.01</td>
<td>0.01</td>
<td>0.01 ± 0.75</td>
<td>-1.46 ± 1.48</td>
<td>0.75</td>
</tr>
<tr>
<td>15 Hz</td>
<td>5.69 ± 1.95</td>
<td>0.12</td>
<td>0.31 ± 0.70</td>
<td>-1.69 ± 1.07</td>
<td>0.77</td>
</tr>
<tr>
<td>10 Hz</td>
<td>5.08 ± 1.72*</td>
<td>0.47</td>
<td>0.92 ± 0.82</td>
<td>-2.53 ± 0.68</td>
<td>1.23</td>
</tr>
<tr>
<td>8 Hz</td>
<td>4.67 ± 1.55</td>
<td>0.69</td>
<td>-1.33 ± 0.95</td>
<td>-3.19 ± 0.53</td>
<td>1.63</td>
</tr>
<tr>
<td>6 Hz</td>
<td>4.13 ± 1.29*</td>
<td>1.60</td>
<td>-1.87 ± 1.14</td>
<td>-4.14 ± 0.37</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Abbreviations: LoA, limits of agreement; RMSE, root mean square error of prediction; CV, coefficient of variation.

*Mean difference (accelerometer vs motion analysis) significant at the .005 level.
Table 2: Data Relating to Accuracy, Effect Size, Agreement, Precision, and Relative Error at Each Acceleration Band, Motion Analysis Versus 20-Hz-Filtered Acceleration Data

<table>
<thead>
<tr>
<th>Acceleration Band (g)</th>
<th>Mean bias ± SD (g)</th>
<th>Cohen d</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;3.0 (n = 25)</td>
<td>0.08 ± 0.42</td>
<td>-0.20</td>
<td>-0.96 to 0.74</td>
<td>0.42</td>
<td>10.8</td>
</tr>
<tr>
<td>3.0–3.99 (n = 85)</td>
<td>-0.04 ± 0.53</td>
<td>-0.09</td>
<td>-1.07 to 0.69</td>
<td>0.53</td>
<td>9.9</td>
</tr>
<tr>
<td>4.0–4.99 (n = 101)</td>
<td>0.20 ± 0.62</td>
<td>0.42</td>
<td>-1.03 to 1.42</td>
<td>0.58</td>
<td>11.7</td>
</tr>
<tr>
<td>5.0–5.99 (n = 123)</td>
<td>0.08 ± 0.73</td>
<td>0.14</td>
<td>-1.35 to 1.51</td>
<td>0.73</td>
<td>9.8</td>
</tr>
<tr>
<td>6.0–6.99 (n = 107)</td>
<td>0.09 ± 0.74</td>
<td>0.16</td>
<td>-1.37 to 1.55</td>
<td>0.75</td>
<td>8.9</td>
</tr>
<tr>
<td>7.0–7.99 (n = 71)</td>
<td>0.04 ± 0.86</td>
<td>0.06</td>
<td>-1.64 to 1.72</td>
<td>0.85</td>
<td>8.7</td>
</tr>
<tr>
<td>8.0–8.99 (n = 57)</td>
<td>-0.21 ± 0.92</td>
<td>-0.30</td>
<td>-2.02 to 1.50</td>
<td>0.94</td>
<td>8.8</td>
</tr>
<tr>
<td>9.0–9.99 (n = 35)</td>
<td>-0.47 ± 0.90</td>
<td>-0.28</td>
<td>-2.22 to 1.29</td>
<td>1.00</td>
<td>7.9</td>
</tr>
<tr>
<td>10.0+ (n = 19)</td>
<td>-0.17 ± 1.02</td>
<td>-0.14</td>
<td>-2.16 to 1.82</td>
<td>1.00</td>
<td>6.6</td>
</tr>
</tbody>
</table>

Abbreviations: LoA, limits of agreement; RMSEP, root mean square error of prediction; CV, coefficient of variation.
*The mean difference (accelerometer vs motion analysis) is significant at the .01 level compared with the 9.0- to 9.99-g acceleration band.

Table 3: Data Relating to Accuracy, Effect Size, Agreement, Precision, and Relative Error for Each Task Performed, Motion Analysis Versus 20-Hz-Filtered Acceleration Data

<table>
<thead>
<tr>
<th>Task</th>
<th>g, mean ± SD</th>
<th>Mean bias ± SD (g)</th>
<th>Cohen d</th>
<th>95% LoA (g)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tackle bag (n = 250)</td>
<td>7.24 ± 1.05</td>
<td>-0.28 ± 0.64</td>
<td>-0.16</td>
<td>-1.52 to 0.97</td>
<td>0.69</td>
<td>6.5</td>
</tr>
<tr>
<td>Bump pad (n = 250)</td>
<td>4.79 ± 1.58</td>
<td>0.20 ± 0.74</td>
<td>0.13</td>
<td>-1.24 to 1.64</td>
<td>0.76</td>
<td>11.3</td>
</tr>
<tr>
<td>Tackle drill (n = 125)</td>
<td>6.00 ± 1.93</td>
<td>0.21 ± 0.82</td>
<td>0.10</td>
<td>-1.39 to 1.81</td>
<td>0.84</td>
<td>11.2</td>
</tr>
</tbody>
</table>

Abbreviations: LoA, limits of agreement; RMSEP, root mean square error of prediction; CV, coefficient of variation.
*The mean difference (accelerometer vs motion analysis) is significant at the .01 level compared with bump-pad and tackle-drill tasks. *The mean difference (task) is significant at the .01 level.

Discussion

The aim of this study was to concurrently validate peak impact acceleration data from an accelerometer and those from an MA system during 3 physical-collision tasks. When filtered at 20 Hz, the accelerometer displayed the strongest relationship with the MA system (ie, accuracy, agreement, precision, etc.). However, raw and 30-Hz-filtered accelerometer data overestimated, and 10-, 8-, and 6-Hz accelerometer data underestimated, physical-collision peak impact accelerations. Furthermore, both the intensity of acceleration recorded and the type of physical collision performed influenced accelerometer validity. Collectively, these results highlight that accelerometers can be used to accurately quantify the intensity of physical collisions experienced in contact sports, provided that the raw data are filtered using an appropriate cutoff frequency (eg, 20 Hz).

The raw accelerometer data overestimated physical-collision peak impact accelerations (mean bias = 0.50 g) and displayed poor agreement and precision with MA peak accelerations. This finding is supported by previous research that has shown that accelerometers contained in wearable tracking devices can overestimate concurrent methods by 15.6% to 30.3%. For example, a physical collision with a true peak-impact-acceleration value of 6.0 g if recorded by the accelerometer will have an error of 1.24 g under or over the actual value when raw data are used.

The poor accuracy of these devices for assessing peak impact accelerations may be due to noise present in the raw accelerometer signal. Noise refers to elements in the raw signal that are not a result of human movement and add characteristics (eg, frequency content) to the true signal. Filtering of a raw signal is commonly used to reduce noise. Although the raw accelerometer data overestimated physical-collision peak accelerations, when filtered at 30, 25, 20, and 15-Hz cutoff frequencies, the validity with the MA system was improved (eg, mean bias = -0.31 to 0.34 g, RMSEP = 0.75 to 0.94). The concurrent validity of the 20-Hz cutoff frequency was equal or superior to all other cutoffs assessed. Indeed, the accuracy (0.01 g), effect size (0.005), agreement (~1.46 to 1.48 g), and precision (0.73 g) values were superior to all other accelerometer cutoff frequencies tested. However, the concurrent validity of the 10-, 8-, and 6-Hz cutoff frequencies was equal to or poorer than the raw data (eg, RMSEP = 1.23–2.19 g). When physical-collision peak accelerations are filtered with a cutoff frequency at or below 15 Hz, the accelerometer data may be overfiltered, thereby underestimating the intensity of the collisions. While this was the case for the lower cutoff frequencies, the 20-Hz cutoff frequency appeared optimal, displaying the strongest concurrent validity with the MA system.

The findings of the current study are similar to previous research. However, the optimal cutoff frequency was different, with 2 of the aforementioned studies suggesting a 10-Hz filter as optimal. The difference in the optimal cutoff frequency between this study (20 Hz) and previous research may be due to the different movement performed, the wearable tracking devices assessed, and the congruent measure chosen (including differences in sampling rates). For instance, previous research suggests that the dominant frequencies of human movement increase with movement intensity. Therefore, physical collisions may have higher-frequency content characteristics than other contact-sport movements.
walking, running) assessed by previous validation work. Caution is advised if filtering accelerometer accelerations below 20 Hz, as this may underestimate physical-collision peak impact accelerations, which are used to quantify the physical demands of sports performance.  

When the 20-Hz-filtered accelerometer data were split into 9 magnitude bands and 3 activities, results showed strong concurrent validity between the accelerometer and MA system, with mean bias values not differing by more than 0.9 g and RMSE values not exceeding 1.0 g. Thus, considering the movements performed and the broad range of peak accelerations assessed, including those considerably larger than previously evaluated (range 0.3–6.0 g; 18–48), the results of this study support the accelerometer’s ability to accurately measure the intensity of physical collisions in contact sports.

In addition, the peak accelerations recorded were different between the 3 activities performed. To this end, the detailed analysis of accelerometer peak impact accelerations, as a discriminatory feature, may be used to identify the type of physical collision performed. Further research should consider the accuracy of the peak-impact-acceleration feature to identify and discriminate between contact-sport movements (e.g., tackling, running, jumping).

A limitation of this study was that the physical collisions assessed were simulated to represent game play. Although game validation would be preferred, current validity measures are not suited to such analyses. As a result, the peak accelerations recorded may be different than those recorded during game play, which should be acknowledged. Another potential source of error is the moment arm of the reflective marker. As the reflective marker must be visible at all times, the moment arm of the marker and accelerometer may be different.

Practical Applications

The accelerometer can be confidently applied to measure the intensity of physical collisions when filtered at 20 Hz. As a result, accelerometers may be useful to measure physical collisions in contact sports. Given the limitations of other sensors in wearable tracking devices to measure physical collisions, accelerometers may provide a valuable tool for the regular monitoring of physical workloads during training and game play. The detailed analysis of accelerometer data (e.g., individual and accumulated collisions) may help disable individual-specific training and recovery programs to improve performance and reduce injury risks. There is also the possibility that accelerometer peak accelerations may help classify the type of movement performed. However, this requires further investigation.

Conclusion

The results of this study suggest that the accelerometer sensor contained in Minaimax X54 wearable tracking-devicer technology can accurately measure physical-collision peak accelerations when data are filtered at a 20 Hz cutoff frequency. With appropriate filtering, the accelerometer can be considered an acceptable objective method to quantify physical collisions in contact sports. Caution is advised, however, when interpreting raw data, with the accelerometer output likely to underestimate the intensity of the physical collision. Detailed analysis of accelerometer data alone or in combination with other wearable-sensor data may help practitioners better understand the physical demands imposed on athletes. Future research should continue to assess the validity of the accelerometer in games or in simulated scenarios where multiple sporting movements are performed.

Acknowledgments

The authors would like to thank the players and staff of the Box Hill Rugby Union Club. They would also like to thank Paul Devoy, who assisted with data analysis.

References

INFORMED CONSENT

PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

Plain Language Statement

Date: 10/10/2012 – 10/02/2013
Full Project Title: Validity of an upper-body mounted accelerometer to measure peak resultant acceleration during tackling and bumping tasks
Principal Researcher: Dr Kevin Netto
Student Researcher: Daniel Wundersitz
Associate Researcher(s): Dr Paul Gastin

11. Your Consent
You have been invited to take part in this research project which involves participation in a tackling and a bumping task. This Plain Language Statement contains detailed information about the research project. Its purpose is to explain to you as openly and clearly as possible all the procedures involved in this project so that you can make a fully informed decision whether you are going to participate. Please read this Plain Language Statement carefully. Feel free to ask questions about any information in the document. You may also wish to discuss the project with a relative or a friend. Feel free to do this. Once you understand what the project is about you will be asked to sign the Consent Form. By signing the Consent Form, you indicate that you understand the information and that you give your consent to participate in the research project. You will be given a copy of the Plain Language Statement and Consent Form to keep as a record.

12. Purpose and Background
The application of accelerometry in sport is widely reported and continues to grow rapidly, as it provides an objective measure of accelerations associated with player movements in training and competitive game environments. However, research investigating the validity of these devices to measure such movements is scarce. The aim of this study is to assess the validity of accelerometer data for quantifying team-sport related movements, specifically tackling and bumping. The data recorded by the accelerometers will be compared statistically with acceleration measurements, collected using a calibrated 12-camera Motion Analysis (MA) system, to establish the criterion validity of the accelerometer devices in team sports during both training and competition.

13. Procedures
Following consent to participate, you will be required to attend a combined familiarisation and testing session. You will be required to complete two movement tasks (tackling and bumping) that have been selected to represent common player
movements performed in team sports. To experience the requirements of the study you will be instructed through both movements and given as much time as required till you feel comfortable performing each task. Once comfortable you will complete 20 trials in total (10 tackling and 10 bumping). The tackling trials will consist of a three meter run-up, followed by a single tackle of a tackling bag, and will end when the bag has been tackled to the floor. The bumping trials will consist of a three meter run-up, followed by a single bump of a hit shield attached to a research assistant. All trials will be completed at a moderate intensity. The duration of each trial will last no longer than five seconds. You will be given a one minute recovery period between each trial. Familiarisation and testing will take approximately one hour to complete.

While completing the tackling and bumping tasks you will be required to wear a small matchbox sized GPS devices which will be securely attached to you in a custom made pouch on the upper-body. This will not interfere with their ability to tackle or bump, and is commonly used in elite team sports during training and competition. Peak impact accelerations will be collected concurrently from the triaxial accelerometer within the GPS device and the MA system.

14. Possible Benefits

We cannot guarantee or promise that you will receive any benefits from this study. While you may not personally receive any benefits from this project, the findings will inform sports scientists and coaches of the actual accuracy of the data produced by these devices. This may then be used to better quantify player loads during competition and training.

15. Possible Risks

The risks to the participants from participating in the research are minimal. The participants will be tackling and bumping into a padded tackling bag, which may result in possibly muscle soreness and contusions from contact with the bag and floor. However, as this will be performed in a controlled setting, at a lower intensity, and using a tackling bag the risk is deemed to be low, and less severe than those that occurring during normal training and competition practices. There are no other foreseen risks. You will be guided through an appropriate warm up and warm down to prevent the risk of any injuries occurring whilst completing the tasks. You are under no obligation to participate and if you give consent to participate in the study, you are free to withdraw at any time.

16. Privacy, Confidentiality and Disclosure of Information

All information provided will remain strictly confidential. Any identifying information, such as your name, and data, will be kept separately from the written copy of the results. These will be identified only by a number. All information will be stored at Deakin University in a locked filing cabinet and will be retained for a period of five years after publication. The information gathered during this study may be published in scientific literature and presented at conferences. However, only pooled anonymous data would be presented, with no information included that would allow any individual to be identified.

17. Participation is Voluntary

Participation in any research project is voluntary. If you do not wish to take part you are not obliged too. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. Any information obtained from the participants to date will not be used.
18. Complaints
If you have any complaints about any aspect of the project, the way it is being conducted or any questions about your rights as a research participant, then you may contact:
The Manager, Research Integrity, Deakin University, 221 Burwood Highway, Burwood Victoria 3125, Telephone: 9251 7129, research-ethics@deakin.edu.au
Please quote project number [HEAG-H 127_2012].

19. Reimbursement for your costs
You will not be paid for your involvement in this project.

20. Further Information, Queries or Any Problems
If you request it, you may obtain a copy of the full results (average of group results) at the end of the study. If you require further information, wish to withdraw your participation or if you have any problems concerning this project, you can contact either of the principal researchers.

Principal Researchers
Dr Kevin Netto
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kevin.netto@deakin.edu.au

Daniel Wundersitz
School of Exercise and Nutrition Sciences
Deakin University
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Burwood VIC 3125
9244 5033
dwunder@deakin.edu.au
TO: Participants

Consent Form

Date:
Full Project Title: Validity of an upper-body mounted accelerometer to measure peak resultant acceleration during tackling and bumping tasks
Reference Number: HEAG-H 127_2012

I have read and I understand the attached Plain Language Statement.
I freely agree to participate in this project according to the conditions in the Plain Language Statement.
I freely agree to the collection of video data during my trials
I have been given a copy of the Plain Language Statement and Consent Form to keep.
The researcher has agreed not to reveal my identity and personal details, including where information about this project is published, or presented in any public form.
I would like to have the results sent to me at the end of the study (Yes □ No □)
Participant’s Name (printed)
……………………………………………………………………
Signature …………………………………………………………..Date
…………………………
PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

Withdrawal of Consent Form

(To be used for participants who wish to withdraw from the project)

Date:

Full Project Title: Validity of an upper-body mounted accelerometer to measure peak resultant acceleration during tackling and bumping tasks

Reference Number: HEAG-H 127_2012

I hereby wish to WITHDRAW my consent to participate in the above research project and understand that such withdrawal WILL NOT jeopardise my relationship with Deakin University.

Participant’s Name (printed) ………………………………………………………………..
Signature …………………………………………………………. Date

………………..

Please mail or fax this form to:
Dr. Kevin Netto
School of Exercise and Nutrition Sciences
Deakin University
221 Burwood Highway
Burwood VIC 3125
Fax: 9244 6017
kevin.netto@deakin.edu.au
Appendix C

STUDY 3

Journal Article

Informed Consent
Validation of a Trunk-mounted Accelerometer to Measure Peak Impacts during Team Sport Movements

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Abstract
This study assessed the validity of an accelerometer to measure impacts in team sports. Participants completed a team sport circuit. Accelerometers were attached to participants' lower backs and filtered at 12 Hz. The output was compared with ground truth data from high-resolution motion analysis systems. The accelerometer underestimated peak acceleration values during running, jumping, and kicking activities, while overestimating peak acceleration values during cutting and changing direction. Lower agreement and reduced precision were associated with sprinting, jumping, and kicking. The accelerometer demonstrated an acceptable level of concurrent validity compared to the motion analysis system when filtered at a cut-off frequency of 12 Hz. These results advocate the use of accelerometers to measure movements in team sport.

Introduction
Human movement analysis can provide valuable information to better understand the physical demands of sport and training [17,18]. This information can be used to provide feedback to athletes [19], design training programs to improve performance [20], and reduce injury risk [21]. The emergence of accelerometry technology has allowed quantification of movement acceleration in team sports, thereby facilitating more sophisticated analysis of the physical demands placed on athletes [17,18,21]. For example, Corduan et al. [7] used accelerometer-derived load to determine different movement patterns in running, jumping, and kicking activities with players of higher standards experiencing greater levels of load. In order for accelerometers to be used with confidence for these and similar purposes, it is essential that the data output be both reliable and valid. Accelerometers have demonstrated excellent reliability in both mechanical and field settings [11]. However, recent research has questioned the validity of accelerometers to accurately assess peak impacts in team sports, with accelerometers generally underestimating peak impacts in team sport [16]. The 12 Hz filter for the accelerometer data yielded a strong correlation with ground truth data (accuracy: 0.9991; R²: 0.999; agreement: 0.999; precision: 0.999). The accelerometer demonstrated an acceptable level of concurrent validity compared to the motion analysis system when filtered at a cut-off frequency of 12 Hz. These results advocate the use of accelerometers to measure movements in team sport.
were peak impacts undertaken during a simulated team sport circuit. Multiple filtering cut-off frequencies were examined and presented.

Methods

76 recreationally active, healthy, male participants (age, 24.4 ± 6.8 years; height, 181.8 ± 7.5 cm; mass, 77.4 ± 12 kg; mean ± SD) competing in one or more national team sport competitions per year were recruited. The study meets the ethical standards of the journal [19]. The study protocol was approved by the relevant Human Ethics Advisory Group (HEAG-H-135, 2013). All participants gave informed consent following full disclosure of the study protocol and procedures.

This was a concurrent validation study in which an accelerometer was compared against a 3-dimensional motion analysis (MA) system, whilst participants performed a simulated team sport circuit. During each trial participants wore a wearable tracking device (Motion Tracking Ltd, Christchurch, New Zealand) in a sports vest [18], which contained a 100 Hz triaxial accelerometer. A single 5-g, 18-mm retro-reflective marker was also attached to the wearable tracking device and its position was determined using a calibrated (root mean square error of prediction RMSEP = 0.000004 m) 36-camera MA system (Raptor III, Motion Analysis Corporation, USA) operating at 100 Hz. In clinical gait laboratories, MA systems are the gold standard measure used to accurately describe the kinematics of motion [21]. Recently, MA systems have been used in sports laboratories to examine the concurrent validity of wearable tracking devices [2, e.g., accelerometer accelerations (28, 33), and GPS position and velocity data [11, 20]].

The simulated team sport circuit used in this study involved a modified version of the circuit developed by Singh et al. [27]. Each circuit included the following movements (in order): 3 double-leg (24) jumps, a 10-m run, 3 charge of direction (COD), 2 throw (11) volleys, 2 sprints (24) to remove high-frequency noise and obtain accurate derivative estimates [29, 29]. To choose the optimal cut-off frequency, a residual analysis of the data was performed on the unfiltered and filtered MA signals over a range of cut-off frequencies was performed for each movement and each artefact with the decision made by visual inspection [21]. As a result of the residual analysis, MA data for all movements were filtered at a 10 Hz cut-off frequency. The filtered displacement data were then differentiated twice to calculate acceleration [21] (i.e., multiples of gravity or g) and the resultant vector was calculated. Accelerometer acceleration data were filtered at 13 different cut-off frequencies (5 g = 25 Hz). The highest time point with the peak acceleration of each activity was then used to output [2 (Microsoft Excel™) peak filtered accelerometer data from peak raw and filtered accelerometer acceleration. Both MA and accelerometer accelerations were filtered in LabVIEW using a zero-lag, linear-phase Butterworth filter.

Data utilised in the statistical analysis were based upon a total of 532 peak accelerations occurring across the 7 movements performed during the third trial of the circuit. The accelerometer was measured across a broad range of peak impact accelerations from 0.6–11.3 g. In order to determine the ability of the accelerometer to quantify peak accelerations, multiple measurement indices of validity were obtained. The level of agreement, accuracy, precision, effect size and relative error for the accelerome-
Discussion

This study examined the validity of an accelerometer to measure peak impacts for multiple movements undertaken during a simulated team sport circuit. Our findings indicate that the accelerometer contained within the wearable tracking device shows acceptable validity under filtered at a cut-off frequency of 12 Hz. However, the type of movement performed appears to influence validity.

Results

The mean±SD for the MA system across all activities was 3.20±1.78 g. As shown in the raw, 20, 30, 40, 50, and 17 Hz filtered accelerometer data significantly underestimated (Cohen’s d=0.32±0.55, P=0.007), and the 6 Hz filtered accelerometer data significantly underestimated MA peak accelerations (Cohen’s d=0.51, P=0.007). All other cut-off frequencies (16-100Hz) displayed no differences with MA peak accelerations (Cohen’s d=0.14 to 0.18, P=0.29 to 0.90). The raw accelerometer data revealed the strongest relationship with MA data (mean bias 1.13±0.08 g, Cohen’s d=0.56, 95% LoA=0.51 to 2.76 g, RMSEP=1.38 g, CV=23.6%); while the 12 Hz filtered accelerometer data revealed the weakest relationship (mean bias 0.01±0.27 g, Cohen’s d=0.09, 95% LoA=0.53 to 0.53 g, RMSEP=0.27 g, CV=5.5%); as shown in Fig. 3a, b, respectively.

The concurrent validity of the 12 Hz filtered accelerometer data for multiple movements is presented in Table 1. The accelerometer underestimated MA peak accelerations during tackling, DL, and 5L jumping (mean bias 0.006 to 0.102 g, Cohen’s d=0.005 to 0.201), and overestimated MA peak accelerations during sprinting, COD, and walking (mean bias 0.033 to 0.143 g, Cohen’s d=0.053 to 0.246). Weak limits of agreement and precision were associated with sprinting, jumping, and tackling. CV values ranged from 3.7% (sprint) to 6.9% (sprint). Of the 21 movement comparisons screened, the average peak acceleration values for jog and COD, and DL jump and sprint were not different from each other (P>0.05). All other movement peak accelerations were significantly different from each other (P<0.001).

Fig. 2. a) Mean bias (95% LoA), b) RMSEP (g), and c) CV (%) of peak acceleration from MA accelerometer variables when compared against the MA system.
The current study confirmed that different team sport movements have different peak acceleration profiles, with only the shot and COG, and DJ jump and sprint not significantly different from one another. However, the movements were performed in a controlled environment, which likely restricted the variation in peak acceleration due to the predictable nature of each movement performed. This study displayed the best, and the worst, validity of all movements assessed. For example, an error of 0.65 g (wrist) or 1.35 g (feet) under the current value recorded by the accelerometer would be expected for each movement. In addition, the 3 movements with the largest peak acceleration profiles (DJ jump, SI jump, and sprint) were underestimated (mean bias: -0.06 to -0.18 g). The chosen cut-off frequency potentially attenuated higher frequency characteristics within the accelerometer signal. That is, a higher cut-off frequency may be more appropriate for team sports that produce larger peak impacts on players (e.g., contact sports such as rugby). Quantifying workloads during larger impacts is important as they are often the most meaningful joints of data that come out of team sports. Future research should consider improving the measurement of team sport movements through extracting more sophisticated information from the accelerometer data. For example, whether combining peak accelerations with other features of the accelerometer signal (such as mean, minimum, and variance in amplitude [22]) increases the ability to measure and classify team sport movements. Research has begun to use such accelerometer data to automatically classify movements that impose larger peak impacts on the body, such as tackling [13, 18]. However, this ability to do so accurately whilst classifying other team sport movements has yet to be established. It may be possible not only to classify the number and intensity of movements performed in team sports using accelerometer data, but also the different types of movements performed.

The current study also confirmed that raw accelerometer data significantly overestimated MA data (mean bias 0.35 g). It appears that matrices derived from the raw accelerometer signal, such as the number of peak accelerations in specified impact zones (e.g., [22]), or through attenuation of accelerations over time (expressed as Player Load [3]), should be interpreted with caution. Filtering improved accelerometer validity, with the 12 Hz cut-off frequency displaying the best accuracy, precision, and relative error of all cut-offs assessed. In addition, the lowest (6 Hz) and highest (25 Hz) cut-offs appear unsuitable for use on any of the movements tested. These findings are in line with previous accelerometer validation research [13, 22, 34]. However, the choice of optimal cut-off frequency differed from previous and methodological differences between the current study and other assessments can explain this. For example, all previous work has focused on a single movement type and assessed only a limited number of cut-off frequencies. Additionally, a previous study used a three-point as a concurrent validity measure [36, 34] and employed a different accelerometer (SPI Pro, GPSports Pty Ltd, Australia). Further, previous work was representative of team sport movements (e.g., in one study all

![Image](image_url)

Table 1: Accelerometer data filtered at 12 Hz compared to MA data of 7 different team sport movements (n=16).

<table>
<thead>
<tr>
<th>Movement</th>
<th>Mean ± SD (g)</th>
<th>Mean Bias ± SD (g)</th>
<th>Cohen’s d</th>
<th>SRM (%)</th>
<th>RMSEP (g)</th>
<th>CV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJ jump</td>
<td>0.11 ± 0.18 gM</td>
<td>-0.15 ± 0.14 gM</td>
<td>-0.22</td>
<td>0.22</td>
<td>0.35</td>
<td>5.6</td>
</tr>
<tr>
<td>DJ</td>
<td>2.59 ± 0.96 gM</td>
<td>0.35 ± 0.17 gM</td>
<td>0.01</td>
<td>0.23</td>
<td>0.32</td>
<td>4.2</td>
</tr>
<tr>
<td>COG</td>
<td>0.31 ± 0.20 gM</td>
<td>0.18 ± 0.22 gM</td>
<td>0.42</td>
<td>0.32</td>
<td>0.27</td>
<td>6.2</td>
</tr>
<tr>
<td>SI jump</td>
<td>0.32 ± 0.40 gM</td>
<td>-0.05 ± 0.19 gM</td>
<td>0.08</td>
<td>0.31</td>
<td>0.31</td>
<td>5.1</td>
</tr>
<tr>
<td>Sprat</td>
<td>0.33 ± 0.21 gM</td>
<td>0.15 ± 0.26 gM</td>
<td>0.14</td>
<td>0.33</td>
<td>0.19</td>
<td>8.7</td>
</tr>
<tr>
<td>Yards</td>
<td>0.33 ± 0.17 gM</td>
<td>0.22 ± 0.17 gM</td>
<td>0.24</td>
<td>0.33</td>
<td>0.19</td>
<td>6.5</td>
</tr>
<tr>
<td>Tackle</td>
<td>0.33 ± 0.17 gM</td>
<td>-0.14 ± 0.22 gM</td>
<td>0.01</td>
<td>0.33</td>
<td>0.27</td>
<td>6.2</td>
</tr>
<tr>
<td>All (n=527)</td>
<td>0.33 ± 0.19 gM</td>
<td>-0.01 ± 0.27 gM</td>
<td>-0.01</td>
<td>0.33</td>
<td>0.35</td>
<td>5.6</td>
</tr>
</tbody>
</table>

* The mean difference is significant at the 0.05 level when compared to all other movements.

The mean difference is significant at the 0.05 level when compared to the DJ jump, DJ, COG, and Squat. The mean difference is significant at the 0.05 level when compared to the DJ jump, DJ, COG, and Squat. The mean difference is significant at the 0.05 level when compared to the DJ jump, DJ, COG, and Squat. The mean difference is significant at the 0.05 level when compared to the DJ jump, DJ, COG, and Squat. The mean difference is significant at the 0.05 level when compared to the DJ jump, DJ, COG, and Squat.
movements were performed on a treadmill [33], whereas this study was more generalized to sports movements performed during sports practice. As a result, the differences in movement patterns between the two studies might be attributed to differences in the testing environment.

Conclusion

The accelerometer combined with a wearable tracking device demonstrated an acceptable level of concurrent validity compared to an MA system when measured at a cut-off frequency of 12 Hz. This result advocates the use of accelerometers to measure peak impacts in team sports. Further, caution is advised when using raw accelerometers to derive impact data, with the output likely to overestimate movement intensity. Detailed analysis of accelerometer data may help practitioners better understand the demands of athletes engaged in team sports. Future research should consider the validity of accelerometers to identify and discriminate between team sport movements.

Acknowledgements

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Conflict of interests: The authors have no conflict of interest to declare.

References


21. Your Consent
You have been invited to take part in this research project, which involves participation in a simulated team sport circuit. This Plain Language Statement contains detailed information about the research project. Its purpose is to explain to you as openly and clearly as possible all the procedures involved in this project so that you can make a fully informed decision whether you are going to participate.
Please read this Plain Language Statement carefully. Feel free to ask questions about any information in the document. You may also wish to discuss the project with a relative or a friend. Feel free to do this.
Once you understand what the project is about you will be asked to sign the Consent Form. By signing the Consent Form, you indicate that you understand the information and that you give your consent to participate in the research project. You will be given a copy of the Plain Language Statement and Consent Form to keep as a record.

22. Purpose and Background
The application of accelerometry in sport is widely reported and continues to grow rapidly, as it provides an objective measure of accelerations associated with player movements in training and competitive game environments. However, research investigating the validity of these devices to measure team sport movements is scarce. The aim of this study is two-fold. Firstly, to identify how accurate an upper-body mounted accelerometer is to measure peak impact accelerations during sequential team sport movements. Secondly, to identify if the accelerometer can identify and discriminate between simulated team sport movements. The data recorded by the accelerometers will be compared statistically with acceleration measurements, collected using a calibrated multi camera Motion Analysis (MA) system, to establish the criterion validity of the accelerometer devices in team sports during both training and competition.

23. Procedures
Following consent to participate, you will be required to attend two testing sessions at Deakin University. You will complete 48 repetitions of a simulated team sport circuit in a controlled (indoor) environment on two occasions separated by one week. Each trial of the circuit will include (in order) a six meter walk, five meter jog, seven meter...
sprint, six changes of direction, three countermovement jumps, a three meter sprint and tackle of a tackle bag, a two meter walk, and a five meter jog back to the start. These movements have been selected to represent common player skills performed in team sports. To experience the requirements of the study you will be instructed through all movements and given as much time as required until you feel comfortable performing each task. Several practice repetitions of the circuit will be given prior to data collection.

You will be given one minute to complete the circuit, the quicker you perform the circuit, the more recovery time you will have prior to the next circuit (approximately 40 seconds to complete). You will be given an additional recovery period at the end of each six laps (referred to as one bout; with eight bouts to be performed in total). Familiarisation and testing will take approximately one hour and ten minutes to complete on both occasions.

While completing the circuit you will be required to wear a small matchbox, sized wearable tracking device, which will be securely attached to you in a custom-made harness on the upper-body. This will not interfere with your ability to move in any way, and is commonly used in elite team sports during training and competition. Peak impact accelerations will be collected concurrently from both accelerometers and several reflective markers located on and around the accelerometer, which the MA system will track and locate.

24. Possible Benefits

We cannot guarantee or promise that you will receive any benefits from this study. While you may not personally receive any benefits from this project, the findings will inform sports scientists and coaches of the actual accuracy of the data produced by these devices. This may then be used to better identify, discriminate between and quantify player movements/loads during competition and training.

25. Possible Risks

The risks to the participants from participating in the research are minimal. Possible muscle soreness and contusions from contact with the bag and ground may be expected. However, as this will be performed in a controlled setting and at a lower intensity the risk is deemed to be low, and less severe than those that occurring during normal training and competition practices. There are no other foreseen risks. You will be guided through an appropriate warm up and warm down to prevent the risk of any injuries occurring whilst completing the tasks. You are under no obligation to participate and if you give consent to participate in the study, you are free to withdraw at any time.

26. Privacy, Confidentiality and Disclosure of Information

All information provided will remain strictly confidential. Any identifying information, such as your name, and data, will be kept separately from the written copy of the results. These will be identified only by a number. All information will be stored at Deakin University in a locked filing cabinet and will be retained for a period of five years after publication. The information gathered during this study may be published in scientific literature and presented at conferences. However, only pooled anonymous data would be presented, with no information included that would allow any individual to be identified.

27. Participation is Voluntary

Participation in any research project is voluntary. If you do not wish to take part you are not obliged to. If you decide to take part and later change your mind, you are
free to withdraw from the project at any stage. Any information obtained from the participants to date will not be used.

28. Complaints
If you have any complaints about any aspect of the project, the way it is being conducted or any questions about your rights as a research participant, then you may contact:
The Manager, Research Integrity, Deakin University, 221 Burwood Highway, Burwood Victoria 3125, Telephone: 9251 7129, research-ethics@deakin.edu.au
Please quote project number [HEAG-H 135_2013].

29. Reimbursement for your costs
You will not be paid for your involvement in this project.

30. Further Information, Queries or Any Problems
If you request it, you may obtain a copy of the full results (average of group results) at the end of the study. If you require further information, wish to withdraw your participation or if you have any problems concerning this project, you can contact either of the principal researchers.

Principal Researchers
Dr Paul Gastin School of Exercise and Nutrition Sciences
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Daniel Wundersitz School of Exercise and Nutrition Sciences
Deakin University 221 Burwood Highway
Burwood VIC 3125 9244 5033
dwunder@deakin.edu.au
TO: Participants

Consent Form

Date:
Full Project Title: Validity of an upper-body mounted accelerometer to measure peak resultant acceleration during tackling and bumping tasks
Reference Number: HEAG-H 135_2013

I have read and I understand the attached Plain Language Statement.
I freely agree to participate in this project according to the conditions in the Plain Language Statement.
I freely agree to the collection of video data during my trials
I have been given a copy of the Plain Language Statement and Consent Form to keep.
The researcher has agreed not to reveal my identity and personal details, including where information about this project is published, or presented in any public form.
I would like to have the results sent to me at the end of the study  (Yes □ No □)
Participant’s Name (printed)

.................................................................

Signature ........................................................
Date...............................
PLAIN LANGUAGE STATEMENT AND CONSENT FORM

TO: Participants

Withdrawal of Consent Form

(To be used for participants who wish to withdraw from the project)

Date:

Full Project Title: Validity of an upper-body mounted accelerometer to measure peak resultant acceleration during tackling and bumping tasks

Reference Number: HEAG-H 135_2013

I hereby wish to WITHDRAW my consent to participate in the above research project and understand that such withdrawal WILL NOT jeopardise my relationship with Deakin University.

Participant’s Name (printed) …………………………………………………….

Signature ……………………………………………………… Date ……………

Please mail or fax this form to:

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School of Exercise and Nutrition Sciences
Deakin University
221 Burwood Highway
Burwood VIC 3125
Fax: 9244 6334
paul.gastin@deakin.edu.au
Appendix D

STUDY 4

Journal Article
Classification of team sport activities using a single wearable tracking device

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Classification of team sport activities using a single wearable tracking device

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ABSTRACT

Wearable tracking devices incorporating accelerometers and gyroscopes are increasingly being used for activity analysis in sports. However, minimal research exists relating to their ability to classify common activities. The purpose of this study was to determine whether data obtained from a single wearable tracking device can be used to classify team sport-related activities. Twenty-six non-elite sporting participants were tested during a simulated team sport trial (involving stationary, walking, jogging, running, changing direction, counter-movement jumping, jumping for distance and tackling activities) in a laboratory setting. A MinnMaxX 34 wearable tracking device was worn below the waist, in-line and dorsal to the left iliac trochanter ventral to the spine, with tri-axial accelerometer and gyroscope data collected at 100 Hz. Multiple-time domain, frequency domain and custom features were extracted from each sensor using 0.5, 10, and 15 s movement capture durations. Features were further screened using a combination of ANOVA and Lasso methods. Relevant features were used to classify the eight activities performed using the Random Forest (RF) Support Vector Machine (SVM) and Logistic Mixed Tree (LMT) algorithms. The LMT (79.82% classification accuracy) outperformed RF (72.42%) and SVM (70.63%) algorithms (77%–90%), obtaining stronger performance using the full model (accelerometer and gyroscope inputs). Processing time can be reduced through feature selection methods (up to 15–30%), however a trade-off exists between classification accuracy and processing time. Movement capture duration also had little impact on classification accuracy or processing time. In sporting scenarios where wearable tracking devices are employed, it is both possible and feasible to accurately classify team sport-related activities.

1. Introduction

Objective measurement of sports activities is essential for understanding the physical and technical demands related to sports performance (Agheby and Falconer, 2010). It is also important in evaluating the effectiveness of training programs designed to increase performance as well as those targeting both the prevention and rehabilitation of injury (Neville et al., 2010). Fundamental to furthering these understandings is the need to accurately collect specific information relating to the type, intensity and frequency of activities performed (Carril et al., 2008).

Consequently, attempts to improve the techniques related to activity analysis in sports have been made in recent years. At least partially responsible for these improvements are the considerable developments that have occurred in commercially available wearable tracking devices. Wearable tracking devices typically integrate multiple sensors (e.g., global positioning system (GPS), accelerometer and gyroscope) into a single, versatile unit worn on the upper back in a sports vest (Kelley et al., 2012). To date, the majority of research has focused on the GPS sensor contained within these devices to obtain basic descriptors of sports activities, such as speed, distance travelled, and the number of high-intensity efforts performed (Cunmin et al., 2013). However, evidence suggests that more detailed analysis can be obtained using the accelerometer sensor (Emmert et al., 2008). Specifically, different activity types can be classified based on the features of the accelerometer signal.


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McNamara et al. (2015) developed a bowling detection algorithm for cricket. The researchers found that the algorithm was able to classify cricket bowling more effectively in training than game-play, with a maximum accuracy of 88.4% (training). Kelly et al. (2012) applied support vector machine (SVM) and hidden conditional random field algorithms to automatically detect tackling in rugby. The algorithm was able to consistently classify collisions, with a maximum accuracy of 95%. Similarly, Gasin et al. (2013) assessed the concurrent validity of a manufacturer-developed tackle detection algorithm (Contact Sports), which was compared against video-report and coded into three intensity categories. The researchers found a maximum classification accuracy of 78%, with tackled players more accurately detected than the players initiating the tackle. However, during game-play the algorithm was only able to correctly detect tackles 8% of the time. Although these findings are promising, more sophisticated and generalizable sport and activity specific algorithms are required (Gasin et al., 2014).

Mitchell et al. (2013) recently proposed a method using a single accelerometer contained within a smartphone worn on the upper back, with the aim of identifying seven different sporting activities (stationary walking, jogging, skipping, hitting a ball, standing and tackling). An overall activity classification success rate of 73% was achieved using classification approaches that included SVM, Logistic Model Trees (LMT), and a range of Neural Network/Quinlan type classifiers. With the aim of achieving higher classification accuracy, multiple sensors (i.e., both accelerometer and gyroscope) have also been considered in the literature, rather than a single accelerometer sensor alone (e.g., Leathley et al., 2013; Ngah et al., 2008). Gyroscopes are sensitive to linear accelerations and gravity, and provide essential information pertaining to the rotational motions of the body during human activity (van Donkelaar et al., 2013). As a gyroscope sensor is typically contained within most wearable tracking devices, this would appear to be a feasible approach to aid in the ability to classify sporting activities.

Another important methodological consideration in the classification literature relates to the duration over which the activity is measured (movement capture duration) for a given classification algorithm (Trost et al., 2012). The optimal duration will ideally be long enough to capture the entire activity as it occurs, while also being short enough not to include any additional activities (Mitchell et al., 2013). Previous work classifying activity type has extracted features in accelerometer data from movement capture duration as short as 0.1 s (Balling et al., 2014) or as long as 60 s (Trost et al., 2012). In team sports, however, most activities (e.g., running, jumping, tackling etc.) can be performed over much shorter durations, for example, the lowest intensity movement (walking) occurs approximately 14–22 times per second (e.g., Peacock et al., 2014). Therefore, much shorter movement capture durations (e.g., 1.5 or 3 s) may be required to capture activities in team sports. Further, this may improve classification accuracy of these activities, as more periods are available for training (Mannini et al., 2013).

The aims of this study were threefold. First, to determine whether data obtained from wearable tracking device inputs (specifically, gyroscope and accelerometer sensors) alone or in combination can be used to classify team sport related activities. Second, to determine the ability of three classification algorithms (LMT, RF, SVM) and movement capture durations (0.5, 1.0 and 1.5 s) for feature extraction to classify activities in team sports. Third, to consider the processing time and data collection burden associated with these methods and identify the best option for practitioners.
improved overall classification performance (Witten and Frank 2005; Robertson et al., 2015). To classify the eight activities of interest, three classification algorithms (LMT, RF, and SVM) were employed. These were chosen for implementation based on their performance in the previous literature investigating similar problems. The LMT is a commonly used classification algorithm, which performs competitively with other machine learning classifiers and has the additional advantage of being easy to interpret (Kuncheva et al., 2003). It consists of two complementary classification techniques of tree induction and linear regression (Kohavi et al., 1996). Random forests is another classification algorithm, whose in-applications grows multiple classification trees and bases upon them until each tree is at its largest (Breiman, 2001). The mean classification performance of the tree is then taken, which further assists in promoting against model overfitting (Breiman, 2001). Overfitting refers to the development of a model so specific to a training set that the findings are not generalizable when validated on a new dataset of data (Robertson et al., 2015; Morgan et al., 2013). Additionally, RF is considered to have various useful features including high efficiency with large data sets and built-in ensemble classifiers (Breiman, 2001). Support Vector Machines differ slightly from the previous two algorithms in that it attempts to find the best separating vector between two groups within a set of descriptors (Scholkopf and Smola, 2000). In this study, a radial kernel was used and best gamma value (10^{-4}, 10^{-3} \text{...} 10^{0} ) values were tried (Morgan et al., 2014). For classification of data with two more than two groups (as seen here), the original problem is split into multiple binary problems which are then classified and compared. The problem remaining the most serious concern to the algorithm is the classifier. Readers interested in a more detailed explanation of these and other classifiers are directed towards the work of (Witten and Frank 2005). As both classification accuracy and processing time was assessed, the analysis was conducted in two phases. First the aim of phase one was to ascertain the data collection kernels to achieve the desired classification accuracy. Specifically, the accuracy of each classification algorithm was investigated in four different ways for
each of the three moment capture datasets. These were: (a) all features from accelerometer, resalient vector and gyroscope (RF), (b) only the accelerometer and resalient vector features (m=35), (c) only the accelerometer features (m=30), and (d) only the resalient vector features (m=25).

Two main points were made: feature selection methodology in three different ways for the full set of input (m=59) features (p<0.05), unless otherwise stated. Therefore, irrelevant features may introduce noise leading to a less accurate and more robust classifier. Moreover, the resalient vector scaling may be more difficult to implement and be more effective in reducing classifier overfitting. Furthermore, the resulting model may take longer to implement and be more difficult to interpret (Liu and Motoda, 2012). In addition to processing time, comparisons of accuracy across different feature selection methods (moment capture duration and classifier selection) were performed. These were: (a) all 59 features were used (RF), (b) only features with (p<0.05) for one-way analysis of variance (ANOVA) across classification groups were selected (Lai et al., 2013), (c) each feature was selected for all classifiers (RF), and (d) all features were (m=59) activity-specific classification accuracies on the basis of 10, 1.0 and 1.5 movement capture durations for all three moment capture durations, classification accuracy extended 90% Walking (96-99%) and stationary (95-98%) were best classified, whereas darting (86-91%) and running (89-95%) showed lower classification rates in the 1.0 (m=35) and 1.5 (m=35) movement capture durations. Differences in movement capture duration classification accuracy ranged from 0% (CCD) for (0.5 versus 1.5) and spring walk (0.5 versus 1.5) to 8% (run and jump) (1.0 versus 1.5).

4. Discussion

The results of this study demonstrate that accurate activity classification using accelerometer and gyroscope inputs is achievable in a team sport environment. Specifically, results showed that the highest performing algorithm for this purpose was LMT with an overall mean classification rate ranging from 93% to 95%. Further, the highest classification rate was achieved by combining all seven inputs from the accelerometer and gyroscope. Notably, the classification rate was substantially lower in the RF and SVM than those obtained using the LMT approach. The findings of the current study are somewhat comparable to previous accelerometer input classification work (Mitchell et al., 2013). Mitchell et al. (2013) found that LMT (74%) outperformed SVM (35%) for activity classification in football (soccer); however, no differences were noted between classifiers when field hockey-specific activities were performed. Similar classification performance with the current study was found when multiple classifiers were compared. The stronger individual classifier results in the current study may be due to differences in experimental methodology. Specifically, Mitchell et al. (2013) did not assess gyroscope inputs, used lower frequency sampled accelerometer data (6-25 Hz), and also assessed activities such as dribbling (soccer) and hitting (field hockey) that were not assessed in this study. As the higher sample rate in the current study (400 Hz) may have contributed to the increased classification performance, it may be that further increases in sample rate (> 100 Hz) could aid classification performance. However, this may have a negative effect on processing time.

When all seven accelerometers and gyroscope inputs were combined, higher rates of activity classification were achieved (e.g. mean classification accuracy of 92%). This was not surprising however; given that there was more information available for algorithm training. For example, previous research has shown that by combining both accelerometer and gyroscope inputs the classification rate increases during daily living and tennis-specific activities can be improved by as much as 14% (Bulling et al., 2014). Interestingly, classification performance was only improved by 2-3% when the three gyroscope inputs were included with accelerometer inputs.
Table 2

Accuracy (Mean ± SD) and processing time (s) of classifiers and model selection variations for the movement capture dataset after 10-fold leave-one-out cross-validation. All comparisons are from accelerometer, gyroscope vector and gyroscope inputs (m = 39, m = 42, m = 50) of differing feature selection methodologies.

<table>
<thead>
<tr>
<th>Feature Selection</th>
<th>Classifier</th>
<th>Movement capture duration (0.5, 1.0, 1.5 s)</th>
<th>Processing time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.5 [185.3]</td>
<td>1.0 [181.6]</td>
</tr>
<tr>
<td>Full model (m = 39)</td>
<td>SVM</td>
<td>0.39 ± 0.04 (15)</td>
<td>0.62 ± 0.02 (16)</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.27 ± 0.03 (12)</td>
<td>0.60 ± 0.05 (19)</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.43 ± 0.03 (10)</td>
<td>0.55 ± 0.04 (10)</td>
</tr>
<tr>
<td>ANOVA (m = 42)</td>
<td>SVM</td>
<td>0.43 ± 0.03 (10)</td>
<td>0.55 ± 0.04 (10)</td>
</tr>
<tr>
<td></td>
<td>LMT</td>
<td>0.43 ± 0.03 (9)</td>
<td>0.55 ± 0.04 (10)</td>
</tr>
<tr>
<td></td>
<td>SVM</td>
<td>0.43 ± 0.03 (10)</td>
<td>0.55 ± 0.04 (10)</td>
</tr>
<tr>
<td>ANOVA and Lasso (m = 37-38)</td>
<td>SVM</td>
<td>0.43 ± 0.03 (10)</td>
<td>0.55 ± 0.04 (10)</td>
</tr>
</tbody>
</table>

ANOVA, Logistic Model Tree, m, total number of observations, n, number of inputs, K, number of bins, SD, standard deviation, SVM, Support Vector Machines. Note that features were reduced in 37 (0.5 s movement capture duration) and 38 (1.0 and 1.5 s movement capture duration) using a combination of ANOVA and lasso regression.

In the current study, this sensor contributed less to activity classification in these contexts (e.g., 8-10% decrease in classification accuracy compared to accelerometer inputs). This study made one of the first attempts to evaluate the effect of gyroscope inputs alone in classifying sporting activities. Generally, lower rates of activity classification for the gyroscope inputs may be due to the upper body being predominantly exposed to linear motions, as compared to rotational motion that a gyroscope measures (Anil & Najafl, 2004). Gyroscopes placed on the shoulders (e.g., wrist and ankle) may be more reliable than classification, as limb motion is essentially a rotation around the corresponding joint (Kurz et al., 2010). Therefore, consideration of the location of the device and the activities performed in sports may be important in deciding on the number of inputs included in future classification assessments. Furthermore, no study has assessed the validity and reliability of the gyroscope contained within a wearable tracking device, whereas a number of studies have been published in regards to the accelerometer (e.g., Wundersitz et al., 2015a; Boyd et al., 2011).

This investigation also analysed how movement capture durations of 0.5, 1.0 and 1.5 s affect the classification accuracy across different input and activity variations. There was no clear influence of movement capture duration on classification accuracy. Comparably, Filling et al. (2014) assessed durations ranging from 0.1 to 9.0 s during daily living and sports-specific activities. The researchers found classification accuracy peaked at 1.0 s and dramatically decreased thereafter. Mitchell et al. (2015) also assessed durations from 10 to 60 s and found classification accuracy was maintained for all movement capture durations during field hockey, however soccer-based activity classification accuracy decreased past 3.0 s. Larger movement capture durations have also been used in lifestyle activity classification settings (e.g., Manini et al., 2013; Pinkiet et al., 2016), and it has been shown that the frequency of sporting activities may result in two or more activities occurring in longer movement capture durations (e.g., greater than 1.0 s), dramatically increasing classification difficulty (Mitchell et al., 2013; Manini et al., 2013). Team sport activities, therefore, may benefit from shorter movement capture durations than are typically employed in the lifestyle activity classification literature. It should also be acknowledged that inter- and intra-participant variations and set movement capture durations as used in the current study may have contributed to the lower than expected classification rates. Future work may consider alternative approaches, such as a sliding window approach, where a capture duration with a time length of 7 s is slid across the data and if an activity is detected within the window it is flagged.

A further practical consideration relates to the effect different model selection variations had on processing time and classification accuracy. The number of features included in the analysis (range 37 to 50) tended to improve classification accuracy, but this was generally at the cost of increased processing time. The classifier chosen also appeared to affect this relationship. For example, the processing burden was shortest for SVM (1.3 to 1.6 s) and longest for LMT (14.3 to 16.0 s), with the LMT falling in the middle (12.5 to 16.7 s). However, movement capture duration had minimal impact on processing time in the current study.

Removing low-level contributing features from the training process can have a positive effect on classification performance, with ANOVA feature selection reducing processing time by approximately 15%. For reduced processing time, using ANOVA or...
ANOVA and Lasso feature selection, the classification accuracy only decreased by 0.5 and 4% respectively. Such a model would require approximately 2.5 s of time for feature extraction to occur and a further 45-54 s for classification of the activities performed using LMT. Comparable results are reported in literature with much larger volumes of data accumulation and smaller number of classification groups. Hartman et al. (2012) using accelerometers and GPS data, gathered over 750,000 measurements and achieved accuracy of over 84% for RF and SVM classifiers. Lehto et al. (2012) also using a large dataset and pre-clustering of the activities, achieved an accuracy of 87% for SVM method. Mitchell et al. (2013) reported a similar trend in classification accuracy with a LMT method, on a much smaller dataset. To this end, the similar between classification rates to previous studies using a reduced number of measurement features is encouraging. This is especially important where real-time classification (e.g. during training and gameplay) may be a future aim. Based on these findings, presently the LMT algorithm combined with accelerometer input alone provided the best trade-off between classification accuracy and processing time for use in this context.

In conclusion, a new classification algorithm, movement capture durations and feature selection methods were compared to determine the most parsimonious approach to classify multiple simulated team sport related activities. The LMT was shown to be highly accurate using data obtained from a single accelerometer and gyroscope sensor contained within wearable tracking device technology. Consequently, in sporting scenarios where wearable tracking devices are employed, it is both possible and feasible to use accelerometer and gyroscope data to accurately classify sporting activities. Further, the processing time can be reduced through feature selection models, however a trade-off exists between classification accuracy and processing time. With this in mind, accelerometer inputs alone appear to be the most parsimonious approach from this location. Further development and validation of algorithms in sports is required. Once developed, the ability of these algorithms to classify team sport activities during gameplay should be performed. Further exploration of accelerometer and gyroscope features, and feature reduction is needed to provide real-time classifications in the future.

Conflict of interest statement
None of the authors have financial or other conflicts of interest in regards to this research.

Uncited reference
Huddle et al. (2007).

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None.

References