Lower Limb Joint Kinematics

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The use of inertial measurement units (IMUs) has gained popularity for the estimation of lower limb kinematics. However, implementations in clinical practice are still lacking. This review shows that methods for lower limb joint kinematics are inherently application dependent. Sensor restrictions are generally compensated with biomechanically inspired assumptions and prior information. Awareness of the possible adaptations in the IMU-based kinematic estimates by incorporating such prior information and assumptions is necessary, before drawing clinical decisions. Future research should focus on alternative validation methods, subject-specific IMU-based biomechanical joint models and disturbed movement patterns in real-world settings.

Keywords: inertial measurement unit ; lower quadrant ; movement analysis ; outside laboratory ; sensor fusion

1. Introduction

Evaluating kinematical characteristics is crucial for a correct clinical understanding of complex functional movements such as gait [1], a forward lunge and other tasks requiring optimal motor control [2]. Studying kinematics can help in the assessment of the patients' functionality and progression in their rehabilitation period. Different lab-based methods are currently available for researchers to obtain kinematical parameters.

A 3D optical motion capture system is currently the gold standard and the most commonly used technique to study lower limb movement [3]. However, optical motion capture systems require a rather expensive set-up of infrared cameras that track reflective markers attached to the body of a subject. This type of movement analysis is therefore only applicable in a dedicated laboratory environment and thus is restricted in physical space. Furthermore, the accuracy in the obtained joint kinematics directly relates to a correct placement of markers [4][5] and soft tissue artifacts [3].

To overcome these restrictions, the use of wearable devices to monitor human movements has been studied extensively [6][7]. Recent reviews concerning kinematic analysis with inertial measurement units (IMUs) are typically conducted either by engineering experts [7][8][9] or by clinicians [10][11][12], who focus on technical aspects or clinical relevance. Previously conducted reviews highlighted the growing interest for inertial sensors in clinical practice [13]. Benson et al. [1] reported the need for gait analysis over longer time periods, with larger number of participants, in natural environments. O'Reilly et al. [14] pointed towards the use of machine learning techniques for lower limb exercise detection and classification with IMUs. Moreover, Picerno [12] presented a history of methodologies for IMU-based joint kinematic estimation of the past 25 years in gait analysis.

However, when applying IMU-based joint kinematics to specific applications in a clinical setting, a good understanding of the methodological requirements is still lacking. The aim of this review is twofold—to evaluate the methodological requirements for IMU-based, lower limb joint kinematic estimation to be applicable in a clinical setting, and to suggest future research directions.

2. Discussion

This review systematically evaluated the methodological requirements for IMU-based lower limb joint kinematic estimation. Human motion analysis with inertial sensors has the potential to increase understanding in movement patterns in trusted well-known environments [10]. However, from an engineering point of view, it is an ambitious goal that is currently the subject of research [1][12]. A general inconsistency in accuracy of the study results (Table 3) indicates that the signal processing characteristics summarized in Section 3.2 (Table 2) highly depend on the application (Table 1) of interest.

In summary, lower limb kinematic estimation from inertial sensors requires a well-defined application and study characteristics. The study characteristics define which sensor modalities will be measured and processed to compensate for the following sensor restrictions: (1) due to their microelectromechanical architecture, raw sensor measurements are prone to noise and non-zero biases; (2) an integration step of measurements is typically necessary to obtain joint kinematics, resulting in drifting estimates of sensor orientations and joint kinematics; (3) inertial sensors are usually not aligned with the bone, which implies that misalignment with respect to anatomical coordinate frames needs to be identified; (4) initial sensor orientations need to be determined.

In order to overcome these sensor restrictions, all of the included articles were required to rely in some way on application-specific prior information and assumptions. However, by including this additional information in the methodology, the resulting kinematic estimates need to be interpreted carefully, taking into consideration a number of factors, before drawing any clinical decision.

First, the biomechanical system yields usable prior information, but this information can be violated in practical applications. For example, assumptions on the range of motion can restrict the kinematic solution to be within a given interval of normal physical ability. However, RoM boundaries are not generalizable across patient populations who might be hypermobile or hypomobile, exceeding or not reaching normal RoM respectively. Also, segment lengths are relevant priors that can be obtained, as described by Crabolu et al. [15]. Multiple studies make use of an estimated vector that describes the position of the center of the joint in the sensor's coordinate frame [16]. Such joint center position vectors implicitly assume that segments are rigid and connected at one common fixed point. However, possible small joint-translational movements and soft tissue artifacts will violate this model [17]. In reality, soft tissue artifacts are present when patients move [18]. Frick et al. [17] recently proposed a method that identifies the time variations of a joint center position vector due to soft skin movement, but lacks a proper validation. Ideally, prior knowledge is estimated from sensor measurements [19][20][15] rather than measured in a movement laboratory or obtained from anthropometric tables.

Second, assuming periodicity in motion dates back to Morris et al. [21], to solve for integration drift by making the beginning and ending of a gait trial equal [22]. Still, a more relaxed assumption on periodicity, instead of resetting, is more convenient [23]. Two studies compensate for integration drift in azimuth angles on a cycle-by-cycle manner during mid-stance in gait [23][24]. Nevertheless, the latter is not a measure of absolute heading and might lead to accumulating errors on the foot progression angle [25]. Along the same lines, symmetry assumptions can help to allow for reducing the number of sensors on the body [26][27], but might over-constrain the system. For example, Bonnet et al. [27] analyzed the execution of a squat movement with a symmetry assumption on the legs. The method intends to only use one sensor, placed at the lower back. However, by applying a symmetry assumption, frontal hip, knee, and pelvis motion are not assessed, while still very relevant in such transitional movements [28]. Multiple studies utilized a zero-acceleration assumption at the contact point of the foot with the ground and therefore expected one foot to be on to the ground on a regular basis. Note that such an assumption might become invalid when applied to movements that lack a regular mid-stance phase such as running or other arbitrary movements.

Moreover, calibration movements are typically required to obtain a misalignment matrix between the sensor and anatomical reference frames. However, predefined calibration movement with a fully extended leg can be difficult within certain patient populations or during post-op periods [29][30]. As a result, the precision of the calibration depends on the accuracy with which the subject or instructor performs the calibration movements. A trend towards calibration-free methods with arbitrary placement of sensors and the avoidance of calibration movements is visible [19][31][32].

The incorporation of additional information such as assumptions and prior information can easily be done in an optimization-based smoothing approach for applications that demand high accuracy [33][34]. Solving such problem in a smoothing way, implicitly uses all available data [33][35] instead of a one-way filtering approach with only samples of the past. On the other hand, biofeedback applications ask for computationally less expensive fusion methods that can provide real-time estimates such as complementary filters [36][37][30].

3. Future Research

This review highlights the application dependency and inherent connection of methodological characteristics for lower limb IMU-based kinematic estimation. Assumptions and prior information are typically used to compensate for sensor limitations and to enhance the quality of kinematic estimates. Because of this, IMU-based kinematic estimates have to be interpreted carefully, before drawing any clinical decision. We identified a number of directions and pieces of advice for future research for the estimation of clinically relevant lower limb kinematics.

4. Reporting Joint Kinematics

For the clinical interpretability of the joint kinematics, the general reporting standards from the International Society of Biomechanics (ISB) [38][39] need to be followed. Only seven out of thirty-one of the included articles mentioned these standards. Joint kinematics are described as the movement of a distal segment with respect to its proximal segment, following a joint coordinate system [40]. The following movements are clinically relevant: (1) flexion/extension movements in the sagittal plane that occurs around the proximal segment-fixed frontal axis; (2) internal/external movements around the body-fixed longitudinal axis of the distal joint describing movements in the transversal plane; (3) abduction and adduction movements around the floating axis perpendicular to the two previously mentioned axes, describing frontal plane movement.

5. Biomechanical Joint Modeling

Gait predominantly occurs in the sagittal plane, and therefore the knee is often modeled as a hinge joint. A hinge joint axis can be estimated from IMU readings [19] to compensate for the misalignment between sensor and bone, which allows for an arbitrary placement of the sensing units. However, smaller joint movement in frontal and transversal planes also occurs and plays a critical role in for example ligament injuries [41][42][43]. Investigation in more complex and even subject-specific tibiofemoral joint models with inertial sensors, may provide highly valuable inside in these secondary joint kinematics for outside laboratory applications [44].

Furthermore, a recent trend is visible towards the inclusion of multiple joints and segments, rather than estimating kinematics for separate joints [33][35][30]. When multiple sensors are exploited, common information can be used to improve kinematic estimates. In this case, an appropriate joint model needs to be chosen for each individual joint [45].

6. Validation with Respect to a Golden Standard Reference

Optical motion capture systems are the most commonly used technique to study lower limb movement. They are therefore also most often used as a reference to evaluate IMU-based joint kinematic estimation methods. However, due to manual marker placement errors [46] and soft tissue artifacts [5][47], a conventional 3D gait analysis system will introduce biases that are predominantly present in smaller frontal and transversal movements. These secondary joint kinematics yield valuable insight into ligament loading and ACL injury [48]. Stagni et al. [5] concluded that flexion/extension at the knee by means of optical external markers can be considered acceptably reliable. However, internal/external rotations and ab/adduction at the knee are critically affected by soft-tissue artifacts. In order to validate internal/external rotations and ab/adduction kinematic estimated by means of IMUs, alternative validation methods (i.e., biplanar radiographic imaging systems [49][50]) that might be superior in tracking underlying bone movements need to be examined.

7. Measurement Duration and Environment

Whilst IMUs are proposed for long term observations, there are still few studies tackling measurements beyond 30 s. With respect to long, in-the-wild studies, measurement duration must be increased [51][52][53]. Resolving this problem could potentially bring the use of IMUs closer to applications in which subjects can be monitored for hours or days, with bursts of activity in-between long in-activity periods [51][52][53]. To meet this requirement, a clear trend is visible towards magnetometer-free methods, only acquiring accelerometer and gyroscope readings. The authors of this review believe that this idea is important, specifically for outside-lab applicability (i.e., hospital environment, sports field), without the need for assumptions on magnetic field homogeneity.

8. Disturbed Movement Patterns

Most of the published work recruited young, healthy participants. However, in clinics, most attention must go to the investigation of different patient populations with disturbed daily functional movement such as gait, sit-to-stand, stand-to-sit or climbing stairs [28]. One of the crucial aspects here is the inability of the patient (e.g. [54], patients with neuromotor disorders or people with severe limb disorders) to perform pre-defined calibration movements, often necessary for the evaluation of functional movements with IMUs. The eligibility criteria in Section 2.1 demand a reproducible description of the algorithm. This might have resulted in studies that lack extensive validation on disturbed movement patterns, which is often done in a later phase. Investigating disturbed movement patterns and calibration-free methods to cope with sensor-to-segment misalignment in different patient populations will be an important avenue of research.

9. Conclusions

This review systematically evaluated the methodological requirements for IMU-based lower limb joint kinematic estimation. *Where are we now?* Despite the ongoing research regarding the computation of joint kinematics by means of IMUs, there still appear to be difficulties which prevent their use in daily clinical practice. It is reasonable to assume that the complexity in obtaining meaningful kinematic measures from noisy and biased measured sensor data and sensor restrictions regarding integration drift, sensor-to-segment alignment and initial sensor orientation explain these study restrictions. *What can already be measured with sufficient accuracy?* Most often, biomechanically inspired assumptions and prior information are used to compensate for sensor limitations. Both clinicians and engineers have to be aware of the possible adaptations in the IMU-based kinematic estimates by incorporating such prior information and assumptions, before drawing clinical decisions. *What needs to be tackled with high priority?* Investigating the appropriate validation methods that might be superior in tracking underlying bone movement and can overcome the restrictions of optical motion capture systems as a reference. *What might yield novel results?* Subject-specific IMU-based biomechanical joint models applied to populations with disturbed movement patterns in real-world settings. Combined efforts of engineers and clinical experts can result in application- and patient-specific implementations that will be valuable to clinicians.

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