

Review

Trends Supporting the In-Field Use of Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review

Valentina Camomilla ^{1,2,*} , Elena Bergamini ^{1,2} , Silvia Fantozzi ^{3,4} 
and Giuseppe Vannozi ^{1,2} 

¹ Interuniversity Centre of Bioengineering of the Human Neuromusculoskeletal System (BOHNES), University of Rome “Foro Italico”, Piazza L. De Bosis 6, 00135 Rome, Italy; elena.bergamini@uniroma4.it (E.B.); giuseppe.vannozi@uniroma4.it (G.V.)

² Department of Movement, Human and Health Sciences, University of Rome “Foro Italico”, Piazza L. De Bosis 6, 00135 Rome, Italy

³ Department of Electrical, Electronic, and Information Engineering “Guglielmo Marconi”, University of Bologna, Viale Risorgimento 2, 40136 Bologna, Italy; silvia.fantozzi@unibo.it

⁴ Health Sciences and Technologies—Interdepartmental Centre for Industrial Research, University of Bologna, Viale Risorgimento 2, 40136 Bologna, Italy

* Correspondence valentina.camomilla@uniroma4.it; Tel.: +39-06-36733-522

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Abstract: Recent technological developments have led to the production of inexpensive, non-invasive, miniature magneto-inertial sensors, ideal for obtaining sport performance measures during training or competition. This systematic review evaluates current evidence and the future potential of their use in sport performance evaluation. Articles published in English (April 2017) were searched in Web-of-Science, Scopus, Pubmed, and Sport-Discus databases. A keyword search of titles, abstracts and keywords which included studies using accelerometers, gyroscopes and/or magnetometers to analyse sport motor-tasks performed by athletes (excluding risk of injury, physical activity, and energy expenditure) resulted in 2040 papers. Papers and reference list screening led to the selection of 286 studies and 23 reviews. Information on sport, motor-tasks, participants, device characteristics, sensor position and fixing, experimental setting and performance indicators was extracted. The selected papers dealt with motor capacity assessment (51 papers), technique analysis (163), activity classification (19), and physical demands assessment (61). Focus was placed mainly on elite and sub-elite athletes (59%) performing their sport in-field during training (62%) and competition (7%). Measuring movement outdoors created opportunities in winter sports (8%), water sports (16%), team sports (25%), and other outdoor activities (27%). Indications on the reliability of sensor-based performance indicators are provided, together with critical considerations and future trends.

Keywords: magneto-inertial sensors; biomechanics; sports; accelerometer; MEMS; gyroscope; performance assessment; athlete; motion analysis

1. Introduction

1.1. Background

A successful coaching outcome can be supported by useful and timely feedback to the athlete targeting performance defects. Systematic, objective, and reliable performance monitoring and evaluation, performed by means of qualitative and quantitative analyses of performance variables can reinforce the link between research and coaching practice, especially in elite sports. An alternative to classical laboratory-based assessment is the use of magneto-inertial sensors that can monitor

performance without hindering it and with no space limitation or cumbersome setup procedure [1–7]. These sensors measure physical quantities related to the motion of a body and their measurements can be used to estimate temporal, kinematic and dynamic parameters. New generation sensors permit executing sport tasks during training and performance, are portable, affordable, easy-to-use, and may provide real-time feedback [8]. Recently, the use of such sensors has been revised in swimming [9,10], running [11,12], and strength and ballistic assessment [13,14]. Their partnership with Global Positioning System (GPS) technology has been highlighted for use in team sports [15–19]. In 2015, a systematic review provided a general overview of the dissemination of this technology through different sports disciplines [1]. However, they excluded papers using only sensors mounted on equipment or dealing with non-sport-specific movements (e.g., running). Moreover, the fast expansion of this topic makes any new review quickly outdated. The current systematic review identifies and evaluates updated evidence to answer the following questions: (i) In which sport domains are magneto-inertial sensors currently adopted for athlete performance evaluation? (ii) Are sensor-based parameters used to assess motor capacity (i.e., the highest possible level of functioning of an athlete in exerting maximal velocity or strength in a standardized environment [20]) and analyse the technique of the athlete? (iii) Can sensors be feasibly used to perform match analysis and assess physical demands during training sessions/competitions? (iv) What is currently the potential for the use of inertia-based instrumentation in the field sport setting?

1.2. Technology, Requirements and Parameters for Wearable Motion Analysis in Sports

In this section, the necessary background is provided about (i) wearable inertial sensor technology applied in sports to support athlete movement analysis; (ii) requirements to guarantee their accurate use in sport applications; (iii) sensor derived parameters for sport performance assessment.

1.2.1. Gyroscope, Accelerometer and Magnetic Sensors

The advent of Micro-Electro-Mechanical Systems (MEMS) technology has allowed for the manufacture of gyroscope, accelerometer, and magnetic sensors that are highly miniaturized, relatively low-cost, and power efficient.

MEMS gyroscope, accelerometer and magnetic sensors quantify angular velocity, the sum of gravitational and inertial linear accelerations, and the local magnetic field vector components, about and along their sensing axes, respectively. Single-, dual- and tri-axis sensors exist. In the latter case, the three sensing axes are mutually orthogonally mounted, and the aforementioned physical quantities are measured with respect to a Cartesian coordinate system.

The quantities measured by the three sensors can also be used to obtain information about the orientation of a body. However, when the orientation is provided by only one type of sensor at a time, the orientation accuracy is often inadequate for specific applications [21]. Therefore, to improve the accuracy of 2D orientation estimation, gyroscopes and accelerometers are commonly combined in an Inertial Measurement Unit (IMU) [22,23], where the term “inertial” is used because both sensors exploit the principle of inertia to provide either angular velocities or accelerations. When 3D orientation is required, magnetic sensors are also embedded within the Magnetic and Inertial Measurement Unit, widely known by the acronym MIMU (or Inertial and Magnetic Measurement Unit, IMMU, or Inertial and Magnetic Measurement System, IMMS). When IMUs and MIMUs are used, the unit’s orientation is commonly provided as an output of the device, as estimated by combining the data measured by two or three sensors, through means of sensor fusion algorithms [21]. The principles underlying these algorithms, together with a list of parameters that can be derived from IMU and MIMU measurements are presented in Section 1.2.3.

1.2.2. Requirements for Measuring Human Movements in Sport

Several gyroscope, accelerometer, and magnetic sensors, as well as IMUs and MIMUs, have been marketed in recent years for use in human movement analysis. The characteristics of these devices

in terms of full-range scale, sampling frequency, power consumption, and portability change considerably according to the application and technology used for data transmission (cabled or wireless). When sporting applications are targeted, care must be taken in order to properly select the measurement system, according to the characteristics of the selected motor task and to the variables that are estimated (e.g., accuracy requirements for trajectory determination in sports [19]). This aspect ranked first in the identification of user requirements for coaches, followed by the request for repeatability, understandable and communicable feedback to athletes, real-time results, suitability for multi-athlete analysis, and non-interference with the athlete or coach [24]. In general, the system used should also be small and light (portable, suitable for in-field use); wearable (wireless); easy and quick to set up and analyse; usable on any surface and in any environmental condition (including under water through hermetic sealing and limited drag, if swimming applications are targeted); power efficient (in case long-time monitoring is required, e.g., marathon monitoring); and have adequate full-range scale and sampling frequency. The latter should be determined according to the motor task, parameters of interest, and measurement system, being a minimum of two times the highest frequency in the signal of interest (according to the Nyquist–Shannon sampling theorem [25]), to minimise the loss of relevant information [13].

Besides the characteristics of the selected device, users must be aware that the signals derived from these sensors are affected by different sources of error which, even if compensated for, currently limit the possible range of applications. Among them is gyroscope and accelerometer bias, caused by changes in the MEMS physical properties and leading to drift errors that increase linearly or quadratically over time when the measured signal is integrated once (to obtain orientation) or twice (for position estimation), respectively [26]. Secondly, the oscillations between body and device, i.e., soft tissue artefacts [27], compete with drift as the most crucial source of error. The fixing technique may limit the oscillations as their compensation is essential [28]. However, as soft tissue artefacts are motor task- [29] and subject-dependent [30], as well as sensitive to the site and method of the unit attachment [31,32] and to unit removal and replacement [33], their compensation is very critical. Moreover, they can be assumed to be larger during explosive tasks; to analyse such tasks, the device mass should be limited to a minimum. Thirdly, ferromagnetic disturbances (particularly indoors) may come from ferromagnetic objects or electrical appliances like, for example, water pumps under the pool. They alter the magnitude and direction of the measured magnetic field vector, thus causing errors in the estimated orientation [34].

1.2.3. Sensor Derived Parameters

Gyroscope, accelerometer, and magnetic sensor data can be used to estimate different parameters. These could be based on the detection of features in the measured signals or on more sophisticated processing techniques, which, for example, enable information provided by two or more sensors to be combined. Sensor derived parameters can be divided into three main categories: temporal, kinematic, and dynamic.

Temporal Parameters

Temporal parameters are typically obtained by detecting features (e.g., maxima, minima or slope changes) in the measured angular velocity or acceleration signals. Some examples of these parameters are: (i) time instants related to the beginning or end of a movement, foot or hand contact, ball release or other events of interest; (ii) phase identification and segmentation of sport tasks using the time instants; (iii) time intervals, such as stride/step/stance duration in locomotion or stroke duration in swimming; and (iv) frequency in cyclic movements.

Kinematic Parameters

Kinematic parameters refer to both angular and linear forms of position, velocity and acceleration. In particular, the estimation of the 3D orientation of a MIMU with respect to an inertial reference

frame is of fundamental importance as it is essential when obtaining either the absolute orientation of body segments or sports equipment (e.g., rackets, clubs, skis), or the orientation of a body segment relative to another (joint kinematics). Moreover, it is necessary to set apart the gravitational and inertial components of the linear accelerations, in order to estimate the linear kinematic parameters, such as MIMU position or linear velocity.

The 3D orientation of a MIMU may be estimated by numerical time-integration of the differential kinematic equations relating the time derivatives of the orientation parameters to the angular velocity provided by the gyroscope. The accuracy of this numerical integration, however, is hindered by errors that increase with time due to gyroscope drift [21,26]. Moreover, the initial conditions of the integration process must be determined. To manage these problems, the signals provided by the accelerometric and magnetic (aiding) sensors are used under the following hypotheses: (i) the accelerometers measure only the gravity vector, true only when the MIMU moves at constant speed or is stationary; (ii) both the gravitational and magnetic field vectors are uniform and constant within the measurement volume, which, as mentioned above (Section 1.2.2), is not necessarily the case for the magnetic field vector. Therefore, the information provided by the three sets of sensors is combined within a sensor fusion framework with the aim of proficiently exploiting all the available information. Examples of sensor fusion approaches are stochastic filtering, often implemented in the form of an Extended Kalman Filter [21,35] and complementary filtering [36,37].

Once orientation is obtained, joint kinematics can be estimated as the relative orientation between adjacent body segments. Its computation requires the definition of a multibody kinematic model, together with its anatomical calibration, and the determination of the reference “zero” joint configuration [38]. Among other angular kinematic parameters, the angular velocity is often exploited as it is directly measured by gyroscopes, while the angular acceleration must be obtained through numerical differentiation of the measured velocity. Like the integration process, computing the derivative of a discrete signal entails errors resulting from the differentiation method and the type of representation used for numbers (precision level) [39].

As for linear kinematic parameters, in theory, the measured linear acceleration can be numerically integrated, once amended by its gravitational component, to obtain an estimate of the linear velocity and, if further integrated, the displacement (trajectory). Again, the initial conditions of this process are required, and drift errors may occur and propagate due to low-frequency gyroscope drift. Moreover, the removal of the gravitational component is prone to errors related to the orientation calculation. For these reasons, model-based approaches are often required [40] and the accurate estimation of linear position from MIMUs still represents a challenging and time-consuming exercise [21,26].

It is noteworthy to specify that centre of mass (CoM) parameters estimated from the acceleration of a single sensor positioned on the lower trunk, nearby the position of the CoM in the static upright posture, is an approximation that does not take into account the dynamics of all the body segments, specifically the lower and upper limbs [41]. Still, this information can be useful in in-field sport performance evaluation without requiring cumbersome setup.

Dynamic Parameters

Like kinematic quantities, dynamic parameters refer to both linear and angular variables. Although, in theory, vertical/leg stiffness, external forces, joint forces, moments, and powers can be estimated from MIMU measurements, the accuracy and reliability of these parameters are contingent on the accurate estimation of kinematic variables (e.g., temporal parameters, orientation, and position). Additionally, the embedding of measures of external forces in hybrid inverse dynamic methods is recommended to reduce errors of pure inverse dynamic estimates of joint loads [42,43].

2. Materials and Methods

2.1. Inclusion and Exclusion Criteria

Using the PICOS framework (which focuses on Population, Intervention, Comparison, Outcomes, and Study design [44]), the selection criteria and search strategy were designed to answer the above-mentioned research questions. Full papers published in English, including studies using MIMUs and IMUs to analyse motor tasks of interest in a sport context, performed by recreational or elite athletes, were considered. During the final screening, selections were made based on the relevance of the identified sources to the assessment of maximum strength and ballistic performance, technique related parameters, and intensity measures for match analysis. The other inclusion and exclusion criteria are described in Table 1.

Table 1. Inclusion and exclusion criteria considered for the current systematic review.

Criteria	Definition
Measurement instruments	magneto-inertial sensors
Motor tasks	tasks of interest in a sport context
Type of assessment	included: <ul style="list-style-type: none"> • motor capacity • performance related parameters • intensity measures for match analysis • refereeing parameters excluded: <ul style="list-style-type: none"> • oxygen uptake, metabolic cost, and activity monitoring • parameters exclusively related with the risk of injury
Publication type	journal papers
Cohort under investigation	recreational, experienced, and elite athletes

2.2. Search Strategy

The review of the literature was performed by selecting articles from Web of Science, Scopus, Pubmed, and Sport Discus databases, published in English, until 12 April 2017. Keywords were selected to define the measurement instruments, the sport activity performed, the participant tested and to exclude studies dealing with patients, risk of injury, and the assessment of physical activity or energy expenditure (the Boolean research strategy used is reported in Table 2). A keyword search was performed to match words in the title, abstract, and keyword fields. Electronic searches were performed by one author (E.B.); references and abstracts were stored alphabetically into a separate worksheet. Additional relevant papers were thereafter selected by examining the reference lists of selected papers.

2.3. Review Process

Conference proceedings, theses, and duplicate journal references due to searches in different electronic databases were removed first. During the subsequent screening, selections were based on the relevance of the identified sources to the inclusion criteria. Two independent reviewers (E.B. and V.C.) evaluated titles and abstracts of the retrieved papers for inclusion. A full text evaluation was then performed if the title and abstract failed to provide adequate information. Any disagreement between the two reviewers was resolved by a consensus meeting of all authors.

Table 2. Boolean search strategy.

Database Keywords
<p>Web of Science: (“accelerometry” OR “accelerometer” OR “gyroscope” OR “inertial sensor” OR “inertial measurement unit” OR “wearable sensor” OR “wearable system” OR “wearable device” OR “IMU” OR “MEMS”) AND (sport OR “baseball” OR “basketball” OR bicycling OR “boxing” OR “football” OR “golf” OR “gymnastics” OR “hockey” OR “martial arts” OR “tai ji” OR “karate” OR “taekwondo” OR “mountaineering” OR “racquet sports” OR “tennis” OR “cricket” OR “softball” OR “badminton” OR “running” OR “jogging” OR skating OR “snow sports” OR ski * OR “soccer” OR “snowboard” OR swimming OR “diving” OR “track and field” OR “volleyball” OR “weight lifting” OR “wrestling”) AND (humans OR athletes) NOT (patients OR pathology OR animals OR “physical activity” OR “energy expenditure”) limit to English</p>
<p>Scopus: “accelerometry” OR “accelerometer” OR “gyroscope” OR “inertial sensor” OR “inertial measurement unit” OR “wearable sensor” OR “wearable system” OR “wearable device” OR “IMU” OR “MEMS” AND sport AND humans OR athletes AND NOT patients OR pathology OR animals OR “physical activity” OR “energy expenditure” limit to English</p>
<p>Pubmed: (“accelerometry” OR “accelerometer” OR “gyroscope” OR “inertial sensor” OR “inertial measurement unit” OR “wearable sensor” OR “wearable system” OR “wearable device” OR “IMU” OR “MEMS”) AND (sports [Mesh] OR karate OR taekwondo OR “cricket” OR softball OR badminton) AND (humans [Mesh] OR athletes [Mesh]) NOT (patients OR pathology [Mesh] OR animals OR “physical activity” OR “energy expenditure”) AND “English” [Language]</p>
<p>Sport Discus: (“accelerometry” OR “accelerometer” OR “gyroscope” OR “inertial sensor” OR “inertial measurement unit” OR “wearable sensor” OR “wearable system” OR “wearable device” OR “IMU” OR “MEMS”) AND (sport OR “baseball” OR “basketball” OR bicycling OR “boxing” OR “football” OR “golf” OR “gymnastics” OR “hockey” OR “martial arts” OR “tai ji” OR “karate” OR “taekwondo” OR “mountaineering” OR “racquet sports” OR “tennis” OR “cricket” OR “softball” OR “badminton” OR “running” OR “jogging” OR skating OR “snow sports” OR ski * OR “soccer” OR “snowboard” OR swimming OR “diving” OR “track and field” OR “volleyball” OR “weight lifting” OR “wrestling”) AND (humans OR athletes) NOT (patients OR pathology OR animals OR “physical activity” OR “energy expenditure”) AND (LA (English))</p>

* Entails truncation, i.e., finding all terms that begin with the string of text written before it.

3. Trends

3.1. Paper Selection and Identification

The duplicate removal yielded 2040 citations (Figure 1). One hundred and eighty-three papers were included based on title and abstract, whereas the full text was reviewed for 119 papers. Three papers were directly included, while 95 papers were discussed during multiple consensus meetings, leading to the inclusion of a further 23 papers. Several studies were excluded for not involving athletes. Fourteen review papers were retrieved from the search [1,3–5,9–11,13,16–19,45,46] and were analysed separately, along with nine additional reviews cited by the selected papers and reviews [2,12,14,15,47–51]. Screening of the selected papers and the 23 reviews produced 77 additional papers. As a result, 286 studies were identified for inclusion in the systematic review [24,41,43,52–334] (Figure 1) and analysed along with the 23 reviews in the following sections. Details of the papers’ aims, performance evidence, sport, motor task, participants, setting, parameters, device characteristics and fixing are reported in the Supplementary Material.

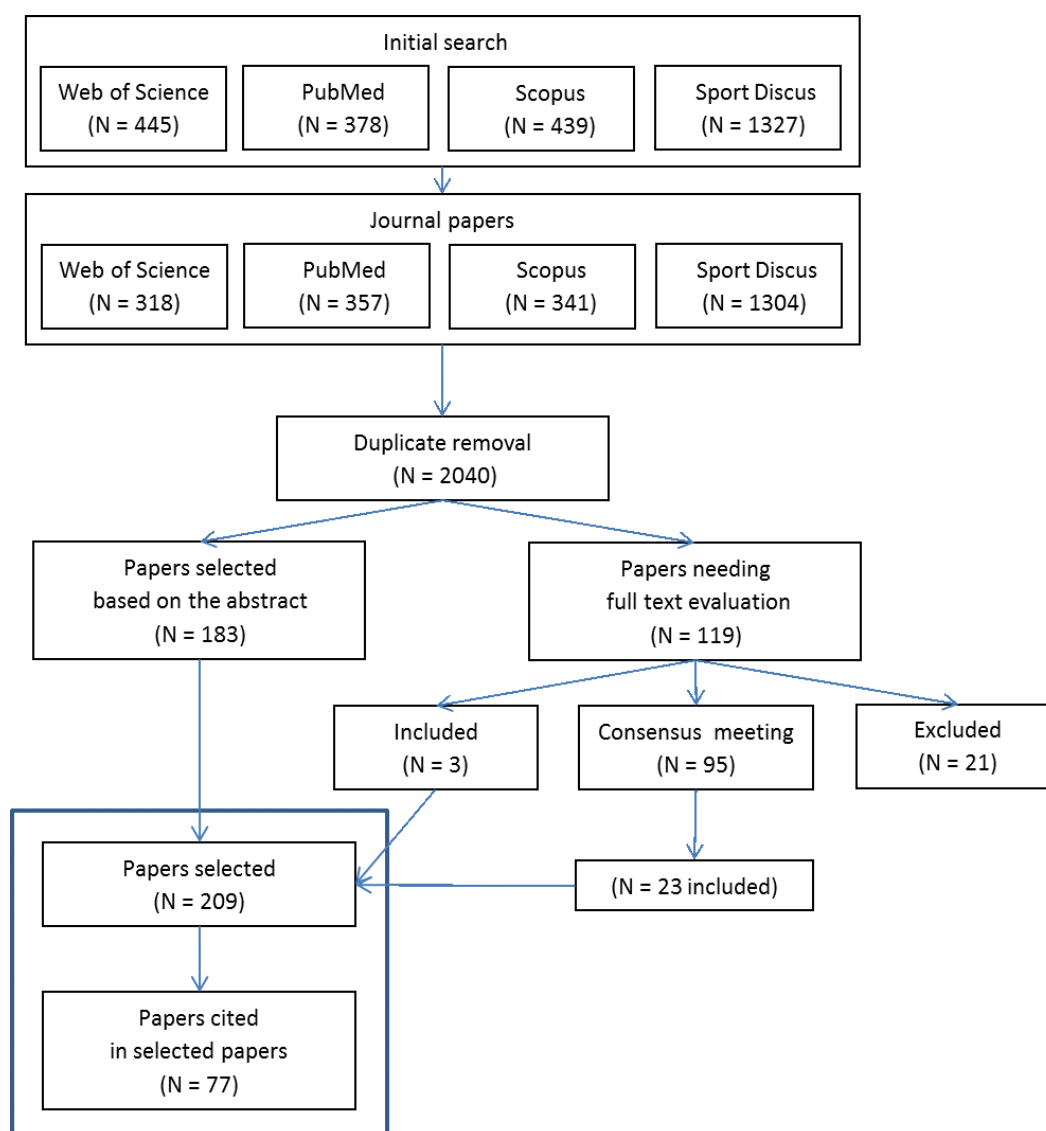


Figure 1. Search strategy flow chart. After the removal of duplicates, 2040 papers were screened for inclusion: 183 were selected based on title and abstract, 119 full texts were further analysed. Three were included directly and 23 out of 95 were included after a consensus meeting. The references of the 209 papers obtained from the database search and those cited in the 23 reviews included in this paper were screened leading to the inclusion of further 77 papers for an overall total of 286 papers.

3.2. Journals and Years

The papers included in the systematic review (286 papers) and the reviews (23 papers), (total: 309 papers) were published in 88 different journals, 71% of which appeared in 14 journals, each publishing at least five papers (Figure 2). Trends of publication along the years are also shown (Figure 2).

3.3. Participants, Setting, Sport, Motor Task

The papers included in the systematic review (286 papers) analysed elite (declared as such, professionals, or national to international level, 38% of the papers), sub-elite (competitive, university, highly trained, and experienced athletes, 21%) and recreational athletes (26%), while multiple experience levels were included in 8% of the papers, and 7% were not specified. Three studies involved Paralympic athletes [124–126] and two involved wheelchair junior athletes [71,292]. Studies analysing

athletes in the field during training or simulated training comprised 62% of the total analysed, with 7% undertaken during competition, and 28% of the studies performed in laboratory settings. When multiple settings were included in a single study, the setting closest to performance was counted.

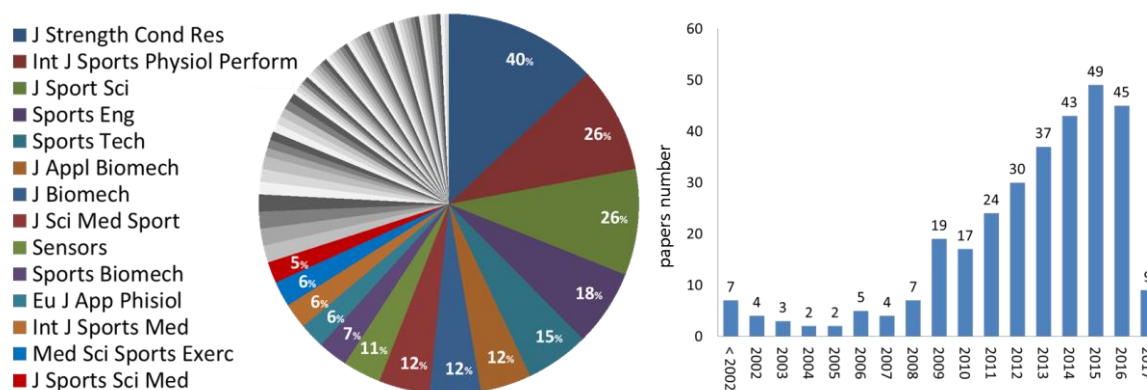


Figure 2. Distribution of the reviews and papers in the systematic review over journals (in %) and time (in absolute values).

As detailed in Table 3, cyclic and team sports comprised 35% and 25% of studies analysed, respectively. The possibility of measuring movement outdoors created opportunities in winter sports (aerial skiing, alpine skiing, cross-country skiing, ski jumping, ski mountaineering, snowboarding: 8%), water sports (diving, swimming, rowing, kayaking: 16%), team sports (American football, Australian football, baseball, basketball, contact sports, cricket, field hockey, Gaelic football, handball, ice hockey, netball, rugby, soccer, softball, volleyball, wheelchair basketball: 25%), and other outdoor activities (sprint and distance running, cycling, golf, tennis, rock climbing, shot-put, roller skiing, skateboarding: 27%).

Regarding the specific motor tasks investigated, almost all belonged to the following broad gross motor skill classifications:

Locomotion:

- aerial movements (diving trampoline jumps, half-pipe snowboard, front/back somersaults)
- agility runs (change of direction, side-cuts, turning)
- bicycling (indoor or outdoor track, jumping)
- horse riding (trot, gallop, circles, change of directions)
- jumping (with and without counter movement, with one or two legs, drop landing, drop jump, stop jump, jump header, moving header, standing short\long jump, springboard)
- climbing
- swimming (starts, front crawl, backstroke, breaststroke, butterfly, freestyle, turns)
- roller skating and skateboarding
- rowing and paddling (single and double scull rowing, kayak propulsion)
- running (treadmill and over ground, distance and sprint running, hurdles)
- skiing and snowboarding (giant slalom, downhill, cross country runs, ski jumping, uphill ski mountaineering, roller skiing)
- wheelchair sprint and turns.

Collisions, takedowns, or weightlifting:

- tackling and sustaining physical collisions
- takedowns
- weightlifting, entailing the use of upper or lower limbs (snatch lift, back squat, pull/throw on bench press).

Throwing, aiming, or hitting:

- kicks (soccer in step kick, karate front kick)
- trunk rotations (golf and baseball swing, ice hockey slap shot, baseball bat swing)
- overarm movements (tennis serve/volley/strokes, pitching, cricket bowling, javelin throwing, shot put) sidearm and underarm movements (air pistol shots, boxing straight punch, karate jabs/crosses/hooks/upper-cuts, fencing lunge and touche, bowling ball throw, golf putt).

Table 3. Number of papers in which each sport has been analysed using sensors. Multiple counts are allowed for papers performing comparative studies across sports.

Team Sports		Other Individual Sports		Cyclic Sports		Winter and Outdoors Sports	
rugby	20	tennis	7	distance running	46	alpine skiing	7
Australian football	12	golf	5	swimming	34	climbing	5
soccer	10	weightlifting	4	cycling	10	cross-country skiing	4
baseball	5	mixed martial arts	3	rowing	8	ski jumping	4
cricket	4	boxing	2	sprint running	3	snowboarding	4
field hockey	4	diving	2	kayaking	2	ski mountaineering	3
volleyball	4	javelin throw /shot-put	2	race walking	1	aerial skiing	1
ice hockey	3	karate	2			roller skiing	1
netball	3	artistic gymnastics	1			skateboarding	1
basketball	2	badminton	1	Motor capacity			
wheelchair basketball	2	bowling	1	jumping	24		
American football	1	fencing	1	overload training	20		
contact sports	1	horse riding	1	agility tests	7		
Gaelic football	1	shooting	1				
handball	1	taekwondo	1				
softball	1						

3.4. Technique Analysis, Intensity Measures for Match Analysis, Motor Capacity Assessment, and Activity Classification

In the revised literature, the primary focus was technique analysis (55.5%), followed by match analysis (20.7%), and capacity assessment (17.3%), with few papers dealing with activity classification (6.5%). Papers are presented as classified into these four categories and referenced in more than one category when appropriate.

3.4.1. Technique Analysis (163 Papers)

Spatio-temporal parameters (phase identification, foot contact timings, stride/step/stroke number, duration, frequency), linear and angular kinematic variables (position/orientation, mean or instantaneous linear/angular velocity, acceleration), and linear and angular dynamic parameters (leg stiffness, joint forces, moments, powers), listed in Table 4, were estimated based on the many possible configurations of sensor fixing on athletes and/or sport equipment depicted in Figure 3.

Table 4. Type of parameters, assessments and sports analysed to support sport technique analysis.

Parameter Type		Type of Assessment	Sport		
Spatio-temporal	temporal	measure critical temporal events	blade–puck contact time in ice hockey cricket ball bowling and release		
		non-cyclic tasks	detect task phases and critical events	artistic gymnastics springboard jumps baseball swing bowling cricket bowling diving trampoline jumps golf half-pipe snowboard instep kick javelin throw karate front kick ski jumping soccer turning manoeuvres swimming tumble turn and start	
			cyclic tasks	characterize cyclic stride/step/ stroke event	cricket ball delivery kayaking multi-person rowing running single sculler rowing skating swimming
				revolution rate	bowling ball cycling
	spatial	Step/cycle length	detect task phases	cross-country skiing front crawl ice hockey skating running on a track running on a treadmill sprint running uphill mountaineering	
				swimming treadmill running	

Table 4. Cont.

Parameter Type	Type of Assessment	Sport	
Centre of mass (CoM)	instantaneous	rowing alpine skiing cycling running simulated cross-country skiing	
		snowboarding swimming vertical jumping	
	average	cross-country skiing running running cycle swimming cycle swimming lane swimming turning uphill mountaineering	
		alpine skiing cross-country skiing jumps while skiing, snowboarding, mountain biking running ski jumping snowboarding uphill mountaineering	
	displacement	forward	running golf swing ski jumping
		vertical	running impacts landing from horizontal jump tennis racket shock
acceleration	event detection and amplitude	running performance, economy, symmetry	
	variations in acceleration amplitude		

Table 4. Cont.

Parameter Type		Type of Assessment	Sport	
Objects	orientation	ski horizontal and V-opening angles	ski jumping	
		ski inclination	alpine skiing	
		whole body movements	boat–oar stroke angle boat orientation	rowing
		swing	bicycle roll and crank angle	cycling
		club face orientation	golf	
	kinematics	whole body movements	bat orientation	baseball swing
			springboard kinematics	gymnastic vaulting
		whole body movements	boat kinematics oar acceleration seat position	rowing
			road incline	running
			shot acceleration	shot put
			ski velocity	ski jumping
		swing	bat position and linear velocity	baseball swing
			club head kinematics	golf
			racquet head forward velocity	tennis
			overarm throw	ball velocity at release
sidearm/underarm movements	javelin kinematics	javelin throw		
	ball velocity	bowling cricket bowling		
	foil speed	fencing lunge and <i>touche</i>		
	puck velocity	ice hockey		

Table 4. Cont.

Parameter Type	Type of Assessment	Sport	
Body segments	orientation	aerial manoeuvres in half-pipe snowboard bike riding swimming	
		trunk inclination	golf swing running on a track snowboarding sprint start
		lower limb orientation	alpine skiing ski jumping trampoline jumps
		upper limb orientation	baseball pitching running on a track tennis
		pelvis orientation	climbing ski jumping swimming
	kinematics	gravity vector removal	running swimming various tasks
		postural tremor	air pistol shooting
		lower limb vibrations	off-road and road cycling
		take off velocity and angle	standing horizontal jump
		shoulder, elbow, wrist displacement	baseball pitching
heel lift and forearm acceleration		running	
tibial linear acceleration		depth jumps	
tibial angular and linear acceleration tibial angular and linear velocity	instep kick		
	pelvis jerk	climbing	

Table 4. Cont.

Parameter Type		Type of Assessment	Sport	
Body segments	joint kinematics	wrist	swimming tennis	
		shoulder	running swimming tennis	
		elbow	swimming	
		hip	angular displacement	cycling horse riding karate front kick
			angular velocity	karate front kick
		knee	angular displacement	alpine skiing ski jumping snowboarding
			angular velocity	karate front kick running
		ankle	angular displacement	cycling ski jumping soccer specific tasks
		main joints	angular displacement	trampoline jumps
		Dynamics	dynamics	aerodynamic force
dissipative forces	bowling ball ski racing			
external forces	ground reaction forces			ski jumping take-off ski racing springboard during diving
	impact force			straight punch
	power			ski racing
joint moments	elbow			baseball pitching
	lower limb			instep kick snowboarding turns

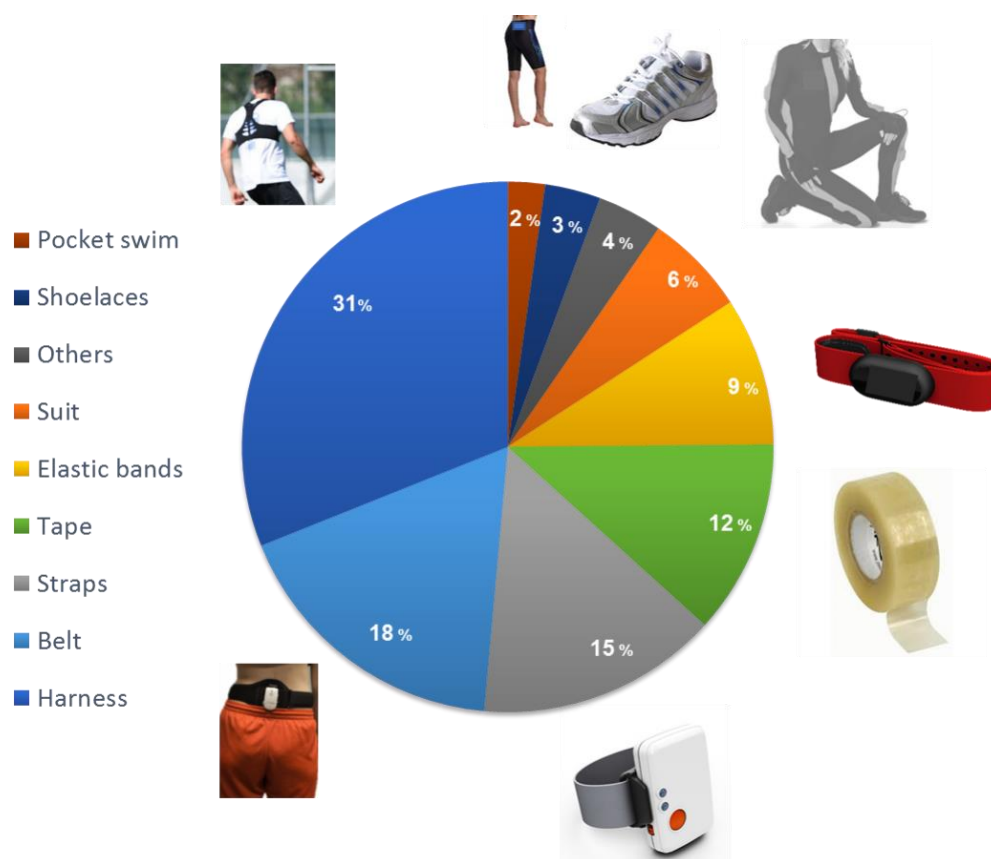


Figure 3. Device fixing mean in percentage (%) of the total papers, excluded those not specifying the fixing modality.

Spatio–Temporal Parameters

For non-cyclic tasks, temporal parameters were identified to measure critical temporal events (blade–puck contact time in ice hockey [206,309], cricket bowling [227] and, more specifically, ball release [288]), or detect task phases and critical events (in ski jumping [90,91], half-pipe snowboard [159], bowling [180], baseball swing [146,179], instep kick [228], karate front kick [273], diving trampoline jumps [161], artistic gymnastics springboard jumps [187], golf [171], javelin throw [270], soccer turning manoeuvres [241], swimming tumble turn [192,197,285] and start [193] and cricket bowling [264]).

For cyclic tasks, temporal identification can entail the simple identification of a stride/step/stroke event to measure their number, rate, duration, or the more complex identification of specific events within the cycle to subdivide it into different phases. Stroke duration and/or number has been identified in kayaking [260], single sculler [116] and multi-person rowing [217,275], and swimming. For swimming, sensor placement at the trunk/limbs/head was used to provide either arm strokes (for front crawl [63,80,107,110,263]), kick strokes (for front crawl [124,126] and freestyle [125]), or generic strokes (for front crawl [24,68,85,108,156,164,168,263,323,332], butterfly [24,68,85,156], breaststroke [24,68,85,164,291]). Stride and step frequency/duration have been assessed during running [153,157,160,162,174,191,202,204,229,230,242,243,262,294,295,302,321,327], skating [293], and in the run up of cricket ball delivery [264]. Revolution rate was characterised for a bowling ball [180] and during cycling [302,313]. Phase segmentation was performed in swimming (to identify front crawl stroke phases [80,164,246,247]), in cross-country skiing [120,207,237] and uphill mountaineering [121] (to determine cycle rate from plant and lift-off of each ski and pole ground contact), in ice hockey skating (to determine cycle rate from initial contact to blade-off for

each skate [293]), and during running on a track (trunk placement [61,149,153,194] and shank or foot placement [140,209,295]), on a treadmill (trunk placement [77,203,315,320] and shank or foot placement [87,140,148,222,229,230,294,318]), and during the acceleration/maintenance phase of sprint running (trunk placement [70] and foot placement [57]).

Corresponding to these temporal parameters, the average step/cycle length was obtained for arm strokes in swimming [63,108,156] and the average stride length was derived from either measured motion and contact times (for treadmill running [87,229,230,294] and track running [327]), and dividing the average cycle velocity by cycle time (in running [328], cross-country skiing [120,237] and uphill mountaineering [121]).

Body Segment and Centre of Mass Kinematics

Obtaining *body segment* and *CoM instantaneous velocity* from the integration of acceleration in the global frame entails the challenge of properly compensating for sensor drift through the design of appropriate processing techniques. These algorithms first remove gravity from acceleration data (see below for orientation estimation methods) and then integrate acceleration by the following method:

- using known treadmill motion information (during simulated cross-country skiing [41,237])
- performing the integration over a short time duration through proper segmentation of the task and using a priori information to reset the error at each cycle (running speed obtained from a shank sensor [328])
- assuming equal initial and final conditions for vertical velocity and position (during vertical jumping [220])
- segmenting the data and removing mean velocity, under the assumption that each temporal segment is at steady-state (mean velocity computed by averaging few rowing cycles with a moving window for single sculling [116], or according to changes in forward acceleration variance for swimming [106])
- through data fusion with GPS based velocity estimates (during running and cycling [302], alpine skiing [122], and snowboarding [333]).

Alternative to the use of measured acceleration, body segment or CoM velocity can be derived from the corresponding angular velocity and definition of a forward kinematic model (used to estimate forward speed of the tennis racket head [54] or for full body CoM during alpine skiing [122]). Subject specific models were also developed to estimate CoM velocity during running, based on step rate measures [242]. The errors entailed in instantaneous velocity estimation can be partially overcome by limiting the velocity analysis to average values in cyclic sports, for example, for each swimming stroke [104–106,108,290] turning action [192], lane [63,80,323], running cycle [162,328], or mean velocity in running [56,160]. The average velocity of progression was also obtained from ski IMUs, removing drift and assuming zero-velocity during a portion of the ski thrust phase, in cross-country skiing [120,237] and in uphill mountaineering [121].

Obtaining *forward horizontal* and *vertical CoM displacement* is less sensitive than estimating velocity due to inaccuracies in the removal of gravitational acceleration and to drift errors amplified by the double integration of acceleration. Such variables have been determined under two possible conditions: either when drift errors were small with respect to the measure of interest, or when displacement was obtained with respect to a known reference position [315]. The former applies, for example, to the assessment of large displacements from a starting position, such as during jumps when skiing, snowboarding, mountain biking (height and horizontal distance obtained using GPS data) [266], cross-country skiing [41,237], and uphill mountaineering [121]. Error can even become negligible when CoM global trajectories are used solely to support the interpretation of other estimated variables, as is done for external force estimates during ski racing [75]. Six possible approaches have been proposed to derive known reference positions:

- subtracting the linear trend line over the analysed time period from the Euler angles [41]
- assuming that the mean value is constant for cyclic events, to derive vertical CoM excursion from peak to peak values within each cycle (while running on a track [295] or on a treadmill [155])
- defining a body model and measuring body segment orientation with respect to a reference to obtain vertical and horizontal CoM displacements (with respect to the skis at take-off during ski jumping [88], with respect to the ground during a golf swing [238] and with respect to a Global Navigation Satellite System (GNSS) antenna placed over the head during alpine skiing [122])
- starting and ending the movement in known positions, to obtain shoulder, elbow and wrist [185], and solely elbow trajectories [267] during baseball pitching
- through data fusion with GPS based position estimates, which simultaneously compensates for short-term GPS outages (during outdoor activities such as snowboarding [333])
- fusing the velocity of a root point (integral of a pelvic sensor acceleration) with the velocity estimated from the lower limb kinematics at ground contact [40,335].

CoM acceleration was also assessed to detect *event* timing, typically the impacts during running (from the upper body [72,295], heel and metatarsal heads [148], and the tibia [140]). Impact *amplitude* was reported for running [140,325], landing from horizontal jumps [248], and for tennis racket shocks [59]. Variations in acceleration amplitude are also considered relevant when characterising running performance [56,174,200,201,203], running economy (acceleration root mean squared value divided by average speed) [224,276] and symmetry [184,191,196], as well as turning manoeuvres in soccer [241].

Body segment kinematics were considered to assess various parameters: postural tremor of air pistol shooters [303]; take off velocity and angle during standing horizontal jumps as obtained from body segment orientations [248]; shank linear and angular velocity, angular acceleration, and antero–posterior linear acceleration during an instep kick [228]; tibial accelerations in depth jumps [283]; heel lift and forearm acceleration to describe running economy [295]; jerk of hip trajectory in climbing [279,280]; and segment vibrations during road and off-road cycling [212] and, in the latter condition, with different wheels [211].

Body Orientation

Body segment orientation was usually estimated by fusing data from different sensors, for example, using MIMU data alone to estimate trunk inclination during a sprint start [69], running on a track [295], during a golf swing [238,314], and during outdoor activities, such as snowboarding [333]. Inclination of body segments and angular velocity about the cranio–caudal axis were also estimated during trampoline jumps [161]. Pelvis orientation was dealt with in swimming [192] and climbing [279]. MIMU data were complemented by seat reaction forces to estimate bike and rider trunk orientation [330], while GPS data were added to estimate limb orientation in ski racing [75]. Constraints specific to a task, such as known starting and ending positions, were used to improve the accuracy of upper limb orientation during running [295] and baseball pitching [185,267]. Similarly, aerodynamic constraints were embedded within a sensor fusion algorithm to estimate sacrum, thigh, and shank orientation during ski jumping [88,89]. Few studies estimated the trunk rotation about a longitudinal axis: one study hypothesised that the accelerometers measure only the gravity vector, i.e., the acceleration directly provides the sensor orientation (swimming [63]) whereas another study used numerical time-integration of gyroscope data to analyse aerial manoeuvres in half-pipe snowboarding [159]. The latter approach was also used to obtain upper arm internal rotation angles in tennis [53,54]. A pioneering application about body orientation using IMUs was given in the definition of human whole body pose during bicycle riding by considering the constraints characterising human–bicycle interaction [331].

Estimating body segment orientation is also essential when *removing the gravity vector* from measured accelerations to assess CoM acceleration in the global frame. In this framework, drift removal

was performed either through data fusion (alpine skiing [189]) or, if all sensors were not available, under task-specific assumptions. For example, during swimming, the average axis about which the sacrum rolls was assumed to be in the forward direction [106] or during running, yaw was assumed to be zero when moving in a straight line [302] or, again, that the net measured acceleration of the runner was equal to gravity and that its orientation was constant during the trial [155].

Joint kinematics require both a good orientation estimate and appropriate anatomical calibration. They were determined for wrist flexion (tennis serve [54], swimming [119]), shoulder angular displacements (internal-external or/and abduction-adduction: tennis serve [53,54], internal-external rotations in running [295], flexion-extension, abduction-adduction, and internal-external rotation in swimming [119]), elbow angular displacements (flexion-extension and pronation-supination in swimming [119]), hip angular displacements (flexion-extension in ski jumping [90], flexion-extension, abduction-adduction, and internal-external rotation in cycling [96], external rotation in horse riding [138]), hip angular velocities on the sagittal plane (karate front kick [273]), knee angular displacements (flexion-extension in ski jumping [90], alpine skiing [187], cycling [214] and snowboarding [188], flexion-extension, abduction-adduction, and internal-external rotation in alpine skiing [333]), knee angular velocity on the sagittal plane (karate front kick [273], running [295]), shank-ski angle on the sagittal plane (ski jumping [90]), ankle angular displacements (plantar-dorsiflexion, inversion-eversion, and internal-external rotation in soccer specific tasks [55], plantar-dorsiflexion in cycling [214]), and for all the main joints during trampoline jumps [161].

Object orientation and kinematics

The estimation of these parameters entails coping with the typical sensor errors but does not entail soft tissue wobbling. Orientation and kinematics have been estimated for several activities:

- alpine skiing (ski inclination in a lateral direction with respect to the Earth's fixed coordinate system, describing the skis' steering and edging manoeuvres [189,231])
- baseball (bat position, orientation, linear velocity during the swing [179]; ball's velocity at release [221])
- bowling (ball velocity [180])
- combat sports (acceleration of the boxing bag at the time of the punch [79,239,284])
- cricket bowling (outward acceleration at ball release [288])
- cycling (roll angle [330], crank angle [95])
- ice hockey (puck velocity [309])
- fencing (foil speed during lunge and *touche* [329])
- golf (clubface orientation, head velocity, and position [181]; clubface orientation, head velocity and acceleration [171])
- gymnastics vaulting (springboard kinematics during jump on and take-off [187])
- javelin throw (javelin kinematics during the throw [270])
- kayaking (instantaneous boat velocity [169])
- rowing (boat acceleration [81,205,260,275,287], orientation [287], velocity [217,287], forward movement and balancing, propulsion, and distance travelled [217], as well as boat-oar stroke angle [205,287], oar acceleration [205]), seat position [287])
- shot-put (shot acceleration [139])
- ski jumping (ski velocity [300], ski horizontal and V-opening angles during jumping [90])
- softball (ball's velocity at release [221])
- tennis (consistency of backhand, forehand, overhand swings [301])
- outdoor running (path incline [162])
- uphill mountaineering (ski slope orientation [121])

- weightlifting (barbell acceleration measured during power snatch, power clean and jerk from the rack [123] and snatch lift [271]).

In some studies, reference values for MIMU data integration were used to estimate instantaneous velocity (GPS data for kayak analysis [169], video cameras for javelin kinematics during the throw [270]).

Dynamics and Power

The estimation of dynamic variables is rarely carried out, due to difficulty in assessing external forces. None of the analysed studies carried out a validation against dynamic measures, but some studies reported data from the literature for comparison [43,75,88]. *External forces* were estimated through inverse dynamics; total aerodynamic force applied on the athlete's body assumed as rigid, during the stable flight phase of ski jumping [88]; hand force applied on the javelin during the acceleration phase of the throw [270]; force and time duration of a strike on a punching bag [79,239,284]; centrifugal force, applied outward on a skier during a turn [231]. To estimate forces exchanged with the environment during skiing, inverse dynamics requires CoM acceleration, estimated from an articulated system of rigid bodies (using a body model). The resultant force acting on the athlete's CoM, perpendicular to the ski table, was obtained during the take-off phase of ski jumping [88]. For overground skiing, information about the ratio of loading between the skis is also required to resolve the indeterminacy of the inverse dynamics problem. An approximation of this ratio was obtained from pressure sensor insoles embedded into the ski boots, in order to estimate the ground reaction force applied to each foot, aerodynamic force, ski friction, power, and energy during ski racing [75]. *Joint dynamics* were obtained through pure inverse dynamics for tasks entailing no exchange of forces with the environment, as is typical for open kinematic chain movements of the upper and lower limbs (elbow forces in baseball pitching [158] and shank dynamic variables during instep kicks [228]). For tasks entailing the exchange of forces with the environment, dynamic measurement systems and a hybrid inverse dynamics approach were used, mounting force plates on the snowboard, to obtain lower limb net joint moments during snowboarding turns [43]. IMUs were also used to obtain *vertical stiffness* during running, by estimating the vertical ground reaction force during the support phase using measured contact times and the participant's body mass [77].

Spectral Analysis

The frequency content of the acceleration of body segments, usually analysed in relation to the risk of injury, was, in some cases, associated with performance in (i) runners, when investigating the association between strike patterns and shock attenuation [157,229,230] or soft tissue vibrations [118]; (ii) air pistol shooters, during aiming, as postural tremor is associated with performance [303]; and (iii) cross country mountain biking, to describe the relationship between vibration mechanics and their interaction with the terrain, bicycle, and rider [211].

Technique Analysis Objectives

The objectives related to technique analysis pursued with MIMUs span a broad spectrum, including

- visual inspection of kinematic data to support qualitative understanding of the technique (kayaking [260], running [321], springboard diving [173], weightlifting [272], cross-country skiing [215])
- pacing strategy, determination by stride/step/stroke rates assessment (detailed references in the spatio-temporal parameters section)
- assessment of inter-segment coordination (lower-limbs during the take-off extension in ski jumping [89], hip, chest, and wrist during baseball swings [146]) and of inter-arm coordination (front-crawl [107,108])

- assessment of symmetry (running gait [184,191,196], wheelchair propulsion [71], horse riding [138]) and regularity\variability (running gait [223], cycling [276,313])
- detection of foot strike type [148,295]
- assessment of the impact of training tools and accessories during running (static stretching [209], wearing graduated lower-leg compression sleeves [294]) or of caffeine supplementation during simulated field hockey [112]
- comparison of different techniques (cross-country skiing [215,237])
- evaluation of the adherence of a movement technique to appropriate normative data (performance model) for both injury management and performance enhancement [52]
- investigation into the mechanisms that maximise speed in multi-articular joint movements (increase in muscular efficiency vs different muscular activation patterns in fencing [329] and karate [273])
- investigation into the effect on performance of varying the sports objects characteristics (e.g., effect of ball size on player reaction and racket acceleration during the tennis volley [59])
- use of technical information to match equipment with athlete, or in crew selection processes (kayaking [260])
- synthesis of athlete motion in competitive game-play by finding related action sequences in a database of reference motions using a sparse set of measurements from the performance (exemplified for tennis shots [177,301])
- differentiation between categories of athletes, based on key performance parameters and technique (elite and sub-elite for ice hockey blade–puck interaction [206,309] and for air pistol shooters [303], and highly trained inter-collegiate and untrained runners in terms of acceleration economy [224])
- monitoring fatigue during running [295]
- determine an optimal gradient and speed during uphill ski mountaineering [254,255].

Wearable sensors have also been embedded into sport-specific feedback and coaching systems which may be used for training and race analysis, providing to the coach/athlete real-time, visual, tactile, and auditory information, as well as data to be analysed immediately. These systems must be designed to comply with user requirements (coaches, biomechanists, and athletes), reliability and sport-specificity being the most important [24]. Acoustic and visual feedback systems have been developed both for sweep rowing [62,275] and sculling [58,116,205,217], for example, performing start and steady-state analysis, under training and race conditions, based on boat velocity and stroke rate [217]. Another promising sport for feedback use is swimming, whose performance and technique parameters, such as CoM velocity, arm strokes, distance per arm stroke, body balance, and body rotation, are assessed and provided to the coach/athlete through a user-friendly interface [24,63,110]. Proof of concept for coaching/training systems has also been demonstrated in skiing [231], golf [147], baseball swing [146], shot-put [139], volleyball [306], and weightlifting [272].

3.4.2. Match Analysis and Load Monitoring/Physical Demands Assessment (61 Papers)

All but one of the studies performed during competition belong to this category (18 papers), while 38 were held in the field during training. Most of the match analysis involving IMUs was carried out using Integrated Technology (IT). IT was developed to increase the sensitivity of GPS systems to abrupt changes in running velocity, direction, and to impacts, typical of most team-sports, by incorporating high-frequency (100 Hz) tri-axial accelerometers in GPS systems. Some systems (e.g., Minimax, Catapult Sports, Melbourne, Australia) also incorporate gyroscopes and magnetometers to improve tackle detection and report the direction of travel, respectively. The MIMUs' role in the context of match analysis is, therefore, complementary to that of GPS systems (see reviews by [15–19]).

Due to the limitation of GPS systems in tracking movement patterns indoors, research based on IT use covers mainly outdoor sports, including American football [317], Australian rules football [73,74,98,111,137,142,143,178,259,298,299], field hockey [253,319], handball [210],

Gaelic football [245], netball [86,99], rugby [101,102,127–135,176,208,225,226,297,311,312,316], rugby sevens [296], soccer [66,109,144,152,235,249,277], aerial skiing [175], and tennis [163]. In indoor studies, training load was assessed solely using accelerometer data in badminton [113], basketball [234,274], mixed martial arts [165,182,183], tennis [145], and volleyball [92,136,170].

The match analysis performed in team sports is most often based on the body's CoM kinematics. This provides information on the amount of the mechanical work associated with the CoM during locomotion and contact-based fatiguing movements generated during training and/or competition [74]. This external component of training load can be used as an activity profile measure (i.e., exercise intensity, body or workload marker). External load is generally determined using IT systems, to measure the distances covered in a variety of locomotor classifications or speed zones. To characterise the intensity of player activity in sports entailing frequent collisions, this approach must be complemented with quantification of the contact demands. Success in such sports is also contingent on the ability to tackle and tolerate physical collisions [48]. Monitoring collisions has implications for injury risk, muscle damage, recovery, and training load manipulations, while the number, type, and magnitude of tackles, as a subset of collisions, are recognised to be crucial to match outcome [102,127,130,131,133,176,208,225,296,316]. The ecological validity of tackle detection depends on the sensor type, algorithm, and sport analysed. An acceleration threshold may not be able to set apart tackles from collisions [133], whereas, both assessing body lean with gyroscopes [143] and developing ad hoc algorithms to identify tackles on acceleration signals [176] were shown to improve ecological validity. This, however, may not transfer across sports [142]. A crucial role can also be attributed to filtering, although this role was only assessed for generic impacts [324], and to the assessment of individual devices, particularly for mechanical damage and signal drift errors, to prevent poor validity [336].

To estimate external load, trunk acceleration has been used, although it was poorly correlated with whole body mechanical loading [240]. The parameter commonly assumed to be proportional to external load is the mean squared instantaneous rate of change in acceleration (i.e., the jerk vector amplitude), termed PlayerLoad™ in some proprietary systems. This external load measure has acceptable within- and between-device reliability [74], moderate to high test–retest reliability, and convergent validity with measures of exercise intensity on an individual basis [67]. Some studies distinguished the jerk contribution to external load along different directions [66,67,98,99,143,249] or its accumulation over time [143]. This parameter varies between sports, training modes, player position/role, etc. [16]. For this reason, methods for quantifying external load should undergo a sport-specific validation, as done, for example, for volleyball [92,170], mixed martial arts [165], and Gaelic Football [245]. External load should also be combined with internal training-load measures (e.g., session rating of perceived exertion) to monitor an individual's response to the training dose [137,144,175,182,208,259,277,316].

Many objectives were pursued using measures of external load, such as

- quantifying physical and technical demands for a specific sport (aerial skiing [175], American football [317], Australian football [259], mixed martial arts [165,182], rugby [130], soccer [109,249,277])
- assessing the effect of playing position (American football [317], Australian Football [73,137,178], handball [210], netball [86,99], rugby [128,130], rugby sevens [296], soccer [152,277]), playing level (elite and sub elite: Australian Football [73], soccer [109,277]), numerical advantage (soccer [235]), playing time [311], playing standard (Australian Football [98], badminton [113], rugby [129,131]), and age group (tennis [163])
- characterising successful teams (rugby [127,129])
- assessing the effect of match score on activity profile and skill performance (Australian football [298])

- determining how external load measures and skill performance contribute to coaches' perceptions of performance (Australian football [299]) and how these vary between matches (Australian football [178])
- assessing the contribution of running to external load, through a correlation analysis of distance covered (field hockey [253])
- assessing the number of collisions and repeated high-intensity efforts [128]
- assessing differences between different training conditions (rugby [133]) and with competition demands (Australian Football [73], mixed martial arts [183], netball [86], rugby [134], soccer [277])
- determining the best load assessment according to training mode (rugby [316])
- investigating agility demands of small-sided games (Australian football [111]), and closed drills [60]
- inferring information about internal load (soccer [144])
- assessing the impact of playing experience on internal load, as estimated through the external load [137]
- assessing fatigue, from training sessions (rugby [133]), from consecutive days of match play (tennis [145]), and in real time (soccer [66]).

More sophisticated match analysis may complement physiological demands with additional information about players' movements within their positional zones, for example, assessing an individual's tactical behaviour with respect to players with the same role [152].

3.4.3. Motor Capacity Assessment (51 Papers)

Exploring the force–velocity relationship during movements that involve complex inter-muscular coordination in a standardised setting can provide useful information when designing strength training programmes [337,338]. To this aim, motor capacity standardised assessments have been developed to determine either velocity or power during the acceleration and deceleration of a constant mass, as is typical in athletic movements (iso-inertial assessment [50,305]). For athletic profiling, these assessments should comprise both measures of the athlete's maximal velocity (*explosive performance*, also referred to as ballistic performance [13]) and *maximal strength* (possibly when lifting a set of increasing loads in classical overload exercises). Both types of assessment have been performed using MIMUs that provide instantaneous acceleration (and therefore force) data along with an integrated measurement of velocity to determine muscular power: *explosive performance* was assessed for the lower limbs during jumps [13,83,84,92,93,97,100,117,150,166,167,199,213,218–220,233,244,251,257,258,281,286] and for the upper limbs [78,141,151,190,236,310]. Force and power production capacity were quantified during *maximum dynamic strength tests* for the upper limbs [76,97,103,172,186,198,252,261,305] and lower limbs [64,65,76,82,97,172,252,265,289]. As an indirect assessment of force production capacity, static muscular stiffness has also been assessed [256]. The accuracy and reliability of both explosive performance [13,14,83,100] and strength assessments [13,50,305] has been widely acknowledged as being dependent on data collection equipment. The MIMU based methods were not always shown to be the most accurate or reliable, but can be considered acceptable according to the subsequent application, once the level of error associated with a given configuration is considered.

Explosive performance has been analysed using MIMUs during various vertical jumping activities, such as squat, countermovement, and rebound jumps, or landings. This data is quantified for the lower limbs in terms of jump height, maximal velocity, and peak power, eventually separating concentric and eccentric contributions. Several studies tested the accuracy, reliability, and validity of MIMUs in providing jump height [13,83,84,92,93,115,117,167,199,213,218,220,233,244,251] or other jump related parameters, such as peak knee flexion and trunk lean during landing [115], take-off velocity, contact and flight time [93,167,220,233,257,258], and force and power [97,100,281]. Upper limb ballistic performance has been analysed in terms of maximum velocity, estimated strength, peak power during explosive bench press [141,151,236], and also upper limb ability to elevate the centre of mass during upper

limb jumps [190]. Based on current reliability findings, all of the reviewed explosive performance assessments may be implemented and used to support different training issues: (i) to determine indices of efficiency relevant to sport-specific performance [190]; (ii) to distinguish between athletes' skill levels [166]; (iii) to select the best training programmes to improve performance [219,286]; (iv) to determine the optimal load for ballistic tasks performed with overloads (such as jump squats [14]); (v) to assess explosive strength in relation to various factors (such as the athlete's respective sport [141], level of engagement (recreational or professional) [141], gender [141], and effect of weight machine design [78,310]).

The reliability and accuracy of velocity and power measures performed using accelerometers during *maximum dynamic strength assessments* were evaluated, often in comparison with other assessment methods for upper limb muscular power [97,305] and during squat lifts [64,97,150,289]. Reliability and reproducibility were also assessed for repetition and time under tension during leg and bench press exercises [76]. The reproducibility of velocity and power estimates during squat lifts [82,172,289] and bench press exercises [172] have been assessed. A critical role has been attributed to participant variability, especially for the lightest loads [82,172], with velocity and acceleration variability having a combined negative impact on power reproducibility [339]. Nevertheless, MIMUs can be considered, within the known limits of reproducibility and accuracy, as a tool for monitoring strength–power potentiating complexes, performed with overloads to describe the load–power and load–velocity relationships for specific exercises [172], to determine the optimal loads for training [14,103,261], to monitor the effects of power training [65,265], and to assess the effect of stability conditions on power production [186].

In this respect, performance related parameters, obtained using sport-specific capacity tests, or during standardised *in-field tests* can be of great benefit. However, thus far, few attempts have been made to develop sport-specific capacity tests measuring the athlete's performance potential in combat sports [269] or to adapt traditional tests, such as vertical jumps, to a specific sport, as done for soccer for analysing vertical jumps with intention to head [257]. Instrumented in-field tests have been developed mainly to assess the performance of wheelchair users [71,216,250,282,292,307], probably because of the higher quality of signal obtainable by attaching the sensors to the wheelchair or athletes' upper limbs, thus limiting the effect of soft tissue wobbling. These papers testify the potential of MIMUs to assess agility (repeated turn tests), by quantifying shoulder and elbow joint kinematics [292] or wheelchair kinematics [307], and muscular power (sprint tests) or endurance (distance tests), by quantifying average and peak wheelchair kinematic parameters [71,216,250,282,292]. A reliable assessment of agility drills in match-like conditions enables prospective research during real matches [60,307], as utilised in wheelchair basketball [308]. The description of individual wheelchair mobility can also be used for classification within the sport [308].

3.4.4. Activity Classification (19 Papers)

Activity classification papers cover

- the identification of different movement patterns through simple visual inspection (cross-country skiing [215])
- the identification/evaluation of techniques and styles/tricks [154,164,268], specific movement phases [114], and events (player tackles and collisions during rugby matches [176], putt detection and characterization for golf training progress [171], arm action and ball release performed by cricket fast bowlers during training and competition [227], eventually used for the detection of illegal events [195,322])
- automatic detection and classification of sports activities during wheelchair rugby matches [94] and team sport activities [326]
- automatic classification of training backgrounds and experience levels in runners [184].

Activity classification has been performed by measuring body segments in relative or absolute orientation, to detect sprinting, jogging, walking [52,195,232,326], jumping, cutting, kicking [52], dribbling, ball strike, tackling [232], swimming style [164,304], trampoline routines [161], climbing phases [114], rugby collisions [176], volleyball actions [306], tennis strokes [301], golf putting [171], and aerial manoeuvres in half-pipe snowboarding [159] and skateboarding [154].

Automatic classification (i.e., mapping input data to a predefined category) may be carried out through the following procedure: (i) acquiring an annotated dataset in which, in cases of supervised classification, each datum is associated to a class label; (ii) pre-processing data by filtering, down-sampling or windowing to identify data segments to be classified; (iii) extracting discriminative features, i.e., quantities that hold the information to be used for classification; (iv) training the selected classifier using the training set; (v) using the generated classification rules for prediction of the test set. Activity classification solutions are then often cross-validated, by running several different splits between the training and test sets, to better assess the quality of the methods. Common approaches for this are the N-fold cross validation and the leave-one-subject-out cross-validation method. The selected features/patterns should encode important and intuitive properties of the athlete's body configuration while remaining constant under global variations. It is desirable that stronger correlations exist between similar features/patterns and poorer correlations between dissimilar features/patterns. They can be simple time/frequency features, such as means, standard deviations, entropy, dominant frequencies, or can be extracted using Discrete Wavelet Transform. Unsupervised approaches for classification cluster the extracted features, often based on k-means analysis, with a predefined cluster number or by selecting the cluster number within a consensus clustering framework [278]. Supervised approaches train the classification system using a set of data with a known classification. The classifiers of this kind used in the revised literature are decision trees (random forest training algorithms [52,326], logistic model trees [232,326]); stepwise discriminant analysis of principal components [184]; k-Nearest Neighbour algorithms (IBk [232], Lazy IBk [52]); Artificial Neural Networks (RBF Network [52], MLP network [232]); Support Vector Machines [176,232,326]; Naïve Bayesian classifiers [52,154,232]; fractals [94]; Hidden Markov or Semi-Markov models [171,304]; and Hidden Conditional Random Field [176].

3.5. Device Characteristics

A systematic analysis of sensors' positioning and configuration, as implemented in the reviewed studies, is provided in Tables 5 and 6; sensors attached on the athlete's body segments are reported in Table 5, while those attached or inserted into sport equipment are depicted in Table 6.

In regard to the type of inertial sensors used, more than half of the reviewed studies (57%) exploited only 1D/3D accelerometers. In the remaining cases, the measurement of the accelerometer was integrated with other sensors, namely, gyroscopes (25%) or gyroscopes and magnetometers (15%). Only a few studies used 1D/3D gyroscopes in isolation (3%). In regard to the sensors' features, the ranges of the accelerometers were largely below 10 g (71%) and more than half of the gyroscopes had a range below 1200 deg/s (61%). The most used commercial system was the MinimaxX (considering all the different versions produced by Catapult) followed by Myotest (Myotest), SPI-PRO (GPSports), Xsens systems (Moven suit and MTx sensor), and Physilog (GaitUP). On the other hand, 68% of the reviewed studies implemented custom-made devices and 15% reported no information in this respect.

With regard to IMU number and position, 67% of the studies exploited a single sensor configuration, 24% used two to five sensors, 7% used more than five sensors, and 2% did not report this information. Typically, the single sensor configuration was inserted into the sport equipment or attached to the trunk–pelvis segment or distal segments, such as the hand and foot. Considering the sports most frequently analysed—swimming and running—the single sensor configuration was preferred in 69% and 60% of the studies, respectively. Several procedures were adopted to attach the sensor onto the athlete's body segments, from double-side tapes, elastic stretch bands, straps, and Velcro fasteners, to body suit and customized vests (Figure 3). When the sensor was attached to the sport equipment, glue was typically used.

Table 5. Sensors' positions and configurations on the athlete's body (front and back views). The different positions are coded with specific body segment capital letters (C—chest-back; U—upper arm; A—forearm; W—wrist; H—hand; P—pelvis; T—thigh; S—shank; F—foot) and numbers (to distinguish different positions for the same body segment). The different configurations are specified in terms of type of device (accelerometer, gyroscope, magnetometer) and number of dimensions (one-, two-, three-dimensional). Each configuration is reported in a different column.

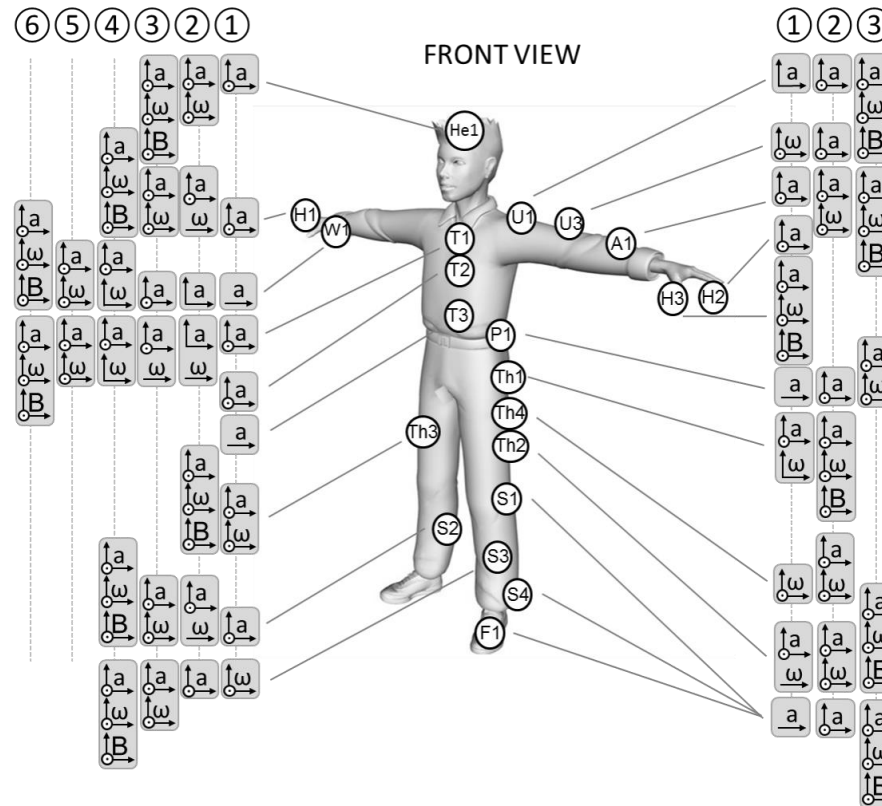
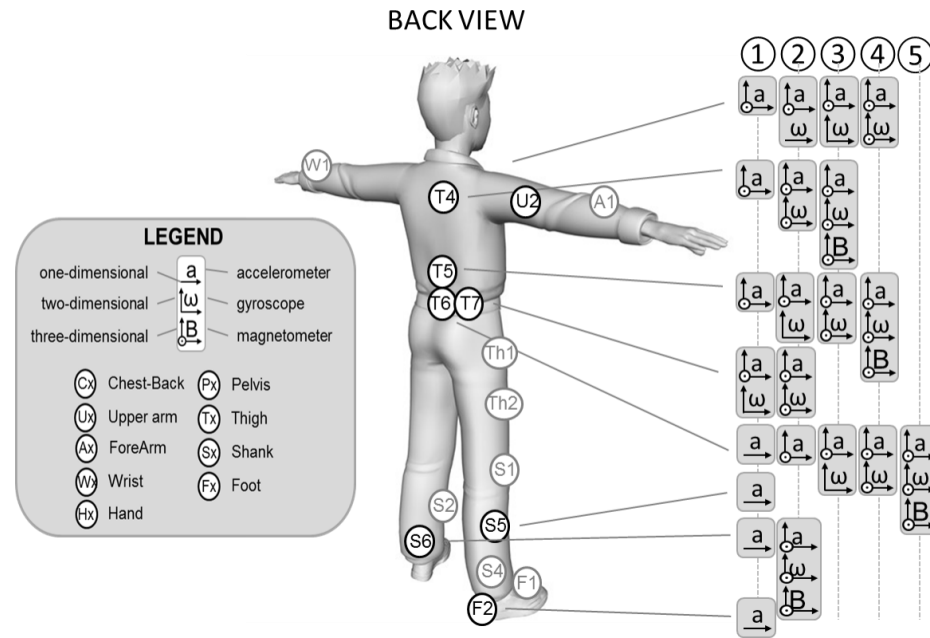


Table 5. Cont.



Device Position	1	2	3	4	5	6
He1 (head-helmet)	[68]	[122]	[212,302]			
U1 (acromion)	[58]	[303]	[119]			
U2 (upper arm posterior)	[80]	[53,54]	[147]	[168,185,267,295,322]		
U3 (upper arm)	[331]	[269]				
A1 (fore arm)	[177,247,303]	[64,107,108,158,185,322]	[114,119,161,211,212,278]			
W1 (wrist)	[71,323]	[76,295]	[63,80,156,164,261,269,288,332]	[146,147]	[266]	[76,295]
H1 (third metacarpal bone)	[303]	[53,158]	[301]	[119]		
H2 (index finger)	[303]					
H3 (thumb)	[180]					
T1 (sternum, clavicles)	[112]	[115]	[53,54]	[146]	[122]	
T2 (sternum bottom)	[174,177,274,306]					
T3 (navel)	[166]					

Table 5. Cont.

T4 (upper back, T6–T10)	[56,60,63,66,67,73,74,80,86,98,99,101,102,111,130–132,135,137,143,152,163,165,175,183,208,225,226,231,232,234,235,240–242,249,253,259,274,277,296,297,311,312,317,319]	[128,129,134,136,182,295,326,330,331]	[161,178,210,215,227,266,295,333]			
T5 (L1–L3)	[63,84,174,177,184,191,197,223,224,320,321]	[24]	[69,70,192,193,290]	[119,212]		
T6 (L4, L5, sacrum, or lower back)	[155]	[61,63,67,72,80,85,110,113,162,170,190,194,196,200,201,203,213,234,237,244,273,304,332]	[147,285]	[41,88–90,104–107,122,168,220,248,251,257,262,263,291]	[114,199,211,238,258,278,281]	
T7 (5 cm left of L5)	[146]	[159]				
P1 (iliac crest)	[264]	[83,218,219,264,265]	[52]			
Th1 (great trochanter-hip)	[147]	[280]				
Th2 (distal thigh)	[126]	[88–90,115,273]	[96]			
Th3 (frontal thigh)	[52,91,231]	[214,228,238,294]				
Th4 (mid lateral thigh)	[331]	[122]				
S1 (head of fibula)	[117,157,229,230,313]	[248,295]				
S2 (medial shank)	[243]	[62,124–126]	[52,88–91,115,231,256,273,328]	[55,161,211,238]		
S3 (frontal shank)	[140,222,228]	[177,240]	[91,122,168]	[214,294]		
S4 (ankle)	[148,248,283,294,295]	[269]	[167]			
S5 (lateral shank)	[256]					
S6 (lower postural shank)	[256]	[212]				
F1 (shoelace)	[160,209,318]	[87,160,202,209,294,318]	[55,57,114,214,278,295]			
F2 (heel)	[118,148,162]					
Moven suit (Xsens Technologies, The Netherlands) (He, T2, U3, A1, H1, Th2/Th4, S5/S6, F1, T6)	[43,75,138,161,188,189,292,300]					

Table 6. Sensors' positions and configurations attached or inserted into the sport equipment. The different positions are coded with specific equipment capital letters (B—barbell; St—strike; L—locomotion) and numbers (to distinguish different positions for the same type of equipment). The different configurations were specified in terms of type of device (accelerometer, gyroscope, magnetometer) and number of dimensions (one-, two-, three-dimensional). Each configuration is reported in a different column.

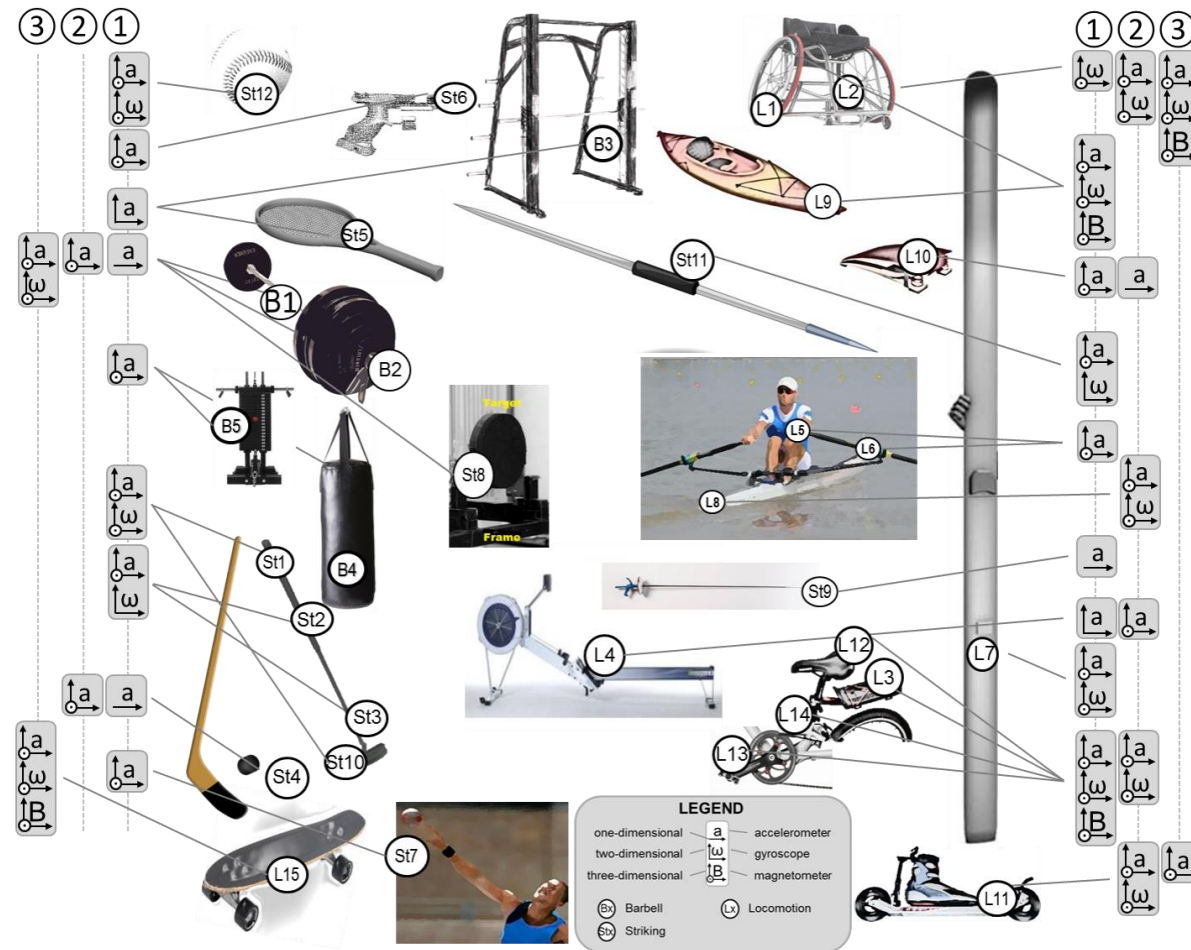


Table 6. Cont.

Device position	1	2	3
B1 (barbell close to handle)	[186]	[65,82,100,123,198,272,310]	[78,289]
B2 (barbell extremity)	[172]	[150,151,271]	
B3 (on the smith press)		[305]	
B4 (punching bag)	[79]		
B5 (weight stack)	[252,284]		
St1 (golf shaft)	[181]		
St2 (golf lower hand)	[147]		
St3 (golf near head)	[147]		
St4 (hockey puck)	[206]	[309]	
St5 (racquet)	[59]		
St6 (pistol)	[303]		
St7 (on the shot put)	[139]		
St8 (frame and target)	[239]		
St9 (on the foil)		[329]	
St10 (golf on the club head)	[171]		
St11 (javelin)	[270]		
St12 (baseball/softball)	[221]		
L1 (wheelchair wheel)	[94,216,282]	[250,308]	
L2 (wheelchair frame)		[308]	[71,282,307]
L3 (rear bike)	[302]	[330]	
L4 (rowing seat)	[58]		
L5 (rowing oar)	[205,295]		
L6 (rowing boat)	[116,205]	[260]	
L7 (skis)	[88,90,121,231,254,255]		
L8 (top of the boat)		[217,275,287]	
L9 (on the kayak)		[169]	
L10 (on the springboard)	[187]	[173]	
L11 (roller ski/skate chassis)		[268]	[293]
L12 (bike seat)			[95,212]
L13 (bike crank)			[95]
L14 (bike frame)		[331]	

4. Discussion

4.1. General Trends

Coaches, athletes, and support staff are benefitting more and more from the use of magneto-inertial sensor technology. In recent years, a high number of publications have testified that this technology is now suitable for assessing player capacity, technique, and match workload, both for individual athletes and sports teams (Figure 2). Monitoring these aspects can enhance training design and evidence biomechanical fatigue, thus facilitating the development of appropriate injury reduction interventions [3,340].

Technique analysis has been performed for more than 37 sports using MIMUs, to obtain predominantly spatio-temporal parameters, centre of mass kinematics, and body segment orientation, spanning a broad spectrum of objectives. The majority of this literature focuses on describing technique, rather than developing tools to correct technique because exploitation of inertial sensors in sport performance evaluation is rather recent. Only after gaining a deep understanding of MIMUs patterns, for different athletes' levels, it will be possible to use this tool to revise or to improve the technique of a given athlete. Regarding experimental errors, gyroscopes have demonstrated greater limitations (i.e., drift) than accelerometers, but they are essential when obtaining orientation both as a parameter in dynamic conditions and when removing gravity from acceleration data. As a result, orientation and joint angle estimates can be inaccurate; accuracy depends on task duration, intensity, and soft tissue wobbling, which are dictated by the task and body segment analysed. Drift errors also hinder the accuracy of velocity and position estimates, as obtained through the numerical integration of MIMU signals.

Combined IMU and GPS data have been used to obtain sensitive and holistic measures of *external loading* in team sports. Specifically, they enable the detection of abrupt changes in running velocity and direction, as well as impact identification and classification [67]. Data have also been used to quantify the technical demands of team sports and have proved to be sensitive to the effect of factors influencing success. These data can support the manipulation of team sport parameters (e.g., rules, field size, player numbers and position, coach feedback, etc.), which facilitates optimisation of training stimuli [48,182,341].

MIMU-derived information has proven to be adequate in assisting routine *capacity assessment* along the vertical direction during explosive performance and maximum dynamic strength tests. This supports the evaluation of learning and progression/regression processes and, therefore, enhances the efficacy of a planned training schedule and the compilation of a training diary. The accuracy and reliability of these assessments are dependent on data collection procedures and equipment. This currently inhibits the development of more complex instrumented in-field tests, occurring in the horizontal plane (e.g., Yo-Yo test, Reactive Agility test).

The current decade has seen a rapid increase in the availability and use of wearable technology [342–345]. As sensor utilisation rises across sports and monitoring is allowed during competition (e.g., rugby, baseball, tennis) [346], the challenge becomes providing more intelligent, real-time, accurate information, making it user friendly and offering coaches and athletes actionable insights [347,348]. In fact, amongst coaches, there is a perceived lack of MIMU related knowledge and known low usage rates, according to a survey of 500 swimming coaches [349]. This aspect can be explained by the fact that most signals obtained from MIMUs are less intuitive than, for example, the position of an anatomical landmark that can be easily investigated and interpreted using standard video analysis. Technology usage is hindered by the expense of adoption and implementation, by the skills required for data collection, extraction, and interpretation (indoor team sports [350]), as well as by the current lack of standardisation procedures [351]. On one hand, technicians and engineers should work on the development of methods aimed at providing coaches with metrics that are informative, concise, and easy to interpret. On the other hand, coaches, athletes, and support staff could enhance their likelihood of use and understanding by partaking in the development process

of second generation monitoring systems, by identifying training needs and opportunities [350,352]. Further, standardisation of relevant procedures is necessary to maximise the technology's potential.

4.2. Technological Advancements and Future Developments

Technological advancements may cause significant changes with lasting impacts on the performance and spectatorism of a sport [159,353]. The most significant recent developments have led to increased commercial sensor affordability and availability of sensor fusion technology and improved power management strategies (for example turning off a gyroscope when not necessary) [347]. Sampling frequency and full range scales are now adequate for most sport applications. The technology has reached a stage whereby, for mainstream sports, data collection is easily possible and affordable. For example, new generation gyroscopes allow tracking of fast rotational movements thus enabling the development of in-field training or monitoring devices (tennis [54]), and support tools for referees [354]. The cost of MEMS has been driven down by smartphones which have built-in sensors, including accelerometers, GPS, and often gyroscopes [347]. This enables smartphones to provide information on the motion, environment, position, and orientation of a device to both inexperienced users and experts alike. However, there is limited evidence supporting the use of smartphones over MIMUs [232,355,356]. This is potentially due to wearability issues [357] and inaccurate sensors. Wearability has been improved by using smaller sensors which transmit data back to the smartphone; alternatively, MIMUs are being substituted by smart fabrics which use garments as a wearable platform in which to embed sensors and processing units and appear as a potential future alternative/integration to MIMU [358]. To partially overcome the accuracy issue, MIMUs can be complemented by new sensors within a sensor fusion framework; ultra-wideband ranging sensors promise to estimate both orientation and position [359], whereas barometer sensors estimate only position [360,361].

Until recently, only professional teams and elite individual athletes had access to highly specialised technology. Recreational athletes were restricted to the use of low cost IMUs, such as step counters, whose outcome is often dissatisfactory. However, increasingly more products are being designed for broad participation; often products designed for elite use are later tailored to recreational athletes (examples with costs ranging \$70–200 can be found in Lightman [347]). Consequently, it is expected that recreational athletes develop a desire for more detailed and accurate performance data and an increased demand for affordable higher quality intensity/performance trackers, at an intermediate cost (wearables 2.0, potentially including virtual reality). This market demand is driving the democratisation of wearable technology. In the near future, fitness trackers requiring manual and subjective interpretation will be replaced by machine learning tools able to provide real-time monitoring and automatic and objective analysis. Furthermore, this data will provide clear actionable insights, benefitting users of all levels.

To support athletes in adapting their training and technique with useful insights, feedback systems are required [362]. These systems also reinforce the relationship between the coach's observations and the athlete's subjective perception of force and movement. The number and type of sensors is of paramount importance to their efficiency and success [363]. Further, visual feedback can help people with limited experience in MIMU use interpret the signal patterns [4]. Communication technologies allow athletes to document and share their training data, which may enable remote training supervision [357,364].

For these insights to become actionable, coaching systems must integrate sensor measurements with machine learning systems for the purpose of providing intelligent, online feedback. This enables tactical use and workload management, in addition to post game analysis [357,365]. Physical movement monitoring first requires the definition of a linguistic framework to represent the data symbolically [366]. Real-time or near real-time systems based on robust wireless network solutions can provide quick access to information. Then, the detection of key information and event classification can be performed using models for pattern recognition and classification of the motion or activity performed. Different methods and models, such as Neural Networks, Hidden Markov models,

and Support Vector Machines, have proven to be appropriate for this purpose (see *Activity classification* for further examples). This approach is essential for feedback systems aiming to recognise and evaluate the quality of specific techniques in the field [301], and eventually during technical–tactical sessions [306]. Machine learning can also automatically provide feedback on how to continue exercising and/or adjust smart sports equipment, depending on environmental conditions [367]. We hypothesise that, using a similar approach, athlete capacity assessment can also be further improved to include measures of sprint ability and agility and by assessing sport-specific tasks covering the entire force–velocity–power spectrum.

4.3. Guidelines and Standards

There is a call for the standardisation of data collection and analysis procedures amongst several contexts. For team sports, standardisation of physical demands and external load quantification are required, to facilitate comparison between skill levels and within a specific sport [101]. For capacity assessment, standardisation of power measurements is required to further understand the load–power relationship and the training adaptation mechanisms [50,368]. A list of general key guidelines is here reported that may help in assessing sensor quality, performing sensor calibration and anatomical calibration, properly fixing the sensors and processing the data (Table 7). Nevertheless, complete guidelines and standards for testing should be application- and sport-specific since, for a selected parameter, error is dependent on the task. Additionally, error compensation methods do not necessarily transfer across sports [143]. Therefore, the choice of methodology should be driven by the parameters and the task, with a balance between accuracy and practicability as well as consideration of environmental factors. Parameter-specific recommendations for both sensor type and sensor placement have been developed for running [243], but more research is required that is specific to other sports and parameters. In open skill sports, for example, the intrinsic variability must be considered in order to obtain reliable performance indicators [369]. Therefore, the sport scientist must have in-depth knowledge of the technology in order to make an informed decision, eventually combining different levels of sensor accuracy according to the aims [370].

Table 7. Guidelines for Magnetic and Inertial Measurement Unit quality assessment, calibration, fixing and data processing.

Guidelines for Magnetic and Inertial Measurement Unit Use
Quality Assessment
<ol style="list-style-type: none"> 1. avoid ferromagnetic disturbances when possible (no iron or magnetic fields) 2. assess accuracy following specific guidelines for sensor spot checks (e.g., [371,372])
Calibration
<ol style="list-style-type: none"> 3. re-calibrate accelerometers, gyroscopes [373–375], and magnetic sensors [376,377] to improve poor accuracy before each acquisition session when possible 4. carefully perform anatomical calibration, either functional or point-based, especially when assessing joint kinematics [38]
Fixing
<ol style="list-style-type: none"> 5. avoid restricting the range of movement 6. limit the movement between body and device (avoid tape) 7. for tasks entailing impacts, avoid elastic belts for fixing 8. avoid areas with “wobbling” soft tissues (fat or muscles) and areas close to joints
Data Processing
<ol style="list-style-type: none"> 9. low-pass filter with various cut-off frequencies depending on the analysed sport task [25,378] 10. use ad hoc algorithms to compensate for drift errors [21,371] 11. compensate ferromagnetic disturbances indoor [334,379] 12. refer to appropriate validation based on reference data or literature that is sport and task-specific 13. interpret data within the limits set by the quality assessment

5. Conclusions

This review demonstrates that magneto- inertial technology, continuously gaining momentum in sports biomechanics, is a reliable tool able to benefit athletes of all levels, especially when complemented within a sensor fusion network. This can ultimately extend and enhance athletes' careers through improved injury prevention and training specificity. While this reliability is fully exploited in the laboratory, there must be a compromise between the technology's potential and practicality in the field. When this compromise is not reached, mainly due to the lack of proper standardisation of data acquisition and of tools for the subsequent analysis, the technology may suffer from low usage rates amongst coaches. Better collaboration between the sport biomechanist and practitioner would facilitate overcoming this issue. Future research should focus on ease of use and improved error compensation and analysis procedures able to provide coaches with informative, concise, and easy to interpret metrics. In doing so, MIMUs can facilitate the provision of actionable insights for both the athlete and coach.

Supplementary Materials: A database with the details of all papers that are not reviews and were included in the systematic review is available online at <http://www.mdpi.com/1424-8220/18/3/873/s1>.

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