Journal of Biomechanics 106 (2020) 109832

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Determining anatomical frames via inertial motion capture: A survey of methods

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ARTICLE INFO

Article history:
Accepted 5 May 2020

Keywords:
Inertial measurement units
Inertial motion capture
Anatomical frame
Sensor-to-segment

ABSTRACT

Despite the exponential growth in using inertial measurement units (IMUs) for biomechanical studies, future growth in "inertial motion capture" is stymied by a fundamental challenge - how to estimate the orientation of underlying bony anatomy using skin-mounted IMUs. This challenge is of paramount importance given the need to deduce the orientation of the bony anatomy to estimate joint angles. This paper systematically surveys a large number (N = 112) of studies from 2000 to 2018 that employ four broad categories of methods to address this challenge across a range of body segments and joints. We categorize these methods as: (1) Assumed Alignment methods, (2) Functional Alignment methods, (3) Model Based methods, and (4) Augmented Data methods. Assumed Alignment methods, which are simple and commonly used, require the researcher to visually align the IMU sense axes with the underlying anatomical axes. Functional Alignment methods, also commonly used, relax the need for visual alignment but require the subject to complete prescribed movements. Model Based methods further relax the need for prescribed movements but instead assume a model for the joint. Finally, Augmented Data methods shed all of the above assumptions, but require data from additional sensors. Significantly different estimates of the underlying anatomical axes arise both across and within these categories, and to a degree that renders it difficult, if not impossible, to compare results across studies. Consequently, a significant future need remains for creating and adopting a standard for defining anatomical axes via inertial motion capture to fully realize this technology's potential for biomechanical studies.

Contents

1. Introduction

In 1983, Grood and Suntay proposed in their landmark publication a method for defining joint coordinate systems (with particular emphasis on the knee) such that the convention would yield rotations of clinical significance that could be easily understood by a broader audience (Grood and Suntay, 1983). Following their lead, the Standardization and Terminology Committee of

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https://doi.org/10.1016/j.jbiomech.2020.109832
0021-9290/

the International Society of Biomechanics standardized the reporting of kinematic data for every joint starting with the knee (Wu and Cavanagh, 1995). In their seminal paper, Wu and Cavanagh observed, "some uniformity in presentation will make publications easier to read and allow for the more straightforward comparison of data sets from different investigators" (p. 1257, Wu and Cavanagh, 1995). However, these early efforts and those that followed, most notably (Wu et al., 2002) and (Wu et al., 2005), focused solely on reporting kinematic data for *optical* motion capture systems, which remain in prevalent use today. Given the ease with which position data are measured using optical motion capture, it is indisputably advantageous to define joint and axis conventions based on position information alone. Consequently, conventions for defining anatomical frames frequently require identifying (palpating) the positions of and placing markers upon anatomical landmarks per ISB conventions (Wu and Cavanaugh, 1995; Wu et al., 2002; Wu et al., 2005). This step may be followed (or even replaced) by functional movements where specific anatomical axes (or landmarks) are identified using selected body segment rotations; refer, for examples, to (Ehrig et al., 2006) for determining the center of rotation of a ball joint.

Unfortunately, this position-based method of defining anatomical frames does not translate directly to *inertial* motion capture, whose strength lies in its ability to measure *motion* (i.e., linear acceleration and angular velocity) via body-worn inertial sensors rather than *position* via cameras. Consequently, the inertial motion capture community finds itself in a similar state as the optical motion capture community roughly 40 years ago in that there is no common convention or method for defining anatomical frames of reference using this relatively new technology. Between advancements to inertial measurement unit (IMU) hardware and signal processing techniques, the accuracy of estimating the orientation of an IMU (hence the orientation of a body segment) has improved considerably and despite the small residual drift errors in IMU-derived orientation estimates. The improvements in IMU-derived orientation estimates follows from including a magnetometer which helps reduce angular drift in the horizontal plane (i.e., magnetometer yields estimate of magnetic north). For simplicity, IMUs (containing an accelerometer and angular rate gyro) and magnetometer-aided IMUs (sometimes referred to as a MIMU) will both hereafter be referred to as IMUs since the majority of the studies make no distinction. In addition, considering the results of several studies ((Sabatini, 2006), (Teufl et al., 2018), and (Della Croce et al., 2005)), we observe that the differences in estimated joint angles obtained by inertial and optical motion capture methods attributable to drift errors are now of the same magnitude as those caused by differences in how anatomical frames are defined. Thus, it is increasingly important to reconcile how anatomical frames are defined using inertial motion capture to advance its use and adoption. Doing so is important in view of significant advantages afforded by inertial motion capture over optical motion capture including its versatility, portability, and relative low cost. For example, optical motion capture restricts movements to modest-sized capture volumes within a laboratory, rendering this method difficult to use in contextually-rich environments where inertial motion capture can be readily deployed, such as outdoors, in the workplace, in clinics, at home, etc. In addition, optical motion capture can require considerable set-up and training time, and systems that do not incorporate automated analysis require considerable post-processing time as well. Inertial motion capture does not suffer from these limitations, especially when post-processing is automated.

The most common approach for estimating 3D joint angles via inertial motion capture begins with fixing IMUs to the body segments on each side of the joint. For example, IMUs affixed to the thigh and the shank yield the data needed to estimate 3D knee rotations. The estimate is achieved in three major steps as depicted in Fig. 1. In the first step, one estimates the orientation of both IMUs relative to a common world frame of reference. This step is usually accomplished using either a probabilistic (e.g., Sabatini, 2006) or complementary (e.g., Madgwick et al., 2011) approach that fuses independent estimates of IMU orientation from the acceleration and angular rate data. Note that either magnetometer data or other assumptions (e.g., initial heading alignment and a sufficiently short trial duration) are also required to obtain IMU orientation estimates in a *common* world frame. In the context of the knee, this first step enables one to then estimate the orientation of the shank IMU relative to the thigh IMU. The second step, which is not as well studied and is the focus of this review, is to further estimate the orientation of each IMU relative to the underlying bony anatomy of the corresponding body segment; that is, the orientation of the shank IMU relative to the shank anatomical frame and the orientation of the thigh IMU relative to the thigh anatomical frame. By combining the results of the first and second steps, one completes the third step which is to estimate the orientation of the shank anatomical frame relative to the thigh anatomical frame. The 3D rotations across the knee immediately follow from this third step (i.e., flexion/extension, internal/external rotation, and abduction/adduction follow from the direction cosine matrix relating the thigh and shank anatomical frames).

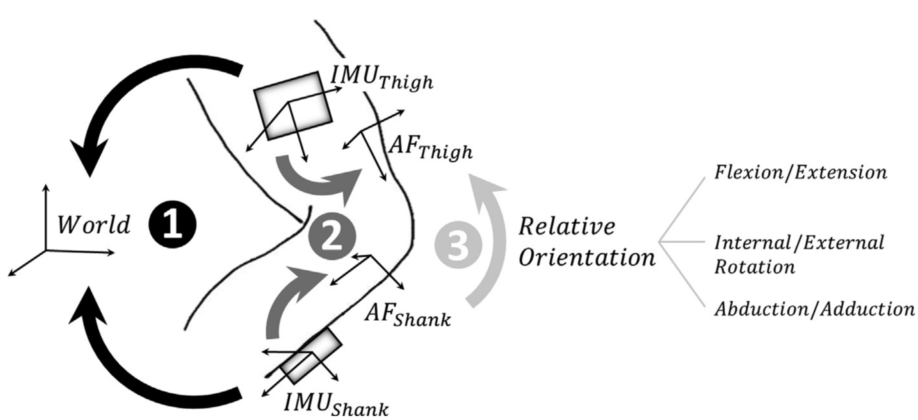

Fig. 1. Schematic illustrating three major steps to estimate 3D knee joint angles using an IMU attached to the thigh and the shank. The first step (black) requires estimating the orientation of each IMU to a common world frame. The second step (dark grey) requires estimating the orientation of each IMU relative to the anatomical frame (AF) of its respective body segment. The third step (light grey) combines the results of first and second steps to estimate the origination of the thigh anatomical frame relative to the shank anatomical frame which yields the 3D knee joint angles.

The second step, which is a fundamental challenge to estimating joint angles, requires establishing body segment anatomical frames from IMU data. The resulting body segment anatomical frames may well differ from those estimated from optical motion capture, particularly given that the data used are distinctly different between the two systems. Exceptions, such as the methods described in (Picerno et al., 2008), may well yield superior agreement. However, distinct estimates of body segment anatomical frames arise even using established motion capture methods. For example, (Robinson and Vanrenterghem, 2012) found significant differences between anatomical frames defined using a traditional anatomical approach (i.e., markers on anatomical bony landmarks) versus a functional approach (i.e., using data collected during specific movements). Consequently, agreement (or disagreement) between the joint angles estimated from optical versus inertial motion capture depends simultaneously on the errors in the IMU orientation estimations (errors associated with the first step) *as well as* the degree of misalignment in the anatomical frames (errors associated with the second step).

The available literature reveals widely differing methods to address this challenge. Focusing on the lower limbs, Picerno (2017) reviews 12 articles that employ divergent methods for estimating rotations across the hip, knee, and ankle arising from different strategies to define the requisite anatomical frames. Focusing on the upper limbs, Walmsley et al. (2018) review 66 articles in considering wearable sensor characteristics, subject population demographics, and psychometric evaluation. They note that these studies, including those employing commercial products, employ distinct methods for estimating joint angles for each joint. In addition, Poitras et al. (2019) review 42 studies of both upper and lower limbs and consider the validity and reliability of joint angles estimated from inertial motion captured compared to optical motion capture. They emphasize that differing methods to align the IMU sense axes to the underlying anatomical frames strongly affect the joint angle comparisons. Collectively, these reviews highlight many methods for defining the underlying anatomical frames for inertial motion capture that are significantly different and significantly affect the estimated joint angles. Consequently, it is difficult, if not impossible, to compare results across studies.

The objectives of this survey are two-fold; namely: (1) to categorize the different methods used to define anatomical frames of reference for inertial motion capture and, (2) to demonstrate their use and evolution in the field of biomechanics. Doing so highlights the need for our community to converge to a common method (or even just a small subset of methods) in the future.

2. Methods

To achieve the above objective, we completed a systematic survey of the literature by searching for relevant articles that employed IMUs for biomechanical measurements including estimating the orientation of body segments. Database searches were conducted in August 2018 using Pubmed (1781–2018), Web of Science (1900–2018), and Scopus (1788–2018) with the following search terms:

- (inertial sensor OR wearable sensor OR accelerometer OR gyroscope OR inertial measurement unit OR IMU) AND ((angle OR rotation OR kinematic) AND (joint OR shoulder OR elbow OR wrist OR hip OR knee OR ankle OR foot))

This search alone produced 1,468 results. The subsequent search process included removing duplicate works and reviewing titles and abstracts with the following initial inclusion and exclusion criteria:

- Must be a peer-reviewed journal article
- Must be published between 2000 and 2018
- Must include measurements on living human subjects
- Must not require invasive means for IMU alignment (e.g., bone screws or surgery)
- Must not require indirect measurement of body segment orientation or joint angles via IMUs (e.g., inferring knee joint kinematics solely from a sacrum-mounted IMU)
- Must not require measurements from other sources external to the IMU (e.g., a Microsoft Kinect) for IMU orientation estimation

Additionally, the methods for each article were carefully reviewed relative to the following additional inclusion criteria:

- If estimating at least one joint angle, at least one accelerometer or angular rate gyro must be attached to the associated body segments *or* one body segment must remain sufficiently stationary during testing. This inclusion requirement was added to distinguish between works that simply estimate the orientation of a body segment relative to a world frame versus those that estimate the orientation of a body segment relative to another body segment.
- It must describe the method for determining the orientation of the IMU-fixed frames relative to the anatomical frame of the body segment to which they were attached. This inclusion requirement was added to eliminate any articles that did not include information about how the anatomical frames were estimated.

Following these inclusion and exclusion criteria, 72 articles remained. An additional 40 articles were then added following iterative manual searching of the references within and citations to the 72 articles, yielding a total of 112 articles included in this survey.

While the survey methods above are similar to those of a systematic review (e.g., Moher et al, 2009), they do not include a meta-analysis analysis due to the presence of many confounding variables associated with the first and the second steps in the joint angle estimation process (refer to Fig. 1 and the discussion in the Introduction). Significant confounding variables are as follows. The length of the data collection greatly impacts any potential agreement between inertial and optical motion capture estimates of joint angles due to the inevitable drift errors in inertial motion capture estimates that increase with collection time. Unfortunately, many articles included in this survey do not indicate the length of trials over which the IMU orientations are estimated. Second, the studies employ distinct IMU generational designs. Advancements in microelectromechanical system (MEMS) fabrication techniques have greatly improved sensor noise characteristics which directly affect the quality (i.e., drift error) of the IMU orientation estimates. Unfortunately, many articles included in this survey do not report the noise characteristics of the IMUs. Third, the studies employ a wide range of algorithms to estimate IMU orientation (e.g., extended Kalman filter, complementary filter, etc.) whose results also depend significantly on the parameterization of the algorithm (e.g., process model and measurement noise) as well as the use (or not) of additional sensor data (e.g., magnetometer data). These and other confounding variables render a meta-analysis to determine which approach to defining anatomical frames is superior difficult to conduct.

3. Results

Fig. 2 illustrates a breakdown of the 112 articles based on the major skeletal joints that were studied including the shoulder,

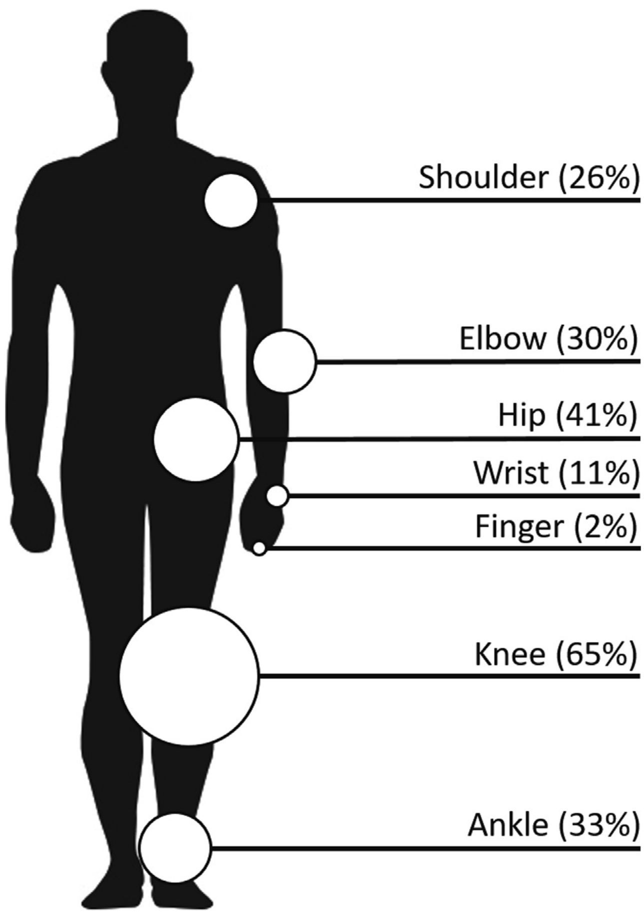

Fig. 2. Percentages of articles that estimated specific joint kinematics.

elbow, wrist, finger, hip, knee, and ankle joints. For context, more than half of the articles (73 articles or 65%) included estimates of knee rotation.

The methods reported in the literature for defining anatomical frames of reference for inertial motion capture can be broadly grouped into one of four categories of methods.

1. Assumed Alignment (AA) Method: In this method, an IMU is attached to a body segment such that the IMU-fixed frame of reference is approximately aligned with the anatomical frame of the body segment to which it is attached.
2. Functional Alignment (FA) Method: In this method, participants complete some known movement(s) or pose(s) for which at least one anatomical axis can be estimated in an IMU-fixed frame of reference.
3. Model Based (MB) Method: In this method, body segment anatomical axes are estimated by using either a kinematic model or a statistical model of the joint.
4. Augmented Data (AD) Method: In this method, a source other than the IMUs (e.g., optical motion capture) provides information needed to determine the relationship between the IMU-fixed frame of reference and the body segment anatomical frames.

Fig. 3 illustrates how each of the four categories of methods would be used in the context of determining anatomical axes for the shank.

Fig. 4 illustrates a breakdown of the four categories of methods employed in the (1 1 2) articles during the period 2000–2018.

Table 1 reports the 112 articles for the period 2000–2018 by method category and by the number of rotational degrees of freedom (DoF) estimated (1, 2, or 3 DoF). Importantly, the DoF prescribe the number of anatomical angles that were estimated by the manuscript's method. However, which anatomical angles were estimated varies by joint (i.e., 2 DoF for the knee includes flexion–extension and abduction–adduction whereas 2 DoF for the elbow includes flexion–extension and pronation-supination).

Fig. 5 illustrates the historical frequency of use of each of the four categories of methods for the period 2000–2018 as functions of year. Also shown is the cumulative total (shaded grey area) of all articles (i.e., across all four categories of methods).

We emphasize the significant variation in the categories of methods used for any one joint by focusing on the prevalent studies of the human knee. Fig. 6 reports the number of articles employing each of the four categories of methods as well as the number of knee joint rotational degrees of freedom examined. The 44 articles examining 1 DoF estimates of the knee focus solely on knee flexion–extension. The 5 articles examining 2 DoF estimates of the knee examine both flexion–extension and abduction–adduction. Finally, the 24 articles examining 3 DoF estimates of the knee examine flexion–extension, abduction–adduction, and internal-external rotations. A further breakdown of the results for the articles estimating 3 DoF knee rotations follows next.

For 3 DoF analyses of the knee joint, only four articles employed AA methods to estimate the anatomical frames of reference, though two offer limited validation. (Ahmadi et al., 2016) offers validation only for flexion–extension estimates while (Sun et al., 2017) offers no validation. (Kun et al., 2011) offers validation for all 3 DoF but employs an invasive procedure where the IMUs are first mounted to rigid links (connected by a universal joint) that are then strapped to the thigh and shank. (Favre et al., 2006) also offers validation for all 3 DoF, but note that the accuracy of the IMU-derived joint angles requires expert placement of the IMUs on the thigh and shank which is particularly challenging for the abduction–adduction (anterior-posterior) axis.

Clearly, the majority (16) of the articles estimating 3 DoF rotations across the knee employ FA methods. However, these 16 articles employ distinct functional alignment movements to establish the anatomical frames for the thigh and shank. For example, in (Favre et al., 2008), participants first stand in a neutral static pose and then execute a hip abduction–adduction movement during which the knee is locked. The pose and movement establish the shank and thigh superior-inferior and posterior-anterior axes, respectively. The third anatomical axes, namely the shank and thigh medial–lateral axes, follow from a subsequent cross-product of the prior two axes. In (Fasel et al., 2017a), participants similarly first stand in a neutral static pose to establish the superior-inferior axes, then complete slow squats to establish the medial–lateral axes. The anatomical frames of reference are again completed by subsequent cross-products. While these two approaches yield anatomical frames of reference for the knee joint for inertial motion capture, it is likely that they are different from one another and also misaligned with those defined using optical (positional) motion capture conventions. In addition, (Fasel et al., 2017a) notes that defining anatomical frames is acceptably repeatable within subjects but not necessarily between subjects.

Finally, it is also noteworthy that six of the seven articles using MB methods focus on the knee, and they range in complexity from (Seel et al., 2014) for 1 DoF to (Bleser et al., 2017) and (Zimmermann et al., 2018) for 3 DoF, with (Bleser et al., 2017) providing the foundation for (Zimmermann et al., 2018). Despite the obvious advantages of MB methods (i.e., they do not require precise alignment of the IMU's on body segments or functional alignment movements), results remain limited to date. The most

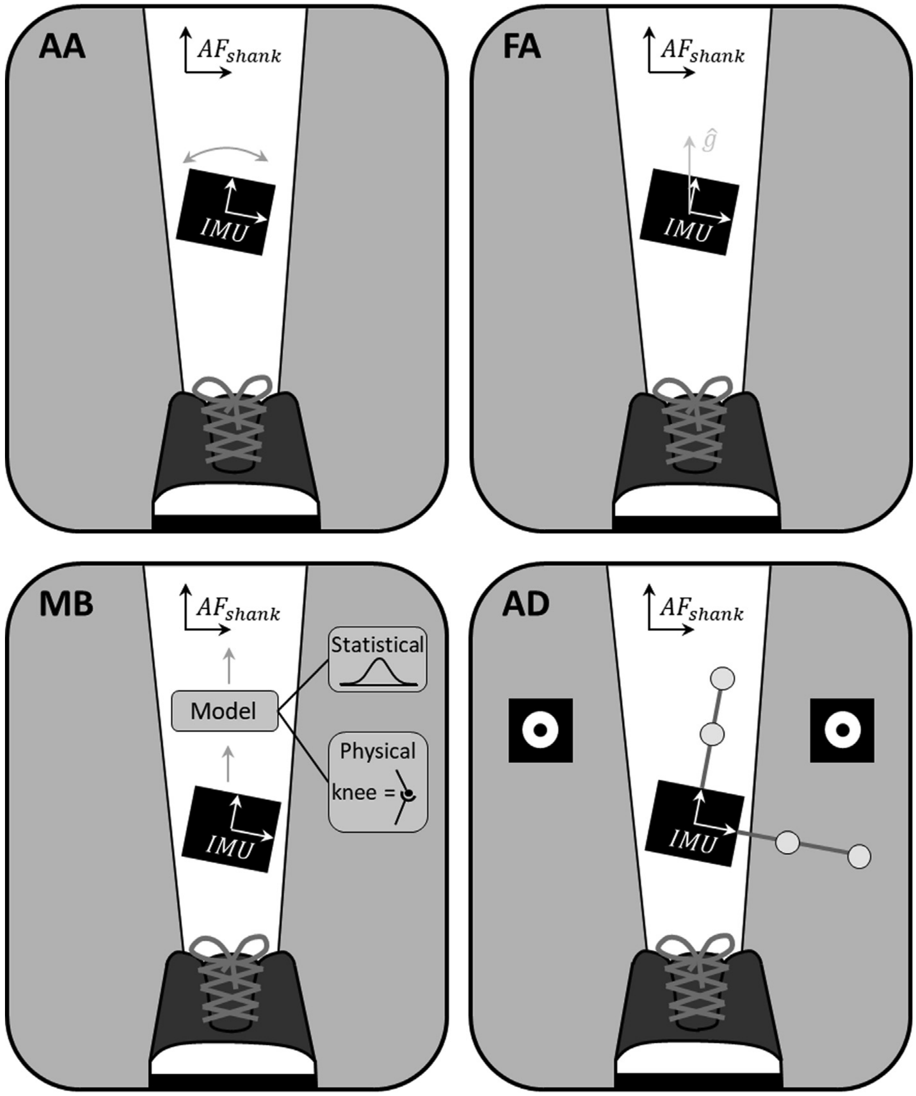

Fig. 3. Schematic of the four categories of methods in the example of determining the anatomical axes of the shank. For the Assumed Alignment (AA) method, the IMU is manually rotated such that its sense axes are aligned with the shank anatomical frame. For the Functional Alignment (FA) method, the measured acceleration during a neutral standing posture yields the direction of gravity which is aligned with the superior-inferior axis of the shank. For the Model Based (MB) method, the IMU data is input into either a statistical or kinematic model of the knee which then estimates the shank anatomical frame. For the Augmented Data (AD) data, reflective markers are attached to the IMU to determine the orientation of the IMU sense axes relative to the shank anatomical frame.

successful MB approach for estimating 3 DoF knee joint angles (Zimmermann et al., 2018) creates a (statistical) model for the knee employing deep learning techniques trained on real and simulated IMU data to estimate the anatomical frames.

4. Discussion

Reflecting on Fig. 2, inertial motion capture has been used pervasively to estimate the major skeletal joint angles for the lower body (knee, hip, and ankle) as well as the upper body (elbow, shoulder, wrist, and finger). From Fig. 4, the great majority of these studies employ either AA or FA approaches, which is likely due to the fact that they are relatively simple to employ for both testing and subsequent data analysis. However, as shown in Table 1, studies aiming to estimate 1D rotations tend to use AA methods whereas those aiming to estimate 3D rotations tend to use FA methods. The remaining two categories of methods, namely MB and AD, have been employed nearly equally between studies that estimate 1D and 3D rotations.

Fig. 5 illustrates the exponential growth in the number of studies using IMUs for estimating joint angles. While the articles included in this survey represent a small fraction of those employing inertial motion capture for all purposes, the growth apparent in Fig. 5 confirms the significant promise and adoption of this technology for biomechanics research. Furthermore, Fig. 6 illustrates that all four categories of methods have been employed for studying the human knee. However, as emphasized above, there is also wide variation in how the methods within each category have been applied to the knee. Given both the significant growth in inertial motion capture as well as the significant variability in the methods used, there is a growing need to establish a convention for defining anatomical frames.

Given the challenges associated with estimating IMU orientation, it is reasonable that the earliest studies would use AA methods followed by FA methods. The MB methods have only just started to appear in the literature starting with (Seel et al., 2014). Only a few studies have employed AD methods, which have also not grown in popularity over the years. This is likely due to the

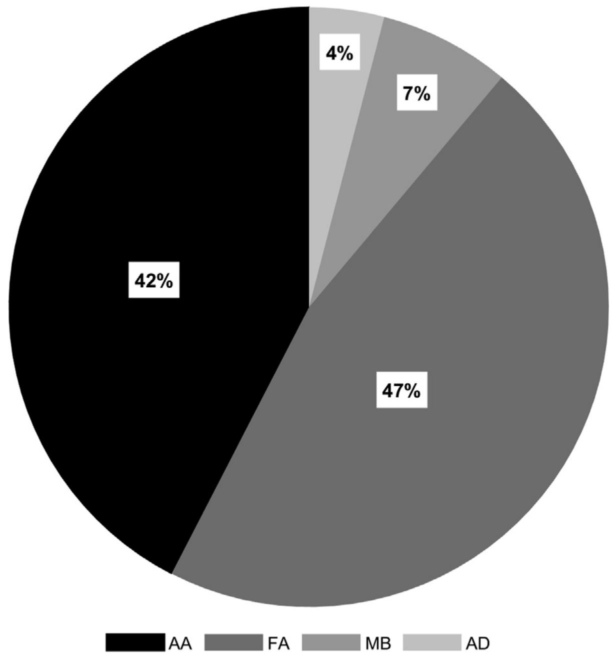

Fig. 4. Breakdown of articles for the period 2000–2018 by category, namely Assumed Alignment (AA) methods, Functional Alignment (FA) methods, Model Based (MB) methods, and Augmented Data (AD) methods.

impracticality of requiring additional motion capture (or other) data and equipment. However, it should be noted that the methods described by (Picerno et al., 2008) for lower limbs (and more recently by (Picerno et al., 2019) for upper limbs) is unique in that the additional equipment is IMU-based and mimics the anatomical approach for establishing anatomical frames for optical motion capture.

The vast majority of the studies included in this survey compare joint angles measured by inertial motion capture to those measured by optical motion capture. While this is a logical comparison, caution should be exercised due to the fundamental differences in how anatomical frames are deduced from position (i.e., MOCAP) data versus motion (i.e., IMU) data. Furthermore, while optical motion capture is largely regarded as the "gold standard" in the biomechanics community, it should not be construed as yielding ground truth data. For instance, optical motion capture is susceptible to marker misalignment errors and soft-tissue artefacts (among other errors) when compared with truth data provided by stereoradiography/dual-plane fluoroscopy or similar techniques (Stagni et al., 2005; Akbarshahi et al., 2010; Li et al., 2012; Fiorentino et al., 2017; Hume et al., 2018).

Finally, we comment on possible limitations. The 112 articles included in this study were limited to those found in peer-reviewed journals and not conference proceedings. This eliminates redundant publications where the same (or very similar) studies are published in both venues. Second, the included articles appeared in 2000–2018 and this excludes several articles published prior to this timespan (see, for example, the historical perspective offered by (Picerno, 2017)). Third, given the exponential growth observed in Fig. 5, many relevant articles likely have appeared since. However, it is also unlikely that these additional articles would alter the two overarching conclusions from the (nearly two decades worth of) prior studies represented in this survey; namely, (1) that there exist qualitatively different ways of establishing anatomical frames, and (2) our research community is now in need of a common convention.

Table 1
Listing of all 112 articles for period 2000–2018 by method category and by the number of rotational degrees of freedom (DoF) estimated.

	1 DoF	2 DoF	3 DoF
AA	Ohtaki et al. (2001), Williamson and Andrews (2001), Dejnabadi et al. (2005), Dejnabadi et al. (2006), Findlow et al. (2008), Zheng et al. (2008), Krüger and Edelmann-Nusser (2010), Djurić-Jovičić et al. (2011), Paulis et al. (2011), Saito and Watanabe (2011), Watanabe et al. (2011), Djurić-Jovičić et al. (2012), Guo et al. (2012), Ockendon and Gilbert (2012), Arosha Senanayake et al. (2013), Caroselli et al. (2013), Guo et al. (2013), Martínez-Solís et al. (2014), Šlajpah et al. (2014), Takeda et al. (2014), Chen et al. (2015), Jaysrichai et al. (2015), Picerno et al. (2015), Kodama and Watanabe (2016), Tannous et al. (2016), Chiang et al. (2017), Djurić-Jovičić et al. (2017), Morrow et al. (2017), Ruiz-Olaya et al. (2017), Villeneuve et al. (2017), Ong et al. (2018)	Takeda et al. (2009a), Lin and Kulić (2012), Ma et al. (2015)	Makikawa et al. (2001), Favre et al. (2006), Liu et al. (2010), Pérez et al. (2010), Kun et al. (2011), El-Gohary and McNames (2012)), Ahmadi et al. (2016), Kirking et al. (2016), Mazomenos et al. (2016), Miezal et al. (2016), Roldán-Jiménez and Cuesta-Vargas (2016), Rose et al. (2016), Sun et al. (2017)
FA	Luinge et al. (2007), Bergmann et al. (2009), Cutti et al. (2010), Zhang et al. (2012), Chardonnens et al. (2013), Tadano et al. (2013), Leardini et al. (2014), Fantozzi et al. (2015), Logar and Munih (2015), Li et al. (2016), Reenalda et al. (2016), Vargas-Valencia et al. (2016), Fasel et al. (2017b)), Nüesch et al. (2017), Blair et al. (2018), Fasel et al. (2018)	Takeda et al. (2009a,b), Penning et al. (2012), El-Zayat et al. (2013), van den Noort et al. (2016)	O'Donovan et al. (2007), Cutti et al. (2008), Favre et al. (2008), Favre et al. (2009), de Vries et al. (2010), Zhang and Wu (2011), Chardonnens et al. (2012), Gil-Agudo et al. (2013), Kim and Nussbaum (2013), Kim et al. (2013a), Laudanski et al. (2013), Öhberg et al. (2013), Zhang et al. (2013), Bouvier et al. (2014), Cockcroft et al. (2014), Li and Zhang (2014), Palermo et al. (2014), Ricci et al. (2014), Bouvier et al. (2015), Khurelbaatar et al. (2015), van den Noort et al. (2015), Álvarez et al. (2016), Ertzgaard et al. (2016), Fantozzi et al. (2016), Kong et al. (2016), Fasel et al. (2017a), Kim and Lee (2017), Ligorio et al. (2017), Mangia et al. (2017), Robert-Lachaine et al. (2017b), Robert-Lachaine et al. (2017a), Al-Amri et al. (2018
MB	Seel et al. (2014), Allseits et al. (2018), Fineman et al. (2018), McGrath et al. (2018		Bleser et al. (2017), Müller et al. (2016), Laidig et al. (2017), Zimmermann et al. (2018)
AD	Cooper et al. (2009), Gastaldi et al. (2016), Alizadegan and Behzadipour (2017)		Picerno et al. (2008), Teufl et al. (2018)

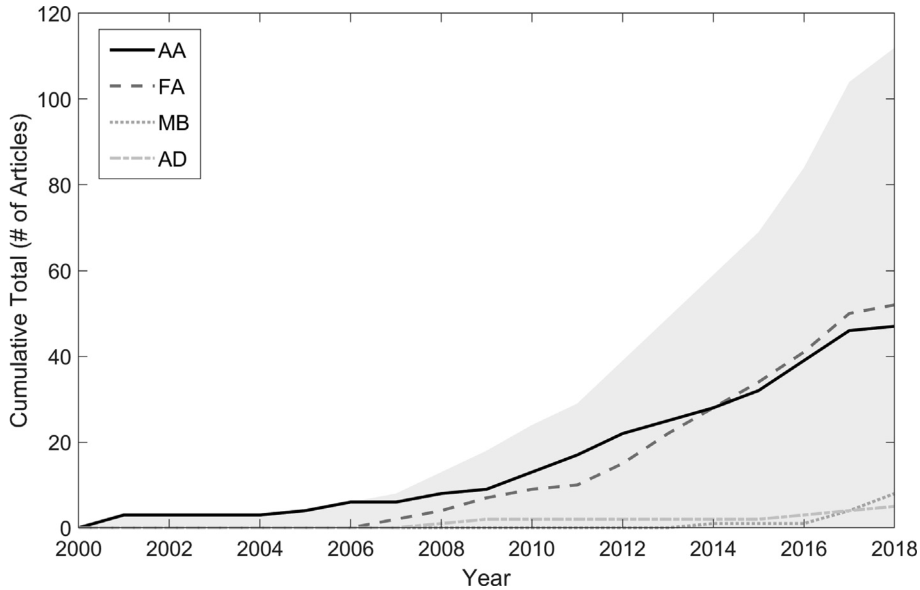

Fig. 5. Cumulative total of articles employing each of the four categories of methods versus publication year. The grey-shaded area illustrates the cumulative sum across all approaches.

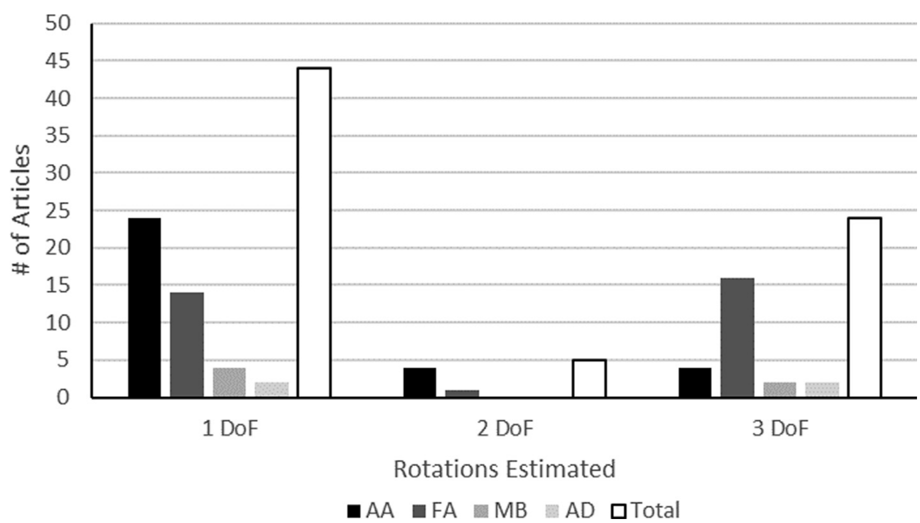

Fig. 6. Numbers of articles focusing on the human knee for the period 2000–2018 by category of method used and by rotational degrees of freedom (DoF) considered across the knee joint. Also shown in white are the totals for each rotational DoF category.

5. Conclusions

This paper surveys the methods used to estimate anatomical frames of reference for inertial motion capture. These methods fall into four main categories; namely, (1) Assumed Alignment (AA) methods, (2) Functional Alignment (FA) methods, (3) Model Based (MB) methods, and (4) Augmented Data (AD) methods. Unfortunately, but not unexpectedly, there is significant variation in the estimates of the anatomical frames of reference between these four categories of methods and also between the differing implementations within each category. In addition, there is significant variation between the anatomical frames estimated from inertial motion capture versus those estimated by optical motion capture. Thus, significant challenges remain in comparing results across studies. Consequently, there is significant motivation to develop a common convention for defining anatomical frames for inertial motion capture to seed future adoption of this promising technology.

Among the four categories, MB methods are promising in that they do not reply on the researchers' ability to carefully orient IMUs to the body segments (as required in AA methods) or for subjects to properly execute functional alignment movements (as required in FA methods). However, the MB approaches are relatively new, joint-specific, and will require significant future validation (and training data as in the case of (Zimmermann et al., 2018)).

Lastly, while the methods presented in the literature (as of August 2018) fall into one of the four categories described herein, it is entirely possible that new categories of methods have yet to be discovered. We also remind the reader that the findings and implications of this work pertain to methods for determining the anatomical frames of reference using inertial motion capture. The definitions of the anatomical frames, the rotation sequences, and the joint angles (including the sign and naming) remain as defined by ISB convention.

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.

Acknowledgements

This material is based upon work supported by the US Army Contracting Command-APG, Natick Contracting Division, Natick, MA, under contract W911QY-15-C-0053. We also thank the reviewers for their thoughtful and diligent comments that helped improve and clarify this manuscript.

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