This is a post-peer-review, pre-copyedit version of an article published in Sports Medicine. The final authenticated version is available online at: http://dx.doi.org/10.1007/s40279-015-0332-9

Running Title: Microsensors and sport-specific movements

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

Ryan Chambers[1,2], Tim J. Gabbett[2,3], Michael H. Cole[2], and Adam Beard[1,4]

1. Welsh Rugby Union, Westgate Street, Cardiff, Wales.
2. School of Exercise Science, Australian Catholic University, Brisbane, Queensland, Australia.
3. School of Human Movement Studies, The University of Queensland, Brisbane, Queensland, Australia.
4. University of Lausanne, Lausanne, Switzerland.

Address correspondence to:
Dr. Tim Gabbett
School of Exercise Science
Australian Catholic University
1100 Nudgee Road
Brisbane, 4014 AUSTRALIA
Email: tim_gabbett@yahoo.com.au

Key Points

Microsensors (accelerometers, gyroscopes and magnetometers) can be effectively used to detect movements that are specific to many individual and team sports, however there are a number of important limitations of current research.

Current research limitations include detailing microsensor manufacturer and devices used as well as sample rate when detecting sport-specific movements.

Detection of sport-specific movements using microsensors potentially provides coaches with an alternate perspective of non-locomotor activities.

Abstract

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

Objective. To determine the extent to which, microsensors (also referred to as inertial measurement units and microelectromechanical sensors) have been utilised in quantifying sport-specific movements.

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

Results. A total of 2,395 studies were initially retrieved from the six databases and 737 results were removed as they were duplicates, review articles or conference abstracts. After screening titles and abstracts of the remaining papers, the full text of 47 papers was reviewed, resulting in the inclusion of 28 articles that met the set criteria around the application of microsensors for detecting sport-specific movements. Eight articles addressed the use of microsensors within individual sports, team sport provided seven results, water sports provided eight articles, and five articles addressed the use of microsensors in snow sports. All articles provided evidence of the ability of microsensors to detect sport-specific movements. Results demonstrated varying purposes for the use of microsensors, encompassing the detection of movement and movement frequency, the identification of movement errors and the assessment of forces during collisions.

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

1. Introduction

The use of global positioning system (GPS) devices has become an integral part of sporting performance analysis, allowing coaches and support staff to understand the physical demands on team sport athletes. Commercially-available microtechnology units have been used extensively to describe the physical movement demands of Rugby Union [1], Rugby League [2], Australian Rules football [3,4] and several other team sports [5]. Such studies have described the distance, intensity and frequency of various match-play demands; this information is subsequently used to assist in the physical preparation of athletes and the prevention of negative consequences that might be associated with excessive or inappropriate training loads [6]. Most commercially-available microtechnology units contain microsensors that include the use of accelerometers, gyroscopes and magnetometers with some commercially-available inertial measurement units (IMUs), such as microelectromechanical sensors (MEMS) containing one or a combination of these sensors. Most commercially-available GPS devices now contain IMUs, which are housed in a small case then worn in a small purpose-built pocket or strapped to the athlete during training and competition. These devices, commonly referred to as wearable sensors, facilitate real-time detailed movement analysis and provide an alternative to labour-intensive video coding [1,5,7]. As previously noted, many researchers have used GPS to quantify the physical demands of sport [5] with some also using accelerometers to identify activity profiles [4,8-10], although few have used this technology to identify sport-specific movements. Recent research has utilised this technology to assess running gait [11] and other continuous movements, but such movements are not sport-specific.

Several studies have described the use of accelerometers to detect the physical activities and movement patterns of the general population [12]. Other types of accelerometers, such as actigraph technology have been used to detect movement and sleep patterns of the general population, by assessing the displacement of the accelerometer to determine stages of sleep and daily activity [13]. Given that sensors can have a sample rate of up to 500 Hz [4,8-11,14] and can measure occurrence and magnitude of movement in three dimensions (anterior-posterior, medial-lateral and vertical) [4], such IMUs have been applied in elite sporting populations to further understand movement demands, particularly in indoor sports, where GPS signal is unavailable.

Some sporting microtechnology companies have attempted to describe the "workload" exerted by the athlete by quantifying the sum of the individual tri-axial accelerometer vectors. Various "workload" terminologies exist in these commercially-available software programs, including 'Player Load' (Catapult Sports, Melbourne, Victoria,) and 'Body Load' (GPSports Systems, Canberra, Australian Capital Territory, Australia). The 'Player Load' that is calculated using the Catapult Sports equipment is an arbitrary unit defined as an 'instantaneous rate of change of acceleration divided by a scaling factor' (Figure 1) utilising the highly responsive accelerometers within the three planes of movement to quantify movement intensity [4]. Similarly, the 'Body Load' measure, as implemented by GPSports Systems is described as an 'arbitrary measure of the total external mechanical stress as a result of accelerations, decelerations, changes of direction and impacts' [14] and is calculated from the square root of the sum of the squared instantaneous rate of change in acceleration in the vertical, anterior-posterior and medial-lateral vectors. Athlete demands can be quantified by the aforementioned workload terminologies by applying formulas to inertial data [4], providing a different perspective to that of other technologies such as GPS [5].

INSERT FIGURE 1.

Physical activity has been measured by MinimaxX units (Catapult Sports, Melbourne, Victoria, Australia) using 'Player Load' to describe the physical demands of sports such as Australian Rules football [4], Basketball [8], and Netball [9, 10]. Boyd et al. [4] found that the accelerometers offered good reliability in quantifying the low and high intensity components of Australian Rules football activity and that the technology could be confidently applied to assess changes over multiple time periods or to assess differences between players. Boyd et al. [4] also found strong relationships between MinimaxX devices (r=0.996-0.999) for high intensity activity, although it was acknowledged that current practice fails to account for skill-based and contact-based activities (passing, jumping, kicking, marking, tackling and blocking). These findings indicate that the overall physical activity of Australian Rules football players may be underestimated, highlighting the potential for these devices to quantify additional movements other than locomotion.

Similarly, Rugby League researchers have quantified the relationship between measures of internal (heart rate and perceived exertion) and external (high-speed distance, 'Body Load' and impacts) loads associated with training [14]. The authors found that the internal and external load measurements provided useful methods of quantifying various training modalities, with impacts and 'Body Load' contributing the highest loadings for skill sessions. However, it was also stated that further investigation was required to examine the derived measures of 'Body Load' and impacts using GPSports microsensors, as training demands may be underestimated using current methods.

Microsensors have the capability to automatically detect various movements and intensities [15]. Bonomi and colleagues [15] found that activities ranging from lying, sitting, standing, dynamic standing, cycling, walking and running could be detected using algorithms and decision trees. Using data from a tri-axial accelerometer, activities were categorised by the dominance in intensity of accelerations occurring along a particular axis. For example, accelerations that were predominantly medial-laterally directed were primarily used to categorise lying, sitting and standing. Intensity was also categorised by quantifying the speed of movement and the resultant accelerometer traces that were produced.

Movements such as jumping have also been assessed using accelerometers [16]. Previous research [16] has validated the use of accelerometers against a Myotest force platform

(Myotest SA, Sion, Valais, Switzerland). The accuracy of the accelerometers were measured against the force platform with participants wearing a microsensor on their hip and measuring vertical force and power as well as leg stiffness and the reactivity index. Results of a five hop protocol, countermovement jump and squat jump demonstrated a high degree of reliability for the accelerometer system in comparison to the force platform (coefficient of variation <10%) [16].

Specific skill-based activities and movements can distinguish the physical demands of one sport from another. Currently there are relatively few studies that have assessed the reliability and validity of inertial sensor technology for detecting and assessing sport-specific skills. To date, current research [5] has demonstrated that it is feasible to use microsensors to quantify work rate patterns and metabolic differences between athletes. However, this research has been heavily dependent on the use of wearable GPS devices to evaluate the locomotor demands associated with specific contact and non-contact sports (see Cummins et al. [5] for a review). Given that a large number of sports include physically-demanding activities that involve few locomotor demands (e.g. volleyball jumping, Rugby Union tackling, and soccer goalkeeping), it is likely that research that has focussed solely on characterising the locomotor demands of team sport [5] has underestimated the 'true' physical demands of the sport. As such, sport scientists now employ wearable sensors to identify sport-specific movements and activities in an effort to better evaluate the demands of a sport and to assist with physical preparation, injury prevention, and technical analysis of these activities. The aim of this review was to provide an overview of the use of microsensor technology, such as accelerometers, gyroscopes and magnetometers to detect non-locomotor activities that are specific to a particular sport.

2. Methods

2.1 Literature Search Strategy

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

2.2 Selection Criteria

The process used for selecting articles is outlined in Figure 2. Duplicate articles were eliminated from the initial search results and the titles and abstracts of remaining articles were then independently reviewed by three assessors (RC, TJG and MHC) for relevance to the review. For the purpose of the review, articles included were required to have used wearable sensors to detect and assess a skill or movement that was specific to a sport (e.g. throwing, tackling, tennis strokes). As such, articles that attempted to categorise activity (e.g. running intensities) of athletes using microsensors or that solely attached microsensors to equipment were excluded. Other criteria for exclusion from this research consisted of review articles, abstracts and studies that used accelerometers to assess movements that are generic to many activities (e.g. running gait). Any disagreements between the three independent reviewers were discussed and resolved. Once articles were selected, the complete manuscript was assessed for inclusion using the same criteria. The references of the selected articles were then scanned to detect any potentially relevant articles not identified by the original search.

3. Results

A total of 2,395 studies were initially retrieved from the six databases, of which 441 were duplicates, 293 were conference abstracts and three were review articles, leaving 1,658 unique research articles. After screening the titles and abstracts of these papers, 1,611 were excluded and 47 remained for full-text review. After full-text review, a further 19 were removed (Figure 2). Therefore, 28 articles remained for inclusion in this review. Eight articles addressed the use of microsensors in individual sports [17-24] including tennis (n=2), track and field (n=2), golf (n=2) trampolining (n=1) and weightlifting (n=1) (Table 1). Seven articles addressed the use of microsensors in team sports [25-31], which incorporated baseball (n=2), Australian Rules football (n=2), Rugby League (n=1), Rugby Union (n=1) and cricket (n=1) (Table 2). Eight used microsensors in water sports [32-39], reporting on detection of various technical elements of swimming (Table 3) and five used microsensors in snow sports [40-44] involving ski jumping (n=2), alpine skiing (n=1), snowboarding (n=1) and cross country skiing (n=1) (Table 4). The manufacturer of microsensors differed between studies although 'MinimaxX' device was the most common (n=7) followed by the 'Physilog inertial measurement unit' (BioAGM, La Tour de Peilz, Vaud, Switzerland) (n=5). Studies used microsensors either to detect sport-specific movements (n=19), analyse sport-specific movement (n=8) or detect and analyse movement (n=1). Sampling frequencies of the devices used ranged from 30 Hz to 500 Hz, although some articles did not report the type or sampling frequency of the sensors used [21,25,39]. Articles varied with respect to the number and type of sensors used, although the selection of the equipment for each study was specific to the research question being addressed and the movement being analysed.

INSERT FIGURE 2.

INSERT TABLES 1 - 4

4. Discussion

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

4.1 The Use of Microsensors to Detect Movements in Individual Sports

Microsensors have had varied uses for detection of specific movements within individual sports. The use of IMUs in tennis has shown that these sensors are capable of detecting specific strokes during training and competition [18,19]. Connaghan et al. [19] used TennisSense devices (based on Tyndall's 25mm Mote platform, Cork, Munster, Ireland) containing accelerometers, gyroscopes and magnetometers, placed on the arm to detect different strokes (serve, forehand and backhand) and non-stroke events. Accelerometer magnitude was used to determine a stroke event, while the addition of gyroscopes and magnetometers improved stroke detection to within 90% accuracy (the use of gyroscopes and magnetometers alone resulted in 88% accuracy of stroke detection). Although Connaghan et al. [19] discussed the use of accelerometer magnitude to identify strokes, no information was provided on the role the magnetometers and gyroscopes played within the stroke detection model. Ahmadi and colleagues [18] found a significant correlation between gyroscope sensors and markers positioned on the arm, hand and chest for detecting serving trends in tennis, accelerometers were located within the device used but it is not revealed as to why these sensors did not contribute to the research. However, as only slow motion serves (not game speed) were performed, it is unclear whether inertial sensors could accurately detect power serves. Ghasemzadeh et al. [21] provided a similar analysis by detecting wrist-rotation errors in golf using microsensors, although the specific nature of the devices used was not reported. Using five microsensors (three located on the participant and two on the club) that were sampling at 30 Hz, Ghasemzadeh et al. [21] created a model to provide feedback based on inertial detection of the different phases of the golf swing. Half the trials performed by the four subjects were used to create the model; the other half was used to test how well the model could detect the movement (i.e. the sensitivity of the model). The model could successfully determine wrist angle during the golf swing and provide feedback on the length of back swing, swing plane and club head speed, although the low sampling frequency of the microsensors may have impaired the detection accuracy of high-frequency events, such as ball impact. A limitation of this study, however, was that the playing ability of the participating subjects was unclear and the framework used to identify the "correct" technique was also not reported.

Adelsberger and Tröster [17] conducted the only research in weightlifting using IMUs to detect completed 'thruster' movements and exhaustion, using three microsensors placed on the ankle, lower back and wrist (although the ankle data was subsequently deemed irrelevant and excluded). Using 75% of the data from the completed 'thruster' movements, Adelsberger and Tröster [17] created an algorithm within a support vector machine to automatically detect successful 'thruster' movements. The remaining 25% of the trials were then used to test the algorithm's accuracy for detecting successful 'thruster' movements. The reliability of the detection algorithm was reported to be greater than 93%, which demonstrated the suitability of microsensors for detecting and assessing weightlifting movements, although the unused sensor at the ankle could have been relocated to another limb, potentially providing greater detection accuracy of movements.

Similarly, Lee et al. [24] used IMUs containing accelerometers, gyroscopes and magnetometers to detect legal and illegal movements in seven race walkers, positioning a single device on the lower back of participants. Compared to high-speed camera footage, the IMU devices were able to detect illegal walking technique in 91% of the gait cycle data collected, providing support for the use of microsensors to assist coaches and judges with providing feedback on performance. Nevertheless, despite the high detection accuracy demonstrated for race walkers, the speed of the walkers was not reported by the authors. As such, it is difficult to confirm the suitability of these devices during competition scenarios.

Helten et al. [22] advanced the use of sport-specific movement detection by using a series of seven MTx IMU devices (Xsens, Enschede, Twents, Netherlands), which incorporate accelerometers, gyroscopes and magnetometers to classify different trampoline jumps. Movements were automatically divided into segments based on the inclination of a limb, enclosed angles between limbs and the angular velocities of the sensors during the routines. Similarly, Ganter et al. [20] assessed a former decathlete performing a discus throw using a suit that was fitted with 17 IMU devices. Synthesis of the data from the 17 independent devices allowed the authors to calculate kinematic variables, such as joint angles and velocities for 22 joints during the performance and detect phases of the throw solely using IMUs. Ganter et al. [20] suggested that IMUs can easily provide feedback for athletes that video-based systems cannot (e.g. determining the velocity of the throwing arm during the discus throw would be labour-intensive when using video-based systems). Collectively, these studies suggest that IMU devices, which incorporate accelerometers, gyroscopes and magnetometers, can be used for the detection of movements and error, as well as the provision of feedback in individual sports.

4.2 The Use of Microsensors to Detect Movements in Team Sports

Accelerometers, gyroscopes and magnetometers have been used in team sports to detect sport-specific movements and to provide feedback on performance. Ghasemzadeh and Jafari [25] evaluated the baseball swing using three sensor nodes placed on the chest, wrist, and hip, but the specific sensor type(s) used was not reported in their article. Nevertheless, the authors initially used twenty-two trials to develop and refine a signal processing model and a further thirty-eight trials were used to validate the accuracy of the model. Data was passed through a five point filtering system to reduce high frequency noise and used to discriminate between 'a swing with proper sequence and timing of motions' and 'a bad swing with improper sequencing of key events'. Although the researchers suggested that this novel method could be used to train a player in baseball, it should be noted that the three participants used had 'no previous swing training' and no elite athletes were used. The demands of baseball were further examined by Koda et al. [29] who investigated the throwing motion using two accelerometer and gyroscopic sensors mounted on the upper and lower arm. Five participants, who included two former professionals, performed several throwing motions. Although the main objective of this research was to analyse the biomechanics of the baseball throw (trajectories of acceleration and angular velocity) this could only be done once the accelerometer and gyroscopic sensors had detected the throw. Therefore, the authors primarily discuss the biomechanical analysis of the throw rather than the reliability of throw detection.

Researchers have also used one MinimaxX S4 device containing an accelerometer, magnetometer and gyroscope in cricket to detect fast-bowling events [31]. Highly skilled fast bowlers performed bowling and non-bowling events during training and competition to validate an algorithm capable of differentiating between bowling and non-bowling events. The algorithm demonstrated 99.0% sensitivity and 98.1% specificity with respect to correctly identifying bowling events during training, but the performance of the algorithm during competition was somewhat reduced (99.5% sensitivity, 74.0% specificity). McNamara et al. [31] suggested that the low specificity during competition could be due to players bowling the ball back to a bowler even when they were not the designated bowler.

Collision sports such as Rugby League [26], Rugby Union [30] and Australian Rules football [27,28] have used commercially-available microsensors to automatically detect the non-running demands of their respective sports. Gabbett et al. [26] used MinimaxX S4 devices to automatically detect collisions in elite Rugby League. To achieve this goal, the authors developed an algorithm that relied on gyroscopic data to recognise when the unit was in a non-vertical position and accelerometer data to identify a spike in 'Player Load'. Collision data were then classified as mild, moderate or heavy depending on the magnitude of the spike in 'Player Load'. All collision events recorded by the MinimaxX S4 device were compared against video notational analysis. Of the 237 events recorded, significant correlations were found between video and automatically-detected events for mild (r=0.89), moderate (r=0.97) and heavy (0.99) collisions. Researchers in Rugby Union [30] used an SPI Pro device (GPSports Systems, Canberra, Australian Capital Territory, Australia) to detect collisions. These researchers used a training set of physical 'contacts' and applied a mathematical learning grid (learning grids were established to classify specific accelerometer data signals of tackle and non-tackle events to create algorithms) and static window features (static window was determined as 128 frames either side of peak detection of collision using accelerometry data). The SPI Pro device used in this research [30] only contains accelerometers, demonstrating that a single inertial sensor is sufficient to detect collisions in Rugby Union, although it is possible that had gyroscopes and magnetometers been used, the authors may have found greater specificity for collision detection (e.g. tackles, scrums, rucks and mauls). Using MinimaxX S4 units, Gastin et al. [27] used the formula proposed by Gabbett et al. [26] to quantify tackle demands in Australian Rules football. Three hundred and fifty-two tackles were recorded, comprising 173 tackles made and 179 tackles against. Of these recorded tackles, most were classified as medium intensity tackles (61%) while 33% were low intensity tackles and 6% were high intensity collisions. In a subsequent investigation, Gastin et al. [28] scrutinised the effectiveness of MinimaxX S4 devices when analysing 'observed tackles versus the MinimaxX device' and 'MinimaxX device versus observed play events' during four Australian Rules football matches. Observed tackles were detected with 78% accuracy by the MinimaxX device, accurately recording 66% of tackles made and 90% of tackles against. However, when the 1,578 "tackle events" recorded by the MinimaxX S4 device was compared against the observed play events, only 18% were correctly identified as tackles, while 82% were incorrectly identified. Movements such as ruck contests, smothering, and shoulder bumps comprised 57% of the incorrectly identified movements, whereas the remaining 25% involved no evident contact or collision. A possible reason for this high percentage of incorrectly identified events in this study is that the algorithm that was used to identify the collision events was specifically produced for Rugby League [26]. Compared to Australian Rules football, the collisions associated with Rugby League tackles are likely to be different to those experienced in Australian Rules football due to opposing teams 'facing off' rather than playing 'man-on-man'. As such, while the ability to distinguish non-contact events from contact events is of great significance in a wide variety of sports, it seems that it may be important for researchers to develop algorithms that are specific to each sport. Given the contrasting results [26,28], clearly further research is required to validate the ability of IMUs to distinguish tackles in collision sports from other contact events such as the ruck, maul and scrum in Rugby Union.

4.3 The Use of Microsensors to Detect Movements in Water Sports

Eight of the twenty-eight studies focused on the use of microsensors to detect movements in swimming. A single accelerometer placed on the head of the swimmer, has been shown to provide reliable accuracy of stroke and turn detection [38]. Detection of turns demonstrated a classification rate of 99.8%, whereas detection of all four main swimming strokes (butterfly, backstroke, breaststroke and freestyle) returned classification results of 95%, although some misclassification was acknowledged between breaststroke and butterfly styles due to similar head movements and positioning of the unit. Beanland et al. [32] applied accelerometer trace data gathered by MinimaxX S4 devices located on the head of swimmers to determine valid automated stroke detection of butterfly (r=1.00) and breaststroke (r=0.99). Quantification of freestyle swimming has also been carried out by Dadashi et al. [33,34], Fulton et al. [35,36], and James et al. [37]. Fulton et al. [35] used gyroscope data obtained from sensors located on each thigh and shank of Paralympic swimmers to detect a valid and reliable form of kick count and kick rate, enabling quantification of the demands of freestyle. Data collected from gyroscope traces located on the shanks were strongly correlated with under water video of swimming trials [35]. James et al. [37] also applied IMUs to understand the demands of freestyle by positioning units on the forearm, trunk and leg. Accelerometer data from the arm provided detection of hand entry, glide, and the catch and recovery phases of freestyle swimming.

Dadashi et al. [33] found that accelerometers encased in Physilog IMUs were accurate for measurement of swimmers' speed when compared with a commercially-available tether. Stamm et al. [39] demonstrated similar capabilities of microsensors for detecting the velocity of push-offs, by positioning a single IMU on the participants' lumbar spine, although the specific sensor was not reported. Research conducted by Dadashi et al. [33] and Stamm et al. [39] reported valid and reliable methods of velocity measurements derived from data collected using microsensors when located on lumbar spine. These findings demonstrate that microsensors provide novel methods of measuring stroke and kick detection, allowing practitioners to quantify stroke and kick rate, and velocity of push-offs in swimming.

4.4 The Use of Microsensors to Detect Movements in Snow Sports

Snow sports accounted for 18% (5 of 28 articles) of the research included within this systematic review. Chardonnens et al., [40] applied Physilog IMUs to detect crossover and crossunder turn events in Alpine skiing, providing feedback on acceleration and angular velocity of the detected incidents. Accelerometers and gyroscopes, encased within Physilog IMUs, were applied in ski jumping and were able to detect temporal patterns of jumps from kinematic signals [41]. The microsensors were able to automatically-detect temporal phases and durations of ski jump sequences of both indoor training sessions and outdoor conditions. Physilog IMUs have also been used to characterise lower-limb coordination during ski jumps [42], by determining the relationship between the position of the shank-thigh and thigh-sacrum segments during take-off. The biomechanical analysis of raw data detected from the IMUs placed on the sacrum and the thigh demonstrated that the movements of these segments during take-off were significantly correlated with the length of the jump [42].

Aerial acrobatics of snowboarders were evaluated using accelerometer and gyroscopic data obtained from a MinimaxX S4 device [43]. Mathematically-derived algorithms derived from these data were able to detect the amount of air-time using gyroscopic data, which determined the magnitude of rotation for the participants. However, it was reported that acrobatics that involved rotations greater than 720 degrees were often incorrectly classified when compared to video analysis. The authors suggested that wearable sensors provided a novel method for coaches and judges to objectively evaluate a snowboarder's acrobatics when the skill that is being assessed involved rotations of 540 degrees or below. These findings are important, as snowboarders are assessed on their performance of these skills in competition, yet they are difficult to assess with the naked eye. Nevertheless, it is important to note that the research conducted by Harding et al. [43] predominantly used data from one axis that only provided detail on flat spins and rotations and not acrobatic activities that included inversion movements. Given that the authors used a MinimaxX S4 device, which contains a three-dimensional accelerometer, gyroscope and magnetometer, it is reasonable to suggest that the data they collected could also be used to provide feedback on inversion movements and acrobatics.

Marsland et al. [44] applied a MinimaxX S4 device containing a three-dimensional accelerometer, gyroscope and magnetometer to identify cross-country skiing movement patterns. Cyclical ski patterns, and kicking and skating actions on each side of the body were clearly identified by single sensors. Collectively, these results suggest that microsensors, coupled with sophisticated algorithms, can be used to detect movements in snow sports.

4.5. Directions for Future Research

The reviewed research demonstrates the ability of microsensors to accurately detect sport-specific movements in a wide range of environments. The specific aim of the research (e.g. to identify correct or incorrect technique or further understand the demands of a sport), will dictate the potential number of sensors used and their application for practitioners. The majority of team sports use single sensors to quantify the running demands placed on athletes during training and competition. As such, further research is required to determine whether movement patterns can be accurately detected during competitive games using a single sensor or whether multiple sensors would be required. This is particularly important in collision sports, given the conflicting results [26,28] reported in this systematic review. Multiple sensors also provide a unique approach to biomechanical performance analysis of movements as demonstrated by research conducted within individual sports by not only detecting movements but detecting errors.

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

5. Conclusion

This paper provides a comprehensive review of the ability of microsensors to detect sport-specific movements. The present results demonstrate that commercially-available microsensors have great potential to detect sport-specific movements and are capable of quantifying sporting demands that other monitoring technologies may not detect. Furthermore, multiple sensor models have the ability to provide researchers with a tool to understand specific movements in greater detail and provide coaches or judges with feedback on correct and incorrect techniques.

Acknowledgements

No funding was received for the conduct of this study and preparation of the manuscript. The authors have no conflicts of interest that are relevant to the content of this review.

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Table 1. Summary of results from studies investigating sport-specific movements using wearable sensors within individual sports.

Study	Sport and sport-specific movement	Sample	Microsensor used	Method	Findings
Adelsberger and Tröster [17]	Weightlifting, "thruster" movement	Sixteen athletes participated (four female and twelve male), experience levels were assigned and ranged from beginner to expert	ETHOS IMU (Zurich, Zurich, Switzerland)	Each athlete equipped with three sensor devices: left ankle, lower back and left wrist. Athletes performed three sets of "thruster" movements, first two sets at a freely chosen weight, the final set consisted of three repetitions of maximum weight. Final set used to provide some data for exhaustion detection.	Algorithm designed to classify "thruster" movements. System found to have an accuracy of 94% when differentiating experts and beginners based on 2 IMUs (ankle excluded) and individual instances defined with above 93% accuracy.
Ahmadi et al. [18]	Tennis, serve	Four right handed, male tennis players (one amateur, two sub-elite and one elite)	ADXRS300 Inertial Sensor (Kionix, Brisbane, Queensland, Australia)	Players performed 30 successful slow motion serves in a controlled environment wearing microsensors located on chest, upper arm and hand to identify rotation and flexion. Also wore marker-based technology (Vicon).	Significant correlation between inertial sensor and marker-based data for serve trends. Only slow motion serves were used as microtechnology used could not provide feedback on power serves.
Connaghan et al. [19]	Tennis, classification of strokes	Eight tennis players (three advanced players, three intermediate and two novice)	TennisSense, Wireless IMU - based on Tyndall's 25mm Mote Platform (Cork, Munster, Ireland)	Single sensor place on player's dominant forearm during a game in order to register spike in accelerometer data due to ball impact. Stroke classified as serves, backhands or forehands. Accelerometer data above 3g were classed as tennis stroke events, below 3g were classified as non-stroke events. Stroke	Wireless IMU was able to recognise tennis stroke performance with 90% accuracy when using information from all 3 sensors (accelerometers, gyroscopes & magnetometers). Accuracy rate was 10% higher than that of accelerometer, which contributed highest single sensor classification.

				recognition was trained on 7 players and then tested on an unseen player.	
Ganter et al. [20]	Track and field, discus throw	One male sports student (former decathlete)	MTx (Xsens, Enschede, Twents, Netherlands)	Athlete performed three discus throws (indoors; 1kg discus) whilst wearing suit comprising 17 inertial sensor units and two transmission units. All throws filmed in high speed. All data from inertial sensors were exported for further processing using MATLAB.	Body angles and velocities of 22 joints analysed, with movement broken down into 6 critical phases. Demonstrated capability of kinematic analysis using full body inertial measurement system emphasising potential of approach when analysing other complex movements.
Ghasemzadeh et al. [21]	Golf, golf swing	Three male subjects, one female	Microtechnology not reported	Five sensors used, three located on each subject (right wrist, left arm and lower back) other two located on golf club (club head and grip). Subjects performed 10 golf swings, addressing the ball with varying degrees of wrist rotation. Each trial divided into four segments (take-away, backswing, downswing, follow-through) and processed using five-point average moving filter to remove effect of noise. 50% of trials were used to build quantitative model, 50% were used to evaluate model.	Body sensor networks demonstrated application to a quantitative feedback model. Results provided good reliability of model with respect to angle of wrist rotation when sensors sampled above 30 Hz. The overall value of absolute mean error was reported as 9.2, 7.7, 6.6 and 6.5 degrees for take away, back swing, down swing and follow through respectively which introduces an average error of less than 10 degrees for all segments.
Helten et al. [22]	Trampoline, jump classification	Four female non-professional athletes with intermediate skills	MTx (Xsens, Enschede, Twents, Netherlands)	Seven inertial microsensors worn on trunk, forearms, upper legs and lower legs. Athletes	Microsensors provided automatic segmentation and classification of jumps. Used (1)

				performed eight predefined routines and 2 self-selected routines with each routine performed two to three times.	inclination of a limb, (2) the enclosed angle between limbs and (3) the angular velocity of sensors. Algorithms developed to assist in the automatic segmentation of movements.
Lai et al. [23]	Golf, golf swing	10 golfers (six beginners and 4 skilled low handicap golfers)	MTx (Xsens, Enschede, Twents, Netherlands)	Four inertial sensors were attached to the swing lead hand, swing lead arm, pelvis and upper back of each subject. Players performed 10 successful drives towards a net. A successful trial was recorded when the ball hit the net, a miss trial was recorded otherwise. Trials were segmented into back swing, down swing and follow-through during pre-processing phase.	Results showed that inertial data of low-handicapped golfers achieved higher mean peak acceleration energy and also achieved higher accuracy than that of the beginners. In all 10 trials, the professional group showed less variation in peak acceleration. Inertial sensor data can be successfully used to differentiate swing patterns between low-handicap golfers and beginners.
Lee et al. [24]	Race walking, walking technique	Seven race walkers (five male and two female)	MTx (Xsens, Enschede, Twents, Netherlands)	Single inertial sensor placed directly on skin over sacral vertebra. Each athlete performed four trials of three walking styles: (a) walking legally at submaximal pace; (b) walking illegally at submaximal pace and (c) walking legally at maximal pace. Analysis of high-speed camera footage was performed.	High-speed footage compared with the sensor-captured data on the same steps. 300 total gait events were tested (i.e. 50 heel strikes and 50 toe offs) and repeated three times. The inertial sensor was 91% accurate. Seven incorrectly identified steps occurred with a time change less than human eye detection.

IMU – Inertial measurement unit
MEMS – Microelectromechanical sensors

Table 2. Summary of results from studies investigating sport-specific movements using wearable sensors within team sports.

Study	Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Ghasemzadeh and Jafari [25]	Baseball, baseball bat swing	Three male subjects, no previous swing training	Microtechnology not reported	Three sensor nodes placed on subjects' chest, right wrist and hip and asked to execute 20 baseball swings with varying timing and sequences of identified key events (hip rotation, shoulder rotation and arm extension). Raw sensor readings passed through five-point moving average filter to reduce effect of high frequency. Twenty-two good swing trials were used to train system, thirty-eight trials (22 good trials, 16 improper trials) were used for validation. Data contributed to designing and validation of an algorithm for analysing the baseball swing technique.	Inertial node data was shown to have the capability to provide feedback on coordination of segmented areas. Inertial coordination data correlated positively with that of video data.
Gabbett et al. [26]	Rugby League, tackle	Thirty male professional Rugby League players	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Units worn in a small vest on the upper back of participants. Collision events from 21 training appearances and one trial match filmed and coded. To detect collision unit was required to be in non-vertical position and require a spike in player load. Collisions were classified as	MinimaxX units found to provide a valid method of quantifying collision load. Strong correlation between video coded data and unit automated detection of mild (r=0.89), moderate (r=0.97) and heavy (r=0.99) contacts.

				mild, moderate and heavy.	
Gastin et al. [27]	Australian Rules football, tackle	Twenty professional male Australian Rules football players (four defenders, five forwards and eleven midfielders)	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	MinimaxX units worn in playing jersey located on upper back. Data relating to tackle events from 4 AFL matches in 2011 season. Tackles made by a player or when tackled by an opponent were coded from video footage. Tackles were classified as low, medium or high intensity based on criteria that considered an observed speed and impact.	Total of 352 tackles recorded comprising 173 made and 179 against. Majority of tackles were medium intensity (61%) only 6% were high intensity. Significant difference found between the three tackle intensities for peak velocity and all accelerometer variables. Suggests ecological validity of tri-axial accelerometers to assess impact forces in tackles.
Gastin et al. [28]	Australian Rules football, tackle	Twenty elite male Australian Rules football players	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Cross-validation approach used to evaluate the effectiveness of MinimaxX in detection of tackle and collision impact events. Unit worn in pocket located in playing jersey. Unit worn in four AFL games during 2011 season. Tackles made by a player or when tackled by an opponent were automatically detected using commercially-available software and coded from video footage. Instances were then matched with MinimaxX data to determine if a “tackle” event had occurred. Allowed assessment of true positive, true negative, false positive and false negative tackle events.	78% of tackles were correctly detected. Tackles against were more accurately detected (90%) than tackles made (66%). 77 tackles were not detected; majority of these (74%) were classified as low intensity. MinimaxX versus observed play event showed detection of 1578 events in the four matches. Of the 1510 events (68 not captured on video) only 18% were verified as tackles, the other 82% were incorrectly identified. Fifty-seven percent of these were from contested ball situations. Of the 1510 events, 385 (25%) detected events

					where no contact was evident.
Koda et al. [29]	Baseball, throwing	Five male volunteers (two of whom were former professional baseball players)	ADXL193 (Analog Devices, Norwood, USA), ADXL320 (Analog Devices, Norwood, Massachusetts, USA) (both accelerometers); Murata ENC03M (Nagaokakyo, Kyoto, Japan), Microstone MG3-01Ab (Nagano, Nagano, Japan) (both gyroscopes)	Two sensors mounted on subjects (forearm and upper arm) who were asked to perform pitching motion several times each. All trials analysed using Vicon systems.	Body mounted sensor indicate use to analyse motion of arm swing, flexion/extension of elbow and hanging of arm during pitching motion. Data used to estimate trajectories of throws and show agreement from position measured from Vicon, although it was suggested that body acceleration had possibility to cause error.
Kelly et al. [30]	Rugby Union, collision	Seven elite Rugby Union players game data used for testing models. Four players assisted creation of classifiers of tackle and non-tackle during training.	SPI Pro (GPSports Systems, Canberra, Australian Capital Territory, Australia)	Device worn in purpose built harness located between shoulder blades. Indicators drawn from changes in temporal pattern and individual acceleration planes spanning from before to after the collision. Other features included impact peaks in accelerometry signals. Artificial learning models used. Analysed 4 models to detect contact: learning grid, support vector machine (static window), support vector machine (impact region) and hidden conditional random field. Models were selected to learn the relationship between source and target data.	Automatically detected collisions were compared to manually labelled collisions and a set of performance measures classified using true and false positives and true and false negatives. Precision and recall analysis of results was also used. Learning grid method provided greatest number of true positives with strong precision and recall scores, with static window features providing low precision and recall scores.

McNamara et al. [31]	Cricket, fast bowling	Twelve highly-skilled bowlers, ten professionals (two international, eight first class) and two in first grade competition.	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Participants were asked to execute normal bowling training to a batter in a net situation, and then perform a series of non-bowling events such as run throughs ending in a single bound and run through with a return throw whilst wearing a microtechnology unit in a small vest located on their upper back. Competition events were also recorded using five bowlers. The aim of the study was to develop an algorithm to automatically detect fast bowling events.	Results from this study proved the unit used accurately detected fast bowling events using the algorithm. The unit provided very strong sensitivity for counting bowling events in training (99.0%) and competition (95.0%) using elite fast bowlers. The unit was also able to detect non-bowling events, although better performance was observed in training (98.1%) as opposed to competition (74.0%).

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

Table 3. Summary of results from studies investigating sport-specific movements using wearable measurement sensors within water sports.

Study	Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Beanland et al. [32]	Swimming, stroke count of butterfly and breaststroke	Twenty-one high level participants (12 males and nine females)	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Criterion validation study. Swimmers completed three 100 metre efforts in outdoor pool wearing GPS device with integrated triaxial accelerometer located on the head to obtain mid-pool velocity and stroke count. Video footage of each effort was captured allowing velocity and stroke count to be obtained.	Strong correlations between stroke count observed on video and data gathered from the unit (r>0.99 for butterfly; r>0.98 for breaststroke). Acceleration data provided clear pattern of undulatory and cyclical mechanics of breaststroke and butterfly body position.
Dadashi et al. [33]	Swimming, front crawl	Eleven elite swimmers (six male, 5 female) and nineteen recreational swimmers (twelve male, seven female)	Physilog IMU (BioAGM, La Tour-de-Peilz, Vaud, Switzerland)	Each swimmer equipped with a single inertial sensor located on sacrum. SpeedRT was attached to waist of swimmers just beneath lower end of the sensor. Swimmers completed consecutive twenty-five metre trials increasing in velocity from 70% to 100%.	Variability assessment showed the range of velocity between inertial sensor and SpeedRT was less than 3.9%.
Dadashi et al. [34]	Swimming, front crawl	Seven well-trained national level swimmers (5 male and 2 female)	Physilog IMU (BioAGM, La Tour-de-Peilz, Vaud, Switzerland)	Waterproof units placed on both forearms and sacrum of swimmer whilst performing three 300 m trials. Verbal instructions given during trial (e.g. glide more or less) in order to perform each trial under different co-ordination mode to test system in broad range of	Adaptive change algorithm applied to inertial signals to detect phases of arm stroke using peak of angular velocity curve. Study validated algorithms providing automated feedback of stroke.

				coordination. Swim speed was controlled using Aquapacer. All trials filmed underwater from 2 angles.	
Fulton et al. [35]	Swimming, freestyle	Twelve Paralympic swimmers (eight males and four females)	MiniTraqua (version 5, Australian Institute of Sport, Canberra, Australian Capital Territory, Australia)	Sensors worn on the thighs of participants. Swimmers performed a maximal-effort 100m freestyle swim time-trial and a 100m kicking only time-trial within 24 hours of each other. All trials were filmed underwater from one angle.	Using an algorithm to detect swimming movements, strong correlations of 0.96 for swimming trials and 1.00 for kicking only trials were found between video and microsensor. Gyroscope traces of troughs allowed for semi-automated analysis of trials. Standard error of kick count validity was found to be higher in swimming trials (coefficient of variation 5.9%) than in kicking only trials (coefficient of variation 0.6%).
Fulton et al. [36]	Swimming, freestyle	Fourteen Paralympic swimmers (eight males and six females)	Single inertial system containing triaxial accelerometer and gyroscope.	Sensors were worn on the calf of the dominant leg to quantify kick-count and kick-rate. Swimmers performed 100m freestyle swimming and 100m kicking only time-trials.	Small to moderate decreases in kick rate were associated with reductions of swimming speed. Sensor identified kick-rate differences and temporal pattern changes between the 2 trials.
James et al. [37]	Swimming, front crawl	Female triathlete	MEMS triaxial accelerometers, MEMS pitch, yaw and roll gyroscopes.	Three accelerometers were placed on forearm, lower back and lower leg. Participant completed three; two lap trials at two race pace settings: 400m and 100m, respectively.	Data analysed using MATLAB (Massachusetts, USA). Primarily used accelerometer data from medial-lateral axis for event identification of movements. Results reported distinct classification of hand entry, glide, catch and recovery phases of front crawl from

					accelerometer trace. Spikes from the trace results made lap data identifiable allowing for potential future ability for automatic detection.
Jensen et al. [38]	Swimming, stroke classification and turn detection	12 German 2nd league swimmers (five female, seven male)	SHIMMER sensor platform (Dublin, Leinster, Ireland)	Sensor node placed on the occiput of subject underneath swimming cap. Subjects were required to swim 200 metre medleys within 80% of their best time. Pattern recognition methods used for turn and swimming style detection.	Demonstrated a high accuracy of turn events and swimming styles with a head worn kinematic sensor. Swimming style classification returned results of 95%. Misclassifications were registered for the butterfly and breaststroke swimming styles. Turn detection had an overall classification rate of 99.8%; algorithm detected a single misclassified turn.
Stamm et al. [39]	Swimming, push-off	Seven male swimmers	Microtechnology not reported	Sensor was taped to lower back of swimmers along with SP5000 tether. Each swimmer used their feet to push-off, and once in the glide position, remained in the same relative body position until out of breath or no longer moving forward. Twelve total repetitions were performed at three effort levels (slow, medium and fast).	Raw acceleration data converted into gravitational units. Near perfect correlation (r=0.94) between tether and sensor derived velocity. Single inertial sensor offered a valid measurement method of push-off velocity.

GPS – Global positioning system
IMU – Inertial measurement unit
MEMS – Microelectromechanical sensor

Table 4. Summary of results from studies investigating sport-specific movements using wearable sensors within snow sports.

Study	Sport and sport specific movement	Sample	Microsensor used	Method	Findings
Chardonnens et al. [40]	Alpine skiing, comparison of cross-over and cross-under turns.	Six alpine skiers (three professional instructors, three experienced skiers)	Physilog IMU (BioAGM, La Tour-de-Peilz, Vaud, Switzerland)	Each skier wore four wireless inertial modules located on middle length of thighs and behind ski boots. Each skier performed two cross-over and two cross-under techniques in a regular slope in their own skis. Each run was recorded by video camera and synchronised.	Wearable system presented knee angle measurements and robust detection of events based on 3D acceleration and 3D angular velocity. System showed high sensitivity regarding timing periods and allowed identification of parameters for intra-turn and the whole run.
Chardonnens et al. [41]	Ski jumping, identify temporal patterns of in-run, take-off, early flight, stable flight and landing phases.	Thirteen young ski jumpers from national ski junior team (five athletes used for indoor validation of jumping techniques)	Physilog inertial measurement unit (BioAGM, La Tour-de-Peilz, Vaud, Switzerland)	Each skier wore four IMU devices attached to thigh and shank of both legs. Indoor validation of different jumping techniques was required. Athletes performed simulated jumps using 5 m ramp and a wheeled board. Forty jumps were recorded and analysed by Vicon motion capture system. For outdoor validation, thirteen athletes performed a maximum of three jumps on a HS-77 jumping hill. Video camera captured all athletes and was analysed using Dartfish.	Could identify temporal patterns of ski jumping phases using an inertial-based system. Relative system precision was calculated at 7% for indoors and less than 9% for outdoor conditions. System automatically and precisely detected durations of three movements within a ski jump. System proved to be robust enough to accommodate differences in jumping durations between indoor and outdoor conditions.
Chardonnens et al. [42]	Ski jumping, Coordination of lower	Thirty-three male athletes of different	Physilog inertial measurement unit	Five IMUs were worn by athletes located on thigh, and	Demonstrated the ability of IMU to assess inter-segment

	limbs and jump length performance	performance level (twenty junior, nine Continental Cup, four World-Cup) from Swiss national ski jumping team	(BioAGM, La Tour-de-Peilz, Vaud, Switzerland)	shank-thigh segments bilaterally and sacrum. Between one and three jumps were recorded for each athlete on HS-117 jumping hill. Data collected from total of 87 jumps.	coordination of the shank-thigh and thigh-sacrum pairs during the take-off and extension in ski jumping using the CRP. IMU data of CRP showed significant relationship of athletes attaining longer jumps with those who had more symmetric movement of the thighs and sacrum.
Harding et al. [43]	Snowboarding, aerial acrobatics	Ten athletes	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Sensor was situated approximately 5 cm to the left of spine. Athletes wore unit during training of 80 m half-pipe runs. Video footage of training was analysed using Dartfish software. Data of 216 acrobatic manoeuvres was collected.	Mathematically-derived algorithms used to automatically detect air-time and air-angle to measure rotational magnitude of acrobatic manoeuvres (180, 360, 540, 720 or 900 degrees of rotation).
Marsland et al. [44]	Cross country skiing, movement patterns and techniques	Two groups of participants: international group (three male, one female) and Australian group (three male, one female)	MinimaxX S4 (Catapult Sports, Melbourne, Victoria, Australia)	Participants wore single micro-sensor unit and were filmed using a stationary camera from side-on performing classified ski techniques. Skiers performed sessions lasting three to four minutes per athlete and instructed to ski at "moderate intensity slightly faster than their normal easy distance skiing pace."	The microsensor was found to be useful in identifying cyclical movement patterns of major ski techniques. A combination of inertial data enabled skiing actions such as kicking to be clearly identified.

CRP – Continuous relative phase
IMU – Inertial measurement unit
MEMS – Microelectromechanical sensor

FIGURE LEGENDS

Figure 1. Equation used to calculate 'Player Load' using the MinimaxX microtechnology unit.

where

$a_y = Forward\ (anterior - posterior)\ acceleration$

$a_x = Sideways\ (medial - lateral)\ acceleration$

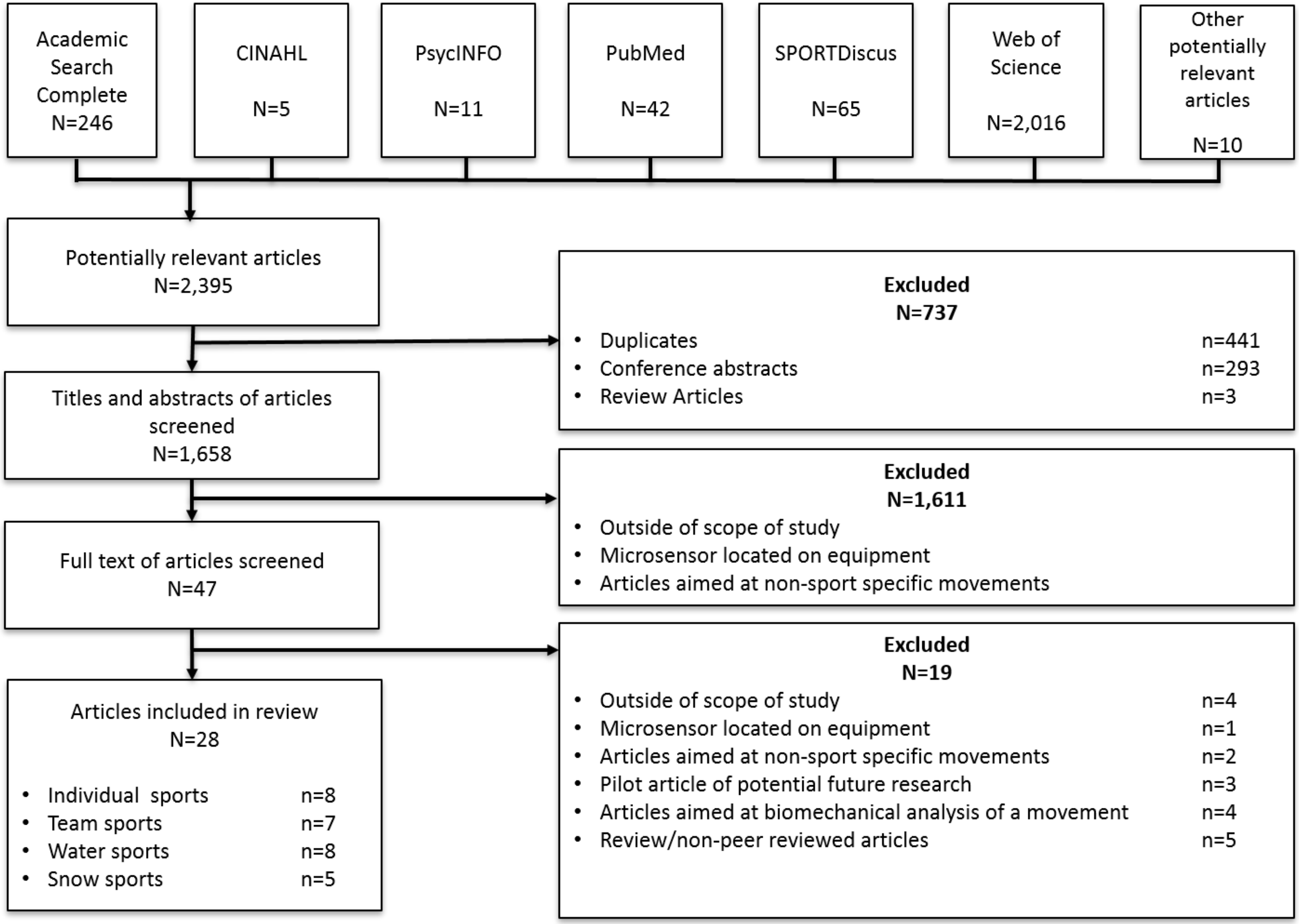
$a_z = Vertical\ acceleration$

Figure 2. Flowchart of the selection process for inclusion of articles in the systematic review

Figure 1.

$$Player\ load = \sqrt{\frac{(a_{y1} - a_{y-1}) + \ (a_x - a_{x-1}) + (a_z - a_{z-1})}{100}}$$

Figure 2.


Academic Search Complete N=246
CINAHL N=5
PsycINFO N=11
PubMed N=42
SPORTDiscus N=65
Web of Science N=2,016
Other potentially relevant articles N=10
Potentially relevant articles N=2,395
Excluded N=737
Duplicates n=441
Conference abstracts n=293
Review Articles n=3
Titles and abstracts of articles screened N=1,658
Excluded N=1,611
Outside of scope of study
Microsensor located on equipment
Articles aimed at non-sport specific movements
Full text of articles screened N=47
Excluded N=19
Outside of scope of study n=4
Microsensor located on equipment n=1
Articles aimed at non-sport specific movements n=2
Pilot article of potential future research n=3
Articles aimed at biomechanical analysis of a movement n=4
Review/non-peer reviewed articles n=5
Articles included in review N=28
Individual sports n=8
Team sports n=7
Water sports n=8
Snow sports n=5