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ISB recommendations on the definition, estimation, and reporting of joint kinematics in human motion analysis applications using wearable inertial measurement technology

Andrea Cereatti [a,*], Reed Gurchiek [b,1], Annegret Mündermann [c,d,e], Silvia Fantozzi [f], Fay Horak [g,h], Scott Delp [i], Kamiar Aminian [j]

[a] Department of Electronics and Telecommunications, Polytechnic University of Torino, Torino, Italy
[b] Department of Bioengineering, Clemson University, Clemson, SC, USA
[c] Department of Orthopaedics and Traumatology, University Hospital Basel, Basel, Switzerland
[d] Department of Biomedical Engineering, University of Basel, Basel, Switzerland
[e] Department of Clinical Research, University of Basel, Basel, Switzerland
[f] Department of Electric, Electronic and Information Engineering "Guglielmo Marconi" – DEI, University of Bologna, Italy
[g] APDM Precision Motion of Clario, Portland, Oregon, USA
[h] Department of Neurology, Oregon Health & Science University, Portland, Oregon, USA
[i] Department of Bioengineering, Stanford University, Stanford, CA, USA
[j] Laboratory of Movement Analysis and Measurement, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

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ABSTRACT

There is widespread and growing use of inertial measurement technology for human motion analysis in biomechanics and clinical research. Due to advancements in sensor miniaturization, inertial measurement units can be used to obtain a description of human body and joint kinematics both inside and outside the laboratory. While algorithms for data processing continue to improve, a lack of standard reporting guidelines compromises the interpretation and reproducibility of results, which hinders advances in research and development of measurement and intervention tools. To address this need, the International Society of Biomechanics approved our proposal to develop recommendations on the use of inertial measurement units for joint kinematics analysis. A collaborative effort that incorporated feedback from the biomechanics community has produced recommendations in five categories: sensor characteristics and calibration, experimental protocol, definition of a kinematic model and subject-specific calibration, analysis of joint kinematics, and quality assessment. We have avoided an overly prescriptive set of recommendations for algorithms and protocols, and instead offer reporting guidelines to facilitate reproducibility and comparability across studies. In addition to a conceptual framework and reporting guidelines, we provide a checklist to guide the design and review of research using inertial measurement units for joint kinematics.

1. Introduction

Advances in inertial measurement technology have had a significant impact on many areas of science, engineering, medicine and industry. Today's inertial measurement units (IMUs) have reduced power consumption, allowing the use for relatively long recordings. They can provide output data at relatively high sampling rates and ranges, integrate other sensors and fuse information to provide additional kinematic data. Due to their small size, low cost, and the ability to measure movements outside of a laboratory for extended periods of time, IMUs have become important tools with applications in health, sports, and basic science (Camomilla et al., 2018; Cinnera et al., 2024). The number of IMU-based studies for the estimation of joint kinematics has increased rapidly in recent years in various areas of biomechanics (Fang et al., 2023; García-de-Villa et al., 2023). IMUs are also used increasingly to obtain biomechanical biomarkers for clinical trials, and very recently,

* Corresponding author.
E-mail address: andrea.cereatti@polito.it (A. Cereatti).
[1] First co-authorship.

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regulatory agencies also provide specific guidance for use of digital technologies including IMUs for clinical or remote data collection (*Framework for the Use of DHTs in Drug and Biological Product Development*, 2023, https://www.fda.gov).

The International Society of Biomechanics (ISB) has published standardization recommendations for estimation of human joint kinematics, but some of these were developed for use with marker-based stereo-photogrammetry and cannot be directly applied to IMU-based applications (Wu et al., 2005, 2002; https://isbweb.org/activities/standards). In fact, inertial measurement technology *does not supply reliable positional information and orientation estimates can be affected by drift*, thus defining, estimating, and reporting human joint kinematics using IMUs requires special attention. Failure to adhere to correct procedures may lead to unreliable results.

Despite the increasing interest in the use of IMUs for human movement analysis, there are no consistent guidelines. The need for ISB recommendations, built on a solid biomechanical foundation, was recently suggested (Hafer et al., 2023) and would benefit not only the biomechanics community, but also the health and sports fields. Reporting guidelines are necessary given the increasing use of open-source data sets and to meet the requirements of reproducibility and validity in biomedical research and regulatory qualification.

The purpose of this work is to present a set of recommendations for definition, estimation, and reporting of human joint kinematics using IMUs. To promote transparency and encourage participation of the biomechanics community in the development of these recommendations, we collected comments during the symposium on "Human Motion Analysis with Wearable Inertial Sensors" at the XXIX ISB congress (2023) and solicited feedback from ISB members through a survey announced on social media. Out of 69 survey respondents, 99 % said they were likely to follow recommendations, if available. These respondents were experienced users in both academia (96 %) and industry (16 %), and for applications in clinical (83 %) or sports (78 %) contexts, methodological development and validation (78 %), and in hardware development (25 %). The primary reason given for standardization was to ensure comparability across studies and to provide a framework for

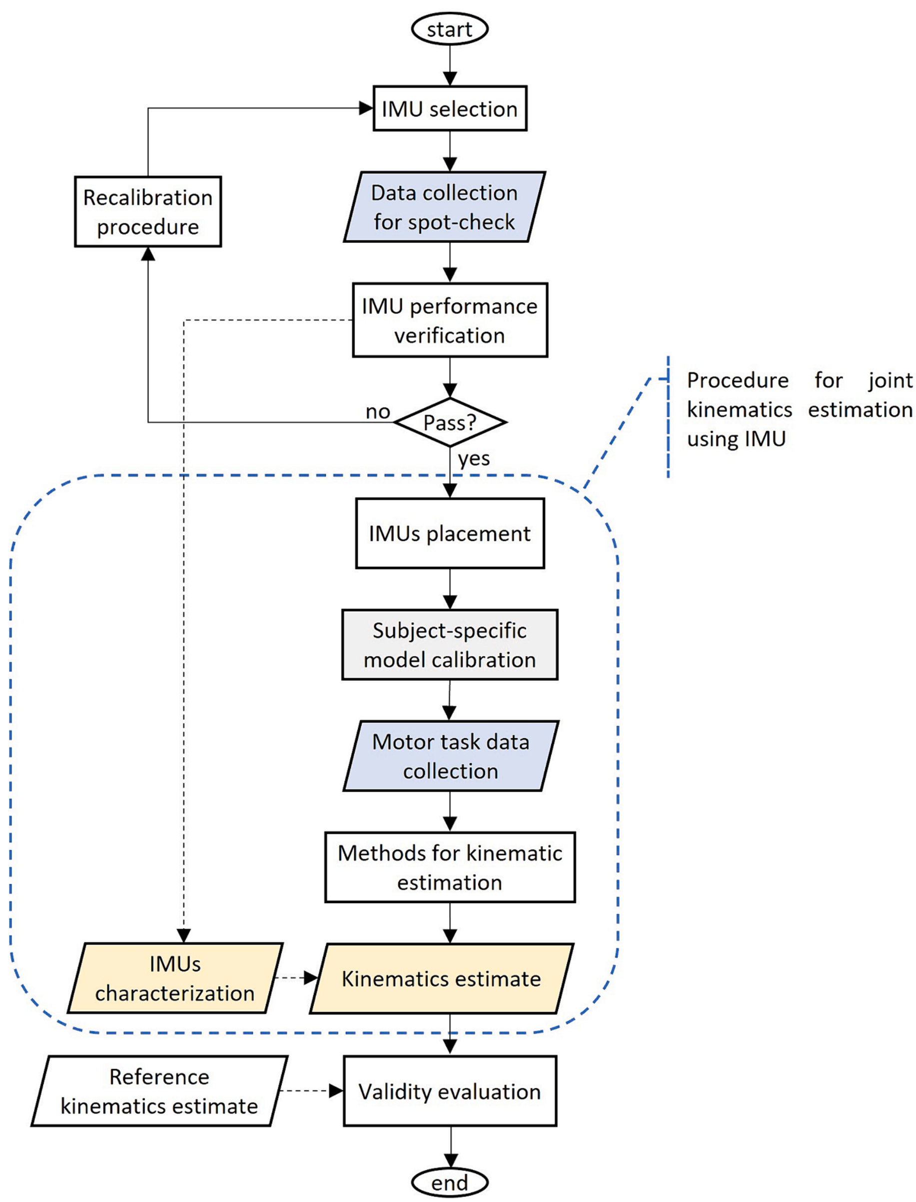

Fig. 1. Conceptual framework for the design and validation of an experimental and analytical protocol for joint kinematics estimation using multiple IMUs. Multi-step procedure for joint kinematics estimation (inside blue-dashed region). Blue rhomboids represent data collection phases; yellow rhomboids represent the outputs of the kinematics estimation process and IMUs metrological characterization.

joint kinematics analysis with IMUs in biomechanics research. Respondents indicated that such a framework would be useful for study design, manuscript writing and review, and student training. Not all respondents favored explicit prescriptions for algorithms and protocols. As an overly prescriptive set of guidelines would not consider the variety of applications in which the optimal methods and protocols may vary, we focused on high level reporting guidelines for joint kinematics estimation to enhance reproducibility and comparability across studies (Fig. 1). Recommendations are organized in sections that address the different experimental and theoretical aspects that should be considered when proposing novel methods or replicating existing methods for human joint kinematics estimation using IMUs.

2. IMU characteristics and sensor calibration

An IMU is an electronic device with both accelerometers and gyroscopes that measure the proper acceleration (i.e., acceleration relative to free-fall) and angular velocity, respectively, of a rigidly attached body. IMUs are often combined with other sensing modalities such as magnetometers, barometric pressure sensors, proximity sensors, global navigation satellite systems, and cameras.

IMUs do not directly measure orientation or position; thus, mathematical integration of the angular velocity and acceleration measurements is required to derive these quantities. During integration, errors can cause drift in the estimated orientations and positions, which is a major problem with using IMUs. These errors arise from electronic noise, bias and bias instability, scale factor error which can vary with temperature, and quantization error depending on the analogue to digital conversion (Beange et al., 2023). The sensitivity of the bias and noise to environmental factors and the nature of the motion, such as its amplitude and speed, can lead to a non-linear drift over time which can be difficult to correct (Fig. 2).

Additional sensors can be used with IMUs to reduce drift errors. For instance, triaxial magnetometers may be incorporated into the IMU to provide the absolute direction of the local Earth's magnetic field. This, combined with the accelerometers, allows the definition of a global coordinate system under static conditions and improves the accuracy of angle estimation (Sabatini, 2006). However, the use of magnetometers introduces magnetic distortion as another source of error in addition to drift. It can arise from ferrous material in building foundations and medical equipment or from nearby alternating currents (e.g. electric motors), leading to significant errors in estimating the yaw angle. If it is not possible to eliminate these sources of error, algorithms can be used to compensate for magnetic distortion (Roetenberg et al., 2013). Drift in gyroscopes can also be corrected for in some applications by resetting the gyroscope to zero when movement of the IMU stops, such as when the foot is flat on the floor while walking with IMUs on the feet (Veltink et al., 2003).

Sensor errors are typically examined during factory calibration using laboratory equipment, involving static or dynamic calibration (Avrutov et al., 2017). While robust factory calibration is important for IMU selection (Zhou et al., 2020), values fluctuate over the lifetime of the sensor. Therefore, various methods have been proposed for refining the sensors' calibration in the field to correct for bias and sensitivity by exploiting the Earth's gravitational acceleration and known rotations (Ferraris et al., 1995; Tedaldi et al., 2014; Cutti et al., 2006), or based on the sensor's noise characteristics (Sabatini, 2006). Some manufacturers offer accompanying calibration algorithms that allow users to calibrate the sensors themselves (Zhou et al., 2020). This allows periodic assessment of the IMU performance to ensure the metrological characteristics of the sensors.

Recommendations for sensors characteristics and calibration

- IMU characteristics. Manufacturer, model and the measurement modes added to the accelerometers and gyroscopes (e.g., magnetometer) should be provided. Sensitivity, scale factor error, bias, noise level, quantization error, environmental factors, and other factors that affect signal processing and data fusion for joint kinematics estimation should be described.
- IMU calibration. The type and the date of the last calibration should be provided to evaluate effects of calibration on joint kinematics estimation.

3. Experimental protocol

Errors inherent in the experimental protocol can be classified as human errors or technological errors (Beange et al., 2023). Human errors include soft tissue artifacts, inaccurate sensor placement and alignment, and insufficient sensor attachment. Technological errors result from limitations of the inertial measurement technology with respect to the motor task under analysis. In this case, in addition to sensor noise and calibration errors, it is important to consider sampling frequency, sensor range, inter-sensor synchronization, wireless transmission, and ferromagnetic interference.

3.1. IMU placement and attachment

Since IMUs are attached to the body segments, recorded data are affected by soft tissue motion which causes a time-variant motion between the IMU and the underlying bony segment. The characteristics of this motion depend on the body segment, the motor task, and the placement protocol (Cereatti et al., 2017). Soft tissue artifacts are also affected by the mass and size of the IMU, the method of attachment (Forner-Cordero et al., 2008), and IMU repositioning (Decker et al., 2011). When comparing a bone-mounted to skin-mounted accelerometer devices, peak tibial acceleration was on average 2.1 g lower than the skin acceleration during running (Lafortune et al., 1995). Invalid data due to accidental collisions or loose attachment is an important error (Yi et al., 2022) that must be eliminated before kinematic analysis. IMUs integrated in garments can be subjected to additional signal artifacts due

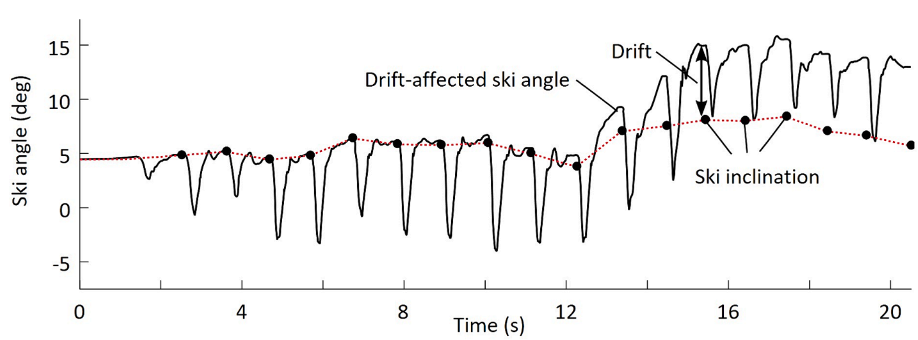

Fig. 2. Drift-affected (black) ski angle during cross-country skiing obtained by integration of medio-lateral ski angular velocity (i.e. sagittal angle angle). Ski inclination computed based on measured gravity during the static moments (instants of time) is marked with black dot (Fasel, 2017).

to movement of the garment relative to the skin. In addition, it should be considered that the acceleration magnitude can vary depending on where the IMU is positioned on the body segment under analysis. For instance, differences in tibia acceleration (e.g., ∼0.7 g, ∼13 %) during running were found when the sensor was placed on the proximal or distal portion of the tibia (Lucas-Cuevas et al., 2016). Optimal IMU placement has been investigated for the estimation of lower limb joint kinematics during Timed-up-and-go tests (Niswander et al., 2020). As a general consideration for reducing soft tissue artifacts on joint kinematics, body segment areas with reduced "wobbling" mass, muscle deformation and skin stretching/sliding are preferred (e.g., distal thigh/shank). However, further research is needed to understand how soft tissue artifact varies with sensor location and the effects on estimating joint kinematics.

Different methods of attaching the IMU on the body segments can be used including placing the IMU in a belt, using double-sided tape on the skin, placing tape over the sensor, or using an elastic strap or rigid frame. In a recent literature review addressing the issue, the main recommendations for tasks involving impacts were tensioning the attachment 'as much as tolerable', avoiding areas close to joints and with soft tissues, avoiding the use of elastic belts, and using low mass devices (Preatoni et al., 2022). Considering these recommendations and previous investigations of soft tissue artifacts (Cereatti et al., 2017), for less dynamic movements (e.g., walking, sit-to-stand) it is adequate to ensure that there is no detectable movement between the sensor and the body segment throughout the task.

3.2. *Sensor range and sampling frequency*

To benefit from the best sensor sensitivity, the choice of sensor range must take into account the motor task being investigated, as the maximum signal magnitude can vary significantly. The peak tibial acceleration varies from 3 g (walking) to about 11 g (running) and 60 g (landing a jump). These peak values also depend on how the IMU is attached to the body segment as slip between the body and the sensor will likely increase the peak acceleration of the sensor (Lafortune, 1991; Zhang et al., 2008). While the shank angular velocity is typically below 400°/s during walking (Aminian et al., 2002), the angular velocity of the arm segment around the shoulder joint during baseball pitching can reach values over 7000°/s (Dillman et al., 1993). On the other hand, if the sensor operating range is too large, there is a reduction in resolution. Similarly, the choice of the sampling frequency must follow the Nyquist criterion, taking into account the motor task, the body segment, and the variables under investigation. For instance, to measure running kinematics, it has been recommended to use a sampling frequency of at least 500 Hz for peak heel acceleration, 333 Hz for stride length, and 200 Hz for peak tibial acceleration, stride duration, foot orientation angle, heel strike angle and peak eversion velocity (Mitschke et al., 2017).

3.3. *Data recording and inter-IMU synchronization*

Data can be recorded in two modalities: logging or streaming. Onboard memory cards log data and have limitations of the speed of their read/write capacity. Wireless transmission devices stream data to a computer and may have variable-length signal delays or failures. Interruptions or delays in data transmission can result in data loss or out-of-sync sensors, when they do not include inter-IMU synchronization. These irregularities within stored data can cause temporal misalignment between IMUs, resulting in errors in metrics derived from several IMUs. Data extrapolation has been reported to correct for some missing data due to poor wireless transmission or sensor saturation (e.g., strong dynamic movement or impact) (Mariani et al., 2010).

The difference between the start time of each IMU and its internal clock can lead to a lack of synchronization which can cause errors in the kinematics derived from the combination of IMUs. Synchronization is also critical when comparing kinematics derived from IMUs to a reference system. Event-based synchronization typically involves a physical action (e.g., clapping, jumping, hitting a surface) along with a spotting algorithm to minimize the delay between IMUs (Bannach et al., 2009). A more precise solution involves the IMUs to record a trigger from an external source (Chardonnens et al., 2013; Spilz and Munz, 2021), synchronize all IMUs through a radio frequency trigger sent at a regular pace (Fasel et al., 2016) or via bidirectional communication configured for master or mesh synchronization (Greenberg et al., 2018). An electronic trigger (Fasel et al., 2017) or a flashlight in front of the cameras is also used to synchronize the reference marker-based stereo-photogrammetry with IMUs (Hamidi Rad et al., 2021).

Recommendations for experimental protocols

- IMU placement and attachment. The design of the IMU setup (i.e., number, location on body segment and attachment modality) should be selected based on the requirements of the specific application and reported.
- Range and sampling frequency. IMU specifications should be selected based on the characteristics of the motor task and the environmental conditions of the acquisition field and reported. To identify the frequency content and maximum values exhibited by the variable under analysis, a pre-test or literature review should be performed.
- Data recording and inter-IMU synchronization. The description should include acquisition modality and methods for inter-unit synchronization and/or for IMU-based system synchronization with external systems (if present). Loss of data resulting from human or technical failure must be reported.
- Protocol. Details on the subject and motor task that may affect results (e.g., use of assistive devices, speed of movement, anthropometry, postural support, disease severity) should be reported.

4. Kinematic model definition and subject-specific calibration

4.1. *Definition of the kinematic model*

The definition of the kinematic model must include the number of rigid bodies and the type of joints that determine the total number of degrees of freedom. The joint models should be consistent with the level of approximation required for the specific application (Kontaxis et al., 2009).

Since IMU-based linear displacements are affected by errors larger than the actual joint linear displacements (e.g., tibiofemoral linear displacements), the latter are neglected and human joints are commonly modeled as a spherical joint. In the general case, the joint kinematics can be fully described by the angular displacements that occur about three independent axes of rotation that define the joint coordinate system (JCS) (Grood and Suntay, 1983). However, joint models will have fewer degrees of freedom when joint rotations about one or two axes can be neglected (Seel et al., 2014; Wells et al., 2019). Consequently, this will simplify the kinematic model calibration and provide numerical advantages in the joint kinematics analysis (see *section 5*).

4.2. *Subject-specific kinematic model calibration*

Once a suitable kinematic model is selected and the IMUs are attached to the body segments of interest (see *section 3.1*), the kinematic model needs to be calibrated to the specific subject under investigation. This calibration procedure is required to determine the JCS for the joint motion description and the bony segment lengths (distance between adjacent joint centers) (Koning et al., 2015; Miezal et al., 2016).

The ISB has published two different recommendations (Wu et al., 2005, 2002) for the JCS definition for the major human joints, starting from the identification of the 3D positions of either internal or external bony landmarks. Unfortunately, while the identification of the bony landmark positions is straightforward using stereo-photogrammetry, it is not possible using IMUs, and therefore the ISB recommendation cannot be directly applied. To overcome this, by taking advantage of the ability of the IMU to identify oriented lines in the 3D space, it is necessary to reformulate the JCS definition starting from oriented 3D lines instead of 3D points. In the following, we describe the most popular approaches used for the identification of the axis directions along with the advantages and disadvantages of each approach (Vitali and Perkins, 2020).

4.2.1. Methods for axes identification

The simplest solution for axes identification is to manually align the geometrical axes of the IMU housing with the axes of the anatomical coordinate system (ACS) of the bony segment associated with the relevant body segment. ("Manual Unit Alignment") (Bouvier et al., 2015; Cutti et al., 2008) (Fig. 3**a**). This approach can only be implemented if the IMU sensitive axes are aligned with the IMU housing. While its simplicity is attractive, the drawbacks are that the accuracy and repeatability of the results depend on the experience of the operator, and visual alignment can be more difficult for IMUs with a small form factor, especially considering that the surfaces of the body segments are generally curved.

A second approach is to infer the direction of the axes of the ACS from the position of a few, palpable, anatomical landmarks ("Anatomical landmark identification approach") using a calibration device. This can be a camera (Bisi et al., 2015; Dejnabadi et al., 2005) or a stereophotogrammetric system (Chardonnens et al., 2012) to record the 3D marker position in the coordinate system of the relevant IMU (Fig. 3**b1**). Another solution is to use a caliper containing an IMU with a magnetometer (Picerno et al., 2008; Picerno et al., 2019). By pointing at two palpable anatomical landmarks, the axis can be estimated with respect to the coordinate system of the IMU attached to the body segment (Fig. 3**b2**). While the anatomical landmark identification approach provides a similar approach to the ISB guidelines for JCS definition, it requires a calibration device.

A third approach is to use joint motion to identify the relevant axes of rotation ("Functional approach") (Favre et al., 2009; O'Donovan et al., 2007). This functional approach is based on the assumption that the subject is able to generate, actively or passively, a pure, repeatable and sufficiently large rotation about one of the joint axes of interest. The direction of this axis is assumed to coincide with the direction of either the mean or first principal component of the attitude vector or angular velocity vector (Fig. 3**c**) (Di Raimondo et al., 2022). This method can identify both the direction and position of the axis. The functional approach can be easily applied to joints with a dominant and well-defined rotational degrees of freedom, such as the knee (Cutti et al., 2010), but also to joints with 2 or 3 degrees of freedoms (e.g., elbow and hip), (Cutti et al., 2008; Favre et al., 2009; Luinge et al., 2007).

A fourth approach uses the direction of gravity sensed by the accelerometers in static conditions during a selected posture ("Static approach") (Cutti et al., 2010) (Fig. 3**d**). This approach can be particularly useful to define the longitudinal axis of some bony segments while the subject is standing in an upright posture. The main advantage of the Static approach is its simplicity, but its accuracy depends on the subject's ability to align one axis of the ACS with gravity, which is not guaranteed particularly for individuals with physical limitations, or the experimenter controlling for the correct posture being assumed.

A combination of multiple approaches may be useful for some applications. Fig. 3 summarizes the four approaches to develop a subject-specific kinematic model.

4.2.2. Methods for joint center identification

Many applications, including musculoskeletal simulation, visual feedback generation, and human-robot interaction, require a spatial representation of the kinematic model and identification of the position of the joint centers (Koning et al., 2015; Roetenberg et al., 2013). By assuming that the joint center coincides with the center of rotation between adjacent bony segments, it is possible to use rigid body kinematic equations to derive the joint position with respect to the IMU coordinate system from the measured accelerations and angular velocities during functional exercises (McGinnis and Perkins, 2013; Seel et al., 2014). However, the accuracy of joint center determination can be affected by the joint angular velocity, and errors may increase when slow joint

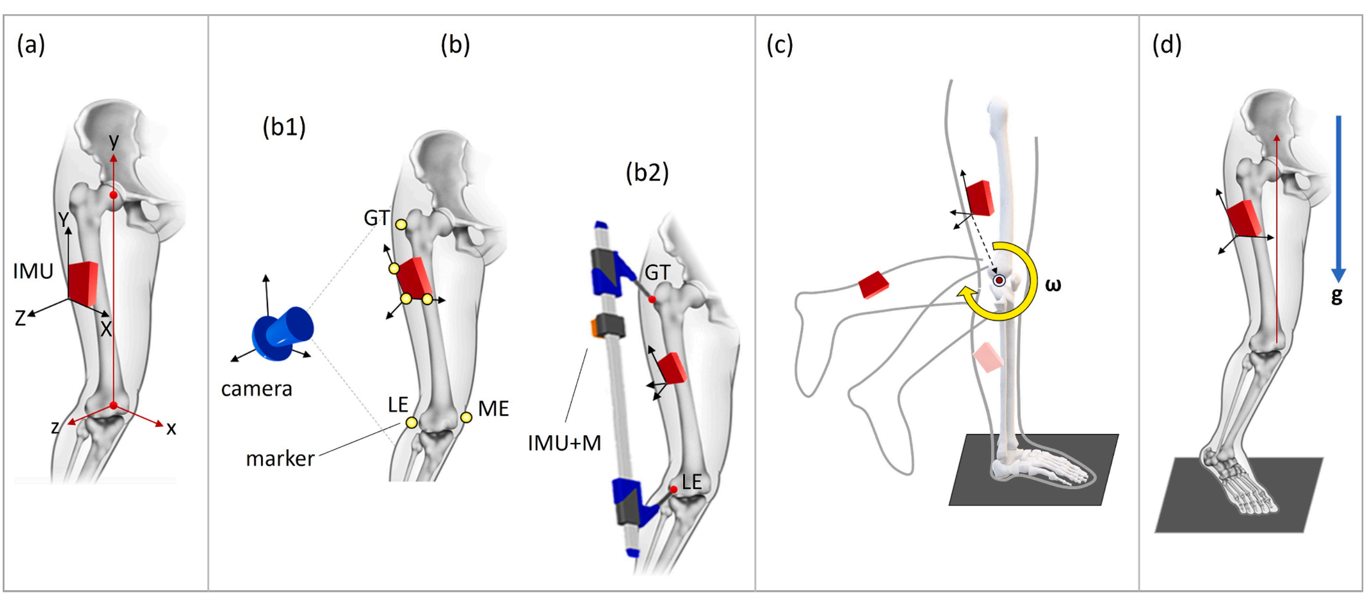

Fig. 3. Methods used to identify the axes with respect to the IMU coordinate system. (a) Manual unit alignment approach. In this example, the X-, Y-, and Z-axes of the femur are assumed to coincide with the x-, y-, and z-axes of the thigh IMU. (b) Anatomical landmark identification approach: In the example (b1), the position of greater trochanter (GT), the femoral lateral epicondyle (LE) and the medial epicondyle (ME) are identified using markers attached to the subject skin and the IMU and a camera; in the example (b2), a caliper carrying a IMU with a magnetometer is used to define the direction of the lines connecting GT to LE. (c) Functional approach: The shank is rotated relative to the thigh in the sagittal plane to determine the direction of the mean axis of rotation (perpendicular to the plane of the paper) and its position (r) with respect to the thigh IMU. (d) Static approach: The direction of the gravity vector is used to identify the longitudinal axis of the femur while the subject is asked to assume an upright standing posture.

movements are used (Crabolu et al., 2016). The bony segment length can then be inferred from the position of the joint centers and joint axes once they are defined in the same IMU coordinate system.

4.2.3. Identification of the JCS

When using IMUs, the problem of identifying the JCS to describe the joint motion can be approached from two different, but equivalent, perspectives: Euler angles decomposition and mechanical joint model (Grood and Suntay, 1983; Wu et al., 2005). The Euler angles decomposition requires the definition of the bone-embedded ACS with respect to the IMU coordinate system to fully determine the "sensor-to-segment calibration". Then, the JCS is defined based on the ACS of the proximal and distal bony segments and rotations are calculated by decomposing the relative orientation of the distal (moving) ACS relative to the proximal (fixed) ACS based on one of the possible Euler decompositions, which should be explicity declared (Euler angles decomposition perspective). This is the same procedure as described in the ISB guidelines (Wu et al., 2005, 2002). Alternatively, in the mechanical joint model perspective, the directions of the "body fixed joint rotation axes" defining the JCS are first identified. Then, for each axis of rotation, the magnitude of rotation is defined based on a reference line perpendicular to that axis (Grood and Suntay, 1983). In this case, the direction of the reference lines can be implicitly determined by imposing a static reference posture, typically the neutral standing posture (e.g., T-pose, A-pose), for which the joint angles are assumed to be equal to zero or a known value (Cooper et al., 2009; Taetz et al., 2016; Wells et al., 2019) (Fig. 4). This approach can be convenient from a practical point of view, as it does not require an explicit determination of the ACS of the bony segments forming the joint. Conversely, a limitation is that the actual values of the joint angles during the reference posture are lost, and the repeatability of the results depends on the subject's ability to resume the same reference posture across the different observations.

In some cases, when an IMU can be assumed to be aligned with the ACS of the parent bony segment, then the reference posture can be used to initialize and identify the ACS of the other bony segments with respect to the corresponding IMU coordinate system (Schepers et al., 2018). In some pathological populations, with irreducible joint flexion or deformities, other postures may be used (Cutti et al., 2010).

Finally, it should be emphasized that simplifying assumptions, related to the joint models, JCS identification and initialization, affect the joint kinematics estimation and must be considered when comparing results or deciding whether the estimation errors are acceptable for the research question of interest (Kontaxis et al., 2009).

Recommendations for kinematic model definition and subject-specific calibration

- Kinematic model. A description of the general kinematic model should be provided, including the number and type of degrees of freedom for each joint and, if applicable, additional details such as bony segment length, joint centers, etc. The model and software implementing the model should be provided with the publication for results reproducibility.
- ACS and JCS definition. To promote interpretability, it is important to report ACS and JCS definitions for each bony segment and joint along with a brief description of the method used for their identification. Templates for summarizing essential information are provided in Appendix A.
- Axes identification. A clear description of the methods used to identify each of the axes involved in the ACS and JCS description should be provided. We recommend that authors acknowledge the limitations associated with their specific method and describe countermeasures taken.
- Reproducibility of ACS and JCS. When presenting an original method or applying a previously validated method to a new cohort, it is good practice to implement a repeated measures experimental design on a subset of subjects to assess the influence of the critical factors according to the specific method (e.g. intra/inter-subject, inter/intra-operator).

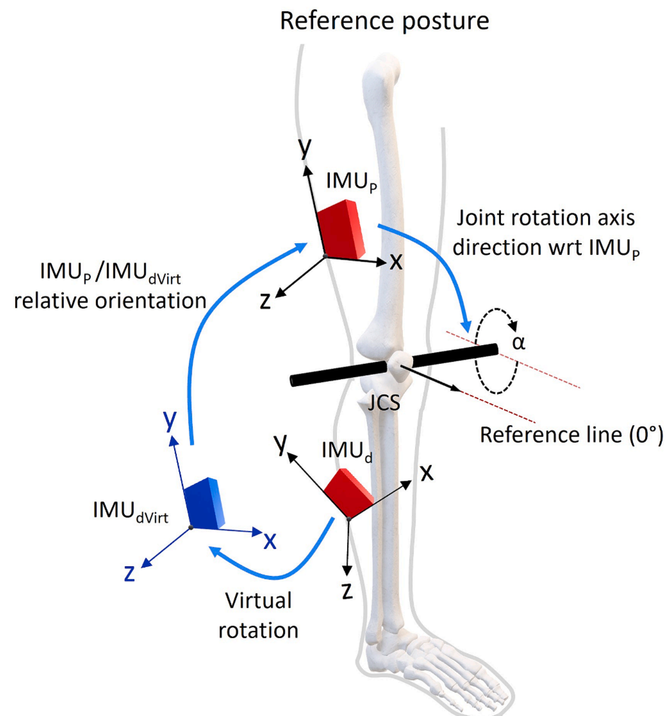

Fig. 4. An example of using the reference posture to define the JCS of the knee joint without explicitly defining the ACS of the femur and tibia segments. Consider the proximal and distal units (IMUp, IMUd) attached to the thigh and shank segments in an arbitrary way with respect to the underlying bony segment. The knee joint is modeled as a revolute joint and the direction of the flexion–extension axis of rotation with respect to the coordinate system of the IMUp is determined using one of the methods described in *section 4.2.1*. It is assumed that the flexion–extension angle of the knee (α) is equal to zero during the reference posture (e.g., upright standing posture). We can mathematically rotate IMUd in order to define a virtual IMU (IMUdVirt) that is aligned with IMUp during the reference posture. Then, the reference line associated with the joint rotation axis of the JCS is assumed to be orthogonal to the rotation axis and fixed with the IMUp. The flexion–extension angle α can then be determined during the knee motion by calculating the relative orientation between IMUp and IMUdVirt and calculating the rotation angle around the rotation axis. This example can be extended to a 2 or 3 DoF joint model without losing validity.

5. Analysis of angular joint kinematics

5.1. Single-body versus multi-body methods

Methods for estimating joint kinematics based on IMU data can be grouped into single-body and multi-body methods. In single-body methods, the orientation of each body segment relative to the global coordinate system is computed independently using only the data recorded by the relevant IMU and a selected orientation estimation algorithm (Madgwick et al., 2011; Mahony et al., 2008; Sabatini, 2011; Vitali et al., 2021). Then, the joint motion is described based on the orientation of each segment relative to each other and the relevant JCS (see *section 4.2.3*). In contrast, multi-body methods estimate the joint angles through an optimization process. While some multi-body methods use rigid body kinematic equations to relate IMU signals directly to joint angles or their derivatives without explicitly calculating body segment orientation (Seel et al., 2014), others do like full-state Kalman filters and moving horizon estimation (Potter et al., 2022; Taetz et al., 2016; Weygers et al., 2020). In the latter case, the algorithm involves operations that affect orientation estimates of multiple body segments simultaneously.

5.2. Determining a global coordinate system

Methods requiring estimation of individual body segment orientation must first identify a common global coordinate system. While the determination of a global coordinate system is straightforward for stereophotogrammetry, which requires that a cluster of three non-collinear markers is visible by a sufficient number of cameras, this is more challenging for IMU-based motion analysis because IMU measurements are made in a local coordinate system. In IMU-based systems, a natural choice for the definition of the global coordinate system orientation is to rely on the "north", "east", and "up" directions (Sabatini, 2011). Under static conditions, the "up" direction can be identified by the accelerometer measurement of the gravitational acceleration vector, and the "east" direction can be identified using a cross product of the magnetometer measurement of the magnetic field vector with the "up" direction (Brodie et al., 2008). If a magnetometer is not available, the IMU yaw angle must be imposed, e.g., initialized to zero during a known, or assumed, pose.

5.3. Estimation algorithms and error compensation

Sensor fusion algorithms combine information from different sensors or enforce biomechanical constraints to mitigate drift error as introduced in *section 2*. Under dynamic conditions, the IMU orientation can be obtained through the gyroscope signal, by numerically integrating the rigid body kinematic equations. Under static conditions, an accelerometer measurement can be used to estimate the angular deviation of the IMU relative to the gravity direction. This is sufficient to describe only two rotational degrees of freedom (roll and pitch, but not yaw) (Ojeda et al., 2017). These accelerometer and gyroscope orientation estimates can be combined using sensor fusion techniques including Kalman and complementary filters and optimization approaches (Nazarahari and Rouhani, 2021). The kinematic model can be used to impose constraints on the estimated kinematic variables. These can be implemented in multiple ways including dynamic constraints in optimal control simulations (Dorschky et al., 2019; Hafer et al., 2023), optimizing with respect to unconstrained coordinates (Al Borno et al., 2022), and as measurement updates in a Kalman filter (Potter et al., 2022).

Estimation accuracy depends on several intrinsic (e.g., algorithm, parameters, sensor noise) and extrinsic (e.g., movement type, speed, and duration) factors. Particularly critical for obtaining good estimation performance is the choice of algorithm parameter values, which should be tuned according to different operating conditions (Caruso et al., 2021) (Fig. 5).

There is no general solution for determining filter parameters and gains that are optimal in every context. Proposed approaches include deriving parameters from hardware specifications (Potter et al., 2021) or empirical tuning (Al Borno et al., 2022; Madgwick et al., 2011). Some algorithms use adaptive gains (Nazarahari and Rouhani, 2021) and apply corrections only under certain conditions, like planar joint motion (Vitali et al., 2017) or static pose (Sabatini, 2011). Therefore, for reproducibility, it is important to clearly describe how an algorithm functions, what the measurement updates are and when they are applied, and how the algorithm parameters are initialized and adapted. Open-source code is arguably the most transparent and unambiguous way to communicate an algorithm. While there are some disadvantages in terms of intellectual property and time, it encourages use by others, enables third-party validation, and allows a more thorough analysis of an algorithm to advance the state-of-the-art. Users sometimes modify open-source algorithms to suit different applications. Such modifications to open-source code should be clearly stated to avoid misrepresentation of the original algorithm.

5.4. IMU orientation parameters

Orientation can be parametrized in several ways (Shuster, 1993). Common choices include direction cosines (Fischer et al., 2013), quaternions (Sabatini, 2011), and Euler angles (Jurman et al., 2007), each with advantages and disadvantages. For example, while Euler angles require minimal memory, are unconstrained, and are more interpretable than quaternions, they do not uniquely parameterize orientation (infinite ambiguities), have a nonlinear kinematic equation, and can have singularities. Quaternions have only one ambiguity (q and −q parameterize the same orientation) and their four elements require only slightly more memory than the three Euler angles, but less than half the nine direction cosines. The main advantages over Euler angles are the linearity of their kinematic equation and the absence of singularities. As a result, quaternions are a popular choice for estimation algorithms onboard many commercially available IMUs. Regardless of the choice of generalized coordinates, it is necessary to clearly describe how the biomechanically relevant joint angles are calculated from the coordinates.

Recommendations for analysis of angular joint kinematics.

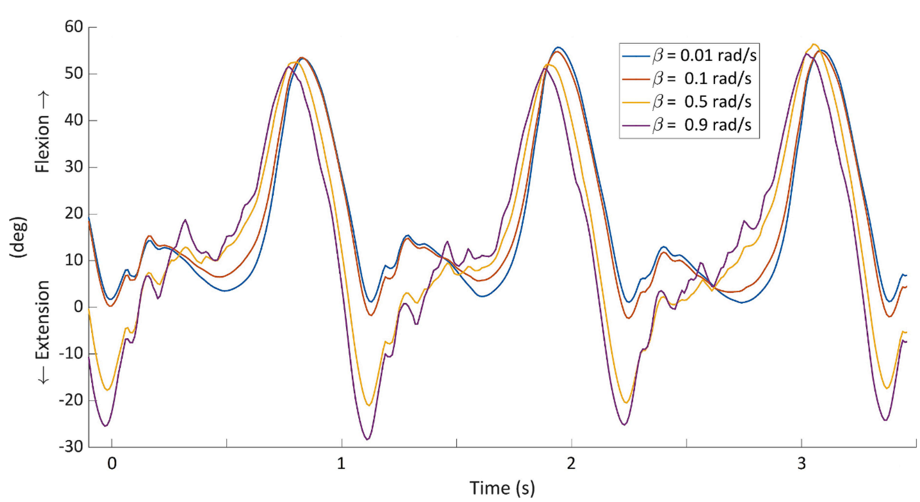

Fig. 5. An example of knee flexion–extension angle estimation during walking as obtained for different values of the orientation filter weight parameter β. Kinematics were reconstructed from data recorded by IMUs attached to the thigh and shank and using the complementary filter proposed by Madgwick and colleagues (2011). For β = 0 only the gyroscope contribution is considered, β = 0.1 is the value chosen for the experiments presented in Madgwick and colleagues (2011).

- Kinematic model. The kinematic analysis should be compatible with the kinematic model. Details on the generalized coordinates used to parameterize the kinematic model, the associated transformation equations, and how the biomechanically relevant joint angles were calculated should be reported.
- Sensor fusion algorithm. Details on raw sensor signals preprocessing (e.g., low-pass filtering) and sensor fusion algorithms used, including measurement and time update equations, application criteria, and parameter initialization and tuning should be described.
- Open-source code. In accordance with intellectual property requirements, open-source code for new algorithms whenever possible should be provided to promote reproducibility and advance the field.

6. Quality assessment

The quality criteria of any measurement system are its accuracy, concurrent validity, reliability, and context-specific validity in assessing the outcome of interest. A three-component framework (verification, analytical validation, and context-specific validation) has been proposed to provide a basic evaluation framework for Biometric Monitoring Technologies (BioMeTs) (Goldsack et al., 2020). This framework is also applicable to IMU-based measurements of joint kinematics.

6.1. Accuracy

Ideally, assessing the accuracy of IMU-based protocols for joint kinematics should involve comparison with direct measurements of skeletal motion, obtained through bone pins and marker-based stereophotogrammetry or dual-plane fluoroscopy. However, the former is highly invasive, and the latter requires expensive equipment with limited practicality due to constrained movement, radiation exposure, and 2D to 3D registration challenges. Notably, IMU-based systems have yet to be evaluated against these direct measurements of joint kinematics.

A potential solution for analytical validation of IMU-based kinematics accuracy is to use robotic joint simulators (Ortigas Vásquez et al., 2022). This allows for assessing uncertainties related to algorithm models and assumptions, albeit without addressing the influence of soft tissue artifacts. Limitations of these systems include heterogeneity, potential errors in kinematic mapping, and challenges in replicating physiological motion (Ortigas Vásquez et al., 2022).

6.2. Concurrent validity

Assessing ground truth joint kinematics is challenging, leading to the common practice of evaluating the concurrent validity of IMU-based methods by comparing them to marker-based clinical protocols (Kobsar et al., 2020), or, rarely, to other IMU-based systems (Cottam et al., 2022). While all motion capture systems that rely on sensor placement on the skin are prone to soft tissue artifacts (Cereatti et al., 2017), their impact on joint angle estimation varies between IMU-based and marker-based stereophotogrammetric systems. In addition, discrepancies in JCS definitions (*section 4.2.3*, *section 5.1*) contribute to differences in derived joint kinematics, (Ferrari et al., 2010). Many studies have reported joint angle trajectory offsets between IMU-based and marker-based stereophotogrammetric systems when different ACSs are used (Al Borno et al., 2022; Bailey et al., 2021; Chan et al., 2022; McGrath and Stirling, 2022; Nijmeijer et al., 2023; Nüesch et al., 2017; Parel et al., 2014).

Another crucial issue when comparing IMU-based methods with another reference motion capture system is to express the relevant kinematic quantities in a common coordinate system. To this end, appropriate alignment procedures can be implemented (Chardonnens et al., 2012).

Concurrent validity describes the agreement between a proposed measurement system (e.g., IMU-based kinematics analysis) and one already accepted in the field (e.g., marker-based motion capture). It is commonly evaluated by comparing kinematic parameters derived from the different systems using metrics such as root mean square error, peak error, or mean relative/absolute error at maximum excursion (Fang et al., 2023). Although less commonly used, Bland-Altman plots (Bland and Altman, 1986) are desirable for comparisons of discrete kinematic parameters and provide insight into systematic bias between systems. Correlation analysis, root mean square error, or statistical parametric mapping with paired t-tests are used to assess agreement in kinematic trajectories.

6.3. Reliability

While evidence for the concurrent validity of IMU-based kinematics is abundant, research on the equally important quality criteria of reliability and clinical validity of IMU-based systems is limited. Assessing within-day reliability (repeatability) or between-day reliability (reproducibility) in clinical populations is challenging due to potential disease-related variations in function (Bartlett and Frost, 2008). In addition, reliability is influenced by technical aspects such as calibration procedures (inter-operator and inter-subject, especially when calibration relies on static posture) and human factors such as sensor or marker placement (Schwartz et al., 2004). Few studies have reported on within-session (Al-Amri et al., 2018; Berner et al., 2020; Nüesch et al., 2017) or between-day (Nilsson et al., 2022) reliability of different IMU systems for assessing joint kinematics in healthy populations or in patients (Berner et al., 2020; Parel et al., 2012). Reliability is typically assessed using standard errors of measurement, appropriate intraclass correlation coefficients (ICCs) (Koo and Li, 2016), and Bland-Altman plots with limits of agreement (and the resulting minimum detectable changes).

6.4. Context-specific validation

According to the BioMeTs framework (Goldsack et al., 2020), clinical validation “evaluates whether a sensor acceptably identifies, measures, or predicts a meaningful clinical, biological, physical, functional state, or experience, in the stated context of use (which includes a specific population)”. This definition, referred to as context-specific validation, extends beyond clinical settings to include general health and/or sports (Camomilla et al., 2018) settings and represents the sensitivity of a system to detect relevant differences or changes in the outcome parameter of interest in the specific setting and population. It is important to consider that the context can also affect the concurrent validity or reliability of the methodology, and hence steps should be taken to mitigate these effects (e.g., implementing proper calibration postures in real-world settings).

To establish the meaningfulness of IMU-based estimates, comparisons with physiological biomarkers, patient/observer-reported, clinically evaluated, and qualitative questionnaires are critical (Berner et al., 2020; Nüesch et al., 2017; Cutti et al., 2016). Clinical meaningfulness can also be demonstrated through the relationship between standardized physician assessments of disease severity and joint angle (Shah et al., 2021). Notably, the Federal Drug Administration now mandates that IMU-based estimates demonstrate meaningfulness to patients for regulatory approval (*Framework for the Use of DHTs in Drug and Biological Product Development*, 2023). For example ambulatory joint angle differences of $> 5^\circ$ are considered clinically relevant (Berner et al., 2020; Nüesch et al., 2017), and the minimum detectable changes of the system, derived from its accuracy and reliability, must be less than the clinically relevant change. When analyzing gait, pre- to postoperative joint kinematics changes in patients undergoing hip arthroplasty, exceeding the IMU-based minimum detectable changes, have been reported. Differences were comparable between the IMU-based and marker-based measurement protocols (Nüesch et al., 2023), and correlated with patient-reported outcomes (Kaufmann et al., 2023). Further, Cutti et al.

(2016) investigated the context-specific validity of augmenting a clinical score with IMU-based measurements of the scapulo-humeral coordination. Ideally, context-specific validation involves comparing relevant outcome parameters assessed in controlled laboratory settings with those in real-life situations. There is evidence that results can vary significantly depending on whether movement is assessed under laboratory conditions or in everyday life (Warmerdam et al., 2020), therefore validation of kinematic characteristics must take into account context, instructions, and environment, as well as the particular cohort.

Overall, demonstrating and reporting evidence of accuracy, concurrent validity, reliability and context-specific validity for the specific outcome of interest is critical for the use of any IMU system in healthcare and sport settings.

Recommendations for quality assessment

- Accuracy. Standard procedures in a controlled setting should be implemented to assess the overall accuracy of the estimated quantities, at least the first time an IMU-based system is proposed, and the results provided.
- Concurrent validity. The biomechanical outcomes of interest should be compared between IMU-based systems and a reference system (current standard: marker-based stereophotogrammetry). Error statistics appropriate for the metric being validated should be reported (e.g., Bland-Altman plots and limits of agreement for discrete parameters such as range of motion, RMSE for time-series data such as joint angle trajectory). Alternatively, appropriate literature for the same outcome and system should be cited.
- Reliability. Reliability as intraclass correlation coefficients (choose appropriate ICC) and standard errors of measurement or Bland-Altman plots and limits of agreement should be reported. Alternatively, appropriate literature for the same outcome and system should be cited.
- Context-specific validation. Sensitivity and specificity of the system-based context-specific biomechanical outcome, including clinically-relevant or performance-relevant differences and/or changes and associations with patient-reported outcome or clinical measures should be reported. Alternatively, appropriate literature for the same outcome and system should be cited.

7. Conclusion

Inertial measurement technology is an attractive solution to measure human motion outside the laboratory. However, there are currently few standards or recommendations for how to obtain accurate and meaningful measures of joint kinematics from IMUs. This paper presents a conceptual framework that highlights the key aspects of estimating joint kinematics using IMUs. A series of recommendations are proposed that cover these aspects ranging from metrological performance to analysis of joint kinematics, including practical considerations for experimental protocols, definition of the kinematic models and subject-specific calibration. This guidance includes the importance of assessing the reliability, accuracy, and validity of the data obtained using IMUs. The specific recommendations are general to avoid becoming obsolete with the inevitable advances in this evolving field, and to be applicable also if machine learning approaches are used for joint angle estimation directly from IMU signals (Gurchiek et al., 2019). We recognize that these recommendations for estimating joint kinematics from IMUs may not address all the aspects that IMU users need, but they are proposed as a first step in establishing good practice for the use of IMUs for human movement analysis, guiding the development of commercial products, and issuing certifications (see checklist in Appendix B).

CRediT authorship contribution statement

Andrea Cereatti: Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Data curation. **Reed Gurchiek:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Conceptualization. **Annegret Mündermann:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Silvia Fantozzi:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **Fay Horak:** Writing – review & editing, Supervision, Conceptualization. **Scott Delp:** Writing – review & editing, Supervision, Conceptualization. **Kamiar Aminian:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2024.112225.

References

Al Borno, M., O'Day, J., Ibarra, V., Dunne, J., Seth, A., Habib, A., Ong, C., Hicks, J., Uhlrich, S., Delp, S., 2022. OpenSense: An open-source toolbox for inertial-measurement-unit-based measurement of lower extremity kinematics over long durations. J. NeuroEng. Rehabil. 19, 22. https://doi.org/10.1186/s12984-022-01001-x.

Al-Amri, M., Nicholas, K., Button, K., Sparkes, V., Sheeran, L., Davies, J., 2018. Inertial measurement units for clinical movement analysis: reliability and concurrent validity. Sensors 18, 719. https://doi.org/10.3390/s18030719.

Aminian, K., Najafi, B., Büla, C., Leyvraz, P.-F., Robert, Ph., 2002. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. J. Biomech. 35, 689–699. https://doi.org/10.1016/S0021-9290(02)00008-8.

Avrutov, V.V., Aksonenko, P.M., Henaff, P., Ciarletta, L., 2017. 3D-calibration of the IMU, in: 2017 IEEE 37th International Conference on Electronics and Nanotechnology (ELNANO). Presented at the 2017 IEEE 37th International Conference on Electronics and Nanotechnology (ELNANO), IEEE, Kyiv, Ukraine, pp. 374–379. doi: 10.1109/ELNANO.2017.7939782.

Bailey, C.A., Uchida, T.K., Nantel, J., Graham, R.B., 2021. Validity and sensitivity of an inertial measurement unit-driven biomechanical model of motor variability for gait. Sensors 21, 7690. https://doi.org/10.3390/s21227690.

Bannach, D., Amft, O., Lukowicz, P., 2009. Automatic Event-Based Synchronization of Multimodal Data Streams from Wearable and Ambient Sensors, in: Barnaghi, P., Moessner, K., Presser, M., Meissner, S. (Eds.), Smart Sensing and Context, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 135–148. doi: 10.1007/978-3-642-04471-7_11.

Beange, K.H.E., Chan, A.D.C., Graham, R.B., 2023. Sources of error during inertial sensing of human movement: a critical review of the fundamentals, in: 2023 IEEE International Symposium on Medical Measurements and Applications (MeMeA). Presented at the 2023 IEEE International Symposium on Medical Measurements and Applications (MeMeA), IEEE, Jeju, Korea, Republic of, pp. 1–6. doi: 10.1109/MeMeA57477.2023.10171885.

Bartlett, J.W., Frost, C., 2008. Reliability, repeatability and reproducibility: analysis of measurement errors in continuous variables. Ultrasound Obstet. Gynecol. 31, 466–475.

Berner, K., Cockcroft, J., Morris, L.D., Louw, Q., 2020. Concurrent validity and within-session reliability of gait kinematics measured using an inertial motion capture system with repeated calibration. J. Bodyw. Mov. Ther. 24, 251–260. https://doi.org/10.1016/j.jbmt.2020.06.008.

Bisi, M.C., Stagni, R., Caroselli, A., Cappello, A., 2015. Anatomical calibration for wearable motion capture systems: Video calibrated anatomical system technique. Med. Eng. Phys. 37, 813–819. https://doi.org/10.1016/j.medengphy.2015.05.013.

Bland, J., Altman, D., 1986. Statistical methods for assessing agreement between two methods of clinical measurement statistical methods for assessing agreement between two methods of clinical measurement. Lancet 1, 307–310.

Bouvier, B., Duprey, S., Claudon, L., Dumas, R., Savescu, A., 2015. Upper limb kinematics using inertial and magnetic sensors: comparison of sensor-to-segment calibrations. Sensors 15, 18813–18833. https://doi.org/10.3390/s150818813.

Brodie, M.A., Walmsley, A., Page, W., 2008. The static accuracy and calibration of inertial measurement units for 3D orientation. Comput. Methods Biomech. Biomed. Eng. 11, 641–648. https://doi.org/10.1080/10255840802326736.

Camomilla, V., Bergamini, E., Fantozzi, S., Vannozzi, G., 2018. Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: a systematic review. Sensors 18, 873. https://doi.org/10.3390/s18030873.

Caruso, M., Sabatini, A.M., Knaflitz, M., Gazzoni, M., Croce, U.D., Cereatti, A., 2021. Orientation estimation through magneto-inertial sensor fusion: a heuristic approach for suboptimal parameters tuning. IEEE Sensors J. 21, 3408–3419. https://doi.org/10.1109/JSEN.2020.3024806.

Cereatti, A., Bonci, T., Akbarshahi, M., Aminian, K., Barré, A., Begon, M., Benoit, D.L., Charbonnier, C., Dal Maso, F., Fantozzi, S., Lin, C.-C., Lu, T.-W., Pandy, M.G., Stagni, R., Van Den Bogert, A.J., Camomilla, V., 2017. Standardization proposal of soft tissue artefact description for data sharing in human motion measurements. J. Biomech. 62, 5–13. https://doi.org/10.1016/j.jbiomech.2017.02.004.

Chan, L.Y.T., Chua, C.S., Chou, S.M., Seah, R.Y.B., Huang, Y., Luo, Y., Dacy, L., Bin Abd Razak, H.R., 2022. Assessment of shoulder range of motion using a commercially available wearable sensor—a validation study. mHealth 8, 30–30. doi: 10.21037/mhealth-22-7.

Chardonnens, J., Favre, J., Aminian, K., 2012. An effortless procedure to align the local frame of an inertial measurement unit to the local frame of another motion capture system. J. Biomech. 45, 2297–2300. https://doi.org/10.1016/j.jbiomech.2012.06.009.

Chardonnens, J., Favre, J., Cuendet, F., Gremion, G., Aminian, K., 2013. A system to measure the kinematics during the entire ski jump sequence using inertial sensors. J. Biomech. 46, 56–62. https://doi.org/10.1016/j.jbiomech.2012.10.005.

Cinnera, A.M., Picerno, P., Bisirri, A., Koch, G., Morone, G., Vannozzi, G., 2024. Upper limb assessment with inertial measurement units according to the international classification of functioning in stroke: a systematic review and correlation meta-analysis. Top. Stroke Rehabil. 31, 66–85. https://doi.org/10.1080/10749357.2023.2197278.

Cooper, G., Sheret, I., McMillian, L., Siliverdis, K., Sha, N., Hodgins, D., Kenney, L., Howard, D., 2009. Inertial sensor-based knee flexion/extension angle estimation. J. Biomech. 42, 2678–2685. https://doi.org/10.1016/j.jbiomech.2009.08.004.

Cottam, D.S., Campbell, A.C., Davey, M.P.C., Kent, P., Elliott, B.C., Alderson, J.A., 2022. Measurement of uni-planar and sport specific trunk motion using magneto-inertial measurement units: The concurrent validity of Noraxon and Xsens systems relative to a retro-reflective system. Gait Posture 92, 129–134. https://doi.org/10.1016/j.gaitpost.2021.11.012.

Crabolu, M., Pani, D., Raffo, L., Cereatti, A., 2016. Estimation of the center of rotation using wearable magneto-inertial sensors. J. Biomech. 49, 3928–3933. https://doi.org/10.1016/j.jbiomech.2016.11.046.

Cutti, A.G., Giovanardi, A., Rocchi, L., Davalli, A., 2006. A simple test to assess the static and dynamic accuracy of an inertial sensors system for human movement analysis. In: In: 2006 International Conference of the IEEE Engineering in Medicine and Biology Society. Presented at the Conference Proceedings. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, New York, NY, pp. 5912–5915. https://doi.org/10.1109/IEMBS.2006.260705.

Cutti, A.G., Giovanardi, A., Rocchi, L., Davalli, A., Sacchetti, R., 2008. Ambulatory measurement of shoulder and elbow kinematics through inertial and magnetic sensors. Med. Bio Eng. Comput. 46, 169–178. https://doi.org/10.1007/s11517-007-0296-5.

Cutti, A.G., Ferrari, A., Garofalo, P., Raggi, M., Cappello, A., Ferrari, A., 2010. 'Outwalk': a protocol for clinical gait analysis based on inertial and magnetic sensors. Med. Biol. Eng. Comput. 48, 17–25. https://doi.org/10.1007/s11517-009-0545-x.

Cutti, A.G., Parel, I., Pellegrini, A., Paladini, P., Sacchetti, R., Porcellini, G., Merolla, G., 2016. The Constant score and the assessment of scapula dyskinesis: proposal and assessment of an integrated outcome measure. J. Electromyogr. Kinesiol. 29, 81–89. https://doi.org/10.1016/j.jelekin.2015.06.011.

Decker, C., Prasad, N., Kawchuk, G.N., 2011. The reproducibility of signals from skin-mounted accelerometers following removal and replacement. Gait Posture 34, 432–434. https://doi.org/10.1016/j.gaitpost.2011.05.024.

Dejnabadi, H., Jolles, B.M., Aminian, K., 2005. A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes. IEEE Trans. Biomed. Eng. 52, 1478–1484. https://doi.org/10.1109/TBME.2005.851475.

Di Raimondo, G., Vanwanseele, B., Van Der Have, A., Emmerzaal, J., Willems, M., Killen, B.A., Jonkers, I., 2022. Inertial sensor-to-segment calibration for accurate 3D joint angle calculation for use in OpenSim. Sensors 22, 3259. https://doi.org/10.3390/s22093259.

Dillman, C.J., Fleisig, G.S., Andrews, J.R., 1993. Biomechanics of pitching with emphasis upon shoulder kinematics. J. Orthop. Sports Phys. Ther. 18, 402–408. https://doi.org/10.2519/jospt.1993.18.2.402.

Dorschky, E., Nitschke, M., Seifer, A.-K., Van Den Bogert, A.J., Eskofier, B.M., 2019. Estimation of gait kinematics and kinetics from inertial sensor data using optimal control of musculoskeletal models. J. Biomech. 95, 109278 https://doi.org/10.1016/j.jbiomech.2019.07.022.

Fang, Z., Woodford, S., Senanayake, D., Ackland, D., 2023. Conversion of upper-limb inertial measurement unit data to joint angles: a systematic review. Sensors 23, 6535. https://doi.org/10.3390/s23146535.

Fasel, B., Spörri, J., Gilgien, M., Boffi, G., Chardonnens, J., Müller, E., Aminian, K., 2016. Three-dimensional body and centre of mass kinematics in Alpine Ski racing using differential GNSS and inertial sensors. Remote Sens. (Basel) 8, 671. https://doi.org/10.3390/rs8080671.

Fasel, B., Spörri, J., Schütz, P., Lorenzetti, S., Aminian, K., 2017. Validation of functional calibration and strap-down joint drift correction for computing 3D joint angles of knee, hip, and trunk in alpine skiing. PLoS One 12, e0181446.

Fasel, B., 2017. Drift Reduction for Inertial Sensor Based Orientation and Position Estimation in the Presence of High Dynamic Variability During Competitive Skiing and Daily-Life Walking. PhD Thesis, ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE.

Favre, J., Aissaoui, R., Jolles, B.M., De Guise, J.A., Aminian, K., 2009. Functional calibration procedure for 3D knee joint angle description using inertial sensors. J. Biomech. 42, 2330–2335. https://doi.org/10.1016/j.jbiomech.2009.06.025.

Ferrari, A., Cutti, A.G., Garofalo, P., Raggi, M., Heijboer, M., Cappello, A., Davalli, A., 2010. First in vivo assessment of "Outwalk": a novel protocol for clinical gait analysis based on inertial and magnetic sensors. Med. Biol. Eng. Comput. 48, 1–15. https://doi.org/10.1007/s11517-009-0544-y.

Ferraris, F., Grimaldi, U., Parvis, M., 1995. Procedure for effortless in-field calibration of three-axis rate gyros and accelerometers. Procedure for Effortless in-Field Calibration of Three-Axis Rate Gyros and Accelerometers 7, 311–330.

Fischer, C., Talkad Sukumar, P., Hazas, M., 2013. Tutorial: implementing a pedestrian tracker using inertial sensors. IEEE Pervasive Comput. 12, 17–27. https://doi.org/10.1109/MPRV.2012.16.

Forner-Cordero, A., Mateu-Arce, M., Forner-Cordero, I., Alcántara, E., Moreno, J.C., Pons, J.L., 2008. Study of the motion artefacts of skin-mounted inertial sensors under different attachment conditions. Physiol. Meas. 29, N21–N31. https://doi.org/10.1088/0967-3334/29/4/N01.

García-de-Villa, S., Casillas-Pérez, D., Jiménez-Martín, A., García-Domínguez, J.J., 2023. Inertial sensors for human motion analysis: a comprehensive review. IEEE Trans. Instrum. Meas. 72, 1–39. https://doi.org/10.1109/TIM.2023.3276528.

Goldsack, J.C., Coravos, A., Bakker, J.P., Bent, B., Dowling, A.V., Fitzer-Attas, C., Godfrey, A., Godino, J.G., Gujar, N., Izmailova, E., Manta, C., Peterson, B., Vandendriessche, B., Wood, W.A., Wang, K.W., Dunn, J., 2020. Verification, analytical validation, and clinical validation (V3): the foundation of determining fit-for-purpose for biometric monitoring technologies (BioMeTs). npj Digit Med. 3, 55. https://doi.org/10.1038/s41746-020-0260-4.

Greenberg, A., Aboy, P.M.R., Pearson, S., Gallino, G., 2018. Wireless Synchronized Apparaturs and System. US010117204B2.

Grood, E.S., Suntay, W.J., 1983. A joint coordinate system for the clinical description of three-dimensional motions: application to the knee. J. Biomech. Eng. 105, 136–144. https://doi.org/10.1115/1.3138397.

Gurchiek, R.D., Cheney, N., McGinnis, R.S., 2019. Estimating biomechanical time-series with wearable sensors: a systematic review of machine learning techniques. Sensors 19, 5227. https://doi.org/10.3390/s19235227.

Hafer, J.F., Vitali, R., Gurchiek, R., Curtze, C., Shull, P., Cain, S.M., 2023. Challenges and advances in the use of wearable sensors for lower extremity biomechanics. J. Biomech. 157, 111714 https://doi.org/10.1016/j.jbiomech.2023.111714.

Hamidi Rad, M., Gremeaux, V., Dadashi, F., Aminian, K., 2021. A Novel Macro-Micro Approach for Swimming Analysis in Main Swimming Techniques Using IMU Sensors. Front. Bioeng. Biotechnol. 8, 597738 https://doi.org/10.3389/fbioe.2020.597738.

Jurman, D., Jankovec, M., Kamnik, R., Topič, M., 2007. Calibration and data fusion solution for the miniature attitude and heading reference system. Sens. Actuators, A 138, 411–420. https://doi.org/10.1016/j.sna.2007.05.008.

Kaufmann, M., Nüesch, C., Clauss, M., Pagenstert, G., Eckardt, A., Ilchmann, T., Stoffel, K., Mündermann, A., Ismailidis, P., 2023. Functional assessment of total hip arthroplasty using inertial measurement units: Improvement in gait kinematics and association with patient-reported outcome measures. J. Orthop. Res. 41, 759–770. https://doi.org/10.1002/jor.25421.

Kobsar, D., Charlton, J.M., Tse, C.T.F., Esculier, J.-F., Graffos, A., Krowchuk, N.M., Thatcher, D., Hunt, M.A., 2020. Validity and reliability of wearable inertial sensors in healthy adult walking: a systematic review and meta-analysis. J. NeuroEng. Rehabil. 17, 62. https://doi.org/10.1186/s12984-020-00685-3.

Koning, B.H.W., Van Der Krogt, M.M., Baten, C.T.M., Koopman, B.F.J.M., 2015. Driving a musculoskeletal model with inertial and magnetic measurement units. Comput. Methods Biomech. Biomed. Eng. 18, 1003–1013. https://doi.org/10.1080/10255842.2013.867481.

Kontaxis, A., Cutti, A.G., Johnson, G.R., Veeger, H.E.J., 2009. A framework for the definition of standardized protocols for measuring upper-extremity kinematics. Clin. Biomech. 24, 246–253. https://doi.org/10.1016/j.clinbiomech.2008.12.009.

Koo, T.K., Li, M.Y., 2016. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. J. Chiropr. Med. 15, 155–163. https://doi.org/10.1016/j.jcm.2016.02.012.

Lafortune, M.A., 1991. Three-dimensional acceleration of the tibia during walking and running. J. Biomech. 24, 877–886. https://doi.org/10.1016/0021-9290(91)90166-K.

Lafortune, M.A., Henning, E., Valiant, G.A., 1995. Tibial shock measured with bone and skin mounted transducers. J. Biomech. 28, 989–993. https://doi.org/10.1016/0021-9290(94)00150-3.

Lucas-Cuevas, A.G., Encarnación-Martínez, A., Camacho-García, A., Llana-Belloch, S., Pérez-Soriano, P., 2016. The location of the tibial accelerometer does influence impact acceleration parameters during running. J. Sports Sci. 35, 1734–1738. https://doi.org/10.1080/02640414.2016.1235792.

Luinge, H.J., Veltink, P.H., Baten, C.T.M., 2007. Ambulatory measurement of arm orientation. J. Biomech. 40, 78–85. https://doi.org/10.1016/j.jbiomech.2005.11.011.

Madgwick, S.O.H., Harrison, A.J.L., Vaidyanathan, R., 2011. Estimation of IMU and MARG orientation using a gradient descent algorithm, in: 2011 IEEE International Conference on Rehabilitation Robotics. Presented at the 2011 IEEE 12th International Conference on Rehabilitation Robotics: Reaching Users & the Community (ICORR 2011), IEEE, Zurich, pp. 1–7. doi: 10.1109/ICORR.2011.5975346.

Mahony, R., Hamel, T., Pflimlin, J.-M., 2008. Nonlinear complementary filters on the special orthogonal group. IEEE Trans. Automat. Contr. 53, 1203–1218. https://doi.org/10.1109/TAC.2008.923738.

Mariani, B., Hoskovec, C., Rochat, S., Büla, C., Penders, J., Aminian, K., 2010. 3D gait assessment in young and elderly subjects using foot-worn inertial sensors. J. Biomech. 43, 2999–3006. https://doi.org/10.1016/j.jbiomech.2010.07.003.

McGinnis, R.S., Perkins, N.C., 2013. Inertial sensor based method for identifying spherical joint center of rotation. J. Biomech. 46, 2546–2549. https://doi.org/10.1016/j.jbiomech.2013.07.017.

McGrath, T., Stirling, L., 2022. Body-worn IMU-based human hip and knee kinematics estimation during treadmill walking. Sensors 22, 2544. https://doi.org/10.3390/s22072544.

Miezal, M., Taetz, B., Bleser, G., 2016. on inertial body tracking in the presence of model calibration errors. Sensors 16, 1132. https://doi.org/10.3390/s16071132.

Mitschke, C., Zaumseil, F., Milani, T.L., 2017. The influence of inertial sensor sampling frequency on the accuracy of measurement parameters in rearfoot running. Comput. Methods Biomech. Biomed. Eng. 20, 1502–1511. https://doi.org/10.1080/10255842.2017.1382482.

Nazarahari, M., Rouhani, H., 2021. 40 years of sensor fusion for orientation tracking via magnetic and inertial measurement units: Methods, lessons learned, and future challenges. Inform. Fus. 68, 67–84. https://doi.org/10.1016/j.inffus.2020.10.018.

Nijmeijer, E.M., Heuvelmans, P., Bolt, R., Gokeler, A., Otten, E., Benjaminse, A., 2023. Concurrent validation of the Xsens IMU system of lower-body kinematics in jump-landing and change-of-direction tasks. J. Biomech. 154, 111637 https://doi.org/10.1016/j.jbiomech.2023.111637.

Nilsson, S., Ertzgaard, P., Lundgren, M., Grip, H., 2022. Test-retest reliability of kinematic and temporal outcome measures for clinical gait and stair walking tests based on wearable inertial sensors. Sensors 22, 1171. https://doi.org/10.3390/s22031171.

Niswander, W., Wang, W., Kontson, K., 2020. Optimization of IMU sensor placement for the measurement of lower limb joint kinematics. Sensors 20, 5993. https://doi.org/10.3390/s20215993.

Nüesch, C., Roos, E., Pagenstert, G., Mündermann, A., 2017. Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor based system and a camera-based system. J. Biomech. 57, 32–38. https://doi.org/10.1016/j.jbiomech.2017.03.015.

Nüesch, C., Ismailidis, P., Koch, D., Stoffel, K., Mündermann, A., 2023. Improvements in gait patterns of patients 1-year after total hip arthroplasty assessed using an inertial sensor system compared to a marker-based system. Gait Post. 100, 81–82. https://doi.org/10.1016/j.gaitpost.2022.11.034.

O'Donovan, K.J., Kamnik, R., O'Keeffe, D.T., Lyons, G.M., 2007. An inertial and magnetic sensor based technique for joint angle measurement. J. Biomech. 40, 2604–2611. https://doi.org/10.1016/j.jbiomech.2006.12.010.

Ojeda, L., Zaferiou, A., Cain, S., Vitali, R., Davidson, S., Stirling, L., Perkins, N., 2017. Estimating stair running performance using inertial sensors. Sensors 17, 2647. https://doi.org/10.3390/s17112647.

Ortigas Vásquez, A., Maas, A., List, R., Schütz, P., Taylor, W.R., Grupp, T.M., 2022. A framework for analytical validation of inertial-sensor-based knee kinematics using a six-degrees-of-freedom joint simulator. Sensors 23, 348. https://doi.org/10.3390/s23010348.

Parel, I., Cutti, A.G., Fiumana, G., Porcellini, G., Verni, G., Accardo, A.P., 2012. Ambulatory measurement of the scapulohumeral rhythm: Intra- and inter-operator agreement of a protocol based on inertial and magnetic sensors. Gait Post. 35, 636–640. https://doi.org/10.1016/j.gaitpost.2011.12.015.

Parel, I., Cutti, A.G., Kraszewski, A., Verni, G., Hillstrom, H., Kontaxis, A., 2014. Intra-protocol repeatability and inter-protocol agreement for the analysis of scapulo-humeral coordination. Med. Biol. Eng. Comput. 52, 271–282. https://doi.org/10.1007/s11517-013-1121-y.

Picerno, P., Cereatti, A., Cappozzo, A., 2008. Joint kinematics estimate using wearable inertial and magnetic sensing modules. Gait Posture 28, 588–595. https://doi.org/10.1016/j.gaitpost.2008.04.003.

Potter, M.V., Cain, S.M., Ojeda, L.V., Gurchiek, R.D., McGinnis, R.S., Perkins, N.C., 2021. Error-state Kalman filter for lower-limb kinematic estimation: evaluation on a 3-body model. PLoS One 16, e0249577.

Potter, M.V., Cain, S.M., Ojeda, L.V., Gurchiek, R.D., McGinnis, R.S., Perkins, N.C., 2022. Evaluation of error-state Kalman Filter method for estimating human lower-limb kinematics during various walking gaits. Sensors 22, 8398. https://doi.org/10.3390/s22218398.

Preatoni, E., Bergamini, E., Fantozzi, S., Giraud, L.I., Orejel Bustos, A.S., Vannozzi, G., Camomilla, V., 2022. The use of wearable sensors for preventing, assessing, and informing recovery from sport-related musculoskeletal injuries: a systematic scoping review. Sensors 22, 3225. https://doi.org/10.3390/s22093225.

Roetenberg, D., Luinge, H., Slycke, P., 2013. Xsens MVN: Full 6DOF Human Motion Tracking Using Miniature Inertial Sensors.

Sabatini, A.M., 2006. Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing. IEEE Trans. Biomed. Eng. 53, 1346–1356. https://doi.org/10.1109/TBME.2006.875664.

Sabatini, A.M., 2011. Estimating three-dimensional orientation of human body parts by inertial/magnetic sensing. Sensors 11, 1489–1525. https://doi.org/10.3390/s110201489.

Schepers, M., Giuberti, M., Bellusci, G., 2018. Xsens MVN: Consistent Tracking of Human Motion Using Inertial Sensing.

Schwartz, M.H., Trost, J.P., Wervey, R.A., 2004. Measurement and management of errors in quantitative gait data. Gait Post. 20, 196–203. https://doi.org/10.1016/j.gaitpost.2003.09.011.

Seel, T., Raisch, J., Schauer, T., 2014. IMU-based joint angle measurement for gait analysis. Sensors 14, 6891–6909. https://doi.org/10.3390/s140406891.

Shah, V.V., Rodriguez-Labrada, R., Horak, F.B., McNames, J., Casey, H., Hansson Floyd, K., El-Gohary, M., Schmahmann, J.D., Rosenthal, L.S., Perlman, S., Velázquez-Pérez, L., Gomez, C.M., 2021. Gait variability in spinocerebellar ataxia assessed using wearable inertial sensors. Mov. Disord. 36, 2922–2931. https://doi.org/10.1002/mds.28740.

Shuster, M., 1993. A survey of attitude representation a survey of attitude representation. J. Astron. Sci. 41, 439–517.

Spilz, A., Munz, M., 2021. Novel Approach To Synchronisation Of Wearable IMUs Based On Magnetometers.

Taetz, B., Bleser, G., Miezal, M., 2016. Towards Self-Calibrating Inertial Body Motion Capture.

Tedaldi, D., Pretto, A., Menegatti, E., 2014. A robust and easy to implement method for IMU calibration without external equipments, in: 2014 IEEE International Conference on Robotics and Automation (ICRA). Presented at the 2014 IEEE International Conference on Robotics and Automation (ICRA), IEEE, Hong Kong, China, pp. 3042–3049. doi: 10.1109/ICRA.2014.6907297.

Veltink, P.H., Slycke, P., Hemssems, J., Buschman, R., Bultstra, G., Hermens, H., 2003. Three dimensional inertial sensing of foot movements for automatic tuning of a two-channel implantable drop-foot stimulator. Med. Eng. Phys. 25, 21–28. https://doi.org/10.1016/S1350-4533(02)00041-3.

Vitali, R., Cain, S., McGinnis, R., Zaferiou, A., Ojeda, L., Davidson, S., Perkins, N., 2017. Method for estimating three-dimensional knee rotations using two inertial measurement units: validation with a coordinate measurement machine. Sensors 17, 1970. https://doi.org/10.3390/s17091970.

Vitali, R.V., McGinnis, R.S., Perkins, N.C., 2021. Robust error-state kalman filter for estimating IMU orientation. IEEE Sensors J. 21, 3561–3569. https://doi.org/10.1109/JSEN.2020.3026895.

Vitali, R.V., Perkins, N.C., 2020. Determining anatomical frames via inertial motion capture: a survey of methods. J. Biomech. 106, 109832 https://doi.org/10.1016/j.jbiomech.2020.109832.

Warmerdam, E., Hausdorff, J.M., Atrsaei, A., Zhou, Y., Mirelman, A., Aminian, K., Espay, A.J., Hansen, C., Evers, L.J.W., Keller, A., Lamoth, C., Pilotto, A., Rochester, L., Schmidt, G., Bloem, B.R., Maetzler, W., 2020. Long-term unsupervised mobility assessment in movement disorders. Lancet Neurol. 19, 462–470. https://doi.org/10.1016/S1474-4422(19)30397-7.

Wells, D., Alderson, J., Camomilla, V., Donnelly, C., Elliott, B., Cereatti, A., 2019. Elbow joint kinematics during cricket bowling using magneto-inertial sensors: a feasibility study. J. Sports Sci. 37, 515–524. https://doi.org/10.1080/02640414.2018.1512845.

Weygers, I., Kok, M., De Vroey, H., Verbeerst, T., Versteyhe, M., Hallez, H., Claeys, K., 2020. Drift-free inertial sensor-based joint kinematics for long-term arbitrary movements. IEEE Sensors J. 20, 7969–7979. https://doi.org/10.1109/JSEN.2020.2982459.

Wu, G., Van Der Helm, F.C.T., (DirkJan) Veeger, H.E.J., Makhsous, M., Van Roy, P., Anglin, C., Nagels, J., Karduna, A.R., McQuade, K., Wang, X., Werner, F.W., Buchholz, B., 2005. ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: shoulder, elbow, wrist and hand. J. Biomech. 38, 981–992. doi: 10.1016/j.jbiomech.2004.05.042.

Wu, G., Siegler, S., Allard, P., Kirtley, C., Leardini, A., Rosenbaum, D., Whittle, M., D'Lima, D.D., Cristofolini, L., Witte, H., Schmid, O., Stokes, I., 2002. ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion—part I: ankle, hip, and spine. J. Biomech. 35, 543–548. https://doi.org/10.1016/S0021-9290(01)00222-6.

Yi, C., Rho, S., Wei, B., Yang, C., Ding, Z., Chen, Z., Jiang, F., 2022. Detecting and correcting IMU movements during joint angle estimation. IEEE Trans. Instrum. Meas. 71, 1–14. https://doi.org/10.1109/TIM.2022.3167771.

Zhang, S., Derrick, T.R., Evans, W., Yu, Y.-J., 2008. Shock and impact reduction in moderate and strenuous landing activities. Sports Biomech. 7, 296–309. https://doi.org/10.1080/14763140701841936.

Zhou, L., Fischer, E., Tunca, C., Brahms, C.M., Ersoy, C., Granacher, U., Arnrich, B., 2020. How we found our IMU: guidelines to IMU selection and a comparison of seven IMUs for pervasive healthcare applications. Sensors 20, 4090. https://doi.org/10.3390/s20154090.