Inertial Sensors for Human Motion Analysis: A Comprehensive Review

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***Abstract*— Inertial motion analysis is having a growing interest during the last decades due to its advantages over classical optical systems. The technological solution based on inertial measurement units allows the measurement of movements in daily living environments, such as in everyday life, which is key for a realistic assessment and understanding of movements. This is why research in this field is still developing and different approaches are proposed. This presents a systematic review of the different proposals for inertial motion analysis found in the literature. The search strategy has been carried out on eight different platforms, including journal articles and conference proceedings, which are written in English and published until August 2022. The results are analyzed in terms of the publishers, the sensors used, the applications, the monitored units, the algorithms of use, the participants of the studies, and the validation systems employed. In addition, we delve deeply into the machine learning techniques proposed in recent years and in the approaches to reduce the estimation error. In this way, we show an overview of the research carried out in this field, going into more detail in recent years, and providing some research directions for future work.**

***Index Terms*— Human motion, inertial measurement units (IMUs), inertial sensors, kinematic analysis, motion analysis.**

I. Introduction

HUMAN motion analysis is an essential support tool for the assessment of the parameters of movements, which is especially important in the evaluation of workout routines, clinical rehabilitation, and preventive treatments [1]. It is also becoming very popular for physical activity monitoring in the elderly. Indeed, as the population of developed countries ages, the demand for home-based rehabilitation and the need to obtain quantitative exercise data remotely will increase [2].

Optical methods are considered the *gold standard* in the motion analysis field because of their accurate measurements of kinematic and spatiotemporal parameters [3]. However, these systems entail several disadvantages, such as the high cost of equipment, the need for trained personnel to use the equipment, the required large spaces for installation, and their restricted margin of maneuverability, which limits their use in controlled indoor environments.

The inertial motion analysis has emerged as a promising alternative to optical methods attracting great scientific interest. Inertial systems are portable and can be used everywhere, which means an advantage to the optical systems, which are commonly constraint to a limited space. That makes the inertial measurement units (IMUs) an affordable and friendly use alternative for the estimation of human kinematics. These devices allow continuous monitoring of human motions in daily environments, which is crucial in order to obtain more reliable information than the obtained in sporadic laboratory tests. For these reasons, the use of IMUs has increased in the last few decades for continuous monitoring of human motions, as reported in [4].

Previous works extensively review the use of portable sensors. A recent review analyzes the integration of portable sensors in clothes to obtain physiological and motion information [5]. However, inertial sensors are not considered in the analysis, in spite of their frequent use in this field. Reviews that take into account the use of inertial sensors are focused on applications, such as sign languages or motion analysis [3], [6]. Works about the inertial motion analysis, as in [3], address the motion monitoring and kinematic feature extraction, but only considering the specific area of sport-related exercises evaluation and their analysis is up to April 2017. A lower limb-focused study is carried out in [7], but it does not provide a complete overview of the literature on inertial motion analysis. To the best of our knowledge, the last in-depth and generic systematic review on inertial sensors for human motion analysis is reported in [4], published in 2016. Since the number of publications about human motion analysis increases over time, as shown in Fig. 1, we consider that there is a need to update the literature review on this topic. According to Fig. 1, the number of existing publications on

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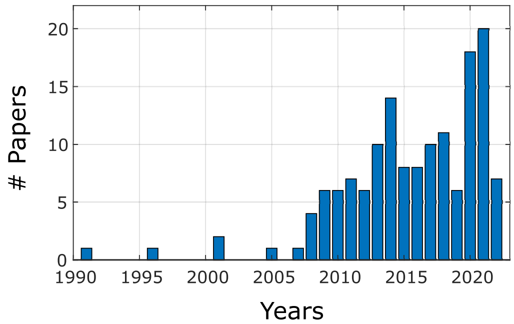

Fig. 1. Number of publications focused on the inertial motion analysis, referred to obtaining kinematic parameters by using portable inertial sensors, found in the literature.

the inertial motion analysis field has considerably increased since the previous review was published [4].

Furthermore, during the last years, machine learning (ML) methods have arisen, and they have been applied to inertial motion analysis. Consequently, it is required an update to provide an overview of the algorithms analyzed in [4], such as the Kalman filters (KFs), complementary filters (CFs), integration, and vector observation, but in combination with the novel ML-based approaches.

For these reasons, the main aim of this work is to review the current state of inertial sensors for human monitoring, especially considering the occurrence and evolution of ML methods for this research field. Another objective of this work is to analyze the current trends and provide insights into inertial motion analysis. To do so, we review the published works on human motion analysis using IMUs and analyze the selected ones in terms of: 1) publisher and years; 2) sensors used; 3) type of estimations referred to the dimensions of the estimated magnitudes; 4) the aimed applications of the proposals; 5) the monitored motion units; 6) the algorithmic approaches, with an in-depth analysis of sensor fusion filters, data science algorithms, and the approaches for error reduction; 7) the study participants; and 8) the validation systems (VSs) and metrics. Finally, on the basis of the findings, we suggest future research directions.

The rest of this document is structured as follows. Section II describes the search strategy and the eligibility criteria applied in this work; Section III details and analyzes the findings according to the terms explained earlier. Section IV discusses the general trends of the studied works and analyzes the future directions. Finally, Section V summarizes the main contributions of this work.

II. Materials and Methods

In this section, we describe the workflow to search and select the works in the state of the art included in this review. We describe this article's screening process and analyze the common publishers of this field. Finally, we detail the data extracted from them for further analysis.

A. Eligibility Criteria

This review focuses on peer-reviewed articles, book chapters, and conference papers. Papers are required to be published in English and describe the methodology employed to obtain human kinematic parameters using only IMUs. Sensor fusion with other devices is not considered. This review only includes those papers that validate their results using a reference system. If a journal article is an extended version of a conference one, only the journal article is included.

TABLE I

Databases Consulted in the Literature Search

Database	Source	# papers
ACM Digital Library	dl.acm.org	17
IEEE Xplore	ieeexplore.ieee.org	145
PubMed	www.ncbi.nlm.nih.gov/pubmed	188
ScienceDirect	www.sciencedirect.com	115
Scopus	www.scopus.com/	1434
Taylor & Francis Online	www.tandfonline.com	2
Web of Science	webofknowledge.com	326
Wiley Online Library	onlinelibrary.wiley.com	21

B. Literature Search Strategy

Considering the eligibility criteria, we select eight databases (ACM Digital Library, IEEE Xplore, PubMed, Science Direct, Scopus, Taylor & Francis Online, Web of Science, and Wiley Online Library) for the search of related papers (see Table I). Following the strategy of the previous review [4] about this topic, we use the same search command, which consists of:

("human motion" OR "human movement") AND ("wearable sensors" OR "inertial sensors" OR "wearable system")

considering their presence in the title, abstract, or keywords. The search includes journals, book chapters, or conference proceedings. This article abstract is required to be available during this search. No restriction was imposed on the date of publication.

The initial search on the databases in Table I leads to a review of 2 248 papers. The papers found in this search do not include important references from the state of the art, such as [8] or [9], so we expand the search. The new search is only performed on the Scopus website since it is the largest database of all those evaluated (see Table I). In this case, we use the following command, which is less restrictive than the previous one:

[("human motion" OR "human movement" OR "joint kinematics" OR "body tracking" OR kinematic OR "joint angle*" OR "joint angle velocity" OR "joint angle acceleration") AND (IMU OR "inertial sensors" OR "inertial measurement unit" OR accelerometer OR gyroscope OR magnetometer)].*

The search criteria are to find these key phrases in the title, abstract, or keywords of articles. This second search adds 1882 documents, so we finally obtain 4130 papers to review.

Starting from the results of this search, we carry out a Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) screening process [10] to determine the documents included in this study. Fig. 2 depicts the processes of identification and screening to determine the works included in this review.

After excluding duplicated citations, the number of documents to screen is reduced to 3775 papers. The results of

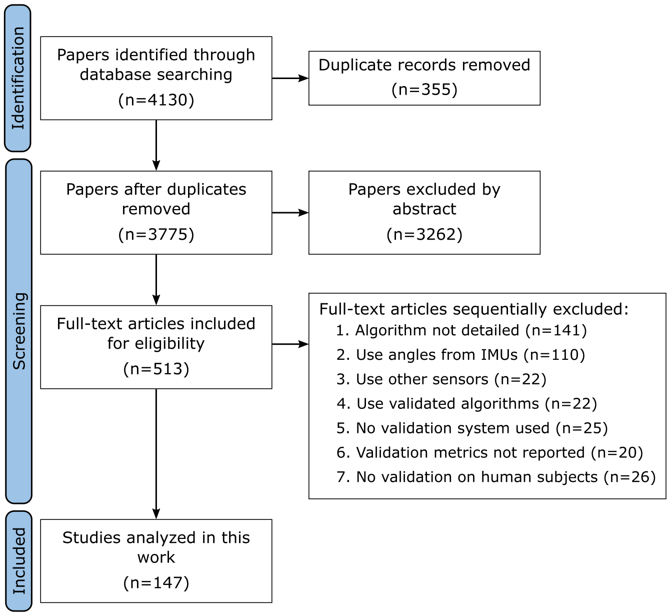

Fig. 2. PRISMA search strategy flowchart.

this search include works in the field of human motion analysis with IMUs. However, this IMU-based motion analysis covers a wide range of topics, such as the estimation of kinematic and spatiotemporal parameters or the motion-based evaluation of health, as depicted in Fig. 3.

The topics of kinematic and spatiotemporal parameters refer to the analysis of different motion magnitudes, such as joint angles, trajectory, or speed, whereas human body calibration includes the location of joints or the estimation of segment lengths. The last two topics, human monitoring and motion-based evaluation, are focused on qualitative analysis, such as recognizing types of motions or activities and identifying behavior patterns. Our study is focused on wearable inertial sensors and kinematic parameters as joint rotation angles, so we discard by abstract reading those works that are focused on any other topic. In this way, we exclude 3262 papers for not being related to the topic of this review.

We found 513 potentially relevant studies of this topic for quality assessment. To consider a study in this review, we set the inclusion criteria detailed in Fig. 2, which are referred to the proposed or applied algorithm, its validation, and the sensor system used. Finally, 147 studies meet the inclusion criteria and are analyzed in this review.

C. Publisher and Years

Most reviewed works are journal articles (72.1%) [see Fig. 4 (top)]. These works are published in 42 journals. 56.7% of them appear in sevenjournals (each of them with at least four papers), as shown in Fig. 4 (bottom). The journals that appear with the highest frequency in this search are *Sensors*, IEEE SENSORS JOURNAL (IEEE SJ), IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING (IEEE TBE), *Journal of Biomechanics* (JBiomech), *Gait & Posture* (G&P), IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT (IEEE TIM), and IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS (IEEE JBHI). The remaining 43.3% of works are distributed in 35 journals.

There is a clear increasing interest in the research field of inertial motion capture (see Fig. 1). This review is not restricted to any date in order to analyze all the works related to this topic and provide a general overview and its evolution. Fig. 1 shows the number of papers published during the five-year periods from 1991 to August 2022. Only twoworks are dated on the first studied decade, 21 works on the second one, and 98 works on the third one. There are also 27 works published in the period 2021–2022, the last years studied in this review.

Since 2016, the last year studied in [4], the number of publications has highly (see Fig. 5). These figures support the need for an update of a systematic review on the research topic of human motion analysis by using IMUs.

D. Data Extraction, Analysis, and Examination

We categorize the selected papers in terms of a set of relevant details. We classify them into two groups in order to ease the study and its reading. First, we evaluate the details related to the implemented algorithms, the sensors in use, and the estimations. Second, we study the specific anatomic part of the human body studied in each work, the VS and metrics used, and the information related to the validation subjects.

Regarding the first set of details, we analyze the following parameters: the fusion algorithm (FA) implemented for the motion analysis, which indicates with “SF” if the work uses sensor fusion approaches, “ML” the application of ML techniques, and “OA” any other proposal; the use of biomechanical constraints (BCs) and their related requirements of anatomical information (ANT) as the segment lengths or the joint location with respect to the IMU sensors; the implementation of other corrections (OCs); the type of sensor used to measure the motions (GS: gyroscope sensor, AS: accelerometer sensor, and MS: magnetometer sensor) and the use of external sensors to train ML-based algorithms, but not in the motion prediction (OS); the type of estimation (EST), considering the possible planar (2-D) or 3-D estimations; and the measured magnitude (ANG: angle or DIS: displacement referred to the change in the position of the corresponding point, i.e., the sensor or the monitoring joint) and the monitored motion unit (JNT: joint or SGM: segment). These details are shown in Table III in Appendix A for the selected papers.

With respect to the human body part, we study the lower group (LG) or upper group (UG) of segments and joints. We also report the VS used as *ground truth* in the studied works and the metrics (RMSE: root mean square error; nRMSE: normalized RMSE; %RMSE: percentage of RMSE; MAE: mean absolute error; AE: average error; CFC: correlation coefficient; LAMs: limits of agreement; MV: maximum variation; accuracy; and error rate), labeled as **M1** and **M2** in Table IV in Appendix A, employed in the proposed methods. Finally, we provide the number of subjects (NS) studied if this population considered presents a motor-related disease (**DSS**). Table IV in Appendix A includes the details of these parameters explained earlier in the selected papers.

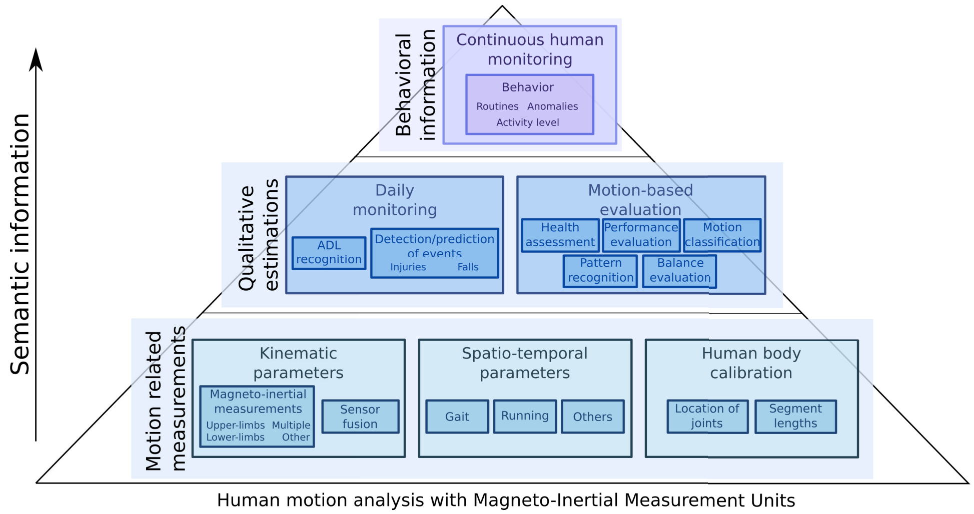

Fig. 3. Distribution of the publications related to human motion analysis and IMUs, sorted by the semantic information obtained. This work focuses on the topic included in the left square of the lower row: kinematic parameters with magnetoinertial measurements.

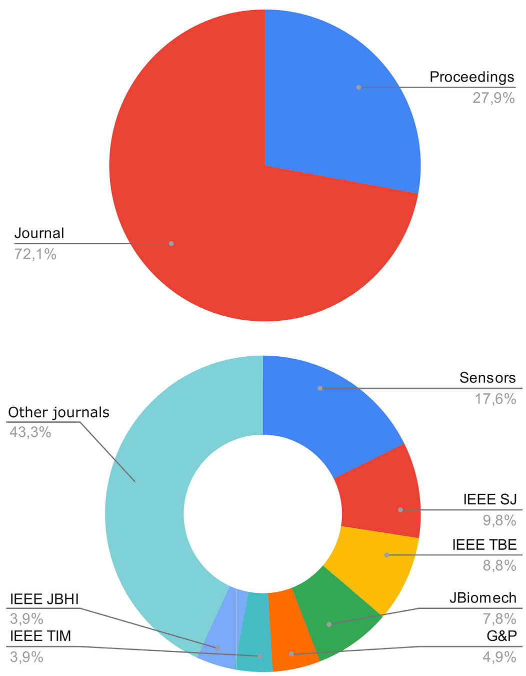

Fig. 4. Distribution of the papers with respect to the type of publication environment in which they were published. Top: conference and journal distribution. Bottom: journals that published the analyzed works.

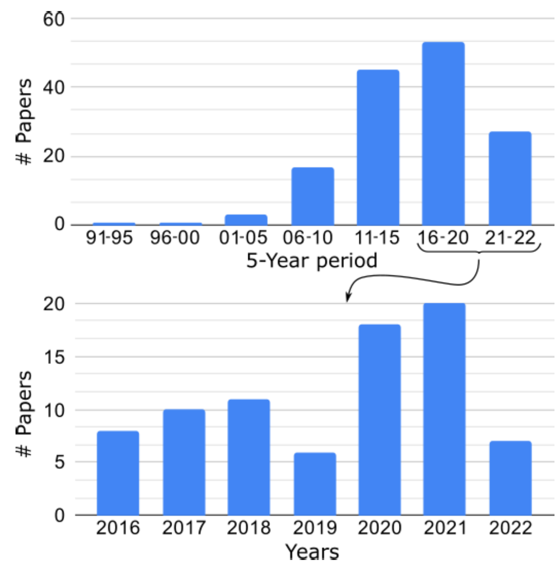

Fig. 5. Year of publication of the reviewed papers. Top: trend from the first motion analysis-related work until nowadays. Bottom: distribution of publications in the last five-year period.

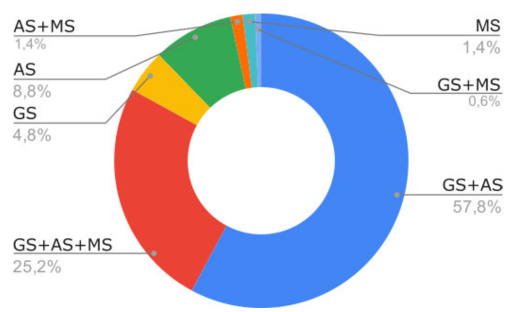

Fig. 6. Sensor type and combination used in the analyzed works (AS: accelerometer sensor; GS: gyroscope sensor; and MS: magnetometer sensor).

III. Review Findings

Based on the categorization of the papers with respect to their relevant characteristics, as presented in Tables III and IV in Appendix A, in this section, we describe the main findings.

A. Sensors

IMUs contain triaxial gyroscopes, accelerometers, and, commonly, magnetometers. The information from these sensors is used separately through the observation of vectors, as gravity in the accelerometer data or the magnetic field in magnetometers, or by integration of the gyroscope data. Another approach is to gather their measurements in different combinations of two or three sensors with different algorithms, such as sensor fusion filters or ML methods. In order to illustrate the proportion of their utilization, separately or fused, Fig. 6 shows the percentage of use of each sensor or combination.

The integration of the turn rate alone entails inherent errors. In the estimations of kinematic parameters, the turn rate integration results in an accumulated error from the gyroscope bias. For that reason, only 4.8% of studies use this sensor alone [11], [12], [13], [14], [15], [16], [17].

Accelerometers are more frequently used separately (8.8%). Their measurement of specific force allows us to obtain a direct observation of the gravity vector, used as orientation reference [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30]. However, the direct observation of the gravity vector is only possible when accelerometers are static, as in gait strides during the stance phase.

Magnetometers are the most limited sensor analyzed because of their sensitivity to magnetic disturbances in the environment. As a consequence, only 1.4% of studies use this sensor independently [31], [32].

Sensor fusion techniques are useful methods to overcome the individual limitations of each of them separately. Most of studies that fuse data from various sensors combine gyroscopes and accelerometers [8], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115] or both sensors with magnetometers [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152]. Few studies join the accelerometer and magnetometer data [153], [154], and only one uses the gyroscope and magnetometer data [155].

The 3-D position of devices can be inferred from the IMU sensor information. The combination of the three sensors, gyroscope, magnetometer, and accelerometer includes information on the angular rate of motion and the references of the vector gravity and Earth's magnetic field references. However, these 3-D positions can also be estimated by sensor fusion techniques using different combinations of the three sensors in IMUs. Most studies give 3-D estimations (71.4%), as shown in Fig. 7. Conversely, only 1.4% of works use accelerometers and magnetometers, and 25.2% of works use both sensors complemented with gyroscopes (see Fig. 6). This fact is noticeable because the combination of the first two sensors is required to obtain the references to overcome the gyroscope drift and get accurate 3-D estimations. It implies that the majority of algorithms that offer 3-D space predictions propose methods for error reduction, which do not rely on vector references. In this way, the magnetic disturbances that cause errors in the magnetic field measurements are avoided.

The 2-D estimations include kinematic parameters in any plane perpendicular to the floor and the two angles with respect to the horizontal plane, in the frontal and sagittal planes. No doubt that the 3-D estimations are more complete since they provide information about the whole motion, even if it is mostly performed in one plane. That is the reason why only 27.9% of studies focus on obtaining estimations in the 2-D space.

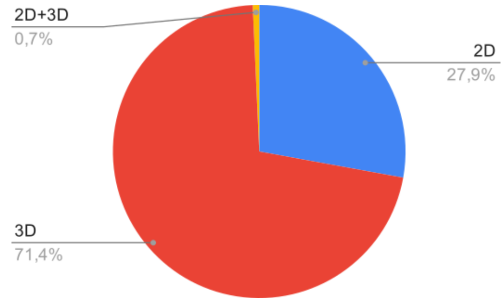

Fig. 7. Type of estimations in terms of their dimensionality, divided between 2-D and 3-D estimations.

Only one study adapts the estimation to 3-D or 2-D spaces according to the motions [41]. In this proposal, the method gives 2-D estimations based on the accelerometer data when the motion is mostly performed in one plane. If deviations from this plane are detected, the method integrates the gyroscope data in order to provide 3-D estimations.

B. Application

Healthcare applications are the most common ones (95.2%) in the inertial motion analysis field (see Fig. 8). These applications include motion capture or analysis, gait and clinical assessment, or rehabilitation. The aim of 33.5% of studies is to motion capture to obtain information about human kinematics for motion analysis or find possible diseases. Gait is the second most common application (19.1%) due to its relationship with cognitive impairments. The prevalence of use for the specific clinical assessment is similar, being the aim of the 14.5% of works. Rehabilitation and sports are also worth mentioning because they are very motivating in research works (19.6% of studies).

C. Monitored Motion Unit

We analyze the anatomical unit measured in the reviewed works. In this work, the anatomical units are called monitored motion units following the nomenclature of previous studies [4]. We divide these monitored motion units into two groups: segments and joints. Segments usually correspond to elements of the skeletal system, such as thighs (femur), and are modeled as rigid-solid bodies. Joints are the unions between segments. The objective of 64.6% of studies is to measure the motion of joints, whereas 27.2% of proposals focus on tracking segments, and the remaining 8.2% combine the monitoring of both monitored motions, segments, and joints, as shown in Fig. 9 (top).

Studies focus more frequently on the lower half (61.2%) of the body than on than upper half (34.7%). Compared to the outcomes in the review of Lopez-Nava et al. [4], this trend is in the most recent works different than in the previous ones. We found that recent research, dated the last three years, extends motion analysis to full-body monitoring, which is an important difference from the findings of previous studies [4]. We consider full body if both upper and lower halves are monitored, which is made in the 4.1% of studies. Fig. 10 (left) depicts the percentage of works that monitor each body half or the full body.

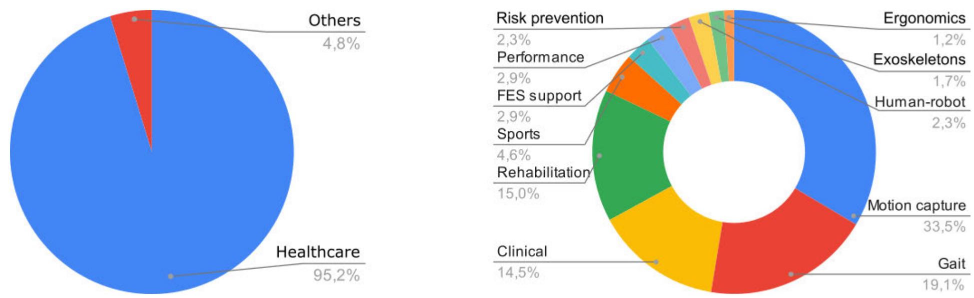

Fig. 8. Analysis of the application of the studied works. Left: percentage of proposals whose aimed field is included in healthcare-related applications. Right: specific application or applications considered in proposals. Some works provide possible uses of their proposals, others focus on a specific application, such as gait, and others refer to the general motion capture field. FES refers to functional electrical stimulation, and the research of human–robot interactions (HRIs) is labeled as "human–robot."

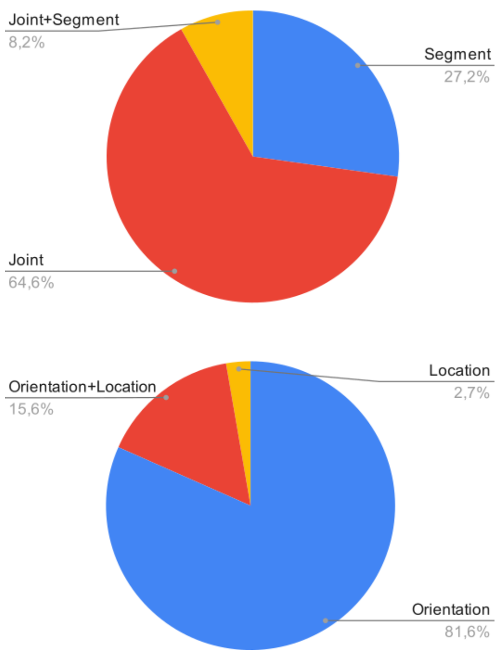

Fig. 9. Monitored motion units and the obtained measurement. Top: percentage of studies that measure each motion unit or their combination. Bottom: type of measurement, orientation, and location.

We study the groups of segments or joints included in each body half for a deeper analysis. We define the groups as sets of monitoring units. We consider that studies focus on one of the groups if they estimate the orientation or location of one of the included monitored units. For example, one study that tracks the motion of wrists is included in the hand group since we establish that the hand group includes the wrist among other motion units.

With respect to the upper half of the body, we divide it into the hand (hand, wrist, and fingers), arm segments (arm and forearm), arm joints (shoulder, elbow, and forearm twist), trunk (back, trunk, and torso), and head and upper back (head/neck/scapula). The upper half groups (51 works) are named follows: arm segments (U1), trunk (U2), arm joints and hand (U3), head and upper back, trunk, arm segments and arm joints (U4), arm joints (U5), head and upper back (U6), arm segments and joints (U7), trunk, arm joints and hand (U8), head and upper arm, trunk and arm (U9), head and upper arm and arm joints (U10), head and upper back and trunk (U11), head and upper back and arm segments (U12), and head and upper back alone (U13). Fig. 10 (right) shows the presence of the combination of these groups in the studied works.

The arm joints group, U5, is the one on which most works are focused (12/51 studies), followed by the trunk (9/51 studies), U2. The next three frequent groups are the arm segments (7/51 studies), U1, the combination of arm and hand joints (7/51 studies), U3, and the head and upper back (6/51 studies), U6. The rest of the groups are only monitored in 1/51 or 2/51 studies according to the case. In this way, research works commonly focus on the study of the arms more than the other upper half body structures.

With regard to the lower half, we divide it into the pelvis, leg segments (thigh and shin), leg joints (hip/knee/ankle), and feet. The names of the groups of their combinations are the following: leg segments and feet (L1), leg joints (L2), leg segments (L3), leg joints and feet (L4), feet (L5), pelvis, leg segments and leg joints (L6), leg segments and joints (L7), pelvis and leg joints (L8), and pelvis (L9). Fig. 10 (right) shows the number of works focused on each of these groups (the total number of works is 90).

In the lower half body, it is noticeable that most of the works focus on the leg joints, L2, which is the object of monitoring most works (63/90 studies). These joints are commonly studied in multiple applications, being the most important the gait analysis because of their relevance in health assessment. It is worth mentioning the contrast of the number of studies about the L2 group in comparison with the L4 group, which combines the leg joints with the feet, meaning that the motion of foot joints is commonly discarded in the studies focused on the lower limb joints. Besides the leg joints, the following most studied groups that are also focused on legs are leg segments, L3 (8/90 studies), leg segments and joints, L7 (7/90 studies), and leg segments and feet, L1 (5/90 studies). The rest of the groups, which include leg joints and feet (L4), feet (L5), pelvis, leg segments and leg joints (L6), and pelvis (L9), are studied in few works (2/90 studies).

The monitored units in these groups are measured regarding their orientation or location. Orientation refers to the rotation angles, which are commonly presented as Euler angles or quaternions. Locations refer to the spatial coordinates, so they are a measurement of distance. Most studies estimate the orientation of monitored units (81.6%), 15.6% give a combination of orientation and location of units, and only 2.7% are focused only on providing locations. Fig. 9 shows the distribution of the measured magnitudes.

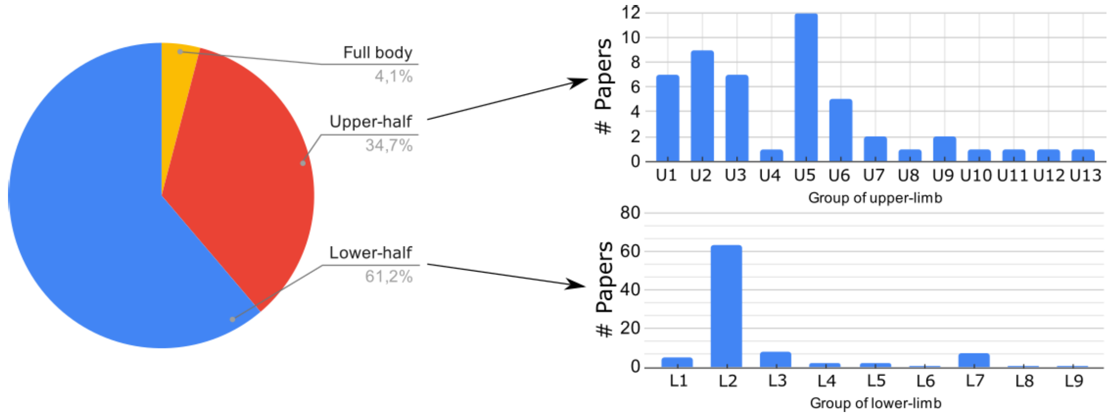

Fig. 10. Anatomical monitored units. Left: location of the monitored units in the upper or lower half part of the body. Right: number of papers per combination of segments and/or joints monitored.

D. Adopted Algorithms

The algorithms used in the estimation of the kinematic parameters can be separated into five different groups: integration, vector observation, sensor fusion filters, ML techniques, and other methods.

1) Sensor Fusion Filters: Sensor fusion filters (SF in Table III in Appendix A), including KFs, particle filters (PFs), and CFs, are the algorithms most frequently used. Specifically, KFs are still the algorithms that are employed the most in the inertial human motion analysis field, following the trend reported in previous studies [4].

The problem formulation of Bayesian filters consists of the identification of the desirable estimations using a series of measurements observed over time containing statistical noise and different inaccuracies [156]. The inputs and observations form the knowledge of the system's behavior both convey errors and uncertainties, namely, the measurement noise and the system errors. These filters fuse the information of sensors with the knowledge of the system in two stages: the estimation stage and the update stage. The initial stage uses the information of the previous time instant to estimate the current state of the state vector. The second stage updates these estimations using the measurements from the sensors.

The motion analysis includes proposals with extended KF (EKF), KF, and *unscented* KF (UKF) in descending order of frequency of use. KF is a sensor fusion technique that estimates the states of a linear system through the minimization of the variance of the estimation error [156]. KFs use a series of measurements observed over time and their statistical noise to produce estimates of unknown variables. EKFs appeared because KFs are limited to linear systems, being their generalization to nonlinear systems. EKFs assume that the nonlinearities in the dynamic and the observation model are smooth, so they expand the state and observation functions in the Taylor series and approximate, in this way, the next estimate of the state vector. However, this approximation can introduce large errors in the true posterior mean and covariance of the variables, which may lead to the divergence of the filter. One of the possible solutions is the use of UKFs, whose distribution of their state vector is a set of sample points called *sigma points*. Sigma points capture the actual mean and covariance of the Gaussian random variables and are obtained though the *unscented transformation* (UT). The UT is a method for calculating the statistics of a random variable that suffers a nonlinear transformation. UKFs are an extension of UTs to the recursive estimation where the UT is applied to the augmented state vector.

EKFs are the KF variation that most frequently appears in motion analysis. EKFs are used for the sensor fusion of gyroscopes and accelerometers in order to estimate the joint orientation [8], [38], [66], [70], [72], [92], [96], joint orientation and location [55], [76], [79], [88], [108], and segment orientation [77], [78]. Researchers also use EKFs to fuse gyroscope and accelerometer data with magnetometer measurements to estimate the orientation of joints [138], [142] or segments [117], [118], [135], [140], [145]. EKFs are also combined with the Gauss–Newton algorithm to fuse the information of gyroscopes and accelerometers, and estimate the orientation of joints [64].

Classical KFs are normally used for the sensor fusion of gyroscope and accelerometer data to estimate the segment orientation [33], [40], [43], [50], [52], [57], [97], [139], the joint orientation [44], [82], [85], [95], [98], the segment location [74], and all of them, the segment and joint orientation and location [42]. KFs have also been used in the fusion of gyroscope, accelerometer, and magnetometer data to estimate segment orientation and location [136], [152].

UKFs appear less frequently in the literature. UKFs are commonly used for the sensor fusion of gyroscopes, accelerometers, and magnetometers to estimate the joint location [137], or orientation [130], [149], the orientation of joints and segments [131], and the orientation and location of both elements, joints and segments [121]. Some works do not use the magnetometer information and only fuse the gyroscope and accelerometer data to estimate joint orientation [99], [106].

PFs are another modification of KFs for their use in nonlinear systems [156]. PFs are close in functioning to UKFs but with a set of differences that approximate PFs to a generalization of UKFs. PFs update the estimations with a randomly generated noise according to the *prior* knowledge of the process noise probability density function (pdf) instead of the update of the UKF that is deterministic. Another difference with UKFs is that the number of particles in PFs is not related to the length of the state vector. Finally, PFs estimate the pdf of the state instead of the mean and covariance, and it converges to the actual pdf as the number of particles increases.

PFs are less popular than any other kind of KFs. PFs are applied to fuse the measurements from gyroscopes, accelerometers, and magnetometers to estimate the orientation of segments and joints [125]. PFs are combined with other KFs, such as EKFs, for the fusion of gyroscope and accelerometer measurements to estimate the orientation of segments [94].

CFs combine the information from different sensors by minimizing the mean square error instead of the error covariance, which is minimized in KFs [157]. CFs are used to fuse the measurements of gyroscopes, accelerometers, and magnetometers to estimate the orientation of joints [123], [126], [133], their orientation and location [119], [144], and their orientation together with the segments orientation [143]. They are also used to estimate the joint either by combining the information of the gyroscope and the accelerometer orientation [45], [47], [62], [65], [101], [109], or just only with the gyroscope [11].

Another alternative to KFs is the weighted Fourier linear combiner (WFLC) filter, which is a model-based adaptive filter. WFLCs exploit the *prior* knowledge of the signal shape and evolution over time, in those occasions when the motion performed is given [93]. These filters are especially effective in periodic signals but adapt to variations between repetitions. Their applications to the human motion analysis include the use of the turn rate measurements to estimate the segment orientation [14] and the combination of these data from the gyroscope with the accelerometer measurements to estimate the orientation of joints [93].

2) Data Science Algorithms: ML techniques represent the second group of algorithms that are applied most frequently for the estimation of human kinematics. Furthermore, supervised learning algorithms are the most widespread in recent years. Supervised learning is one of the most employed learning paradigms, which tries to discover the unknown function $f(\mathbf{x}, \omega)$ that relates the input space $X \subset \mathbb{R}^n$ (which, in this work, are the inertial measurements), with the output space $Y \subset \mathbb{R}$ (which describes the motion kinematics). Each pair $(\mathbf{x}_i, y_i)$ is composed of the value of a set of n predictive variables $\mathbf{x}_i = (x_1, \ldots, x_n)_i \in \mathbb{R}^n$ of the input space, which is measured by the IMUs, and its corresponding output value $y_i \in \mathbb{R}$, which are the target value of joint or segment orientation and location. During the process called *training*, supervised algorithms retrieve the map $f \in F$ from the provided training dataset $\mathcal{D}$, typically establishing an optimization problem that minimizes a *loss function* $\mathcal{L}$. Different parametric function spaces F with different learning methods correspond to the existent variety of supervised methods, as described in depth in Table II.

Gaussian processes (GPs) are kernel-based probabilistic ML models. The GP is a kind of continuous random process $f(t)$ such that every finite set of random variables has a multivariate Gaussian distribution [158]. The GP method estimates the output y by introducing a set of latent variables $\{f(t_k)\}_{k=1}^{n}$ from a GP and explicit link functions, $g(\cdot)$. GP latent variable (GPLV) models are used with the gyroscope and accelerometer data to estimate the segment positions [58].

Other classical ML methods are decision trees (DTs) and support vector machines (SVMs). A DT is a classical ML method that builds a tree, a particular graph without cycles, by branching decision paths for each considered input variable to make the final classification [159]. During the training process, databases are used to compute thresholds (the parameters in DTs) that better branch the input variable for optimizing a criterion, usually the best gain of information possible in the current node (optimizing the entropy), for a better prediction of the output variable.

SVM is one of the most used ML methods for classification [160], [161]. It establishes an optimization problem to find the so-called *support vectors*, those training data that are close to the separation hyperplane, and maximize the *soft margin*. Frequently, this method uses the kernel trick that consists of choosing an appropriate nonlinear mapping $\boldsymbol{\phi}$ that maps input samples into a higher dimensional space where they are likely to be linearly separable. In regression problems, the support vectors are used to provide a continuous value through a link function instead of classes.

However, these classical ML methods are less promising than artificial neural networks (ANNs) in the human motion analysis field, as proved in [109] for the correction of the joint angles initially obtained from sensor fusion filters. ANNs consist of a set of connected base units known as artificial neurons that emulate the biological neurons of animal brains [162]. ANNs are usually organized in layers, which interconnect themselves to create a huge variety of networks that try to represent the functional relation between the input and output variables. ANNs have revolutionized the ML field due to their ability to model very complex nonlinear input–output relations and their capacity to learn them from a huge amount of data. The single-multilayer perceptrons (MLPs) were the first ANNs.

In the inertial motion capture field, ANNs use the accelerometer data as inputs to estimate the segments' orientation and location [27], combine the gyroscope and accelerometer data to estimate joint orientations [68], [71], [84], [91], or fuse the information of the three sensors integrated into IMUs to estimate the segment angles [147]. Other specific types of ANNs merge the estimation of joint angles with gyroscopes and accelerometers, such as the general regression NNs [49], [90] or the Elman neural networks [115].

Deep neural networks (DNNs) arise later than ANNs and encompass a huge amount of modern network architectures with a high number of interconnected layers [163]. The current technology allows massive computation during the training process and, hence, a new variety of interconnections and predictions in real time. DNNs start with the convolutional neural networks (CNNs), a large sequence of convolutional layers configured in a cascade where each layer computes the convolution operation (see [164]) from the previous one. They are able to extract intrinsic local features, called *deep features*, which surpass the results of the classical ML methods. VGG [165] and residual networks (RESNETs) [166] are famous CNNs included in this category. Most of the DNNs including CNNs are feedforward networks, which means that the information flows forward, and they do not include cycles. However, DNNs also include recurrent networks, which memorize internal states, frequently exploited for temporal sequences, such as the improved recurrent neural network (RNN) [167], which evolved to the novel long short-term memory (LSTM) [168], the gate recurrent unit (GRU) [169], and the nonlinear autoregressive neural network with exogenous inputs (NARX) [170].

Among the deep learning algorithms, LSTMs are the most utilized. LSTMs are made by a sequence of cells capable to keep previous states and specifically keep two kinds of temporal information and the LSTM. They have replaced the RNNs that suffer from the vanishing gradient problem during the training and include forget gates to quickly adapt to the new changes of data. These DNNs can use just the information of accelerometers and the orientation of a set of body segments to estimate the whole-body posture [29] or fuse the information of specific force with the turn rate to estimate the joint angles [53], [69], [86], [103]. A less common approach includes the fusion of gyroscopes and magnetometers to estimate the joint angles [155]. LSTMs can also be used to estimate the orientation of the whole-body joints using the orientation obtained with sparse commercial sensors [148]. In [69], LSTMs are combined with CNN to estimate the joint angles. CNNs are also used to obtain the joint angles only using the accelerometer data [21] or fusing the gyroscope and accelerometer data [56], [111], [114]. Mundt et al. [34] made a comparison of these previous methods, CNNs and LSTMs, together with MLPs for the estimation of joint orientation. Using the information from gyroscopes and accelerometers, CNNs provided the most favorable metrics. Other RNNs are also used to estimate joint orientation. To estimate the joint angles from gyroscopes and accelerometers, Tham et al. [54] propose an NARX; Conte Alcaraz et al. [134] also include the magnetometer data with NARX and LSTMs.

The ML-based algorithms that are used for human motion analysis are supervised methods. These methods need training data, which must include reference data of the parameter to estimate, i.e., the joint or segment orientation or location. In this review, we found 26 works that use reference data, which can be obtained from a stereophotogrammetric system (17/26) [21], [27], [34], [49], [53], [54], [56], [58], [68], [69], [86], [90], [91], [103], [111], [114], [115], electrogoniometer and encoders (2/26) [71], [84], or inertial sensors (7/26) [29], [100], [109], [134], [147], [148], [155]. Fig. 11 shows the percentage of use of the different external sensors for obtaining reference data.

The use of optical systems also allows data generation in order to have data for the training and testing of the algorithms and to increase the available data to train the models. These tasks can be performed with simulation software, e.g., OpenSim [171], as in [86], [103], and [148], by applying kinematic relationships from the stereophotogrammetric measurements, as in [19], [53], [56], [68], [69], [91], and [103], or with data augmentation techniques [68].

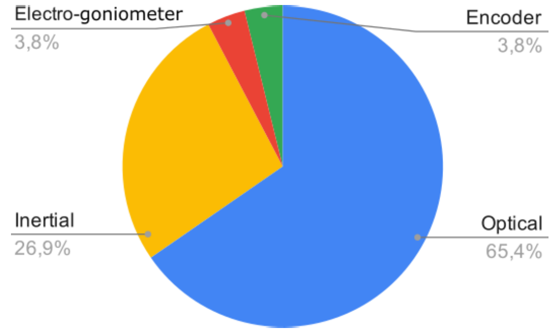

Fig. 11. External sensors used to obtain the reference measurements for the training and testing stages of the ML algorithms.

3) Other Algorithms: Over the years of research on motion analysis with inertial sensors, proposals have been based on various algorithms other than sensory fusion filters and data science methods. These proposals cover the integration of the gyroscope data to estimate the joint orientation [12], [15], [16], [17], [41] to its combination with the direct use of the data from accelerometers to estimate the orientation of joints [80], [104], [105] and segments [59], [60], [63], [81], and to estimate the orientation and location of segments [110], [112]. The measurements from gyroscopes and accelerometers are also used directly to obtain the orientation and location of joints [35] and segments [46], and to estimate the orientation of both joints and segments [48], [51], [113]. The information of the three sensors in the IMU is also directly used for the estimation of the segments orientation [141].

Different works exploit the observation of the gravity vector by the accelerometer for the estimation of the orientation of joints [18], [22], [24], [30], [61], segments [28], or both [20]. Other works also use the data of the magnetometer to estimate the joint orientation and location [31] or combine this information with the measurements of accelerometers to obtain the joint orientation [153]. The gravity vector can also be observed by eliminating the linear acceleration of the motions, which can be estimated from the turn rate measurements [73].

Besides the gyroscope integration and the direct observation of vectors, the measurements from IMU sensors can be combined through the use of virtual sensors. The use of virtual sensors consists of the estimation of the measurements that a sensor would obtain if it was located in the joint. This measurement projection is commonly performed because it is not possible to place the sensors in the joints. This is commonly used to simulate the measurements in joints, whereas the IMUs are placed in segments. This approach is used to combine the gyroscope and accelerometer measurements to estimate only the joint orientation [37], [46], [83] or both the joint orientation and location [89]. Another application of virtual sensors is to combine the turn rate, specific force, and magnetic field to obtain these magnitudes in joints to estimate their orientation [129], [132], [150], [151] and also not considering the measurements from gyroscope for the joint orientation estimation [154].

Another common method used is the gradient descent. Gradient descent is applied to obtain the joint orientation by using the measurements from gyroscopes [13] and combined

TABLE II

OUTCOMES OF THE ANALYSIS OF INPUTS USED IN THE ML ALGORITHMS, ALGORITHMS APPLIED IN EACH WORK, AND OUTPUTS AIMED AS TARGETS WITH THE CAPTURE SYSTEM EMPLOYED. SF: SPECIFIC FORCE; TR: TURN RATE; OR: ORIENTATION; CAP.: CAPTURE; SNN: SHALLOW NEURAL NETWORK; DNN: DEEP NEURAL NETWORK; AND VS.: VERSUS

Work	Inputs			Specifications of inputs	Algorithm	Outputs	
	SF	TR	OR			Magnitudes	Cap. system
[90]	✓	✓		Time instant	GRNN	Joint angle	Optical
[49]	✓	✓		Time instant	GRNN Aux. Sim. Info.	Joint angle	Optical
[84]	✓	✓		Time instant	ANN	Joint angle	Other
[58]	✓	✓		Sparse IMUs	GPLVM	Whole-body posture	Optical
[147]	✓		✓	Sparse IMUs 5 samples (0.55 s) windows	SNN & DNN	Segment location Whole-body posture	Inertial
[109]		✓	✓	Joint angle from Bayesian filters	NN (vs.) SVM (vs.) DT	Joint angle	Inertial
[53]	✓	✓		Simulated inertial data Different IMU combination + PCA From 100 to 1000 time-steps	LSTM	Joint angle	Optical
[21]	✓			600 ms windows Sparse IMUs for leg kinematics	1D-CNN	Joint angle	Optical
[56]	✓	✓		Experimental and simulated data combined 100 time-steps for each walking cycle	CNN	Joint angle Joint moment GRF	Optical
[27]	✓	✓		Time instant	ANN	Joint angle Joint moment GRF	Optical
[68]	✓	✓		Simulation of IMUs Data augmentation 10 frames windows Full gait cycles	ANN	Joint angle Joint moment	Optical
[91]	✓	✓		Simulated inertial data Segmentation into gait cycles	ANN	Joint angle Joint moment	Optical
[29]	✓		✓/✗	Sparse IMUs Window of 50 samples = 0.50 s	LSTM	Whole-body posture	Inertial
[69]	✓	✓		Simulated inertial data Calibration for alignment Marker trajectories filtered 1 s & 2 s windows	1D-CNN (vs.) LSTM & Optimizer	Joint angle time series	Optical
[86]	✓	✓		100 samples (100 Hz) windows	CNN LSTM	Joint angle time series	Optical
[103]	✓	✓		Experimentally measured IMU data, Simulated inertial data 200 time-steps Time wrapping of strides as inputs	LSTM	Joint angle time series	Optical
[155]	✓	✓		Sparse IMUs Synthetic and experimental data 300 frames windows	LSTM	Joint angle time series Whole-body posture	Inertial
[148]			✓	IK outputs as biRNN inputs +Joint parmeter Sparse IMUs 300 time-steps windows	LSTM	Whole-body posture	Inertial
[53]	✓	✓		Experimental and simulated data 101 frames windows	MLP LSTM CNN	Joint angle time series	Optical
[71]	✓	✓	✓	Time instant	ANN	Joint angle Walking speed	Other
[54]	✓	✓		Time instant	NARX (vs.) CF	Segment angle	Optical
[134]	✓	✓	✓	Sparse IMUs for leg kinematics Gait cycle segmentation	NARX LSTM	Joint angle	Inertial
[100]	✓	✓		Sparse IMUs for knee angle Short intervals 0.05 s	LSTM	Joint angle	Inertial
[111]	✓	✓		Sparse IMUs for leg kinematics Evaluation of classifier combinations	CNN RNN	Joint angle time series	Optical
[114]	✓	✓	✓	Initial gyro integration for joint orientation estimation	Elman NN	Joint position	Optical
[115]	✓	✓		Gait variations	LSTM	Joint angle time series	Optical

with the specific force measurements [39], [64], [102]. This approach also allows the gathering of the measurements of the three sensors to estimate the segment orientation [116].

The remaining proposals use a wide variety of methods and approaches to monitor the measurement units. These methods include probabilistic graphical models [122], which

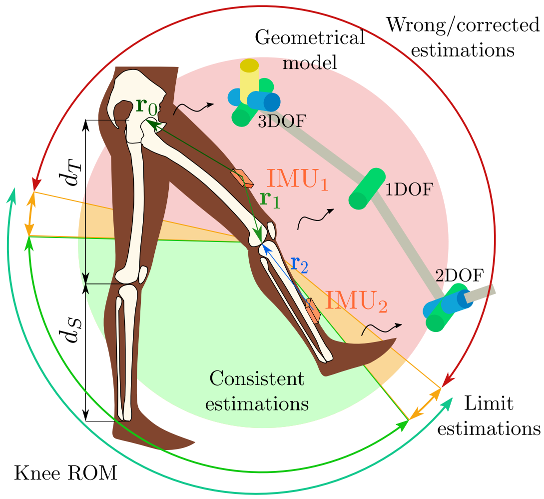

Fig. 12. Scheme of the BCs commonly implemented in the kinematic models for the inertial motion analysis. It includes the geometrical model with a reduced number of DOF in the knee and ankle joints, and the limitations with respect to the ROM using the knee as an example. The lengths and the IMU-joint vector used in the soft constraints are labeled as d_S, d_T, and $\boldsymbol{r}_i$ with $i = 0, 1, 2$, respectively.

are employed with the gyroscope, accelerometer, and magnetometer measurements to estimate the orientation of joints, smoothing algorithms [36], bidirectional low-pass filters [19], least squares [75], [87], optimization techniques [25], [67], [107], and modified iterative algorithms [23]. The latest worth mentioning approach consists of the double-sensor difference-based algorithm [26], which combines the measurements from two accelerometers placed on the same segment with the knowledge of their positions with respect to the joint.

4) Approaches for Error Reduction: This section describes the main approaches found in the literature in order to reduce the errors in the estimation of kinematic parameters. First, we focus on the explanation of the proposals based on BCs, and then, we summarize the approaches for error reduction based on the properties of the inertial sensors and their motions.

BC is a promising resource to improve inertial human motion analysis. A common approach is to model the rotations of different joints with different degrees of freedom (DOF), which are depicted with cylinders in the geometrical model in Fig. 12. The three rotational DOFs recorded by IMUs can be modeled as one or two DOF joints, according to the possible anatomical motions.

In the literature, the knee is assumed to be a hinge joint with just one DOF (flex-extension; see Fig. 12) [8], [39], [45], [55], [62], [71], [80], [87], [88], [96], [101], [130], [135], [136], [151] because its internal rotation allows a negligible range of motion (ROM). Some works also consider the knee's internal rotation together with its flex-extension, so the modeled joint presents two DOFs [82]. The same approach can be used to simplify the ankle orientation estimation, using only the knee-flex extension rotation, so one DOF [136], or also including the internal rotation, resulting in two DOFs [55], as depicted in Fig. 12. Despite being less commonly used due to its actual DOF and complexity, hips are modeled as joints with two DOFs [101], [151].

This DOF reduction can be also applied to upper limbs. Elbows can be assumed to have only two DOFs, gathering the elbow flex-extension rotation and the forearm internal–external rotation [13], [55], [98], [99], [106], [121], [122], [143], [149], [150] or considering only the elbow flex-extension [125]. The wrist can be also modeled as one DOF joint [121], [122] or allowing a second rotation with two DOFs [150].

Another approach related to the simplification of motions to a lower amount of DOF is to model the motions as if they occur in one or two planes. This approach reduces the 3-D space in, at least, one dimension. Different motions, such as gait or squats, can be approximated as 2-D in the sagittal plane [105], [109], [134] or with the combination of the sagittal and coronal planes [52], [97].

The separation of motions in the DOF available for the joints allows another restriction based on the joint anatomical ROM. This constraint is based on the correction of the estimations that are not consistent with the anatomically possible ROM per DOF of joints. As depicted in Fig. 12, the ROM of a joint, in this case, the knee, includes the consistent estimations and the estimations on the limit of the ROM. The values of angles outside this range are wrong estimations of the algorithm, and the objective is to detect and correct them. This approach can be found in several proposals in the literature [59], [79], [87], [120], [136], [143].

Another common approach for the error reduction in most of the biomechanical models is to take into account the anatomic parameters, such as the joints location with respect to the sensors or the segments length [8], [17], [19], [20], [23], [24], [25], [26], [35], [37], [38], [46], [46], [64], [73], [76], [77], [78], [79], [83], [87], [88], [89], [91], [92], [93], [94], [95], [96], [98], [99], [105], [106], [107], [108], [119], [129], [132], [137], [138], [143], [150], [151], [154]. Fig. 12 shows these parameters, labeled as $\boldsymbol{r}_i$, where $i = 0, 1, 2$, d_S, and d_T, respectively. The IMU-joint vector and the segment length are used to impose that the relationship between magnitudes has to be consistent with the anatomy of participants and the location of sensors on the body. These constraints can be applied by the relationship between the velocity in the common joint between two segments and the turn rate measured by the gyroscopes of the corresponding IMUs using (1) (see Fig. 12)

$$\boldsymbol{v}_{knee} = \boldsymbol{\omega}_{IMU_1} \times \boldsymbol{r}_1 = \boldsymbol{\omega}_{IMU_2} \times \boldsymbol{r}_2. \tag{1}$$

An alternative approach is to relate the linear acceleration suffered by the IMUs with the linear acceleration in the common joint between segments. This approach requires the consideration of the gravity influence from the specific force measured by accelerometers. If the gravity influence is eliminated, (2) can be applied with the derivation of the turn rate

$$\begin{aligned}\boldsymbol{a}_{knee} &= \boldsymbol{a}_{IMU_1} + \dot{\boldsymbol{\omega}}_{IMU_1} \times \boldsymbol{r}_1 + \boldsymbol{\omega}_{IMU_1} \times \left(\boldsymbol{\omega}_{IMU_1} \times \boldsymbol{r}_1\right)\\ &= a_{IMU_2} + \dot{\boldsymbol{\omega}}_{IMU_2} \times \boldsymbol{r}_2 + \boldsymbol{\omega}_{IMU_2} \times \left(\boldsymbol{\omega}_{IMU_2} \times \boldsymbol{r}_2\right).\end{aligned} \tag{2}$$

The IMU-joint vectors combined with the segment lengths or the joint–joint vectors are commonly used to estimate the kinematic of chains of segments. This is frequently performed with the Denavit–Hartenberg (D-H) notation, which uses four angular and distance parameters to relate reference frames with the links of spatial kinematic chains [172]. In order to apply the D-H convention, one reference frame is defined for each DOF included in the biomechanical model. The axes of the consecutive reference frames, $i-1$ and i, must follow two rules: the x_i-axis must be perpendicular to z_{i-1}, and the x_i-axis must intersect with z_{i-1}. In this way, the transformation matrix $T_{i-1,i}$ detailed in (3) defines the transformation between consecutive frames

$$T_{i-1,i} = \begin{bmatrix} \cos\theta_i & -\cos\beta_i\ \sin\theta_i & \sin\beta_i\ \sin\theta_i & r_i\cos\theta_i \\ \sin\theta_i & \cos\beta_i\ \cos\theta_i & -\sin\beta_i\ \cos\theta_i & r_i\sin\theta_i \\ 0 & \sin\beta_i & \cos\beta_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

where θ_i is the angle between the x_{i-1}- and x_i-axes, about the z_{i-1}-axis, and β_i is the angle between the z_{i-1}- and z_i-axes, about the x_i-axis. This transformation of consecutive frames allows the estimation of the forward kinematics of a chain of joints by using (1) and (2), as performed in [74], [79], [87], [121], and [122].

The location of joints and the segment lengths are not imposed as the limitation of DOF or ROM, which directly models or corrects the estimations. However, they are used to impose constraints on the measured magnitudes. For that reason, the restrictions forced through these conditions are commonly known as *soft constraints*. It is worth mentioning that the errors in the estimation of the IMU-joint vector directly influence the estimation of joint angles that use these soft constraints [87].

OCs found in the literature that are not related with biomechanical properties include the following: modeling the bias of sensors or including them in the state vector [13], [19], [30], [33], [36], [44], [46], [52], [57], [60], [61], [62], [63], [70], [75], [82], [83], [95], [117], [118], [119], [123], [125], [139], [153], [173]; calibrating this bias [30], [44], [46], [97], [104], [105], [121], [124], [133], [150]; low-pass filtering the recorded signals [11], [14], [37], [41], [45], [63], [71], [143], [145]; or optimizing them [67], updating the estimations when a direct observation of gravity is available or with its dynamic compensation [35], [43], [48], [51], [59], [81], [140], [141], [174] or the zero-angle during the zero-turn rate time instants [11], [47], [48]; modeling the disturbances in the magnetometer and gyroscope [31], [118]; using virtual sensors, discriminating the quasi-static and dynamic motions [41]; eliminating the errors from the soft tissue artifacts [44], [127]; and, in the case of KFs, the optimization of the Kalman parameters [33], [50], [79].

E. Participants of the Study

This work also analyzes the NS that participate in the studies to validate the methods. Fig. 13 (top) shows the *boxplot* of the distribution of subjects in the studies analyzed in this work (147). The boxplot presents the first, second, third, and fourth quartiles of the studied subjects together with the *outliers*. In this work, the outliers represent the punctual studies that test their proposals in more than 18 subjects (8/147 studies). According to Fig. 13 (top), most results provided in the studies correspond to a population of fewer than ten subjects.

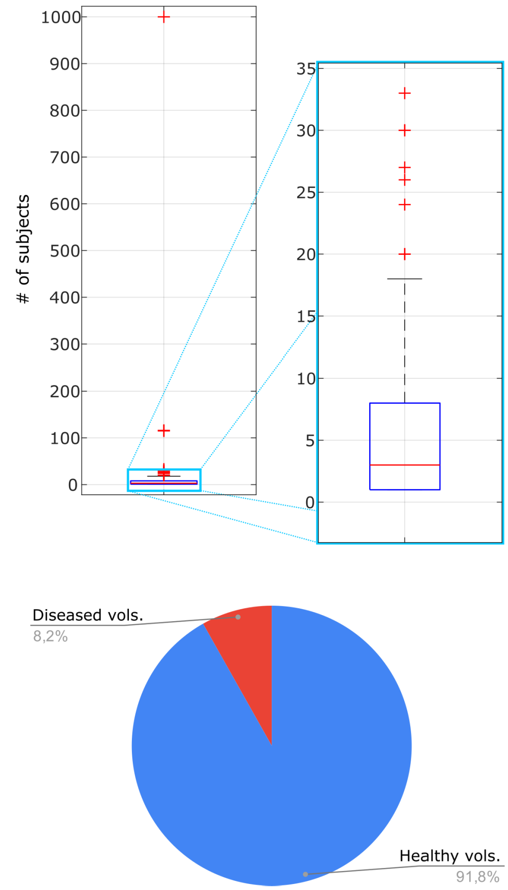

Fig. 13. Characteristics of the population of study in the human motion analysis literature. Top: percentage of works that evaluate their proposal in each number of participants. Bottom: percentage of works that consider a population with (diseased vols.) or without (healthy vols.) disease.

It is worth mentioning that the median is 3 subjects per study, which makes the results hardly generalizable to all populations. Furthermore, more than one-third of studies test their proposals with only one person (34.7%).

The studies that validate their proposal with the highest amount of volunteers commonly test ML-based algorithms. This amount of volunteers is required by these algorithms because they work with a high amount of data in order to develop generalizable models. However, 65.4% of these studies use the data from the optical systems to generate simulated inertial data, as shown in Fig. 11.

Studies analyze volunteers with or without diseases related to the motor system. We assume that, if there is no statement about whether unhealthy people are included, the studied population is healthy or with no illness that affects the performance of motions. In this way, only a small percentage (8.2%) of proposals are tested on population with these motor limitations [see Fig. 13 (bottom)]. This is remarkable since most proposals claim healthcare applications among their possible uses, as seen in Section III-B (95.2%).

F. Validation Systems and Evaluation Metrics

For the validation of the reviewed works, researchers use different systems, as shown in Fig. 14. The gold standard is the 3-D optical motion capture system, such as the

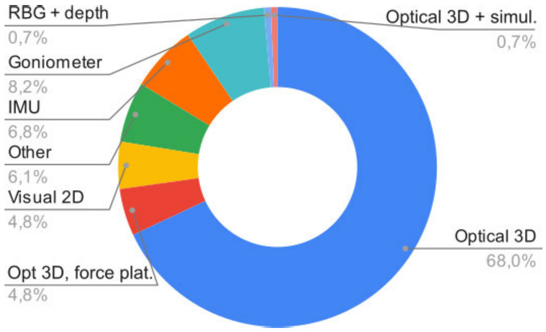

Fig. 14. VS used to assess the proposals. Force platforms and simulations are abbreviated as force plat. and simul., respectively.

commercial Vicon [175] or Optitrack [176], being the most widely employed. This system is commonly used for the validation of proposals (68.0%) and, sometimes, (4.8%), in the combination of force platforms or with simulation software (0.7%). 2-D optical systems that can obtain a reference in the image plane are also used (4.8% of the works). In some works, the 2-D optical systems are combined with depth sensors (0.7%).

Another approach to validate the algorithms that is worth mentioning is the use of output values of commercial inertial systems that provide highly accurate measurements, as done in the 6.8% of studies. IMUs of the Xsens commercial brand are the most frequently used for the validation of proposals [177]. Four of the eleven works that validate their algorithms against inertial sensors outputs use these sensors [109], [110], [147], [148], whereas the remaining seven works use IMUs of seven different brands.

A less common solution includes the use of analog and electronic goniometers (8.2%). Other VSs, which, in combination, sum 6.8% of works, include different programs of motion simulation, encoders, and potentiometers.

The accuracy metric reported most frequently for the validation of proposals is the RMSE. In some works, the CFC or the MAE is also provided. For the case of angles measurement, the studied works report an RMSE between 2.59° and 7.67°. Even if, on average, most of the studies provide similar metrics, it is worth mentioning that the RMSE range of ML methods is between 2.48° and 5.70°, whereas the RMSE provided by the classical methods is between 2.24° and 7.80°. These results prove that ML methods are promising approaches in the human motion analysis field in spite of their limitations related to data availability.

IV. Discussion

After the previous in-depth study, we discuss the review findings in terms of the general trends and the future guidelines in the inertial motion monitoring field.

A. General Trends

This article analyzes the current state and the research trends in the inertial motion analysis field. The analyzed works show interest in developing an alternative to the *gold standard* system, based on cameras, due to their high cost and the required space of use. As a consequence, the research focused on developing an IMU-based system for human motion analysis has increased over the last years, as seen in Fig. 5.

The sensors integrated into IMUs, accelerometer, gyroscope, and magnetometer are fused in different ways in the analyzed works, as shown in Fig. 6. The fusion of gyroscopes and accelerometers is more common than the use of magnetometers, being one of the main differences with respect to the findings in previous reviews [4]. However, the use of magnetometers is spreading during the last year with ten works. Bayesian filters and trigonometric approaches are the ones that most frequently employ the data from the magnetometer. ML proposals barely rely on the measurements of the magnetic field and only use them in the training step of the algorithms. In this way, the works focused on ML proposals are not limited by magnetic disturbances.

The common objective in 72.4% of studies (see Fig. 7) is to obtain 3-D kinematic parameters. The 2-D estimations are useful in human motion analysis because some movements can be simplified as motions in one plane, e.g., knee or elbow flex extension or even gait and squats. However, these estimations can miss relevant information in motions, about correctness or symptoms of motion-related diseases. Obtaining complete kinematic information is especially important in healthcare applications, which is considered in the 95.2% of works (see Fig. 8).

Most of the analyzed works (33.5%, as shown in Fig. 8) mention the generic motion capture field for human motion analysis, closely followed by the gait evaluation, as aimed applications for their work. That reflects the interest in developing more affordable and user-friendly alternatives to optical systems, as previously discussed. Consequently, the analyzed works propose algorithms to monitor frequently the orientation of joints, which is commonly measured by stereophotogrammetric systems, such as Vicon [175]. 64.6% of works focus on joints and 81.6% on the estimation of the orientation. These percentages imply a great advance in the direction of inertial solutions for human motion analysis, especially compared to the trends reported in [4], where most works studied the orientation of segments.

Another interesting analysis is focused on the distribution of works with respect to the analyzed body part, divided into the upper and lower halves. 61.2% of works (see Fig. 10) study the lower half of the body, and most of them focus on the leg joints, which is also consistent with the trend of gait evaluation besides the motion analysis. Conversely, only 34.7% (see Fig. 10) study the upper half, which includes arms and trunk, which are difficult to monitor due to the DOF and the complexity of joints as shoulders or neck. The results in Fig. 10 mean that, during the last years, the research has been focused mostly on the lower half of the body, the opposite of what happened in [4], and most of the reviewed works analyzed upper limbs. However, monitoring this upper half of the body is crucial for the evaluation of motions, being especially important in the rehabilitation of cognitive alterations or illnesses, such as strokes. The remaining 4.1% (see Fig. 10) of proposals are aimed at monitoring the whole-body posture, which is the most complete approach for the human monitoring. Even though the gait analysis is commonly performed by monitoring the lower limbs, the upper limbs are also important to study relevant features, such as balance, in clinical assessments. The rising interest in considering the full body is also another noteworthy difference compared to previous findings.

For full-body monitoring, ML methods are especially attractive. Sensor FAs use one IMU per segment to monitor the whole-body posture or model biomechanical relationships between segments to reduce this number with different constraints. Conversely, the approach in ML-based proposals focused on the whole-body posture is the optimization of the number of devices with the use of the so-called *sparse* IMUs, as in [29], [58], [147], [148], and [155]. This approach is also used to monitor specific limbs, such as legs, reducing the number of sensors [21], [100], [134].

The biomechanical approaches for error reduction can restrict motions and might not be generalized for populations with motor-related diseases. For instance, the ROM of joints can be different in people with anomalous physical abilities. Likewise, the assumption of a number of DOF can miss relevant information about motions out of the main directions. Also, the knowledge of the segment length or the location of the sensors on the body is not always available in practical applications. Different IMU-joint calibration methods have been proposed to address this limitation. The first approach is to obtain an average location of joints with respect to the sensors, which has been validated for the upper and lower limbs [178], [179], respectively, but requires specific calibration motions. The second method consists of estimating an adaptive position vector, considering the changes in the location of IMUs due to soft tissue artifacts [180], [181], [182], [183], which has been validated for the calibration of hips performing leg circles [182]. These proposals assume that the joints are fixed, but it is not the case in all the activities in daily living. In [184], the calibration of moving joints with soft tissue artifacts is addressed.

As in previous findings [4], the sensor FAs are employed more commonly than other approaches. However, their use during the last decade remains stable (around 24 papers), whereas the use of ML techniques has increased from four papers to 18 papers. These ML techniques provide a slight improvement in the accuracy metrics, referred to as a reduction of the maximum RMSE in 2° in angle measurements. However, none study analyzed in this work includes research that makes a fair comparison using common data to test both approaches.

Sensor fusion filters and data science algorithms differ in terms of their computational costs. Computational time varies among the different methods depending on their implementations. Sensor fusion filters are faster than data science methods, which require more calculations, especially DNN-based ones whose number of parameters is superior. Also, ML- and DNN-based methods usually demand more memory than the sensor fusion solutions, especially in their training stage, making their implementations more expensive.

ML algorithms are more robust to variation in the intrinsic noise of the sensors with which they are trained. In addition, their robustness can increase by generating synthetic data to which more noise models are added. Conversely, the sensor FAs include parameter tuning to adapt them to the sensors used, e.g., the covariance matrix of KFs. Thus, sensor FAs would require a previous study to estimate these sensor-dependent matrices.

ML methods require a high amount of reference data to be trained. Two alternative trends are followed in order to generate reference data: 1) to simulate the inertial data from the optical data to use them as inputs or 2) to use the orientation data obtained by commercial systems as reference. In the first case, the simulation of inertial data might not present the intrinsic errors of IMUs, whereas, by using inertial data as reference, it presents an error around 0.5° depending on the commercial brand, which is less accurate than optical systems.

With regard to the validation, new reference systems have appeared during the last few years. Among them, we find 2-D visual systems, encoders, and computational models. The 3-D optical systems are still the ones most frequently used (68.0% of studies; see Fig. 14). However, the use of this VS entails the limitation of testing the proposals in daily activities and alternative validation methods should be investigated [7].

The reviewed studies generally analyze a low amount of participants for the validation of the algorithms. This limitation was detected in [4] and still remains in recent works. Most studies test their results only on one volunteer, and the average of study subjects is four participants. It makes the proposals hard to generalize for the whole population. In those studies in that more participants are involved, the inertial data are simulated from the optical data, or their reference consists of the orientation outputs obtained from the IMUs, including the errors previously indicated.

Most studies analyze healthy participants. That is noticeable since most studies consider healthcare applications as possible uses of their proposals. However, only a few of them (8.2%) test their proposals on subjects with motor-related diseases.

B. Future Advancements and Developments

This review highlights a set of clear trends. The studies describe the motions in the 3-D space more frequently than reducing them to planar motions. This is crucial to describe complex motions that can be performed during daily life, so it is required for an out-of-the-lab analysis. Furthermore, the reduction of the gait or simpler motions, such as knee flex-extension to a plane, eliminates relevant information about these motions.

The reviewed works focus on the lower limbs, specifically on the orientation of the hip, knee, and ankle. Future research should include upper limbs or even focus on the development of whole-body posture monitoring for a complete description

TABLE III

RELEVANT DETAILS RELATED TO THE IMPLEMENTED ALGORITHMS, THE SENSORS IN USE, AND THE ESTIMATIONS OF THE SELECTED STUDIES. WITH RESPECT TO THE FA ACRONYMS, SF: SENSOR FUSION; ML: MACHINE LEARNING; AND OA: OTHER ALGORITHMS. OTHER ACRONYMS: BC: BIOMECHANICAL CONSTRAINT; ANT: ANATOMICAL PARAMETERS IN USE; OC: OTHER CONSTRAINTS; ML LEARNS: REFERS TO THAT THESES ML-BASED ALGORITHMS LEARN FOR REAL MOTIONS, SO THEY ARE CONSTRAINT TO ANATOMICAL JOINT LIMITS; EST: REFERS TO THE USE OF ANATOMICAL OR SOFT CONSTRAINTS AFTER ESTIMATE THE REQUIRED PARAMETERS; GS: GYROSCOPE SENSOR; AS: ACCELEROMETER SENSOR; MS: MAGNETOMETER SENSOR; OS: OTHER SENSORS FOR TRAINING; EST: TYPE OF ESTIMATION; ANG: ANGLE; DIS: DISPLACEMENT OR POSITION; JNT: JOINT; AND SGM: SEGMENT

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
A basic study on variable-gain Kalman filter based on angle error calculated from acceleration signals for lower limb angle measurement with inertial sensors [33]	SF			✓	✓	✓			2D	✓			✓
A Comparison of Three Neural Network Approaches for Estimating Joint Angles and Moments from Inertial Measurement Units [34]	ML	✓	ML learns	✓	✓	✓		✓	3D	✓		✓	
A fast quaternion-based orientation optimizer via virtual rotation for human motion tracking [116]	OA			✓	✓	✓	✓		3D	✓			✓
A Full-State Robust Extended Kalman Filter for Orientation Tracking during Long-Duration Dynamic Tasks Using Magnetic and Inertial Measurement Units [117]	SF			✓	✓	✓	✓		3D	✓			✓
A Human Motion Tracking Algorithm Using Adaptive EKF Based on Markov Chain [118]	SF			✓	✓	✓	✓		3D	✓			✓
A method for gait analysis in a daily living environment by body-mounted instruments [35]	OA	✓	✓		✓	✓			2D	✓	✓	✓	
A Method for Lower Back Motion Assessment Using Wearable 6D Inertial Sensors [36]	OA			✓	✓	✓			3D	✓			✓
A Miniature Sensor System for Precise Hand Position Monitoring [119]	SF	✓	✓		✓	✓	✓		3D	✓	✓	✓	
A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes [37]	OA	✓	✓		✓	✓			2D	✓		✓	
A new quaternion-based kalman filter for human body motion tracking using the second estimator of the optimal quaternion algorithm and the joint angle constraint method with inertial and magnetic sensors [120]	SF	✓			✓	✓	✓		3D	✓			✓
A nonlinear dynamics-based estimator for functional electrical stimulation: Preliminary results from lower-leg extension experiments [38]	SF	✓	EST		✓	✓			3D	✓		✓	
A novel 7 degrees of freedom model for upper limb kinematic reconstruction based on wearable sensors [121]	SF	✓	✓		✓	✓	✓		3D	✓	✓	✓	✓
A Novel Application of Flexible Inertial Sensors for Ambulatory Measurement of Gait Kinematics [39]	OA	✓	EST		✓	✓			3D	✓		✓	

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
A novel approach to motion tracking with wearable sensors based on Probabilistic Graphical Models [122]	ML	✓	✓		✓	✓	✓		3D	✓		✓	
A novel complimentary filter for tracking hip angles during cycling using wireless inertial sensors and dynamic acceleration estimation [123]	SF		EST		✓	✓	✓		3D	✓		✓	
A novel data glove for fingers motion capture using inertial and magnetic measurement units [124]	SF			✓	✓	✓	✓		3D	✓			✓
A novel hierarchical information fusion method for three-dimensional upper limb motion estimation [125]	SF	✓		✓	✓	✓	✓		3D	✓		✓	✓
A Novel Kalman Filter for Human Motion Tracking With an Inertial-Based Dynamic Inclinometer [40]	SF				✓	✓			3D	✓			✓
A novel method for estimating knee angle using two leg-mounted gyroscopes for continuous monitoring with mobile health devices [11]	SF			✓	✓				3D	✓		✓	
A novel method of using accelerometry for upper limb FES control [18]	OA					✓			2D	✓			✓
A novel sensor-based assessment of lower limb spasticity in children with cerebral palsy [41]	OA			✓	✓	✓			2D+3D	✓		✓	
A patient-centric sensory system for in-home rehabilitation [126]	SF				✓	✓	✓		3D	✓		✓	
A preliminary test of measurement of joint angles and stride length with wireless inertial sensors for wearable gait evaluation system [42]	SF				✓	✓			2D	✓	✓	✓	✓
A study of gait analysis with a smartphone for measurement of hip joint angle [12]	OA				✓				2D	✓		✓	
A Wearable Human Motion Tracking Device Using Micro Flow Sensor Incorporating a Micro Accelerometer [43]	SF			✓	✓	✓			2D	✓			✓
A Wearable Magnetometer-Free Motion Capture System: Innovative Solutions for Real-World Applications [44]	SF			✓	✓	✓			3D	✓		✓	
Accuracy Improvement on the Measurement of Human-Joint Angles [127]	OA			✓	✓	✓	✓		3D	✓		✓	
Accuracy of a custom physical activity and knee angle measurement sensor system for patients with neuromuscular disorders and gait abnormalities [45]	SF	✓			✓	✓			3D	✓		✓	
Adaptive Gain Regulation of Sensor Fusion Algorithms for Orientation Estimation with Magnetic and Inertial Measurement Units [128]	SF			✓	✓	✓	✓		3D	✓			✓
Alignment-Free, Self-Calibrating Elbow Angles Measurement Using Inertial Sensors [13]	OA	✓	EST		✓				3D	✓		✓	

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Ambulatory estimation of knee-joint kinematics in anatomical coordinate system using accelerometers and magnetometers [129]	OA	✓	✓		✓	✓	✓		3D	✓		✓	
Ambulatory measurement and analysis of the lower limb 3D posture using wearable sensor system [46]	OA	✓	✓		✓	✓			3D	✓		✓	
An adaptive complementary filter for inertial sensor based data fusion to track upper body motion [47]	SF				✓	✓			3D	✓		✓	
An auto-calibrating knee flexion-extension axis estimator using principal component analysis with inertial sensors [130]	SF	✓	EST		✓	✓	✓		3D	✓		✓	
An inertial human upper limb motion tracking method for robot programming by demonstration [110]	OA		✓	✓	✓	✓			3D	✓		✓	
An inertial sensor system for measurements of tibia angle with applications to knee valgus/varus detection [48]	OA				✓	✓			3D	✓		✓	✓
An instance-based algorithm with auxiliary similarity information for the estimation of gait kinematics from wearable sensors [49]	ML	✓		✓	✓	✓		✓	3D	✓		✓	
An investigation into the accuracy of calculating upper body joint angles using MARG sensors [131]	SF				✓	✓	✓		3D	✓		✓	✓
An optimized Kalman filter for the estimate of trunk orientation from inertial sensors data during treadmill walking [50]	SF			✓	✓	✓			2D	✓			✓
Analysis of a mobile system to register the kinematic parameters in ankle, knee, and hip based in inertial sensors [51]	OA				✓	✓			3D	✓		✓	✓
Analyzing 3D knee kinematics using accelerometers, gyroscopes and magnetometers [132]	OA	✓	✓		✓	✓	✓		3D	✓		✓	
Angle measurements during 2D and 3D movements of a rigid body model of lower limb: Comparison between integral-based and quaternion-based methods [52]	SF	✓		✓	✓	✓			2D	✓			✓
Artificial neural networks in motion analysis—applications of unsupervised and heuristic feature selection techniques [53]	ML	✓	✓	✓	✓	✓		✓	3D	✓		✓	
Biomechanical Ambulatory Assessment of 3D Knee Angle Using Novel Inertial Sensor-Based Technique [54]	ML	✓	ML learns	✓	✓	✓			3D	✓		✓	
Calibrated 2D angular kinematics by single-axis accelerometers: From inverted pendulum to N-Link chain [19]	OA	✓	✓			✓			2D	✓			✓
Closed-chain pose estimation from wearable sensors [55]	SF	✓	NO?	✓	✓	✓			3D	✓	✓	✓	
CNN-Based Estimation of Sagittal Plane Walking and Running Biomechanics From Measured and Simulated Inertial Sensor Data [56]	ML	✓		✓	✓	✓		✓	2D	✓		✓	
Comparison of angle measurements between integral-based and quaternion-based methods using inertial sensors for gait evaluation [57]	SF				✓	✓			2D	✓			✓

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Data-Driven Reconstruction of Human Locomotion Using a Single Smartphone [58]	ML	✓		✓	✓	✓		✓	3D		✓		✓
DeepBBWAE-Net: A CNN-RNN Based Deep SuperLearner For Estimating Lower Extremity Sagittal Plane Joint Kinematics Using Shoe-Mounted IMU Sensors In Daily Living [111]	ML		ML learns		✓	Y		✓	2D	✓		✓	
Deriving kinematic quantities from accelerometer readings for assessment of functional upper limb motions [20]	OA	✓	✓			✓			3D	✓		✓	✓
Design and validation of an ambulatory inertial system for 3-D measurements of low back movements [59]	OA	✓		✓	✓	✓			3D	✓			✓
Detecting absolute human knee angle and angular velocity using accelerometers and rate gyroscopes [60]	OA			✓	✓	✓			2D	✓			✓
Development of a body joint angle measurement system using IMU sensors [61]	OA			✓	✓	✓			3D	✓		✓	
Development of a wearable glove system with multiple sensors for hand kinematics assessment [133]	SF			✓	✓	✓	✓		3D	✓		✓	
Development of a wearable sensor system for quantitative gait analysis [187]	OA	✓	✓	✓	✓	✓			2D	✓	✓		✓
Digital inclinometer for joint angles measurements with a real-time 3D-animation [153]	OA			✓		✓	✓		3D	✓		✓	
Drift-Free 3D Orientation and Displacement Estimation for Quasi-Cyclical Movements Using One Inertial Measurement Unit: Application to Running [112]	OA			✓	✓	✓			3D	✓	Y		✓
Drift-Free and Self-Aligned IMU-Based Human Gait Tracking System with Augmented Precision and Robustness [62]	SF	✓		✓	✓	✓			3D	✓		✓	
Drift-Free Foot Orientation Estimation in Running Using Wearable IMU [63]	OA		EST	✓	✓	✓			3D	✓			✓
Drift-Free Inertial Sensor-Based Joint Kinematics for Long-Term Arbitrary Movements [64]	SF	✓	EST	✓	✓	✓			3D	✓		✓	
Effect of walking variations on complementary filter based inertial data fusion for ankle angle measurement [65]	SF		EST		✓	✓			3D	✓		✓	
Efficiency of deep neural networks for joint angle modeling in digital gait assessment [134]	ML	✓	ML learns	✓	✓	✓	✓	✓	2D	✓		✓	
Estimate of lower trunk angles in pathological gaits using gyroscope data [14]	SF			✓	✓				3D	✓			✓
Estimating Lower Body Kinematics Using a Lie Group Constrained Extended Kalman Filter and Reduced IMU Count [135]	SF	✓	✓	✓	✓	✓	✓		3D	✓			✓
Estimating lower extremity running gait kinematics with a single accelerometer: A deep learning approach [21]	ML	✓		✓		✓		✓	3D	✓		✓	

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Estimating Lower Limb Kinematics Using a Reduced Wearable Sensor Count [136]	SF	✓	✓	✓	✓	✓	✓		3D	✓	✓	✓	
Estimation and Observability Analysis of Human Motion on Lie Groups [66]	SF			✓	✓	✓			3D	✓		✓	
Estimation of gait kinematics and kinetics from inertial sensor data using optimal control of musculoskeletal models [67]	OA		✓	✓	✓	✓			2D	✓		✓	✓
Estimation of Gait Mechanics Based on Simulated and Measured IMU Data Using an Artificial Neural Network [68]	ML	✓		✓	✓	✓		✓	3D	✓		✓	
Estimation of kinematics from inertial measurement units using a combined deep learning and optimization framework [69]	ML	✓	ML learns	✓	✓	✓		✓	3D	✓		✓	
Estimation of knee joint angle during gait cycle using inertial measurement unit sensors: a method of sensor-to-clinical bone calibration on the lower limb skeletal model [113]	OA	✓			✓	✓			3D	✓		✓	✓
Estimation of lower limb joint angles during walking using extended kalman filtering [70]	SF			✓	✓	✓			3D	✓		✓	
Estimation of the continuous walking angle of knee and ankle (Talocrural joint, subtalar joint) of a lower-limb exoskeleton robot using a neural network [71]	ML	✓	ML learns	✓	✓	✓		✓	2D	✓		✓	
Estimation of the knee flexion-extension angle during dynamic sport motions using body-worn inertial sensors [72]	SF			✓	✓	✓			2D	✓		✓	
Evaluation of wearable gyroscope and accelerometer sensor (PocketIMU2) during walking and sit-to-stand motions [15]	OA				✓				3D	✓		✓	
Feasibility of a Wearable, Sensor-based Motion Tracking System [16]	OA				✓				3D	✓		✓	
Feasibility study of inertial sensor-based joint moment estimation method during human movements: A test of multi-link modeling of the trunk segment [17]	OA	✓	✓		✓				2D	✓		✓	
Gait posture estimation using wearable acceleration and gyro sensors [73]	OA	✓	✓	✓	✓	✓			2D	✓		✓	
Geometrical kinematic modeling on human motion using method of multi-sensor fusion [74]	SF	✓	✓		✓	✓			3D		✓		✓
Grasp pose estimation in human-robot manipulation tasks using wearable motion sensors [75]	OA				✓	✓			3D	✓	✓	✓	
Hand Motion Measurement using Inertial Sensor System and Accurate Improvement by Extended Kalman Filter [76]	SF	✓	✓		✓	✓			3D	✓	✓	✓	
Human Arm Motion Tracking by Inertial/Magnetic Sensors Using Unscented Kalman Filter and Relative Motion Constraint [137]	SF	✓	✓		✓	✓	✓		3D		✓	✓	
Human body model based inertial measurement of sit-to-stand motion kinematics [77]	SF	✓	✓		✓	✓			2D	✓			✓

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Human Motion Kinematics Assessment Using Wearable Sensors [138]	SF	✓	✓		✓	✓	✓		3D	✓		✓	
Human motion tracking based on complementary Kalman filter [139]	SF				✓	✓	✓		3D	✓			✓
Human pose recovery for rehabilitation using ambulatory sensors [78]	SF	✓	✓		✓	✓			3D	✓			✓
Human pose recovery using wireless inertial measurement units [79]	SF	✓	✓		✓	✓			3D	✓	✓	✓	
IMU-Based joint angle measurement for gait analysis [80]	OA	✓	EST		✓	✓			3D	✓		✓	
Inertia-based angle measurement unit for gait assistive device [22]	OA					✓			2D	✓		✓	
Inertial Motion Capture Using Adaptive Sensor Fusion and Joint Angle Drift Correction [140]	SF	✓		✓	✓	✓	✓		3D	✓			✓
Inertial sensing in ambulatory back load estimation [81]	OA			✓	✓	✓			3D	✓			✓
Inertial sensor-based knee flexion/extension angle estimation [82]	SF	✓			✓	✓			3D	✓		✓	
Joint angle estimation with accelerometers for dynamic postural analysis [23]	OA	✓	✓			✓			2D	✓		✓	
Joint Inertial Sensor Orientation Drift Reduction for Highly Dynamic Movements [83]	OA	✓	EST	✓	✓	✓			3D	✓		✓	
Knee angle estimation based on IMU data and artificial neural networks [84]	ML	✓		✓	✓	✓		✓	3D	✓		✓	
Knee joint angle measuring portable embedded system based on inertial measurement units for gait analysis [85]	SF				✓	✓			2D	✓		✓	
Lower body kinematics estimation from wearable sensors for walking and running: A deep learning approach [86]	ML	✓	ML learns	✓	✓	✓		✓	3D	✓		✓	
Lower Extremity Angle Measurement with Accelerometers—Error and Sensitivity [24]	OA	✓	✓			✓			2D	✓		✓	
Magneto: Joint angle analysis using an electromagnet-based sensing method [31]	OA						✓		3D	✓	✓	✓	
Magnetometer robust deep human pose regression with uncertainty prediction using sparse body worn magnetic inertial measurement units [155]	ML	✓	ML learns	✓	✓		✓	✓	3D	✓		✓	
Monitoring of Hip and Knee Joint Angles Using a Single Inertial Measurement Unit during Lower Limb Rehabilitation [87]	OA	✓	✓	✓	✓	✓			3D	✓		✓	
Multi-Inertial Sensor-Based Arm 3D Motion Tracking Using Elman Neural Network [114]	ML				✓	✓		✓	3D	✓	✓	✓	
Nonlinear optimization for drift removal in estimation of gait kinematics based on accelerometers [25]	OA	✓	✓	✓		✓			2D	✓	✓		✓

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Novel approach to ambulatory assessment of human segmental orientation on a wearable sensor system [26]	OA	✓	✓	✓		✓			2D	✓		✓	
Online tracking of the lower body joint angles using IMUs for gait rehabilitation [88]	SF	✓	✓		✓	✓			3D	✓	✓	✓	
Optimization of Inertial Sensor-Based Motion Capturing for Magnetically Distorted Field Applications [141]	OA			✓	✓	✓	✓		3D	✓			✓
Physical-Sensor and Virtual-Sensor Based Method for Estimation of Lower Limb Gait Posture Using Accelerometers and Gyroscopes [89]	OA	✓	✓		✓	✓			3D	✓	✓	✓	
Pose estimation by extended Kalman filter using noise covariance matrices based on sensor output [142]	SF			✓	✓	✓	✓		3D	✓		✓	
Predicting Knee Joint Kinematics from Wearable Sensor Data in People with Knee Osteoarthritis and Clinical Considerations for Future Machine Learning Models [115]	ML				✓	✓		✓	2D	✓		✓	
Predicting lower limb joint kinematics using wearable motion sensors [90]	ML	✓		✓	✓	✓		✓	2D	✓		✓	
Prediction of lower limb joint angles and moments during gait using artificial neural networks [91]	ML	✓		✓	✓	✓		✓	3D	✓		✓	
Prediction of lower limb kinetics and kinematics during walking by a single IMU on the lower back using machine learning [27]	ML	✓	✓	✓		✓			2D	✓	✓		✓
Quasi-real time estimation of angular kinematics using single-axis accelerometers [92]	SF	✓	✓		✓	✓			2D	✓		✓	
Real-time estimate of body kinematics during a planar squat task using a single inertial measurement unit [93]	SF	✓	✓		✓	✓			2D	✓		✓	
Real-Time Human Motion Capture Based on Wearable Inertial Sensor Networks [152]	SF		✓	✓	✓	✓	✓		3D	✓	✓	✓	
Reconstructing an accelerometer-based pelvis segment for three-dimensional kinematic analyses during laboratory simulated tasks with obstructed line-of-sight [28]	OA		✓			✓			2D	✓			✓
Reconstruction of angular kinematics from wrist-worn inertial sensor data for smart home healthcare [94]	SF	✓	✓		✓	✓			2D	✓			✓
Reducing drifts in the inertial measurements of wrist and elbow positions [95]	SF	✓	✓		✓	✓			3D		✓	✓	
Research on Human Motion Monitoring Method Based on Multi-Joint Constraint Filter Model [143]	SF	✓	✓	✓	✓	✓	✓		3D	✓		✓	✓
Rhythmic EKF for pose estimation during gait [96]	SF	✓	✓	✓	✓	✓			3D	✓		✓	
Rhythmic Extended Kalman Filter for Gait Rehabilitation Motion Estimation and Segmentation [8]	SF	✓	✓	✓	✓	✓			3D	✓		✓	

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Rigid body motion capturing by means of a wearable inertial and magnetic MEMS sensor assembly-from reconstitution of the posture toward dead reckoning: An application in bio-logging [144]	SF				✓	✓	✓		3D	✓	✓		✓
Robust and Accurate Capture of Human Joint Pose Using an Inertial Sensor [145]	SF			✓	✓	✓	✓		3D	✓			✓
Sensorial system for obtaining the angles of the human movement in the coronal and sagittal anatomical planes [97]	SF	✓			✓	✓			2D	✓		✓	✓
Shoulder and elbow joint angle estimation for upper limb rehabilitation tasks using low-cost inertial and optical sensors [98]	SF	✓	✓		✓	✓			3D	✓		✓	
Shoulder and elbow joint angle tracking with inertial sensors [99]	SF	✓	✓		✓	✓			3D	✓		✓	
Synergy-based knee angle estimation using kinematics of thigh [100]	ML	✓	ML learns	✓	✓	✓		✓	3D	✓		✓	
System for measurement of joint range of motion using inertial sensors [101]	SF	✓			✓	✓			2D	✓		✓	
The head mouse - Head gaze estimation 'In-the-Wild' with low-cost inertial sensors for BMI use [146]	SF				✓	✓	✓		3D	✓			✓
The manumeter: A wearable device for monitoring daily use of the wrist and fingers [32]	OA						✓	✓	3D	✓		✓	
The online estimation of the joint angle based on the gravity acceleration using the accelerometer and gyroscope in the wireless networks [102]	OA				✓	✓			2D	✓		✓	
The use of synthetic IMU signals in the training of deep learning models significantly improves the accuracy of joint kinematic predictions [103]	ML	✓	ML learns	✓	✓	✓		✓	3D	✓		✓	
Three dimensional gait analysis using wearable acceleration and gyro sensors based on quaternion calculations [104]	OA			✓	✓	✓			3D	✓		✓	
Time coherent full-body poses estimated using only five inertial sensors: Deep versus shallow learning [147]	ML	✓		✓	✓	✓	✓		3D	✓	✓		✓
Towards a portable human gait analysis & monitoring system [105]	OA	✓	EST		✓	✓			2D	✓		✓	
Towards kinematically constrained real time human pose estimation using sparse IMUs [148]	ML	✓	ML learns	✓	✓	✓	✓		3D	✓		✓	
Training Data Selection and Optimal Sensor Placement for Deep-Learning-Based Sparse Inertial Sensor Human Posture Reconstruction [29]	ML	✓	ML learns	✓	-	✓	-	✓	3D	✓			✓
Ubiquitous human upper-limb motion estimation using wearable sensors [149]	SF	✓			✓	✓	✓		3D	✓		✓	

Title	Algorithms				Sensors				Estimation characteristics				
	FA	BC	ANT	OC	GS	AS	MS	OS	EST	ANG	DIS	JNT	SGM
Unrestrained measurement of arm motion based on a wearable wireless sensor network [30]	OA			✓		✓			2D	✓		✓	
Upper limb joint angle measurement in occupational health [150]	OA	✓	✓	✓	✓	✓	✓		3D	✓		✓	
Upper limb joint angle tracking with inertial sensors [106]	SF	✓	✓		✓	✓			3D	✓		✓	
Use of multiple wearable inertial sensors in upper limb motion tracking [107]	OA	✓	✓		✓	✓			3D	✓	✓	✓	
Validation of a low-cost inertial exercise tracker [108]	SF	✓	EST	✓	✓	✓			3D	✓	✓	✓	
Visual and quantitative analysis of lower limb 3D gait posture using accelerometers and magnetometers [154]	OA	✓	✓	-		✓	✓		3D	✓		✓	
Visual estimation of lower limb motion using physical and virtual sensors [151]	OA	✓	✓	-	✓	✓	✓		3D	✓		✓	
Wearable inertial sensor system towards daily human kinematic gait analysis: Benchmarking analysis to MVN BIOMECH [109]	ML, SF	✓		✓	✓	✓		✓	2D	✓		✓	✓

TABLE IV

RELEVANT DETAILS ABOUT THE MONITORED ANATOMIC UNIT, THE NS OF STUDY IN THE SELECTED STUDIES THE VALIDATION SYSTEM, AND THE METRICS FOR EVALUATION. LG: LOWER LIMB GROUP; UG: UPPER LIMB GROUP; NS: NUMBER OF SUBJECTS FOR THE ANALYSIS; DSS: PRESENCE OF SUBJECTS WITH DISEASES; VS: VALIDATION SENSORY SYSTEM; AND M1 AND M2: METRICS PROVIDED FOR THE VALIDATION OF THE PROPOSALS

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
A basic study on variable-gain Kalman filter based on angle error calculated from acceleration signals for lower limb angle measurement with inertial sensors [33]	Leg Feet		3		Optical 3D	RMSE	
A Comparison of Three Neural Network Approaches for Estimating Joint Angles and Moments from Inertial Measurement Units [34]	Hip/knee/ankle		116		Optical 3D, Force plates	Difference in nRMSE between methods	
A fast quaternion-based orientation optimizer via virtual rotation for human motion tracking [116]		Arm	1		Optical 3D	RMSE	
A Full-State Robust Extended Kalman Filter for Orientation Tracking during Long-Duration Dynamic Tasks Using Magnetic and Inertial Measurement Units [117]	Leg Feet		9		Optical 3D	RMSE	
A Human Motion Tracking Algorithm Using Adaptive EKF Based on Markov Chain [118]		Arm	1		Optical 3D	RMSE	
A method for gait analysis in a daily living environment by body-mounted instruments [35]	Hip/knee/ankle		6		Optical 3D, Force plates	RMSE	-
A Method for Lower Back Motion Assessment Using Wearable 6D Inertial Sensors [36]		Back/trunk/torso	8		Optical 3D	RMSE	-
A Miniature Sensor System for Precise Hand Position Monitoring [119]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	6		Optical 3D	RMSE	-
A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes [37]	Hip/knee/ankle		8		Visual 2D	RMSE	Corr. coeff.
A new quaternion-based kalman filter for human body motion tracking using the second estimator of the optimal quaternion algorithm and the joint angle constraint method with inertial and magnetic sensors [120]		Arm	1		Optical 3D	RMSE	
A nonlinear dynamics-based estimator for functional electrical stimulation: Preliminary results from lower-leg extension experiments [38]	Hip/knee/ankle		3		Other	RMSE	-

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
A novel 7 degrees of freedom model for upper limb kinematic reconstruction based on wearable sensors [121]		Head/neck/scapula Back/trunk/torso Arm Arm joints: shoulders/elbow/forearm twist	1		Optical 3D	RMSE	-
A Novel Application of Flexible Inertial Sensors for Ambulatory Measurement of Gait Kinematics [39]	Hip/knee/ankle		3		Optical 3D	RMSE	
A novel approach to motion tracking with wearable sensors based on Probabilistic Graphical Models [122]		Arm joints: shoulders/elbow/forearm twist	1		Optical 3D	RMSE	
A novel complimentary filter for tracking hip angles during cycling using wireless inertial sensors and dynamic acceleration estimation [123]	Hip/knee/ankle		1		Optical 3D	MAE	-
A novel data glove for fingers motion capture using inertial and magnetic measurement units [124]		Hand/wrist/fingers	1		Visual 2D, Reconstruction	RMSE	-
A novel hierarchical information fusion method for three-dimensional upper limb motion estimation [125]		Arm Arm joints: shoulders/elbow/forearm twist	4		Optical 3D	RMSE	-
A Novel Kalman Filter for Human Motion Tracking With an Inertial-Based Dynamic Inclinometer [40]		Arm	10		Optical 3D	RMSE	-
A novel method for estimating knee angle using two leg-mounted gyroscopes for continuous monitoring with mobile health devices [11]	Hip/knee/ankle		5		Optical 3D	LAM	Avg. error
A novel method of using accelerometry for upper limb FES control [18]		Arm	2	2 post-stroke	Optical 3D	MAE	
A novel sensor-based assessment of lower limb spasticity in children with cerebral palsy [41]	Hip/knee/ankle		33	28 patients cerebral palsy	Optical 3D	RMSE	Test-retest inter-rater reliabilities
A patient-centric sensory system for in-home rehabilitation [126]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	1		Other	RMSE	
A preliminary test of measurement of joint angles and stride length with wireless inertial sensors for wearable gait evaluation system [42]	Hip/knee/ankle Feet		3		Optical 3D	RMSE	Corr. coeff.
A study of gait analysis with a smartphone for measurement of hip joint angle [12]	Hip/knee/ankle		14		Optical 3D	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
A Wearable Human Motion Tracking Device Using Micro Flow Sensor Incorporating a Micro Accelerometer [43]		Arm	1		IMU	RMSE	
A Wearable Magnetometer-Free Motion Capture System: Innovative Solutions for Real-World Applications [44]		Arm joints: shoulders/elbow/forearm twist	10		Optical 3D	RMSE	
Accuracy Improvement on the Measurement of Human-Joint Angles [127]		Arm joints: shoulders/elbow/forearm twist	15		Optical 3D	RMSE	
Accuracy of a custom physical activity and knee angle measurement sensor system for patients with neuromuscular disorders and gait abnormalities [45]	Hip/knee/ankle		10		Goniometer	RMSE	
Adaptive Gain Regulation of Sensor Fusion Algorithms for Orientation Estimation with Magnetic and Inertial Measurement Units [128]	Leg Feet		9		Optical 3D	RMSE	
Alignment-Free, Self-Calibrating Elbow Angles Measurement Using Inertial Sensors [13]		Arm joints: shoulders/elbow/forearm twist	1		Optical 3D	RMSE	
Ambulatory estimation of knee-joint kinematics in anatomical coordinate system using accelerometers and magnetometers [129]	Hip/knee/ankle		5		Optical 3D	RMSE	
Ambulatory measurement and analysis of the lower limb 3D posture using wearable sensor system [46]	Hip/knee/ankle		8		Optical 3D	RMSE	
An adaptive complementary filter for inertial sensor based data fusion to track upper body motion [47]		Arm joints: shoulders/elbow/forearm twist	4		Optical 3D	RMSE	
An auto-calibrating knee flexion-extension axis estimator using principal component analysis with inertial sensors [130]	Hip/knee/ankle		15		Optical 3D	RMSE	
An inertial human upper limb motion tracking method for robot programming by demonstration [110]		Hand/wrist/fingers	1		IMU	MAE	
An inertial sensor system for measurements of tibia angle with applications to knee valgus/varus detection [48]	Leg		3		Optical 3D	RMSE	
An instance-based algorithm with auxiliary similarity information for the estimation of gait kinematics from wearable sensors [49]	Hip/knee/ankle		8		Optical 3D	Absolute deviation	
An investigation into the accuracy of calculating upper body joint angles using MARG sensors [131]		Back/trunk/torso Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	1		RBG + depth	RMSD	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
An optimized Kalman filter for the estimate of trunk orientation from inertial sensors data during treadmill walking\citeMazza2012		Back/trunk/torso	18		Optical 3D	RMSE	
Analysis of a mobile system to register the kinematic parameters in ankle, knee, and hip based in inertial sensors [51]	Hip/knee/ankle		1		Visual 2D	Max. error	
Analyzing 3D knee kinematics using accelerometers, gyroscopes and magnetometers [132]	Hip/knee/ankle		1		Optical 3D	Avg. error	
Angle measurements during 2D and 3D movements of a rigid body model of lower limb: Comparison between integral-based and quaternion-based methods [52]	Leg		1		Optical 3D	RMSE	
Artificial neural networks in motion analysis—applications of unsupervised and heuristic feature selection techniques [53]	Hip/knee/ankle		115	24 knee arthroplasty	Optical 3D	RMSE	Corr. coeff.
Biomechanical Ambulatory Assessment of 3D Knee Angle Using Novel Inertial Sensor-Based Technique [54]	Hip/knee/ankle		5		Optical 3D	RMSE	
Calibrated 2D angular kinematics by single-axis accelerometers: From inverted pendulum to N-Link chain [19]		Back/trunk/torso	1		Optical 3D	RMSE	
Closed-chain pose estimation from wearable sensors [55]	Hip/knee/ankle		3		Optical 3D	Avg. error	RMSE
CNN-Based Estimation of Sagittal Plane Walking and Running Biomechanics From Measured and Simulated Inertial Sensor Data [56]	Hip/knee/ankle		10		Optical 3D, Force plates	RMSE	
Comparison of angle measurements between integral-based and quaternion-based methods using inertial sensors for gait evaluation [57]	Leg Feet		3		Optical 3D	RMSE	
Data-Driven Reconstruction of Human Locomotion Using a Single Smartphone [58]		Head/neck/scapula Back/trunk/torso Arm	1		Optical 3D	RMSE	
DeepBBWAE-Net: A CNN-RNN Based Deep Super-Learner For Estimating Lower Extremity Sagittal Plane Joint Kinematics Using Shoe-Mounted IMU Sensors In Daily Living [111]	Hip/knee/ankle		10		Optical 3D	RMSE	
Deriving kinematic quantities from accelerometer readings for assessment of functional upper limb motions [20]		Hand/wrist/fingers	1		Optical 3D	RMSE	
Design and validation of an ambulatory inertial system for 3-D measurements of low back movements [59]		Back/trunk/torso	2		Optical 3D	RMSE	
Detecting absolute human knee angle and angular velocity using accelerometers and rate gyroscopes [60]	Hip/knee/ankle		2	1 Paraplegic	Goniometer	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
Development of a body joint angle measurement system using IMU sensors [61]	Hip/knee/ankle		1		Optical 3D	Avg. error	
Development of a wearable glove system with multiple sensors for hand kinematics assessment [133]		Hand/wrist/fingers	1		Goniometer	MAE	
Development of a wearable sensor system for quantitative gait analysis [46]	Leg		10		Optical 3D	RMSE	Corr. coeff.
Digital inclinometer for joint angles measurements with a real-time 3D-animation [153]		Head/neck/scapula Arm joints: shoulders/elbow/forearm twist	1		Goniometer	Max. error	
Drift-Free and Self-Aligned IMU-Based Human Gait Tracking System with Augmented Precision and Robustness [62]	Hip/knee/ankle		1		Optical 3D	RMSE	
Drift-Free Foot Orientation Estimation in Running Using Wearable IMU [63]	Feet		26		Optical 3D	RMSE	
Drift-Free 3D Orientation and Displacement Estimation for Quasi-Cyclical Movements Using One Inertial Measurement Unit: Application to Running [112]	Leg		4		Optical 3D	RMSE	
Drift-Free Inertial Sensor-Based Joint Kinematics for Long-Term Arbitrary Movements [64]	Hip/knee/ankle		11		Optical 3D	RMSE	
Effect of walking variations on complementary filter based inertial data fusion for ankle angle measurement [65]	Hip/knee/ankle		10		Optical 3D	RMSE	
Efficiency of deep neural networks for joint angle modeling in digital gait assessment [134]	Hip/knee/ankle		20		IMU	RMSE	
Estimate of lower trunk angles in pathological gaits using gyroscope data [14]		Back/trunk/torso	27	13 hemiplegia, 14 Parkinson	Optical 3D	RMSE	
Estimation of knee joint angle during gait cycle using inertial measurement unit sensors: a method of sensor-to-clinical bone calibration on the lower limb skeletal model [113]	Leg Hip/knee/ankle		8		Optical 3D	RMSE	
Estimating Lower Body Kinematics Using a Lie Group Constrained Extended Kalman Filter and Reduced IMU Count [135]	Leg Hip/knee/ankle		14		Optical 3D	MAE	
Estimating lower extremity running gait kinematics with a single accelerometer: A deep learning approach [21]	Hip/knee/ankle		10		Optical 3D	RMSE	
Estimating Lower Limb Kinematics Using a Reduced Wearable Sensor Count [136]	Hip/knee/ankle		9		Optical 3D	RMSE	
Estimation and Observability Analysis of Human Motion on Lie Groups [66]			-		Optical 3D	MAE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
Estimation of gait kinematics and kinetics from inertial sensor data using optimal control of musculoskeletal models [67]	Pelvis Leg Hip/knee/ankle		10		Optical 3D, Force plates	RMSE	
Estimation of Gait Mechanics Based on Simulated and Measured IMU Data Using an Artificial Neural Network [68]	Hip/knee/ankle		30	24 Knee arthroplasty	Optical 3D, Force plates	RMSE	
Estimation of kinematics from inertial measurement units using a combined deep learning and optimization framework [69]	Hip/knee/ankle		1000	running-related injury	Optical 3D	RMSE	
Estimation of lower limb joint angles during walking using extended kalman filtering [70]	Leg Hip/knee/ankle		3		Optical 3D	MAE	
Estimation of the continuous walking angle of knee and ankle (Talocrural joint, subtalar joint) of a lower-limb exoskeleton robot using a neural network [71]	Hip/knee/ankle		1		Other	MAE	
Estimation of the knee flexion-extension angle during dynamic sport motions using body-worn inertial sensors [72]	Leg Hip/knee/ankle		7		Optical 3D	RMSE	
Evaluation of wearable gyroscope and accelerometer sensor (PocketIMU2) during walking and sit-to-stand motions [15]	Leg Hip/knee/ankle		1		Optical 3D	RMSE	
Feasibility of a Wearable, Sensor-based Motion Tracking System [16]		Arm Arm joints: shoulders/elbow/forearm twist	8		Optical 3D	RMSE	
Feasibility study of inertial sensor-based joint moment estimation method during human movements: A test of multi-link modeling of the trunk segment [17]		Back/trunk/torso	3		Optical 3D	RMSE	
Gait posture estimation using wearable acceleration and gyro sensors [73]	Hip/knee/ankle		3		Optical 3D	RMSE	
Geometrical kinematic modeling on human motion using method of multi-sensor fusion [74]	Hip/knee/ankle		1		Other	RMSE	
Grasp pose estimation in human-robot manipulation tasks using wearable motion sensors [75]		Hand/wrist/fingers	1		Other	Absolute errors	
Hand Motion Measurement using Inertial Sensor System and Accurate Improvement by Extended Kalman Filter [76]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	1		Optical 3D	RMSE	
Human Arm Motion Tracking by Inertial/Magnetic Sensors Using Unscented Kalman Filter and Relative Motion Constraint [137]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	1		Optical 3D	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
Human body model based inertial measurement of sit-to-stand motion kinematics [77]		Back/trunk/torso	1		Optical 3D	RMSE	
Human Motion Kinematics Assessment Using Wearable Sensors [138]	Hip/knee/ankle		5		Optical 3D, Force plates	Absolute errors	
Human motion tracking based on complementary Kalman filter [139]	Leg		1		Optical 3D	RMSE	
Human pose recovery for rehabilitation using ambulatory sensors [78]	Leg		7	Joint replacement inpatients	Other	RMSE	
Human pose recovery using wireless inertial measurement units [79]	Hip/knee/ankle		20		Optical 3D	RMSE	
IMU-Based joint angle measurement for gait analysis [80]	Hip/knee/ankle		1	Transfemoral amputee	Optical 3D	RMSE	
Inertia-based angle measurement unit for gait assistive device [22]	Hip/knee/ankle		1		Goniometer		
Inertial Motion Capture Using Adaptive Sensor Fusion and Joint Angle Drift Correction [140]	Hip/knee/ankle		1		Optical 3D	Error	
Inertial sensing in ambulatory back load estimation [81]		Back/trunk/torso	9		Optical 3D	% Error	
Inertial sensor-based knee flexion/extension angle estimation [82]	Hip/knee/ankle		7		Optical 3D	RMSE	
Joint angle estimation with accelerometers for dynamic postural analysis [23]	Hip/knee/ankle		1		Other	RMSE	
Joint Inertial Sensor Orientation Drift Reduction for Highly Dynamic Movements [83]		Back/trunk/torso	6		Visual 2D	MAE	
Knee angle estimation based on IMU data and artificial neural networks [84]	Hip/knee/ankle		1		Goniometer	RMSE	
Knee joint angle measuring portable embedded system based on inertial measurement units for gait analysis [85]	Hip/knee/ankle		12		Visual 2D	RMSE	
Lower body kinematics estimation from wearable sensors for walking and running: A deep learning approach [86]	Pelvis Hip/knee/ankle		27		Optical 3D	MAE	
Lower Extremity Angle Measurement with Accelerometers—Error and Sensitivity [24]	Hip/knee/ankle		1		Optical 3D	Avg. errors	
Magneto: Joint angle analysis using an electromagnet-based sensing method [31]		Arm joints: shoulders/elbow/forearm twist	13		Goniometer	MAE	
Magnetometer robust deep human pose regression with uncertainty prediction using sparse body worn magnetic inertial measurement units [155]					Other	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
Monitoring of Hip and Knee Joint Angles Using a Single Inertial Measurement Unit during Lower Limb Rehabilitation [87]	Hip/knee/ankle		10		Optical 3D	RMSD	
Multi-Inertial Sensor-Based Arm 3D Motion Tracking Using Elman Neural Network [114]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	1		Optical 3D	MAE	
Nonlinear optimization for drift removal in estimation of gait kinematics based on accelerometers [25]	Leg		10		Optical 3D	RMSE	
Novel approach to ambulatory assessment of human segmental orientation on a wearable sensor system [26]	Leg		8		Optical 3D	RMSE	
Online tracking of the lower body joint angles using IMUs for gait rehabilitation [88]	Hip/knee/ankle		5		Optical 3D	RMSE	
Optimization of Inertial Sensor-Based Motion Capturing for Magnetically Distorted Field Applications [141]		Head/neck/scapula Back/trunk/torso Arm	8		Optical 3D	RMSE	
Physical-Sensor and Virtual-Sensor Based Method for Estimation of Lower Limb Gait Posture Using Accelerometers and Gyroscopes [89]	Leg Hip/knee/ankle		5		Optical 3D	RMSE	
Pose estimation by extended Kalman filter using noise covariance matrices based on sensor output [142]	Hip/knee/ankle		3		Optical 3D	RMSE	
Predicting Knee Joint Kinematics from Wearable Sensor Data in People with Knee Osteoarthritis and Clinical Considerations for Future Machine Learning Models [115]	Hip/knee/ankle		17	17 osteoarthritis	Optical 3D	RMSE	
Predicting lower limb joint kinematics using wearable motion sensors [90]	Hip/knee/ankle		8		Optical 3D	MAE	
Prediction of lower limb joint angles and moments during gait using artificial neural networks [91]	Hip/knee/ankle		12		Optical 3D	RMSE	
Prediction of lower limb kinetics and kinematics during walking by a single IMU on the lower back using machine learning [27]	Leg Feet		7		Optical 3D, Force plates	%RMSE	
Quasi-real time estimation of angular kinematics using single-axis accelerometers [92]	Hip/knee/ankle		1		Optical 3D	RMSE	
Real-time estimate of body kinematics during a planar squat task using a single inertial measurement unit [93]	Hip/knee/ankle		8		Optical 3D	RMSE	
Real-Time Human Motion Capture Based on Wearable Inertial Sensor Networks [152]	Hip/knee/ankle Feet		1		Optical 3D	RMSE	
Reconstructing an accelerometer-based pelvis segment for three-dimensional kinematic analyses during laboratory simulated tasks with obstructed line-of-sight [28]	Pelvis		1		Optical 3D	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
Reconstruction of angular kinematics from wrist-worn inertial sensor data for smart home healthcare [94]		Arm	2		IMU	MAE	
Reducing drifts in the inertial measurements of wrist and elbow positions [95]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	8		Optical 3D	RMSE	
Research on Human Motion Monitoring Method Based on Multi-Joint Constraint Filter Model [143]			1		Goniometer	RMSE	Max. error
Rhythmic EKF for pose estimation during gait [96]	Hip/knee/ankle		3		Optical 3D	RMSE	
Rhythmic Extended Kalman Filter for Gait Rehabilitation Motion Estimation and Segmentation [8]	Hip/knee/ankle		5	2 post-stroke	Optical 3D	RMSE	
Rigid body motion capturing by means of a wearable inertial and magnetic MEMS sensor assembly-from reconstitution of the posture toward dead reckoning: An application in bio-logging [144]	Feet		1		Visual 2D	MAE	
Robust and Accurate Capture of Human Joint Pose Using an Inertial Sensor [145]		Head/neck/scapula Back/trunk/torso	14		Optical 3D & RGB + depth	RMSE	
Sensorial system for obtaining the angles of the human movement in the coronal and sagittal anatomical planes [97]		Back/trunk/torso Arm	1		Other	RMSE	
Shoulder and elbow joint angle estimation for upper limb rehabilitation tasks using low-cost inertial and optical sensors [98]		Arm joints: shoulders/elbow/forearm twist	1		Goniometer	RMSE	
Shoulder and elbow joint angle tracking with inertial sensors [99]		Arm joints: shoulders/elbow/forearm twist	8		Optical 3D	RMSE	
Synergy-based knee angle estimation using kinematics of thigh [100]	Hip/knee/ankle		8		IMU	RMSE	
System for measurement of joint range of motion using inertial sensors [101]	Hip/knee/ankle		1		Goniometer	MAE	
The head mouse - Head gaze estimation 'In-the-Wild' with low-cost inertial sensors for BMI use [146]		Head/neck/scapula	1		IMU	RMSE	
The manumeter: A wearable device for monitoring daily use of the wrist and fingers [32]		Hand/wrist/fingers	7		Goniometer	MAE	
The online estimation of the joint angle based on the gravity acceleration using the accelerometer and gyroscope in the wireless networks [102]	Hip/knee/ankle		1		Optical 3D	RMSE	

Title	Monitored anatomic unit		Subjects of study		Validation approach		
	LG	UG	NS	DSS	VS	M1	M2
The use of synthetic IMU signals in the training of deep learning models significantly improves the accuracy of joint kinematic predictions [103]	Hip/knee/ankle		30	17 knee arthroplasty	Optical 3D	RMSE	
Three dimensional gait analysis using wearable acceleration and gyro sensors based on quaternion calculations [104]	Hip/knee/ankle		5		Optical 3D	RMSE	
Time coherent full-body poses estimated using only five inertial sensors: Deep versus shallow learning [147]			6		IMU	MAE	
Towards a portable human gait analysis monitoring system [105]	Hip/knee/ankle		3		Optical 3D	RMSE	
Towards kinematically constrained real time human pose estimation using sparse IMUs [148]			15		IMU	MAE	
Training Data Selection and Optimal Sensor Placement for Deep-Learning-Based Sparse Inertial Sensor Human Posture Reconstruction [29]			4		IMU	MAE	
Ubiquitous human upper-limb motion estimation using wearable sensors [149]		Arm joints: shoulders/elbow/forearm twist	4		Optical 3D	RMSE	
Unrestrained measurement of arm motion based on a wearable wireless sensor network [30]		Arm joints: shoulders/elbow/forearm twist	1		Goniometer	MAE	
Upper limb joint angle measurement in occupational health [150]		Arm joints: shoulders/elbow/forearm twist	1		Visual 2D	Typical deviation	MAE
Upper limb joint angle tracking with inertial sensors [106]		Arm joints: shoulders/elbow/forearm twist	1		Optical 3D	Corr. coeff.	
Use of multiple wearable inertial sensors in upper limb motion tracking [107]		Arm joints: shoulders/elbow/forearm twist Hand/wrist/fingers	4		Optical 3D	RMSE	
Validation of a low-cost inertial exercise tracker [108]	Leg Hip/knee/ankle		7		Optical 3D	RMSE	
Visual and quantitative analysis of lower limb 3D gait posture using accelerometers and magnetometers [154]	Hip/knee/ankle		5		Optical 3D	RMSE	Corr. coeff.
Visual estimation of lower limb motion using physical and virtual sensors [151]	Hip/knee/ankle		3		Optical 3D	RMSE	Corr. coeff.
Wearable inertial sensor system towards daily human kinematic gait analysis: Benchmarking analysis to MVN BIOMECH [109]	Hip/knee/ankle		11		IMU	RMSE	

of motions. In this line of work, the proposal of sparse-IMU utilization is promising to decrease the number of sensors in use, which is required for motion analysis in all environments. Moreover, the monitoring of complex joints, such as shoulders or hips, which are usually modeled as 3-DOF joints, should include all their DOF for a proper kinematic analysis.

With regard to the algorithms in use, the current trend moves from the Bayesian filters, which we consider the classical ones, to ML algorithms, especially deep learning algorithms. For the development of these novel proposals, more data with an accurate reference are required, as described in [185] and [186], in order to avoid the use of data from IMUs and simulations from the optical systems as ground truth. One of the main limitations of the BCs found in the literature is their generalization of use in wide and varied populations, where the constraints based on ROM and DOF exclude people with motor diseases. In this way, new proposals should be adaptable to the populations under study. Also, alternatives to obtain the IMU-joint vector based on inertial devices are needed in order to make suitable proposals that exploit the biomechanical relationships in out-of-the-lab environments.

Common data with inertial measurements and its reference are needed in order to obtain a fair comparison of the existent and new proposals. In that line of research, future proposals are required to be validated on a larger number of volunteers than in the current case. This also should ensure the variability of motions and not be focused on the gait.

V. Conclusion

This work has reviewed the studies focused on human motion analysis based on IMUs. The date of publication of the reviewed papers is not limited, so we provide an overview of the proposals from the first study to the current date. This overview summarizes the algorithms, the combination of sensors, the anatomical units monitored, the subjects of study, and the validation approaches in the research of inertial monitoring. The review also focuses on the studies of the last decade, so we analyze the last trends in this research field. Most of the analyzed works focus on obtaining the 3-D estimation of the kinematics of lower limb joints, presenting a lack of studies of the upper half of the body. The Bayesian filters are still the most used methods, but their trend is to be applied less frequently, whereas the ML algorithms are being used now with a higher incidence. This review includes a description of the main algorithms used with their inputs and outputs for a better understanding of the existent methods. In this way, we show that, nowadays, these groups of algorithms present also differences in the selected sensors: Bayesian filters tend to use more the magnetometer and try to compensate for its limitations, but ML algorithms commonly rely only on gyroscopes and accelerometers. Both groups of algorithms present also differences in the range of accuracy, obtaining slightly lower maximum errors by using ML methods. This work also analyzes the proposed approaches for error reduction, highlighting the need for proposals suitable for all the population and IMU-joint calibration methods. Finally, this work remarks the requirement of testing future proposals on a highly NS, which helps to create common databases that allow the comparison among the existent and new proposals.

Appendix A
Tables of the Data Extracted

See Tables III and IV.

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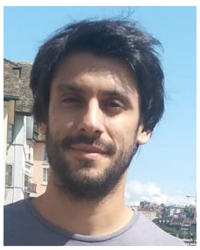

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