Wearable Inertial Sensors for Human Motion Analysis: A Review

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***Abstract*— This paper reviews the research literature on human motion analysis using inertial sensors with the aim to find out: 1) which configuration of sensors have been used to measure human motion; 2) which algorithms have been implemented to estimate position and orientation of segments and joints of human body; 3) how the performance of the proposed systems has been evaluated; and 4) what is the target population with which the proposed systems have been assessed. These questions were used to revise the current state-of-the-art and suggest future directions in the development of systems to estimate human motion. A search of literature was conducted on eight Internet databases and includes medical literature: PubMed and ScienceDirect; technical literature: IEEE Xplore and ACM Digital Library; and all-science literature: Scopus, Web of Science, Taylor and Francis Online, and Wiley Online Library. A total of 880 studies were reviewed based on the criteria for inclusion/exclusion. After the screening and full review stages, 37 papers were selected for the review analysis. According to the review analysis, most studies focus on calculating the orientation or position of certain joints of the human body, such as elbow or knee. There are only three works that estimate position or orientation of both, upper and lower limbs simultaneously. Regarding the configuration of the experiments, the mean age of the test subjects is 26.2 years (± 3.7), indicating a clear trend to test the systems and methods using mainly young people. Other population groups, such as people with mobility problems, have not been considered in tests so far. Human motion analysis is relevant for obtaining a quantitative assessment of motion parameters of people. This assessment is crucial for, among others, healthcare applications, monitoring of neuromuscular impairments, and activity recognition. There is a growing interest for developing technologies and methods for enabling human motion analysis, ranging from specialized *in situ* systems to low-cost wearable systems.**

***Index Terms*— Human motion analysis, human motion measurement, inertial sensors, wearable sensors.**

I. Introduction

A. Human Motion Analysis

HUMAN motion analysis is defined as any procedure involving any means for obtaining a quantitative or qualitative measure of it [1]. Quantitative analysis involves the measurement of biomechanical variables, such as pressure distribution, joint angles, spatio-temporal gait parameters, among others. Because of the huge amount of data to be collected and processed, this analysis requires computer-based calculations [2].

The human motion analysis helps specialists and researchers in the field to obtain a quantitative assessment of motion parameters of the patients. Measuring body movements accurately is crucial to identify abnormal neuromuscular control, biomechanical disorders and injury prevention.

Among the most common applications of the analysis of human movement we can mention medical evaluation, monitoring people, and activity recognition. In particular, human activity recognition supported by highly accurate specialized systems, ambulatory systems or wireless sensor networks has a tremendous potential in the areas of healthcare, personal fitness, entertainment, or serious games.

Specialized systems, such as Vicon (Vicon Motion Systems Ltd., Oxford, UK) or Optotrak (Northern Digital Inc, Ontario, Canada), have a high accuracy when operating in controlled environments, e.g. several fixed cameras calibrated and correlated in a specific place and capturing configuration. These systems can provide a large amount of redundant data. Ambulatory systems, such as those using a Kinect (Microsoft Corporation, WA, USA) to capture human motion, are set in relatively uncontrolled environments and have a restricted field of view. These systems have a restricted margin of manoeuvrability and are intended for indoor use mainly. In contrast, wearable sensors have the advantage of being portable and suitable for outdoor environments [3]. These systems are arranged with respect to an anatomical reference of the human body to measure specific biomechanical variables or motion patterns.

Continuous monitoring of human motion in daily environment provides valuable and complementary information to that obtained in laboratory tests. However, it has been extremely difficult to go beyond the laboratory and obtain accurate measurements of human physical activity in daily life environments [4]. As alternative to laboratory tests, wearable inertial sensor systems are important to reach a larger population than current systems for motion analysis can do. Since these systems have gained importance in recent years, and there are few published works revising and comparing their features and performance [5]–[11], we strongly believe it is crucial to update the literature review about research involving human motion analysis using wearable inertial sensors.

B. Taxonomy of Human Motion Analysis Using Wearable Sensors

Wearable inertial (*i.e.* accelerometers or gyroscopes) and magnetic (*i.e.* magnetometer) sensors have been used in some

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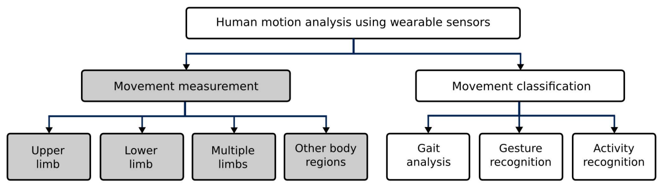

Fig. 1. Taxonomy of clinical applications of Human Motion Analysis. In gray boxes the classes reviewed in this review are highlighted.

clinical applications. Fig. 1 depicts a taxonomy introduced in this article based on the application of published works in the field of human motion analysis. The first class corresponds to works focused on measuring or quantifying movements of a specific segment of the human body, such as the limbs. The outcome of these systems can be a common unit of measurement such as angles, for instance. The second class groups works whose outcome is based on an interpretation or high-level classification of human movements, such as "running" or "walking".

In the first class of our taxonomy works focused on measurements based on the human regional anatomy or topographical anatomy [12] are considered. Common examples are upper, lower or multiple limbs, as well as other regions such as the head, neck and trunk.

Studies included in the second category are too diverse and comprise the estimation of spatio-temporal gait parameters and assessment of gait abnormalities [13]–[18], the recognition of meaningful human expressions involving hands, arms, face or body [19], [20], fall detection [21], [22], classification of activities of daily living [23]–[25]. Previous reviews of classification of human movement studies have been published recently. These reviews address mainly specific aspects of the problem, such as technical characteristics of the sensors used [26], algorithms for classifying [27], clinical human movement assessments [28], and recognizing [29], [30] human activity.

In this review only works of the first class are reviewed. In contrast to previous reviews, in this review multiple dimensions concerning technical, methodological and experimental issues are documented and compared.

C. Relevant Characteristics of Studies of Human Motion Analysis

There are five relevant characteristics to assess in the studies of human motion analysis using wearable inertial sensors: (1) the sensor used for the measurement, (2) the measuring motion unit, (3) the sensor fusion algorithms, (4) the evaluation system, and (5) the subjects of study. These characteristics are detailed below.

The **sensors** may be inertial as accelerometers and gyroscopes, and magnetic as magnetometers, or a combination of previous sensors. The **measuring motion unit** can be divided into two dimensions: position or orientation measure, and segment or joint on which the sensors are positioned. Common classes of **algorithms** for inertial sensor data fusion are: integration, vector observation, Kalman filtering, and complementary filtering. Concerning the **evaluation** of the performance of the studies, five approaches are identified: optical motion systems such as Vicon (Vicon Motion Systems Ltd., Oxford, UK) or Optotrak (Northern Digital Inc, Ontario, Canada), commercial inertial sensors such as MTw (Xsens Technologies BV, Enschede, Netherlands), magnetic position systems such as Liberty (Polhemus Inc., Vermont, USA), goniometers such as PS-2137 (PASCO, California, USA), and expert human evaluation. Finally, two aspects of the **subjects** of study are analyzed: the number of participants, and the age range of participants. Only studies in which the evaluation was conducted with people were considered.

The remainder of this paper is organized as follows: in Section II the search and analysis of the literature is presented; in Section III the findings of relevant studies are reviewed according to the taxonomy introduced in this article; Sections IV and V present, respectively, the discussion and conclusions drawn from this study.

TABLE I
DATABASES USED FOR THE LITERATURE SEARCH

Database	Source
ACM Digital Library	dl.acm.org
IEEE Xplore	ieeexplore.ieee.org
PubMed	www.ncbi.nlm.nih.gov/pubmed
ScienceDirect	www.sciencedirect.com
Scopus	www.scopus.com/scopus/home.url
Taylor & Francis Online	www.tandfonline.com
Web of Science	webofknowledge.com
Wiley Online Library	onlinelibrary.wiley.com

II. METHODS

In this section, the steps followed to conduct the search and the analysis of the literature are described.

A. Literature Search Strategy

A search of literature was conducted on eight Internet databases and includes medical, *i.e. PubMed*; technical, *i.e.* IEEE Xplore; and all-science, *i.e.* Scopus, literature (see Table I). Two groups of keywords were used in the literature search: group 1 (*"human motion" OR "human movement"*) and group 2 (*"wearable sensors" OR "inertial sensors" OR "wearable system"*).

A total of 880 studies were reviewed based on the criteria for inclusion/exclusion: English language; abstract available; published in journals, conferences or as book chapters; reporting a study based on wearable inertial sensors and studies that involve movement measurement determined from a screening of each abstract. No restriction has been imposed on the date of publications. This process yielded 107 papers from a first selection. A final selection was obtained from a full-paper revision in order to obtain the most relevant papers according to the characteristics described in section I-C, and as a result of this review 37 papers were obtained. A peer-review process was applied during the screening and full-review stages in which two reviewers have participated. An agreement was reached by mutual consent of the reviewers in the few cases of disagreement. The stages of the literature selection process are shown in Fig. 2.

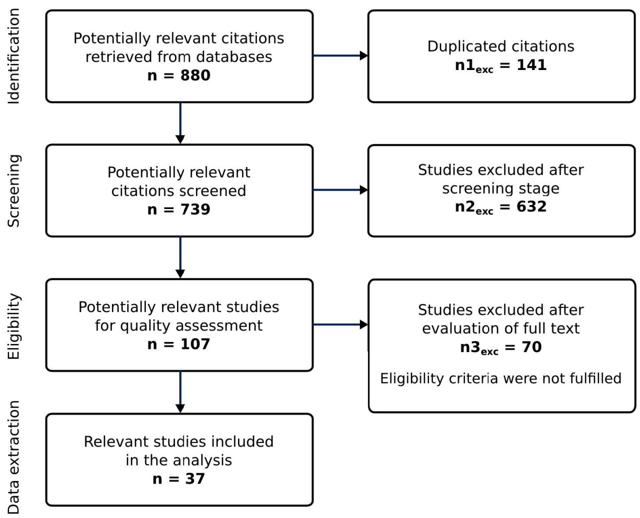

Fig. 2. Flow of information through the different phases of the review.

TABLE II

SELECTED STUDIES ACCORDING TO THE MEASURED MOVEMENT

Measured movement (Anatomical reference)	**Includes**	**First selection** (107 papers)	**Final selection** (37 papers)
Upper limb	Shoulder, arm, elbow, forearm or hands	51	19
Lower limb	Thigh, knee, leg or foot	39	12
Multiple limbs	Upper and/or lower limbs at the same time	10	3
Other body regions	Head, trunk, back or hip	7	3

A list of the topics and classification of relevant papers is provided in Table II. Twenty three (23) were studies published in Journals and fourteen (14) in conferences. Most of the works (29/37) pertain to engineering and computer science (*Eng/CSc*) subject area, only three (3/37) works refer to medical and biological (*Med/Bio*) subject area, while five (5/37) were published in media classified as both, *Eng/CSc* and *Med/Bio* areas. Fig. 3 shows a ratio of subject areas per publication type. Moreover, the distribution of the relevant studies per year is shown in Table III, in which a particular increase in recent years is observed.

B. Data Extraction, Analysis and Examination

A review and examination was carried out on full relevant papers which were categorized in terms of the type of sensor used to measure human motion (Acc: accelerometer, Gyr: gyroscope, Mag: magnetometer); the measuring motion unit (PS: position of a segment, OS: orientation of a segment, PJ: position of a joint, OJ: orientation of a joint); the class of algorithm applied or implemented, (IN: integration, VO: vector observation, KF: Kalman filtering, CF: complementary filtering, or Other algorithm); and the system used to evaluate the performance of the studies (OP: optical motion system, MG: magnetic position system, IS: inertial sensors, GO: goniometer, EH: expert human); the number of participants during the evaluation of each study, and if the age of the subjects was reported. For details, see Table IV.

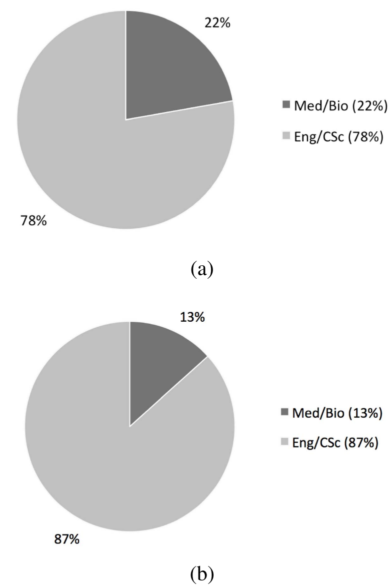

Fig. 3. Distribution of studies by subject area, 3(a) journal and 3(b) conferences studies.

TABLE III

SELECTED STUDIES ACCORDING TO PUBLICATION YEAR

Year	**Author**
2016	Alvarez et al. [31]
2015	Ligorio and Sabatini [32], Chen et al. [33]
2014	Bergamini et al. [34], Ruffaldi et al. [35], Cockcroft et al. [36], Hu et al. [37], Lambrecht and Kirsch [38], Slajpah et al. [39]
2013	Hsu et al. [40], Peppoloni et al. [41], Sim et al. [42], To and Mahfouz [43], Zhang et al. [44]
2012	Alvarez et al. [45], Bonnet et al. [46], Bruckner et al [47], El-Gohary and McNames [48], Lin and Kulic [49], Liu et al. [50], Meng et al. [51], Yuan and Chen [52], Zhang et al. [53]
2011	Brigante et al. [54], Charry et al. [55], Yang and Ye [56]
2010	Harms et al. [57], Lee et al. [58], Schepers et al. [59]
2009	Lee and Park [60], Liu et al. [61], Charry et al. [62]
2008	Goulermas et al. [63], Zhou et al. [64], Cutti et al. [65]
2007	Roetenberg et al. [66], Plamondon et al. [67]

III. REVIEW FINDINGS

The relevant articles that were analyzed are distributed as follows: 52% focus on measuring upper limb movements only, 32% focus on only measuring lower limb movements; 8% measure movements of both, upper and lower limbs simultaneously; and 8% measure movements of other anatomical references, such as head or trunk. All these works use “strap-down” systems, in which the sensors are fixed to certain parts of the human body [68]. The anatomical landmarks on which the sensors are commonly attached are: trunk, back, scapula, lumbar region, upper arm, forearm and hand for upper limb motion measurements; and, trunk, lower back, sacrum, hip, pelvis, HAT (head, arms and trunk as structure), thigh, shank and feet for lower limb motion measurements. The distribution of anatomical references used in the cited studies is shown in Fig. 4. Note that the arm and forearm are extensively used

TABLE IV
RELEVANT CHARACTERISTICS OF SELECTED STUDIES

Paper title	**Sensors**			**Measuring motion unit**				**Algorithms**	**Evaluation system**	**Subjects**	
	Acc	Gyr	Mag	PS	OS	PJ	OJ			No.	Age
Upper limb											
Upper limb joint angle measurement in occupational health [31]	✓	✓	✓				✓	IN	GO	1	
A Novel Kalman Filter for Human Motion Tracking With an Inertial-Based Dynamic Inclinometer [32]	✓	✓			✓			KF	OP	10	
Estimating orientation using magnetic and inertial sensors and different sensor fusion approaches: accuracy assessment in manual and locomotion tasks [34]	✓	✓	✓		✓			KF, CF	OP	6	✓
A novel approach to motion tracking with wearable sensors based on Probabilistic Graphical Models [35]	✓	✓	✓				✓	Other	OP	1	
Miniature low-power inertial sensors: promising technology for implantable motion capture systems [38]	✓	✓	✓				✓	Other	OP	1	
A Wearable Inertial-sensing-based Body Sensor Network for Shoulder Range of Motion Assessment [40]	✓	✓	✓				✓	CF	IS	10	✓
A novel 7 degrees of freedom model for upper limb kinematic reconstruction based on wearable sensors [41]	✓	✓	✓	✓	✓	✓	✓	KF	OP	1	
Improved Extended Kalman Fusion Method For Upper Limb Motion Estimation With Inertial Sensors [44]	✓	✓	✓		✓			KF	MG	1	
Ambulatory human upper limb joint motion monitoring [45]	✓	✓	✓				✓	IN	EH	1	
Evaluation of inertial sensor fusion algorithms in grasping tasks using real input data: Comparison of computational costs and root mean square error [47]	✓	✓	✓		✓			IN, VO, KF	OP	1	
Shoulder and elbow joint angle tracking with inertial sensors [48]	✓	✓					✓	KF	OP	8	
Adaptive information fusion for human upper limb movement estimation [53]	✓	✓	✓				✓	KF	OP	4	
Towards Miniaturization of a MEMS-Based Wearable Motion Capture System [54]	✓	✓	✓		✓			KF	IS	1	
A calibration process for tracking upper limb motion with inertial sensors [56]	✓	✓	✓	✓	✓			KF	EH	1	
ETHOS: Miniature orientation sensor for wearable human motion analysis [57]	✓	✓	✓		✓			CF	IS	1	
Unrestrained measurement of arm motion based on a wearable wireless sensor network [58]	✓						✓	IN	GO	1	
A Fast Quaternion-Based Orientation Optimizer via Virtual Rotation for Human Motion Tracking [60]	✓	✓	✓		✓			VO	OP	1	
Use of multiple wearable inertial sensors in upper limb motion tracking [64]	✓	✓	✓			✓	✓	KF	OP	4	✓
Ambulatory measurement of shoulder and elbow kinematics through inertial and magnetic sensors [65]	✓	✓	✓				✓	Other	OP	1	✓

TABLE IV

(Continued.) RELEVANT CHARACTERISTICS OF SELECTED STUDIES

Paper title	**Sensors**			**Measuring motion unit**				**Algorithms**	**Evaluation system**	**Subjects**	
	Acc	Gyr	Mag	PS	OS	PJ	OJ			No.	Age
Lower limb											
A Novel Complimentary Filter for Tracking Hip Angles During Cycling Using Wireless Inertial Sensors and Dynamic Acceleration Estimation [36]	✓	✓	✓				✓	CF	OP	1	
An inertial sensor system for measurements of tibia angle with applications to knee valgus/varus detection [37]	✓	✓			✓			IN	OP	3	
Kinematics based sensory fusion for wearable motion assessment in human walking [39]	✓	✓	✓				✓	KF	OP	5	✓
Modular wireless inertial trackers for biomedical applications [43]	✓	✓	✓		✓			Other	OP	1	
A least-squares identification algorithm for estimating squat exercise mechanics using a single inertial measurement unit [46]	✓	✓					✓	VO	OP	10	✓
Human pose recovery using wireless inertial measurement units [49]	✓	✓					✓	KF	OP	20	✓
Physical sensor difference-based method and virtual sensor difference-based method for visual and quantitative estimation of lower limb 3D gait posture using accelerometers and magnetometers [50]	✓		✓				✓	Other	OP	5	✓
Displacement estimation for different gait patterns in micro-sensor motion capture [51]	✓	✓	✓	✓	✓			KF	OP	1	
Human velocity and dynamic behavior tracking method for inertial capture system [52]	✓	✓	✓	✓	✓			KF	OP	1	
A study on band-pass filtering for calculating foot displacements from accelerometer and gyroscope sensors [62]	✓	✓		✓				IN	OP	2	
Development of a wearable sensor system for quantitative gait analysis [61]	✓	✓			✓			IN	OP	10	✓
An instance-based algorithm with Auxiliary Similarity Information for the estimation of gait kinematics from wearable sensors [63]	✓	✓	✓				✓	Other	OP	8	
Multiple limbs											
Real-time human motion capture driven by a wireless sensor network [33]	✓	✓	✓				✓	VO	OP	1	
Ambulatory human motion tracking by fusion of inertial and magnetic sensing with adaptive actuation [59]	✓	✓	✓	✓	✓			KF	OP	1	
Ambulatory Position and Orientation Tracking Fusing Magnetic and Inertial Sensing [66]	✓	✓	✓	✓	✓			KF	OP	1	
Other anatomical references											
The head mouse - Head gaze estimation "In-the-Wild" with low-cost inertial sensors for BMI use [42]	✓	✓	✓		✓			KF	MG	5	✓
Design and validation of an ambulatory inertial system for 3-D measurements of low back movements [55]	✓	✓			✓			IN	OP	2	
Evaluation of a hybrid system for three-dimensional measurement of trunk posture in motion [67]	✓	✓	✓		✓			CF	OP	6	✓

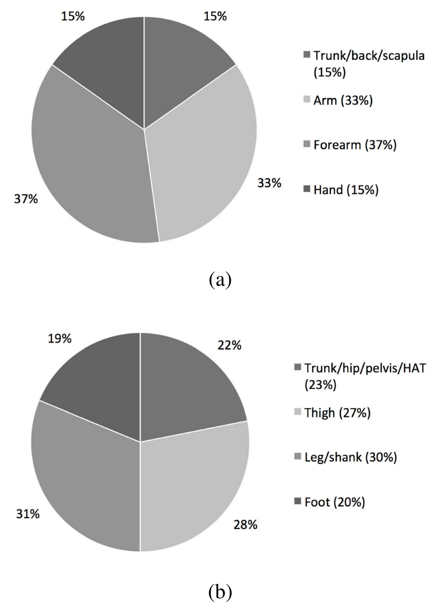

Fig. 4. Anatomical references of upper and lower limb to which the sensors are attached to measure motion, 4(a) upper limb anatomical references and 4(b) lower limb anatomical references.

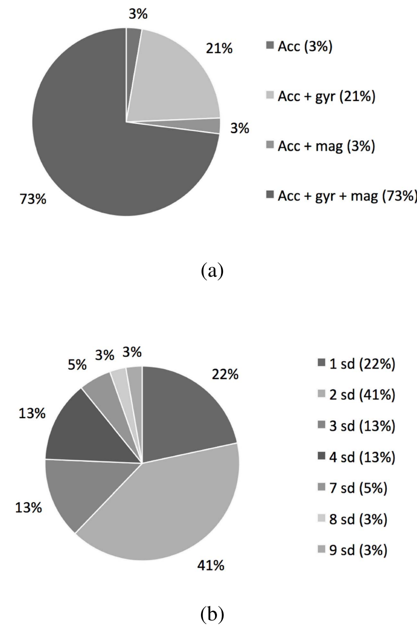

Fig. 5. Distribution of studies by sensor used, 5(a) type and combination of sensors 5(b) number of sensing devices.

when measuring motion of upper limbs whereas the shank is preferably used when measuring motion of lower limbs.

A. Sensors

There are two levels of analysis of sensors used in these studies, the first one concerns the type of sensor used to estimate human motion: accelerometer, gyroscope, magnetometer or a combination of them. The second level concerns the composition of the measurement units or modules used for acquiring motion parameters. From now on the term "sensing device" describes any encapsulated unit that may contain one or more of the previously cited sensors, as well as additional components such as batteries, communication modules, microprocessors and so on, arranged to jointly operate, see Fig. 5.

In Table IV the first level of analysis is shown, most of studies (27/37) combine the magnitudes of three types of sensors: accelerometer, gyroscope and magnetometer. Eight studies (8/37) use only magnitudes of both inertial sensors: accelerometer and gyroscope. One work (1/37) combines information of accelerometers and magnetometers to estimate hip and knee angles [50]. One work (1/37) uses only two accelerometers to estimate arm motion [58]. Finally, no one has reported the combination of information from gyroscopes and magnetometers.

Regarding the second level of analysis, most of studies (15/37) used **a pair** of sensing devices to estimate human motion. In general, the devices are attached to adjacent segments to the elbow and knee joints, upper arm and forearm for elbow joint measures, and to the thigh and shank for knee joint measures. The elbow and knee joint (hinge joints) permit only flexion and extension movements that occur in one plane (sagittal), due to hinge joints are uniaxial joints their analysis is less complex than the analysis of joints with more degrees of freedom (DOF) [12]. Seven works (8/37) use only **one** sensing device, six of these works individually measure the hand [54], [56], forearm [32], [60], arm [57], foot [62] and head [42] motion; and in one of these [46] the sensing device is placed on the lower back to estimate the lower limb movement. Five works (5/37) use **three** sensing devices to model most of the upper or lower limb, in [41] and [44] the devices are attached to the forearm, upper arm, and to a region of the trunk for measuring upper limb motion; in [49], [50], and [61] the devices are attached to the shank, thigh, and to a region of the trunk for measuring lower limb motion. Three works (5/37) use **four** sensing devices to measure whole motion of one upper limb or most part of motion of both lower limbs; in [31], [38], and [45] the devices are placed on the hand, forearm, upper arm, and back, thus they can estimate the movement of the three main joints of the upper limb: wrist, elbow and shoulder; in [65] sensing devices are placed on the forearm, upper arm, scapula, and thorax for modeling shoulder and elbow joints; in [63] the sensors are attached on the both shanks and thighs, in order to measure motion of both lower limbs. Finally, three works (3/37) use **seven** and **eight** sensing devices for measuring motion of both lower limbs, in [39], [51], and [52] the devices are placed on the feet, shanks, thighs and to the trunk, thus the movement of the three main joints of the lower limb: ankle, knee and hip can be estimated. In [33] **nine** sensing devices were placed on both upper and lower limbs. In summary, thirty-three studies (89%) use up to four sensors, and the rest (11%) uses seven or eight sensing devices.

There are several drawbacks that affect the use of inertial and magnetic sensors for measuring human motion. In table V the drawbacks reported in the revised articles are divided into two families according to the stage of the process for motion measurement: data acquisition or data processing.

TABLE V
DRAWBACKS PRESENTED BY SENSORS DURING HUMAN MOTION MEASUREMENT

Stage	Drawback
Data acquisition	Transmision lag [33], [43], [58]; higher accelerations [32], [33], [38], [39], [52], [53], [60], [62], [63], [66]; magnetic disturbances [31], [38], [44], [45], [47], [54], [57], [60], [66], [67]; and soft skin issues [36], [37], [48], [50], [51], [53], [60], [64], [65], [63].
Data processing	Bias offset [32], [36], [38], [48], [67]; drift errors [34], [36], [37], [47], [48], [49], [50], [51], [53], [55], [59], [61], [64], [66], [67].

Drawbacks during data acquisition comprise mainly technical problems such as transmission lags or noise recorded by the sensors. A transmission lag is the time loss occurred during the process of transmission [33]. Additionally, the signals can be contaminated by noise introduced in the acceleration or magnetic signals, by the nature of the sensors, or due to human motion artifacts derived from placing sensors on human soft tissue. Higher raw acceleration, happened especially during fast movements, and interferences of conductive and magnetic materials [66], are issues encountered by accelerometer and magnetometer sensors. Soft skin issues are related to the vibrations from impacts of the body with the ground and tremulous motions of the body [32].

Drawbacks related to processing data comprise issues related to the bias that affects the sensor signals used for human motion estimations. Bias generally consists of two parts: a deterministic part called bias offset, and a random part also known as drift [48]. The bias offset refers to the offset in the measurement naturally introduced by the inertial sensors. Bias offset can be removed by applying a calibration step or a signal preprocessing during a time period where the bias is modelled. The drift refers to the rate of error accumulation over time present in inertial sensors. Usually, inertial random drift can be modelled as a stochastic process to reduce the estimated error.

The sensors used in the studies discussed in this section are summarized in columns two to four of Table IV.

B. Measuring Motion Unit

The measuring motion unit can be divided into two dimensions: (1) position or orientation measures, and (2) segment or joint whose position or orientation is measured. The first dimension refers to the mathematical or numerical description using a position vector or an orientation vector of one or more body segments or joints [69]; Euler angles and quaternions are commonly used for orientation representation [70]. The second dimension refers to the motion description of body segments, that are modelled as rigid bodies, such as forearm or upper arm [71], or motion description of body joints (articulations) such as elbow, that are unions or junctions between two or more body segments [12]. The distribution of studies concerning the combination of the two dimensions is shown in Fig. 6. Also, the distribution of works according to the dimensions detailed in this section is shown in Fig. 7.

In most of works, 78% (29/37), only the orientation of a segment or a joint has been measured. In fifteen works (15/37)

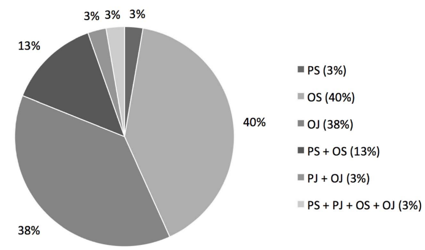

Fig. 6. Distribution of studies according to measured motion unit. PS = position of a segment, OS = orientation of a segment, PJ = position of a joint, OJ = orientation of a joint.

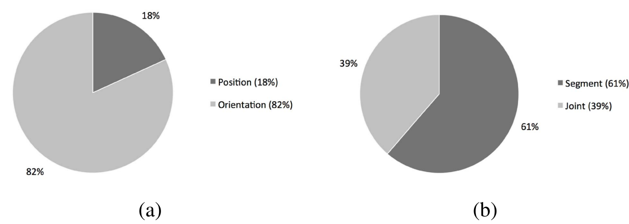

Fig. 7. Distribution of studies according to measured motion unit: position or orientation 7(a) and by human reference to measure: segment or joint 7(b).

the **orientation of a segment** was measured. From these, in [32], [42], [54], [57], and [60] one sensing device was used to estimate the orientation of the head, hand, forearm [32], [60] and upper arm segments, respectively; in [34], [37], [55], and [67] two sensing devices were used to estimate the back, trunk, forearm and shank orientation, respectively; in [40], [47], and [43] a sensing device was placed on each reference: forearm and upper arm, and shank and thigh to estimate their orientations; only in two studies [44], [61] the three principal segments of the upper and lower limb were measured; finally, in [45] hand, forearm, upper arm and back orientations were estimated using four sensing devices.

In fourteen works (14/37) the **orientation of a joint** was estimated. From these, in [36], [53], and [58], two sensors were placed in contiguous segments connected by the elbow or hip to estimate the orientation of each joint; in [35], [48], and [65] two and four sensing devices were used to estimate shoulder and elbow orientations; in [49] and [50] hip and knee orientations were calculated using three sensors placed on the segments connected by these joints; in [31], [38], [39], and [63] the three relevant joint orientations of limbs were estimated: shoulder, elbow and wrist of upper limb, and hip, knee and ankle of lower limb, respectively, the authors used a pair of sensing devices for estimating the orientation of each joint; in [33] shoulder, elbow, hip and knee orientations of both upper and lower limbs were estimated; finally, in one study [46] three joint orientations: hip, knee and ankle, were estimated using only one sensing device placed on the lower trunk.

There is only one study (1/37) that estimated individually the **position of a segment**, in [62] the displacement of a foot was measured using one sensing device. No studies were reported on individual estimation of the **position of a joint**.

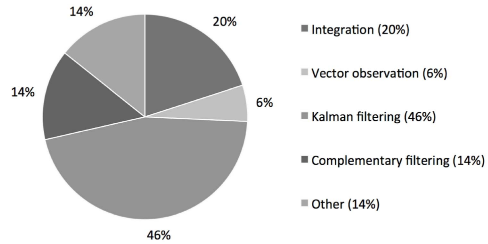

Fig. 8. Distribution of studies according to the algorithms used to estimate position or orientations of segments or limbs.

There are six studies (16%) concerning the estimation of **position and orientation of a segment or a joint**. From these, in five works (5/37) position and orientation of a segment are estimated; in [56] a sensing device was used to estimate the hand motion; in studies in which seven and eight sensing devices were used [51], [52], the center of mass of human body or main segments of both lower limbs were estimated; two works [59], [66] that combine information from both limbs, upper and lower, estimate the position and orientation of the arm and leg using two sensing devices; there is one work (1/37) that estimates the position and orientation of joints, in this case two sensing devices were used to estimate the position and orientation of shoulder, elbow and wrist [64].

Finally, in a work (1/37) the **position and orientation of segments and joints** were estimated. Three sensing devices placed on forearm, upper arm, and scapula were used to estimate the position and orientation of these segments, and to estimate the position and orientation of the elbow and shoulder joints [41].

The measurement motion units estimated in the studies discussed in this section are summarized in columns five to eight of Table IV.

C. Sensor Fusion Algorithms

The algorithms used to estimate orientation or positions are divided into five classes: integration, vector observation, Kalman filtering, complementary filtering, and other algorithms. The distribution of studies according to the algorithms implemented is shown in Fig. 8.

In most studies (16/37) **Kalman filter based algorithms** were implemented to estimate orientation or position. These algorithms use knowledge of the expected dynamics of a system to predict future system states given both the current state and a set of control inputs [72]. This family of algorithms comprises optimal estimators with respect to the minimization of the error covariance. In [32], [42], [52], and [64] a Kalman filter was applied to estimate position and orientation of segments and joints. The extended Kalman filter [34], [39], [44], [49], [54], [56], [59] was used to estimate orientation of segments and joints, and position of segments. The unscented Kalman filter [41], [48], [53] was implemented to estimate orientation of segments and position of a joint. The complementary Kalman filter [51], [66] was applied to estimate orientation and position of segments. In two [48], [49] of these studies a fusion of only inertial sensors was used.

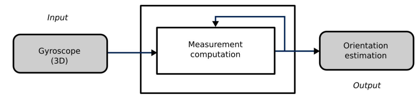

Fig. 9. Gyroscope integration structure (based on the Rate gyroscope integration described in [73]).

Complementary filtering algorithms (5/37) fuse the information of both, inertial and magnetic sensors to estimate orientation of segments and joints. Complementary filters can be used to combine two different measurements of a common signal with different noise properties to produce a single output [73]. These algorithms take into consideration the complementary spectral characteristics of noisy signals to compute a final estimation. Three variants of the complementary filter [33], [57] are reported: passive complementary filter [36], complementary nonlinear filter [40] and complementary quaternion attitude filter [67].

Algorithms based on an **integration** of inertial sensors (7/37) are used to estimate orientation of lower limb segments [37], [55], [61], orientation of upper limb joints [31], [45], [58], and foot segment position [62]. In practice, an integrated estimation will present drift in each step due to noise, bias, and numerical integration errors [74].

Vector observation algorithms (2/37) provide optimized estimations for a given set of measurements. For inertial sensor data fusion, it is common to compute orientation based on accelerometer and magnetometer data. These algorithms do not suffer from gyroscope drift, but are dependent on reliable magnetometer and accelerometer measurements, therefore they are only accurate while tracking slow moving objects. In [46] an estimation of joint orientation based on information acquired from inertial sensors was obtained. In [60] a fusion of inertial and magnetic sensors was used to estimate orientation of segments.

There are **other algorithms** (5/37) used to estimate the orientation of segments or joint. Probabilistic Graphical Models [35] were proposed as a technique for upper limb motion tracking, using probabilistic reasoning to explicitly declare the actual dependencies among sensor readings. Heading fusion algorithm [38] and auxiliary similarity information algorithm [63] were used to estimate joints' orientation by combining information from inertial and magnetic sensors. Sequential Monte Carlo method [43] or particle filter were used to estimate the orientation of lower limb segments. In [50] a physical sensor difference-based algorithm was implemented to estimate hip and knee orientations, and fuse information from accelerometers and magnetometers.

Previous algorithmic approaches can be analyzed from the integration of the magnitude of a type of sensor to the fusion of magnitudes from multiple sensors.

Rate gyroscope integration provides an estimate of the relative rotation from an initial known rotation, see Fig. 9. As the angular velocity measured by the rate gyroscopes is directly integrated this method provides smooth estimates even during rapid movements [73]. Nevertheless, the integration process has two significant disadvantages. First, any bias in the angular rate vector will result in an increasing cumulative error

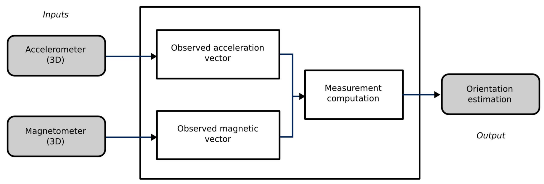

Fig. 10. Vector observation structure (based on the description in [73]).

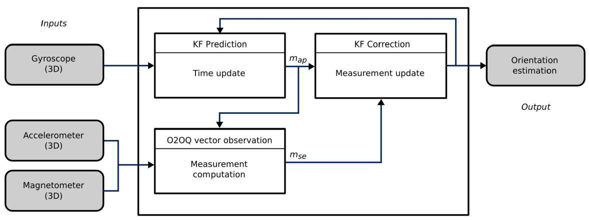

Fig. 11. Kalman filter structure (based on the Minimum-Order Kalman Filter proposed in [76]). m_{dy} and m_{st} are the dynamic and static measurements. O2OQ is the Optimal Two-Observation Quaternion algorithm.

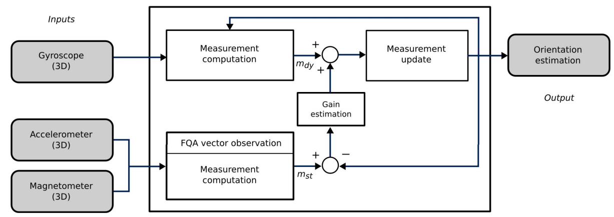

Fig. 12. Complementary filter structure (based on the Adaptive-Gain Complementary Filter proposed in [78]). m_{ap} and m_{se} are the approximated and selected measurements. FQA is the Factored Quaternion Algorithm.

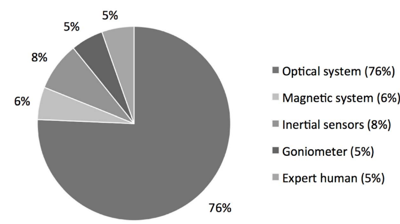

Fig. 13. Distribution of studies according to the system used for comparison.

in the estimated orientation. Second, the initial orientation of the device must be known.

Concerning vector observation algorithms, they provide an estimate of the orientation relative to a fixed world coordinate frame. By measuring the position of two, or more vectors in the local coordinate frame of a device and comparing these with the known position of the vectors in a fixed coordinate frame, the rotation between the two frames can be calculated. For tracking orientation the used reference vectors are both the direction of acceleration due to gravity, and the direction of the Earth's magnetic field vector projected into the horizontal plane. A general description of this algorithm is shown in Fig. 10. As there are no correction steps, this approach is only accurate for tracking objects that move slowly [47].

In order to provide accurate estimates, which preserve the high frequency response of rate gyroscope integration and the absolute estimate provided by vector observation, data fusion algorithms are used. Data fusion is achieved using either Kalman filter variants or complementary filtering techniques [75].

In [76] a Kalman filtering algorithm for orientation estimation using an inertial/magnetic sensor is presented. This algorithm is designed to have two main steps that are connected in a feedback relationship: a measurement computation step with a vector selector scheme, and a Kalman filter (KF) step. The entire structure of the Kalman filtering algorithm is illustrated in Fig. 11. Once the time update is done in the KF, the approximated measurement m_{ap} is sent to the measurement computation step using the Optimal Two-Observation Quaternion algorithm (O2OQ) [77]. Using the approximated measurement m_{ap} and readings from accelerometer and magnetometer, the measurement computation step calculates the selected measurement m_{se} that is sent back to the measurement update step in the KF and used as its measurement input.

In [78] a complementary filtering algorithm for estimating orientation based on inertial/magnetic sensor measurements is described. The algorithm takes advantage of the complementary nature of the information offered by high-frequency angular rate sensor data and low-frequency accelerometers and magnetometers. The filtering algorithm utilizes a single gain that can be adaptively adjusted to achieve satisfactory performance while tracking two or more different types of motion. A block diagram of this complementary filter is shown in Fig. 12. The complementary filter has two branches: the static measurement m_{st} and the dynamic measurement m_{dy}. The static measurement is computed using the Factored Quaternion Algorithm (FQA) [79].

In [47] the authors present a comparison among three methods: integration, vector observation and Kalman filter algorithms for the estimation of orientation of upper limb segments. Finally, in [65] the authors developed a protocol for measuring scapulothoracic, humerothoracic, and elbow kinematics.

The algorithms used in the studies discussed in this section are summarized in column nine of Table IV.

D. System Used for the Evaluation

In studies that estimate human motion using inertial and magnetic sensors, an external system was required to compare the results obtained from the experiments. The evaluation systems can be divided into five categories: optical systems, magnetic systems, inertial sensors, goniometers or evaluation by expert human. The distribution of studies according to the system used for the evaluation is shown in Fig. 13.

In most of studies (75%) **optical motion systems** were used as reference to evaluate the performance of each study. The optical systems that are more commonly used for comparison were Vicon and Optotrak systems. In three studies concerning upper limb estimation: shoulder orientation [40], hand orientation [54] and arm orientation [57], inertial sensors by Xsens were used as ground truth. In [42] and [44] a magnetic position system was used as reference to estimate segments' orientation: upper limb and head. Goniometers were used in [31] and [58] to evaluate an elbow joint estimated by an

TABLE VI
STUDIES ACCORDING TO THE AGE RANGE OF TEST SUBJECTS (*AVG*: AVERAGE OF THE TEST SUBJECTS)

Number of studies	**Age of the test subjects**																								
(Total = 37)	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44
26													Non reported												
1 [61]		*avg*																							
1 [49]				*avg*																					
1 [65]				✓																					
1 [40]			✓	✓	✓																				
1 [42]				✓	✓	✓	✓																		
1 [50]			✓	✓	✓	✓	✓	✓	✓																
1 [39]					✓	✓	✓	✓	✓	✓	✓	✓													
1 [34]					✓	✓	✓	✓	✓	✓	✓	✓	✓												
1 [46]						✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓									
1 [64]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				
1 [67]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

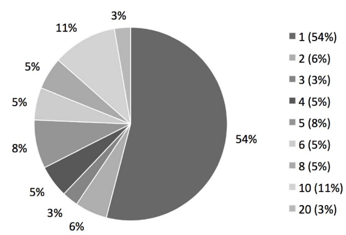

Fig. 14. Studies according to the number of test subjects.

integration algorithm. Finally, in [45] and [56] expert humans evaluate the experimental measures that were estimated.

The systems used for the evaluation in the studies discussed in this section are summarized in column ten of Table IV.

E. Subjects of Study

Concerning the number of subjects involved in experiments, it can be noticed that around 54% of studies (20/37) have validated their ideas using one test subject, whereas the rest (17/37) have used a population between 2 and 20 subjects. Most studies involving more than one test subject for validation reported experiments using between 2 and 10 individuals, that represents 43% of the total, and there is only one study reporting experiments using a population of 20 test subjects that represents 3% of the total. The detailed distribution of works according to the number of test subjects is shown in Fig. 14.

Regarding the range of age there is a wide variation in the age of test subjects that participated in the studies. An important proportion of the studies, around 70% (26/37), did not report the range of age of test subjects, around 8% (3/37) reported only the average of test subjects that was between 21 and 23 years, and 22% (8/37) of studies reported experiments using different intervals of age between 20 and 44 years. Regarding the configuration of the experiments, the mean age of the test subjects is 26 years The number of test subjects that participated in the studies and whether or not information of their age is provided are summarized, respectively, in columns eleven and twelve of Table IV. The detailed distribution of works according to the age range of test subjects is shown in Table VI.

It is important to notice that there is not a direct correlation between the number of test subjects and the range of age of these subjects in the reported studies.

IV. DISCUSSION

According to our analysis, most studies focus on calculating the orientation or position of certain joints of the human body. As stated in the results reported in these studies, the estimation of position and orientation of the hand scored an average root mean square (RMS) of 1.25 cm [56] (evaluated by a magnetic system) and 2.82º [54] (evaluated by inertial sensors), respectively. The most studied upper joints are the shoulder, elbow and wrist, and the estimation position and orientation of these joints scored an average RMS of 4 mm, 5 mm and 7 mm [64] (evaluated by optical systems), and 3º [38] (evaluated by optical systems), 3.5º [58] (evaluated by goniometers) and 4.1º [38] (evaluated by optical systems). The results reported in the estimation of orientation of the thigh, shank and foot scored an average RMS of 1.23º, 1.3º [43] and 2.99º [52] (evaluated by optical systems) respectively. The most studied lower joints are the hip, knee and ankle, and the estimation of position and orientation of these joints scored an average RMS of 2.1º, 1.7º [63] and 3º [46] (evaluated by optical systems). In a recent study [80], a high precision industrial robot arm was used to evaluate the performance of the method reported in [48] during slow, normal and fast movements over continuous recording durations lasting 15 minutes, obtained an average RMS of 3º.

No studies were reported about estimation of position or orientation of both upper limbs (right and left) at the same time, as it was the case for some studies concerning simultaneous estimation of motion for both lower limbs [37], [39], [51], [52], [63]. There are only two works that estimate position or orientation of both, upper and lower limbs simultaneously [59], [66], scoring an average RMS for orientation estimation of 2.6º for the upper limb and of 3.2º for the lower limb [66], evaluated by an optical system. For other anatomical references, an average RMS of 2.5º [42] (evaluated by a magnetic system), 2.1º [55] and 4.5º [67] (evaluated by an optical system) were reported for head, back and trunk, respectively. In general, the algorithms based on Kalman

TABLE VII
STUDIES ACCORDING TO EXPERTISE AREAS OF AUTHORS

Expertise areas of research teams	Number of studies
1	23
2	10
3	3
4	1
5	0

filtering that fuse information from the three: accelerometer, gyroscope and magnetometer, are more accurate than both, other algorithms and other sensor combinations.

In general there are two approaches to estimate and analyze human motion: straightforward estimation, and combined estimation [81]. In **straightforward estimation** each position or orientation of a segment is estimated as if it were disconnected from the adjacent segments. The data supplied by accelerometer, gyroscope and magnetometer are combined through sensor-fusion algorithms to measure the orientation of the sensing device with respect to a global system of reference, and being fixed to a body segment is assumed for having a common system of reference. These studies [32], [34], [37], [40], [42]–[47], [54], [56], [57], [59]–[62], [66] do not incorporate kinematic constraints of the human joints in the estimation. In **combined estimation**, human kinematic constraints are embedded in the estimation model and take into account one or more of the anatomical constraints of the human joints at the same time, using information of sensing devices placed on contiguous body segments. Knowing the surface geometry and soft-tissue constraints [33], [36], [51], [53], [55], [58], [67], the position or orientation of a joint can be analyzed to provide basic information of human motion from joint kinematics models [31], [35], [38], [39], [41], [48]–[50], [52], [63]–[65].

Regarding the configuration of the experiments, the mean age of the test subjects is 26.2 years ($\pm$ 3.7) according to the studies that reported this information, indicating a clear trend to test the systems and methods only with young people. Other population groups such as people with mobility problems have not been considered in tests so far. Also, in most of studies (54%) only one test subject participated in the evaluations, whereas ten or more test subjects have participated in four studies (14%), which shows a noticeable tendency to conduct experiments on single individuals.

A different aspect of the studies analyzed in this review that can be considered is related to the expertise areas of the research teams co-authoring these studies rather than their content. This aspect can shed light on the background of researchers that are investigating the problem of measuring human motion using wireless technologies on the one hand, and can tell us something about how is this community interacting and collaborating on the other hand.

The number of expertise areas identified in the research team that signed each paper has been counted. Five areas of expertise have been distinguished: Computer science, bioengineering and biomedical engineering, electrical and electronic engineering, medical sciences and health sector, and private sector. Table VII summarizes the results of this analysis. Two important remarks can be highlighted in this table. First, most studies (62%) are made by teams from only one area of expertise. And second, research teams with a high heterogeneous composition, *i.e.*, more than three expertise areas, are uncommon (3%). These results show a visible lack of diversity in the composition of the research teams that conducted the reviewed studies.

V. CONCLUSIONS

According to the screening stage, in the last five years the studies measuring human motion using inertial sensors have almost tripled, going from eight before 2009 to twenty-nine after that year. It is worth to remark that these studies demand the expertise and know-how of specialists from diverse fields of knowledge, including engineering, computer science and health sector. Human motion analysis is effectively a niche opportunity that poses challenging issues for multidisciplinary research.

The trends of the research on human motion analysis revised in this article can be grouped into two main trends: used sensors and systems used for evaluation, as summarized below.

First, in terms of the sensors used for recording motion, we see an evolution going from the use of single sensors, such as accelerometers or gyroscopes, towards the use of complex unit sensing devices, such as inertial/magnetic measurements units, in order to compensate the drawbacks of certain sensors with the power of other ones.

Second, in terms of the systems used for evaluation, we see on the one hand, a tendency to measure human motion over longer periods of time with the final goal to measure motion in realistic situations. In effect, early studies reported experiments over short time periods lasting seconds whereas more recent studies reported experiments lasting up to 20 minutes. Also, we see on the other hand a tendency to use visual motion capture systems, such as Vicon, as a gold standard for evaluation purposes.

According to the trend of future research, we consider that major efforts shall go to improve collaboration and cooperation among researchers from diverse expertise area, that can complement and learn from each other. Other aspects of wearable technologies, such as social acceptance [82] and technology attachment must be also investigated since these issues are crucial for designing successful applications.

An open issue for engineers is to investigate proper configurations and arrangements of sensors for designing portable and tiny e-textils capable of operating in daily environments, such as electronic gloves to measure hand motion, an area in which we have identified a lack of literature and research.

In the field of computer science, there is a constant need for algorithms able to estimate the position and orientation of upper and lower limbs in real-time simultaneously using local devices mainly. These algorithms are needed for applications involving full-body motion tracking, such as exergaming and active gaming, posture and gesture recognition, and human motion analysis, namely in outdoor environments or indoor environments where multiple occlusions might happen.

In these environments camera-based systems are unfeasible and wearable sensors could be a promising alternative for tracking motion.

Additionally, it is necessary to investigate methods and technologies for dealing with complex joints involving several DOF, such as the shoulder and hip. These joints have a wide range of motion around different planes [83], [84]. The shoulder, for instance, can perform abduction and adduction in the frontal plane; flexion and extension in both the sagittal and transverse planes; elevation and depression in the frontal plane; protaction and retraction in the transverse plane; and rotation in the median plane; whereas the hip can perform abduction and adduction in the frontal plane; flexion and extension in both the sagittal and transverse planes; and rotation in the median plane. Multi-plane maneuvers not only require the capability of tracking motion in different axes but also the capability of removing the bias that the movement in different axis might have on the tracked axes. Characterizing the movement of these parts of the body is necessary for recognizing a broader range of human gestures and for enhancing high-level classification of human motion.

Finally, it is important to validate studies using more representative population samples than the ones used so far as well as diversify the selection of test subjects including, for instance, elders, people with impairments, and so on. A good alternative for extending and standardizing studies in human motion might be sharing repositories where data sets of human gestures and patterns expressed in motion data on a common basis are collected. The communities of machine learning and natural language processing have taken advantage of similar services. The recording of common data sets and sharing of experimental know-how will be certainly key aspects for enhancing the research on human motion analysis.

REFERENCES

[1] V. T. Inman, H. J. Ralston, and F. Todd, *Human Walking*. Baltimore, MD, USA: Williams & Wilkins, 1981.

[2] D. Knudson, *Fundamentals of Biomechanics*. Boston, MA, USA: Springer, 2007.

[3] I. H. López-Nava, F. Márquez-Aquino, A. Muñoz-Meléndez, D. Carrillo-López, and H. S. Vargas-Martínez, "Automatic measurement of pronation/supination, flexion/extension and abduction/adduction motion of human limbs using wearable inertial and magnetic sensors," in *Proc. 4th Int. Conf. Global Health Challenges (IARIA)*, Jul. 2015, pp. 55–60.

[4] X. Chen, "Human motion analysis with wearable inertial sensors," Ph.D. dissertation, Dept. Mech., Aerosp. Biomed. Eng., Univ. Tennessee, Knoxville, 2013.

[5] A. Hadjidj, M. Souil, A. Bouabdallah, Y. Challal, and H. Owen, "Wireless sensor networks for rehabilitation applications: Challenges and opportunities," *J. Netw. Comput. Appl.*, vol. 36, no. 1, pp. 1–15, 2013.

[6] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *J. Neuroeng. Rehabil.*, vol. 9, no. 1, p. 21, 2012.

[7] J. Ko, C. Lu, M. B. Srivastava, J. A. Stankovic, A. Terzis, and M. Welsh, "Wireless sensor networks for healthcare," *Proc. IEEE*, vol. 98, no. 11, pp. 1947–1960, Nov. 2010.

[8] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2688–2710, Oct. 2010.

[9] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 40, no. 1, pp. 1–12, Jan. 2010.

[10] H. Zhou and H. Hu, "Human motion tracking for rehabilitation—A survey," *Biomed. Signal Process. Control*, vol. 3, no. 1, pp. 1–18, 2008.

[11] W. Y. Wong, M. S. Wong, and K. H. Lo, "Clinical applications of sensors for human posture and movement analysis: A review," *Prosthetics Orthotics Int.*, vol. 31, no. 1, pp. 62–75, Mar. 2007.

[12] K. Moore, A. Dalley, and A. Agur, *Clinically Oriented Anatomy*, 7th ed. Philadelphia, PA, USA: Lippincott Williams & Wilkins, 2014.

[13] R. B. Davis, S. Ounpuu, P. A. DeLuca, and M. J. Romness, *Clinical Gait Analysis and Its Role in Treatment Decision-Making*, vol. 1. New York, NY, USA: Medscape General Medicine, 2002.

[14] I. Tien, S. D. Glaser, and M. J. Aminoff, "Characterization of gait abnormalities in parkinson's disease using a wireless inertial sensor system," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug./Sep. 2010, pp. 3353–3356.

[15] A. Ferrari *et al.*, "First *in vivo* assessment of 'Outwalk': A novel protocol for clinical gait analysis based on inertial and magnetic sensors," *Med. Biol. Eng. Comput.*, vol. 48, no. 1, pp. 1–15, 2010.

[16] J. C. van den Noort, A. Ferrari, A. G. Cutti, J. G. Becher, and J. Harlaar, "Gait analysis in children with cerebral palsy via inertial and magnetic sensors," *Med. Biol. Eng. Comput.*, vol. 51, no. 4, pp. 377–386, 2013.

[17] I. H. López-Nava, A. Muñoz-Meléndez, A. I. P. Sanpablo, A. A. Montero, I. Q. Urióstegui, and L. N. Carrera, "Estimation of temporal gait parameters using bayesian models on acceleration signals," *Comput. Methods Biomech. Biomed. Eng.*, vol. 19, no. 4, pp. 396–403, 2016.

[18] I. González, I. H. López-Nava, J. Fontecha, A. Muñoz-Meléndez, A. I. Pérez-SanPablo, and I. Quiñones-Urióstegui, "Comparison between passive vision-based system and a wearable inertial-based system for estimating temporal gait parameters related to the GAITRite electronic walkway," *J. Biomed. Informat.*, vol. 62, pp. 210–223, Aug. 2016.

[19] S. Mitra and T. Acharya, "Gesture recognition: A survey," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 37, no. 3, pp. 311–324, May 2007.

[20] K. Liu, C. Chen, R. Jafari, and N. Kehtarnavaz, "Fusion of inertial and depth sensor data for robust hand gesture recognition," *IEEE Sensors J.*, vol. 14, no. 6, pp. 1898–1903, Jun. 2014.

[21] G. Wu and S. Xue, "Portable preimpact fall detector with inertial sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 2, pp. 178–183, Feb. 2008.

[22] L. Tong, Q. Song, Y. Ge, and M. Liu, "HMM-based human fall detection and prediction method using tri-axial accelerometer," *IEEE Sensors J.*, vol. 13, no. 5, pp. 1849–1856, May 2013.

[23] M. Lawton and E. Brody, "Assessment of older people: Self-maintaining and instrumental activities of daily living," *Gerontologist*, vol. 9, no. 3, pp. 179–186, 1969.

[24] K. Altun, B. Barshan, and O. Tunçel, "Comparative study on classifying human activities with miniature inertial and magnetic sensors," *Pattern Recognit.*, vol. 43, no. 10, pp. 3605–3620, Oct. 2010.

[25] I. H. López-Nava and A. Muñoz-Meléndez, "Complex human action recognition on daily living environments using wearable inertial sensors," in *Proc. 10th EAI Int. Conf. Pervas. Comput. Technol. Healthcare*, Jun. 2016, doi: 10.4108/eai.16-5-2016.2263332.

[26] S. C. Mukhopadhyay, "Wearable sensors for human activity monitoring: A review," *IEEE Sensors J.*, vol. 15, no. 3, pp. 1321–1330, Mar. 2015.

[27] A. Mannini and A. M. Sabatini, "Machine learning methods for classifying human physical activity from on-body accelerometers," *Sensors*, vol. 10, no. 2, pp. 1154–1175, 2010.

[28] M. Iosa, P. Picerno, S. Paolucci, and G. Morone, "Wearable inertial sensors for human movement analysis," *Expert Rev. Med. Devices*, vol. 13, no. 7, pp. 641–659, 2016.

[29] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, and P. Havinga, "Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey," in *Proc. 23rd Int. Conf. Archit. Comput. Syst. (ARCS)*, Feb. 2010, pp. 1–10.

[30] T. Shany, S. J. Redmond, M. R. Narayanan, and N. H. Lovell, "Sensors-based wearable systems for monitoring of human movement and falls," *IEEE Sensors J.*, vol. 12, no. 3, pp. 658–670, Mar. 2012.

[31] D. Alvarez, J. Alvarez, R. Gonzalez, and A. Lopez, "Upper limb joint angle measurement in occupational health," *Comput. Methods Biomechanics Biomed. Eng.*, vol. 19, no. 2, pp. 159–170, 2016.

[32] G. Ligorio and A. M. Sabatini, "A novel Kalman filter for human motion tracking with an inertial-based dynamic inclinometer," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 8, pp. 2033–2043, Aug. 2015.

[33] P. Chen, J. Li, M. Luo, and N. Zhu, “Real-time human motion capture driven by a wireless sensor network,” *Int. J. Comput. Games Technol.*, vol. 2015, Jan. 2015, Art. no. 695874.

[34] E. Bergamini, G. Ligorio, A. Summa, G. Vannozzi, A. Cappozzo, and A. M. Sabatini, “Estimating orientation using magnetic and inertial sensors and different sensor fusion approaches: Accuracy assessment in manual and locomotion tasks,” *Sensors*, vol. 14, no. 10, p. 18625, 2014.

[35] E. Ruffaldi, L. Peppoloni, A. Filippeschi, and C. Avizzano, “A novel approach to motion tracking with wearable sensors based on probabilistic graphical models,” in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2014, pp. 1247–1252.

[36] J. Cockcroft, J. Muller, and C. Scheffer, “A novel complimentary filter for tracking hip angles during cycling using wireless inertial sensors and dynamic acceleration estimation,” *IEEE Sensors J.*, vol. 14, no. 8, pp. 2864–2871, Aug. 2014.

[37] W. Hu, E. Charry, M. Umer, A. Ronchi, and S. Taylor, “An inertial sensor system for measurements of tibia angle with applications to knee valgus/varus detection,” in *Proc. IEEE 9th Int. Conf. Intell. Sensors, Sensor Netw. Inf. Process. (ISSNIP)*, Apr. 2014, pp. 1–6.

[38] J. M. Lambrecht and R. F. Kirsch, “Miniature low-power inertial sensors: Promising technology for implantable motion capture systems,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 22, no. 6, pp. 1138–1147, Nov. 2014.

[39] S. Slajpah, R. Kamnik, and M. Munih, “Kinematics based sensory fusion for wearable motion assessment in human walking,” *Comput. Methods Programs Biomed.*, vol. 116, no. 2, pp. 131–144, Oct. 2014.

[40] Y. Hsu *et al.*, “A wearable inertial-sensing-based body sensor network for shoulder range of motion assessment,” in *Proc. Int. Conf. Orange Technol. (ICOT)*, Mar. 2013, pp. 328–331.

[41] L. Peppoloni, A. Filippeschi, E. Ruffaldi, and C. A. Avizzano, “A novel 7 degrees of freedom model for upper limb kinematic reconstruction based on wearable sensors,” in *Proc. IEEE 11th Int. Symp. Intell. Syst. Informat. (SISY)*, Sep. 2013, pp. 105–110.

[42] N. Sim, C. Gavriel, W. Abbott, and A. Faisal, “The head mouse—Head gaze estimation ‘in-the-wild’ with low-cost inertial sensors for BMI use,” in *Proc. 6th Int. IEEE/EMBS Conf. Neural Eng. (NER)*, Nov. 2013, pp. 735–738.

[43] G. To and M. R. Mahfouz, “Modular wireless inertial trackers for biomedical applications,” in *Proc. IEEE 13th Topical Meeting Silicon Monolithic Integr. Circuits RF Syst. (SiRF)*, Jan. 2013, pp. 243–245.

[44] S. Zhang, K. Xiao, Q. Zhang, H. Zhang, and Y. Liu, “Improved extended Kalman fusion method for upper limb motion estimation with inertial sensors,” in *Proc. 4th Int. Conf. Intell. Control Inf. Process. (ICICIP)*, Jun. 2013, pp. 587–593.

[45] D. Ã'lvarez, J. C. Alvarez, R. C. Gonález, and A. M. López, “Ambulatory human upper limb joint motion monitoring,” in *Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC)*, May 2012, pp. 15–19.

[46] V. Bonnet, C. Mazzà, P. Fraisse, and A. Cappozzo, “A least-squares identification algorithm for estimating squat exercise mechanics using a single inertial measurement unit,” *J. Biomech.*, vol. 45, no. 8, pp. 1472–1477, 2012.

[47] H. P. Brückner, C. Spindeldreier, H. Blume, E. Schoonderwaldt, and E. Altenmuller, “Evaluation of inertial sensor fusion algorithms in grasping tasks using real input data: Comparison of computational costs and root mean square error,” in *Proc. 9th Int. Conf. Wearable Implant. Body Sensor Netw. (BSN)*, May 2012, pp. 189–194.

[48] M. El-Gohary and J. McNames, “Shoulder and elbow joint angle tracking with inertial sensors,” *IEEE Trans. Biomed. Eng.*, vol. 59, no. 9, pp. 2635–2641, Sep. 2012.

[49] J. F. S. Lin and D. Kulić, “Human pose recovery using wireless inertial measurement units,” *Physiol. Meas.*, vol. 33, no. 12, pp. 2099–2115, Dec. 2012.

[50] K. Liu, Y. Inoue, and K. Shibata, “Physical sensor difference-based method and virtual sensor difference-based method for visual and quantitative estimation of lower limb 3D gait posture using accelerometers and magnetometers,” *Comput. Methods Biomech. Biomed. Eng.*, vol. 15, no. 2, pp. 203–210, Feb. 2012.

[51] X. Meng, G. Tao, Z. Zhang, S. Sun, J. Wu, and W.-C. Wong, “Displacement estimation for different gait patterns in micro-sensor motion capture,” in *Proc. 15th Int. Conf. Inf. Fusion (FUSION)*, Jul. 2012, pp. 1315–1322.

[52] Q. Yuan and I.-M. Chen, “Human velocity and dynamic behavior tracking method for inertial capture system,” *Sens. Actuators A, Phys.*, vol. 183, pp. 123–131, Aug. 2012.

[53] Z.-Q. Zhang, L.-Y. Ji, Z.-P. Huang, and J.-K. Wu, “Adaptive information fusion for human upper limb movement estimation,” *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 42, no. 5, pp. 1100–1108, Sep. 2012.

[54] C. M. N. Brigante, N. Abbate, A. Basile, A. C. Faulisi, and S. Sessa, “Towards miniaturization of a MEMS-based wearable motion capture system,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 8, pp. 3234–3241, Aug. 2011.

[55] E. Charry, M. Umer, and S. Taylor, “Design and validation of an ambulatory inertial system for 3-D measurements of low back movements,” in *Proc. 7th Int. Conf. Intell. Sensors, Sensor Netw. Inf. Process. (ISSNIP)*, Dec. 2011, pp. 58–63.

[56] H. Yang and J. Ye, “A calibration process for tracking upper limb motion with inertial sensors,” in *Proc. Int. Conf. Mechatronics Autom. (ICMA)*, Aug. 2011, pp. 618–623.

[57] H. Harms, O. Amft, R. Winkler, J. Schumm, M. Kusserow, and G. Troester, “Ethos: Miniature orientation sensor for wearable human motion analysis,” in *Proc. IEEE Sensors*, Nov. 2010, pp. 1037–1042.

[58] G. X. Lee, K. S. Low, and T. Taher, “Unrestrained measurement of arm motion based on a wearable wireless sensor network,” *IEEE Trans. Instrum. Meas.*, vol. 59, no. 5, pp. 1309–1317, May 2010.

[59] H. Schepers, D. Roetenberg, and P. Veltink, “Ambulatory human motion tracking by fusion of inertial and magnetic sensing with adaptive actuation,” *Med. Biol. Eng. Comput.*, vol. 48, no. 1, pp. 27–37, 2010.

[60] J. K. Lee and E. Park, “A fast quaternion-based orientation optimizer via virtual rotation for human motion tracking,” *IEEE Trans. Biomed. Eng.*, vol. 56, no. 5, pp. 1574–1582, May 2009.

[61] T. Liu, Y. Inoue, and K. Shibata, “Development of a wearable sensor system for quantitative gait analysis,” *Measurement*, vol. 42, no. 7, pp. 978–988, 2009.

[62] E. Charry, D. Lai, R. Begg, and M. Palaniswami, “A study on band-pass filtering for calculating foot displacements from accelerometer and gyroscope sensors,” in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 4826–4827.

[63] J. Goulermas *et al.*, “An instance-based algorithm with auxiliary similarity information for the estimation of gait kinematics from wearable sensors,” *IEEE Trans. Neural Netw.*, vol. 19, no. 9, pp. 1574–1582, Sep. 2008.

[64] H. Zhou, T. Stone, H. Hu, and N. Harris, “Use of multiple wearable inertial sensors in upper limb motion tracking,” *Med. Eng. Phys.*, vol. 30, no. 1, pp. 123–133, 2008.

[65] A. G. Cutti, A. Giovanardi, L. Rocchi, A. Davalli, and R. Sacchetti, “Ambulatory measurement of shoulder and elbow kinematics through inertial and magnetic sensors,” *Med. Biol. Eng. Comput.*, vol. 46, no. 2, pp. 169–178, 2008.

[66] D. Roetenberg, P. J. Slycke, and P. H. Veltink, “Ambulatory position and orientation tracking fusing magnetic and inertial sensing,” *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 883–890, May 2007.

[67] A. Plamondon *et al.*, “Evaluation of a hybrid system for three-dimensional measurement of trunk posture in motion,” *Appl. Ergonom.*, vol. 38, no. 6, pp. 697–712, 2007.

[68] J. Bortz, “A new mathematical formulation for strapdown inertial navigation,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. AES-7, no. 1, pp. 61–66, Jan. 1971.

[69] A. Cappozzo, U. D. Croce, A. Leardini, and L. Chiari, “Human movement analysis using stereophotogrammetry: Part 1: Theoretical background,” *Gait Posture*, vol. 21, no. 2, pp. 186–196, 2005.

[70] H. Brückner, B. Krüger, and H. Blume, “Reliable orientation estimation for mobile motion capturing in medical rehabilitation sessions based on inertial measurement units,” *Microelectron. J.*, vol. 45, no. 12, pp. 1603–1611, 2014.

[71] M. Kadaba, H. Ramakrishnan, and M. Wootten, “Measurement of lower extremity kinematics during level walking,” *J. Orthopaedic Res.*, vol. 8, no. 3, pp. 383–392, 1990.

[72] D. Simon, “Kalman filtering,” *Embedded Syst. Program.*, vol. 14, no. 6, pp. 72–79, 2001.

[73] A. D. Young, “Comparison of orientation filter algorithms for realtime wireless inertial posture tracking,” in *Proc. 6th Int. Workshop Wearable Implant. Body Sensor Netw.*, 2009, pp. 59–64.

[74] A. D. Young, M. J. Ling, and D. K. Arvind, “IMUSim: A simulation environment for inertial sensing algorithm design and evaluation,” in *Proc. 10th Int. Conf. Inf. Process. Sensor Netw. (IPSN)*, Apr. 2011, pp. 199–210.

[75] A. Young, “Use of body model constraints to improve accuracy of inertial motion capture,” in *Proc. Int. Conf. Body Sensor Netw.*, Jun. 2010, pp. 180–186.

[76] J. Lee and E. Park, "A minimum-order Kalman filter for ambulatory real-time human body orientation tracking," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2009, pp. 3565–3570.
[77] F. L. Markley, "Fast quaternion attitude estimation from two vector measurements," *J. Guid., Control, Dyn.*, vol. 25, no. 2, pp. 411–414, 2002.
[78] J. Calusdian, X. Yun, and E. Bachmann, "Adaptive-gain complementary filter of inertial and magnetic data for orientation estimation," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2011, pp. 1916–1922.
[79] X. Yun, E. R. Bachmann, and R. B. Mcghee, "A simplified quaternion-based algorithm for orientation estimation from earth gravity and magnetic field measurements," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 3, pp. 638–650, Mar. 2008.
[80] M. El-Gohary and J. McNames, "Human joint angle estimation with inertial sensors and validation with a robot arm," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 7, pp. 1759–1767, Jul. 2015.
[81] K. An, "Kinematic analysis of human movement," *Ann. Biomed. Eng.*, vol. 12, no. 6, pp. 585–597, 1984.
[82] R. Steele, A. Lo, C. Secombe, and Y. K. Wong, "Elderly persons' perception and acceptance of using wireless sensor networks to assist healthcare," *Int. J. Med. Informat.*, vol. 78, pp. 788–801, Dec. 2009.
[83] G. Wu *et al.*, "ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion—Part I: Ankle, hip, and spine," *J. Biomech.*, vol. 35, no. 4, pp. 543–548, 2002.
[84] G. Wu *et al.*, "ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: Shoulder, elbow, wrist and hand," *J. Biomech.*, vol. 38, no. 5, pp. 981–992, 2005.

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