Comprehensive Comparison of Methods for Estimating Lower-limb Joint Kinematics with Inertial Measurement Units: A Preliminary Study

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Abstract (261 words)

While accurate estimation of lower-body kinematics using inertial measurement units (IMUs) would revolutionize the field of biomechanical research and remote rehabilitation, it remains a significant challenge due to the drifting issue over a long period. Over the past few years, many sensor fusion algorithms have been developed to overcome this issue. However, of these algorithms, it is unclear which one performs the best and which one should be used in which situation to maximize estimation performance. In addition, recent years have witnessed advancements in biomechanical modeling with the purpose of improving kinematics estimation for human movement analyses. Well-known among these biomechanical models is OpenSense developed by researchers from Stanford University. However, whether biomechanical modeling (specifically using OpenSense) could bring significant benefits to joint kinematics estimation remains unknown. To fulfill this knowledge gap, we conducted a comparative study to compare performance of different sensor fusion algorithms with or without using OpenSense from motion data collected from four participants. We found that the complementary filters performed as well as Kalman filters which previously have been believed to achieve the best performance. No solid evidence showing that the biomechanical model of OpenSense improves the estimation accuracy. However, it could help correct the estimation of a specific joint angle with some cost to others. Lastly, our results suggested a simple and low-cost solution to eliminate skin or soft-tissue motion artifacts in real life by wrapping the sensor tightly to body segments. Our work provides useful information for future studies to develop new methods for improving IMU-based motion capture or to apply IMUs for clinical applications.

Keywords: Inertial Measurement Units, Joint Kinematics, Sensor Fusion Algorithms, OpenSense, Biomechanical Modeling.

INTRODUCTION (817 words)

Inertial measurement units (IMUs) have been used for more than 30 years as alternatives to traditional marker-based systems for motion capture. These devices typically consist of an accelerometer measuring linear accelerations and a gyroscope measuring rotational rates in three dimensions. IMUs can also be integrated with a magnetometer for heading correction or other sensors like a barometer or thermal. They are affordable, wearable, and easy to use, which enables motion measurements in open spaces or natural environments (Picerno, 2017; Schall Jr, et. al., 2022; Díaz, et. al., 2019). The use of IMU-based joint kinematics estimation has a number of applications. Gait analysis and mobility assessments can help monitor people with knee osteoarthritis or total knee replacement or provide assessments for possible treatments for children with cerebral palsy (Picerno, et. al., 2021; Iosa, et. al., 2016; van der Straaten, et. al., 2018). Daily-life activity monitoring can give more holistic views into movements in natural environments (Benson, et. al., 2018). Not only does IMU-based joint kinematics estimation enable analysis in natural environments, but it's also relatively inexpensive in comparison to traditional marker-based systems, making it a good choice for assessment across a larger population.

To estimate orientation from IMU measurements, sensor fusion algorithms are widely applied (Picerno, 2017; Nazarahari and Rouhani, 2021; Nazarahari and Rouhani, 2021). These algorithms combine data from the accelerometer, gyroscope, and magnetometer to obtain more accurate and reliable orientation estimates. Overall, they can be grouped into two categories: the complementary filter and the Kalman filter (Nazarahari and Rouhani, 2021). The complementary filter (e.g., Madgwick or Mahony) combines data from the accelerometer and gyroscope to obtain a smoother and more accurate orientation estimate by proportionally using each sensor's orientation estimate based on a few tunable parameters (Madgwick, 2010; Mahony, et. al., 2008). The Kalman filter uses a mathematical model of the system–specifically noise and covariance–to dynamically change these tunable parameters to better predict the orientation (Kalman, 1960). The orientation estimates can then be used to obtain joint kinematics for various applications in computer graphics or biomechanics. However, orientation estimates involved in gyroscope measurements often fail due to the accumulation of errors through the integration of angular velocities. While sensor fusion helps address this by using data from other sensors it has a number of assumptions and entry points for noise that can cause a loss in accuracy. The performance of IMUs, which include accelerometers, gyroscopes, and magnetometers, is limited by several factors. These include significant noise in MEMS architecture, susceptibility of magnetometer measurements to ferromagnetic disturbances, assumptions made about linear acceleration that may not hold for all human movements–specifically linear acceleration's quasi-static nature–and filters with parameters tuned for specific use cases, resulting in a lack of robustness(Schall Jr, et. al., 2022; Madgwick, 2010; Mahony, et. al., 2008; Roetenberg, et. al, 2005; Sabatini, 2006).

Recent years witnessed the emergence of biomechanical modeling for estimating joint kinematics. Popular open-source software like OpenSim reconstructs musculoskeletal models from experimental measurements (Delp, et. al., 2007). For IMU-based biomechanical modeling, for example, OpenSense toolkit of OpenSim, virtual IMUs are placed on the segments of a skeletal model according to a user-defined mapping (Al Borno, et. al., 2022). Since the model requires the orientation of IMUs and segments to be known at the initial frame, a calibration step needs to be done by having subjects holding a specific pose at the beginning. The inverse kinematics (IK) process is then performed to minimize the difference between the orientation of predefined IMUs on the biomechanical skeletal model and that of real IMU records, subjected to the constraints defined by the skeletal model (Al Borno, et. al., 2022; Tagliapietra, et. al., 2018; Slade, et. al., 2021). After the IK, joint kinematics can be extracted for further analyses, depending on the demands of the downstream applications.

Commercial IMU systems, such as Xsens, incorporate biomechanical modeling for joint kinematics estimation, but details are not publicly available (XSens Technologies B.V., 2009; Roetenberg, et. al., 2009). Recent studies suggest biomechanical modeling can help mitigate drift and reduce magnetic disturbances (Al Borno, et. al., 2022). However, there is limited literature comparing the advantages of biomechanical modeling to sensor fusion methods alone or its potential to improve accuracy in other challenging conditions.

The main objective of this study is to validate benefits of using the biomechanical model from OpenSense to improve accuracy of joint kinematics estimation during sit-to-stand. Specifically, OpenSense is used to perform optimization using biomechanical modeling. In addition to investigating possible improvements with these additional biomechanical simulations, this study also investigates how OpenSense may improve estimation accuracy in other conditions, including sensor misplacement and soft-tissue motion artifacts. Sensor misplacement can be a source of error when IMU placements move after calibration and soft-tissue motion artifacts can introduce noise from the compliance of skin and underlying soft tissues. Finally, this study also evaluates the minimization of the drifting effect across different state-estimation filters with and without biomechanical modeling.

METHODS (1172 words)

In this research study, four male participants (age: 25 ± 2.7 years; weight: 66.6 ± 3.0 kg; height: 174.8 ± 4.3 cm; and leg length: 92.1 ± 6.0 cm), who are currently students at Carnegie Mellon University, were recruited. All participants provided verbal consent prior to their participation in this study. There were no exclusion criteria for this study. One had a history of an anterior cruciate ligament (ACL) strain in the right leg.

During the experiment, participants were guided through a series of walking and combined tasks, performed in the order depicted in Fig. 1. For the walking task, we let the subject do the neutral pose (i.e., N-pose) for 5 s for IMU calibration, jump 3 times vertically for synchronization, walk around the area in a circle for 10 minutes, and finally jump 3 times vertically again. For the combined task, the subject followed the same procedure at the beginning and completed the combined task of sit-to-stand 10 times, forward jumping 3 times or more, walking back to the seat, and sitting down to relax. This process was repeated three times, followed by 3 vertical jumps at the end. Before each task, participants were guided through a short practice trial to familiarize themselves with the requirements of the task. Verbal instructions were given throughout the protocol, and breaks of 2 minutes were incorporated after each experimental task to minimize the effects of fatigue.

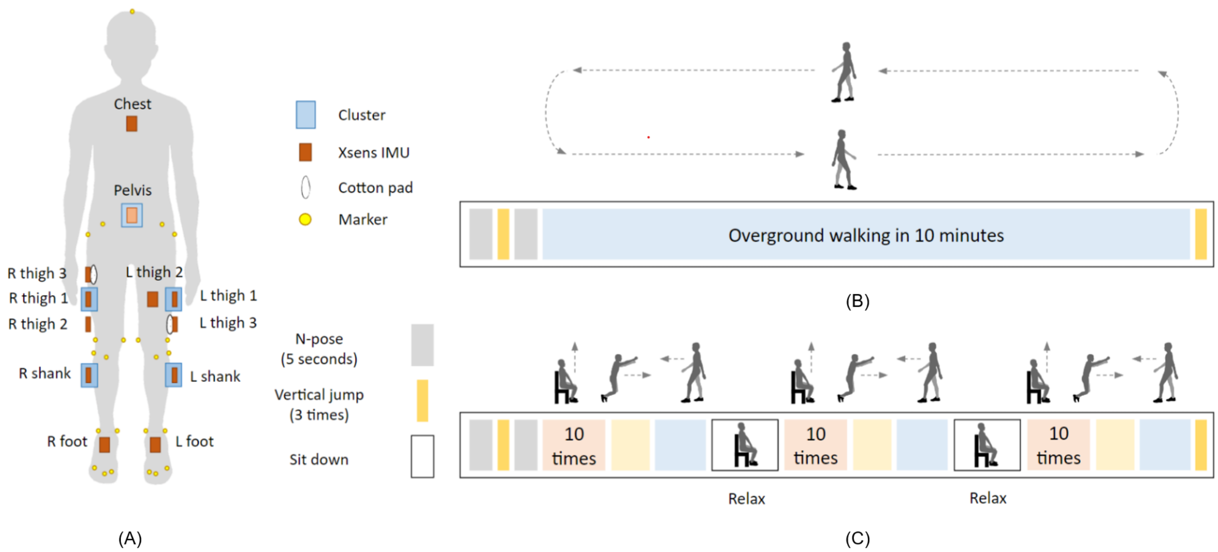

Fig. 1 The experimental setup and tasks performed in this study. (A) The placement of Xsens IMUs, motion capture markers, clusters, and cotton pads on all subjects to investigate sensor-to-body misalignment, soft tissue, and skin motion artifacts. (B) The 10-minute walking task. (C) The combined tasks, including sit-to-stand, forward jumping, and walking, with three repetitions and resting periods in between.

A marker-based motion capture system (OptiTrack, OR, USA) and an IMU system (Movella, NV, USA) were utilized for data collection. Reflective markers were placed on the subjects, following the modified Rizzoli marker set, with 41 markers on the anatomical landmarks of the lower body and marker clusters at the pelvis, thighs, and shanks. A total of 12 IMUs were positioned for various aims. Eight IMUs were affixed to the chest, pelvis, lateral thighs, lateral shanks, and feet. Additional IMUs were placed to evaluate the effects of sensor-to-body misalignment, soft tissue, and skin motion artifacts.

The marker data (collected at 100 Hz) underwent preprocessing, followed by unconstrained inverse kinematics (IK) to obtain ground truth joint angles. The preprocessing steps included low-pass filtering of the data at 15 Hz using a 4th-order Butterworth filter. In addition, the motion capture data were downsampled from 100 Hz to 40 Hz to align with the sampling rate of the Xsens IMU system, facilitating subsequent comparisons. Unconstrained inverse kinematics were executed using the recorded trajectories of anatomical markers. Since the movements of both tasks in this study mainly happened in the sagittal plane, we considered only flexion angles of the hips, knees, and ankles.

IMU data (collected at 40 Hz) were also preprocessed to obtain joint angles for comparison with the ground truth. We first identified the timestamp of the N-Pose for each participant by looking for periods when the vertical acceleration from the x-axis of the pelvis IMU was approximately 9.81 m/s². This was further confirmed visually using OpenSense. The N-Pose timestamp was then used as our reference timestamp for calibration. We then evaluated several sensor fusion filters to convert the acceleration, gyroscopic, and magnetometer data from the IMU sensors into orientation. These filters included the Madgwick, Mahony, Complementary, and Extended Kalman filters (EKF). With the quaternion orientations from the chosen filters and the determined N-pose timestamp (i.e., sensor-to-body calibration), we calculated the joint angles. This was completed under the assumption that the pelvis IMU during N-pose had the same orientation as the joints during N-pose. Euler angles were extracted from these quaternions to determine flexion angles of the hips, knees, and ankles. Additionally, we applied OpenSense, an open-source toolbox of the OpenSim software, for joint kinematics estimation using orientation data obtained from various sensor fusion algorithms. The process involved two main steps: model calibration and IMU inverse kinematics. During model calibration, we utilized data from a static N-pose to calibrate the skeletal model *(Rajagopal et al., 2015)*.

Since the default parameters from the sensor fusion algorithms are not set for biomechanical applications, we performed the tuning process. Data (only from the sit-to-stand task) of Participant 1 were used for tuning to maximize the estimation performance of the hip, knee, and ankle flexion angles of this participant. We then performed the evaluation on the data of the remaining participants to avoid overfitting.

To evaluate the effect of sensor-to-body misalignment, we placed additional IMUs on the anterior side of the left thigh (L Thigh 2) and compared it with the lateral thigh IMU (L Thigh 1) (Fig. 1). The goal was to investigate the potential impact of inaccuracies that may occur due to misalignment between the sensor and the body, which can affect the accuracy of motion tracking and joint kinematics analysis. Joint kinematics were calculated using XSens, Mahony, Madgwick, extended Kalman (EKF), and complementary filters. Parameters for these filters were manually tuned on subject 1 and used for evaluation on all other subjects. Due to poor performance, results from the complementary filter were discarded. Joint kinematics were calculated both with and without OpenSense to assess the influence of constrained biomechanical modeling on estimation accuracy in the context of sensor-to-body misalignment.

To simulate skin and soft-tissue motion artifacts, additional IMUs were placed along the longitudinal axis of both legs (Fig. 1). The L Thigh 3 IMU was placed on top of a piece of cotton to enhance the skin and soft tissue artifact and compared to the more rigid L Thigh 1 IMU placed on a cluster. Similarly, on the right leg, R Thigh 3 was compared to R Thigh 1. Additionally, R thigh 2 was strapped to the right thigh along the longitudinal axis for further comparison. Soft tissue and skin motion artifacts can affect the accuracy of IMU-based motion tracking by introducing noise and errors in sensor measurements, ultimately impacting joint kinematics. The placement of additional IMUs along both thighs provided insights into the magnitude and direction of these artifacts in relation to location and soft-tissue simulation. Joint kinematics were calculated using XSens, Mahony, Madgwick, and EKF filters. Parameters for these filters were manually tuned on subject 1 and used for evaluation on all other subjects. Joint kinematics were also calculated both with and without OpenSense to demonstrate how constrained biomechanical modeling affects estimated joint angles in the presence of soft-tissue artifacts.

All codes were developed using Python 3.8. We utilized several libraries, such as numpy, pandas, math for numerical and data manipulation tasks; matplotlib and plotly for visualization; and AHRS for sensor fusion algorithms. Our customized codes for this project are available on the GitHub repository at https://github.com/vuu-phan/IMU_Kins.git, where you can find detailed documentation and instructions for replicating the experiments and further extending the work.

RESULTS (426 words)

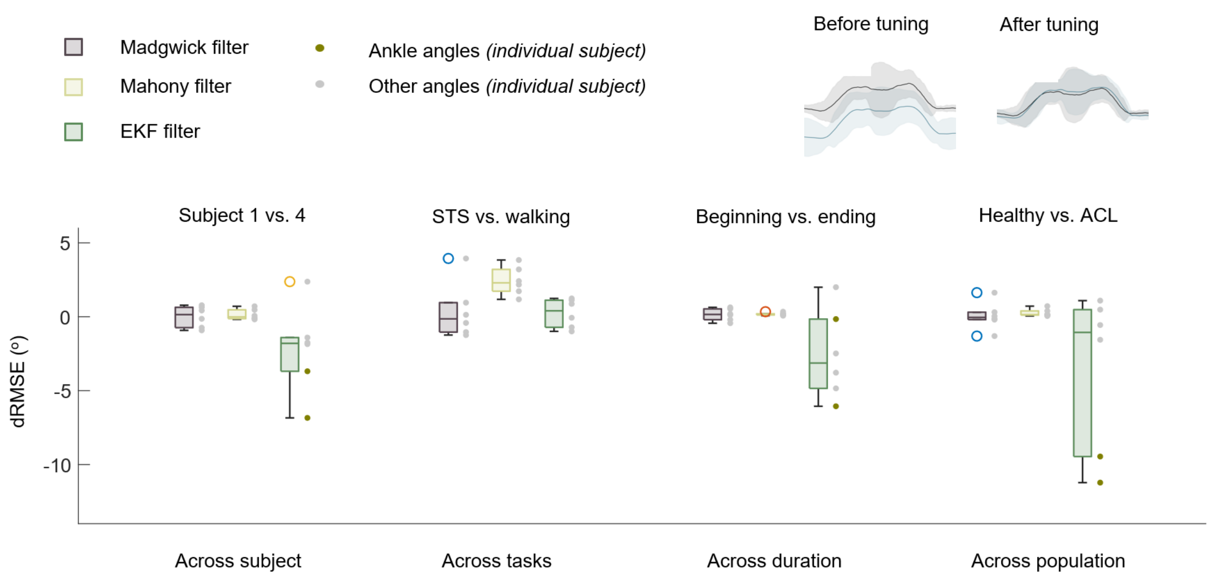

Fig. 2 Generalizability of tuned parameters for Mahony, Madgwick, and EKF filters. Change in joint angle estimation RMSE after state-estimation filter parameter tuning across different scenarios. The plot shows the RMSE differences (i.e., dRMSE) for each filter across various situations, including the subject (tuned on subject 1 and evaluated on 4), task (tuned on the sit-to-stand and evaluated on walking task, both were from the beginning trial), duration (beginning versus ending), and population (tuned on the healthy subject and evaluated on that with anterior cruciate ligament injury). Improvement was observed with EKF tuning, especially for the ankle angle.

The generalizability of the state-estimation filter parameter tuning across multiple scenarios, including subject, task, duration, and population (Fig. 2). The EKF filter demonstrated consistent RMSE improvement in all scenarios (i.e., reduction from nearly 3 to around 5 degrees in RMSE median) except for time. In contrast, the Madgwick and Mahony filters show no significant change in RMSE values (i.e., dRMSE is almost equal to 0 degrees). The ankle joint benefits the most from EKF filter tuning, as shown by its consistently improved RMSE values across all scenarios for all trials (i.e., reduction up to 10 degrees when evaluating the effectiveness of tuning across the population).

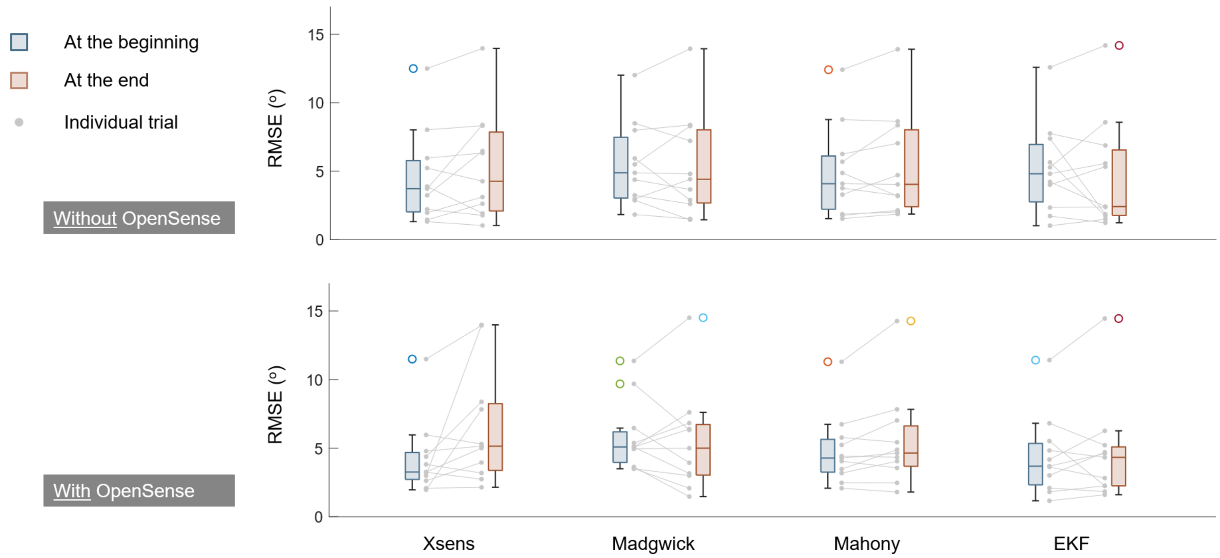

Fig. 3 Comparison of various sensor fusion algorithms with and without biomechanical modeling on joint angle estimation. The plot presents the RMSE values for Xsens, Madgwick, Mahony, and EKF algorithms across different scenarios, including variation in time and the use of OpenSense for biomechanical modeling. There was no difference across sensor fusion algorithms whether OpenSense was applied or not.

No significant difference in RMSE values is observed among the four algorithms (Fig. 3). Most sensor fusion methods achieved the median RMSE from 4 to 5 degrees. Estimation of the hip angle was the worst with the RMSE values possibly being up to above 14 degrees. The Xsens built-in filter exhibited slightly increased RMSE variability across joints over time, indicating potential limitations in its performance for long-duration experiments. Additionally, incorporating biomechanical modeling using OpenSense did not yield a noticeable improvement (despite reducing the variation of estimation across subjects) in estimation performance.

All sensor fusion methods were severely impacted given sensor misplacement. Since there is a consistent trend across different methods, here, we presented results from the Xsens built-in filter only as a representative example. RMSE values of the hip and knee angles noticeably increased (up to 65 degrees) when the thigh sensor was misplaced (i.e., 90 degrees rotation by the x-axis, or from the lateral side to the anterior) regardless of the use of OpenSense (Fig. 4).

While biomechanical constraints from OpenSense reduced the estimation error of the hip angles (i.e., from up to 65 degrees without constraints to above 30 degrees with constraints), it increased the error in estimated knee and ankle angles. Since data from the misplaced sensor were not involved in the calculation of the ankle kinematics, the ankle angles remained the same for inverse kinematics without using OpenSense. However, this was not the case when using OpenSense where the estimated ankle angle became less accurate.

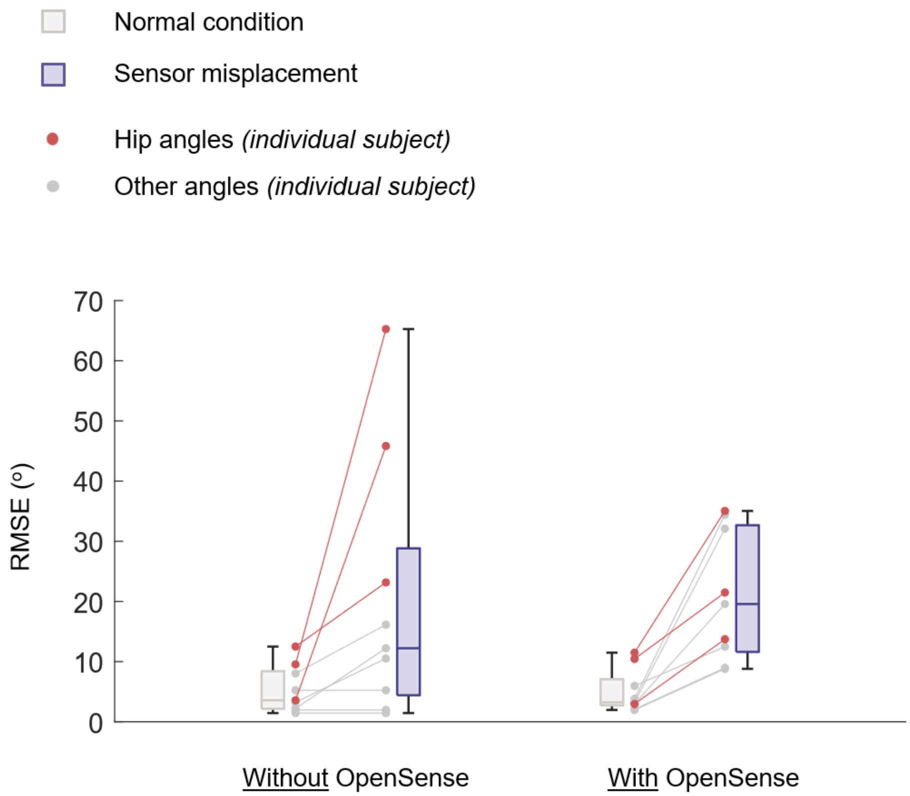

Fig. 4 Impact of sensor misplacement on the estimation accuracy of joint angles using Xsens built-in filter. The RMSE values of the hip and knee flexion angles noticeably increase as the left thigh sensor is misplaced (i.e., from the lateral side to the anterior). However, the estimation of the other angles (i.e., knee and ankle) was adversely affected.

Whether the sensors were attached directly to the skin or the soft cotton pads, no difference in kinematics estimation was found (Fig. 5). Even though sensors attached to the cotton pads produced higher variation in estimated angles, similar median RMSE values were observed. Consistent with the results reported in Fig. 3, no improvement was found when applying biomechanical constraints from the Opensense software on the estimated angles.

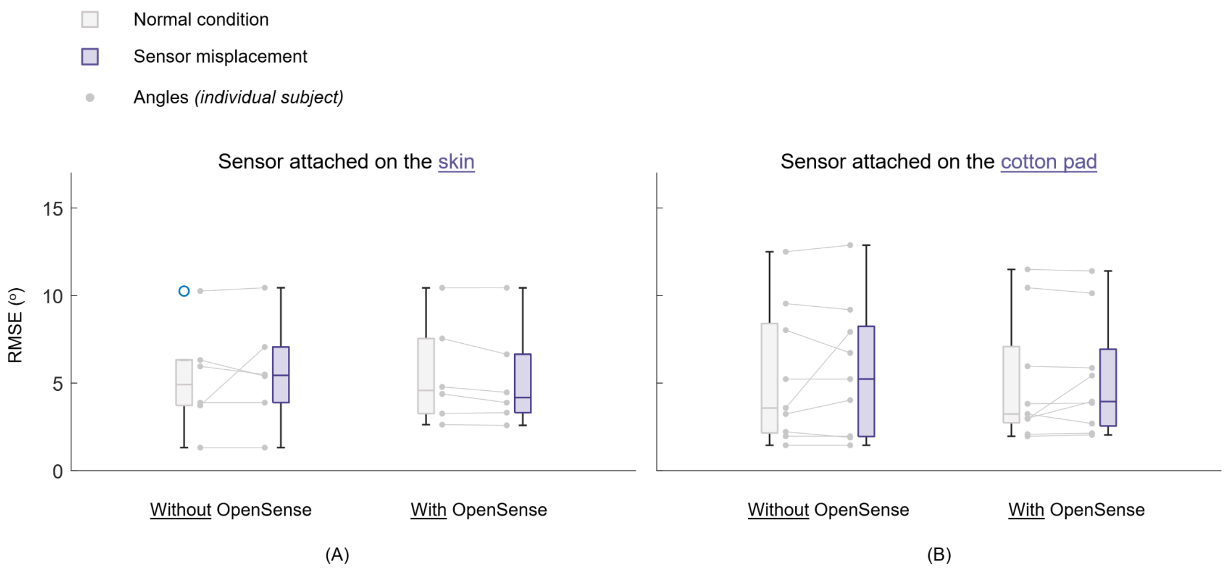

Fig. 5 Impact of skin motion and cotton-simulated soft motion artifacts on estimation accuracy of joint angles using Xsens built-in filter. (Left) Estimation performance with skin motion artifacts; (Right) Estimation performance with cotton-simulated soft motion artifacts. No significant differences in estimated joint angles regardless of applying artifacts and/or using OpenSense due to the tight wrapping of sensors on the body segments in our experiment.

DISCUSSION (1127 words)

The main objective of this study was to (1) identify effective sensor fusion algorithms for estimating lower-body kinematics, and (2) determine whether biomechanical modeling would improve the estimation accuracy. Impacts of sensor misplacements and skin/soft-tissue motion artifacts were also qualitatively examined. We observed that any filters from either the complementary (e.g., Madgwick) or Kalman (e.g., EKF) family could produce consistent performance given proper tuning. The biomechanical model (of OpenSense), however, did not clearly improve the kinematics estimation as expected. While the biomechanical model helped correct the estimation of the hip flexion given a misplaced thigh sensor, this came with the cost of undermining the estimated accuracy of the other angles (i.e., knee flexion or ankle flexion). Importantly, we suggested another simple and effective way to minimize skin or soft-tissue motion artifacts by tightly wrapping the sensors around the body segments.

Tuned parameters of considered sensor fusion algorithms can be generalized across subjects, duration, and population for lower-body kinematics estimation. However, only estimation with EKF indicated visible improvement after the tuning process. This may be because EKF is less generalizable than the other filters, and the default parameters of EKF were not specifically set for biomechanics research. Tuning is, thus, beneficial to EKF when it is applied to a different application. In addition, of all estimated angles, the ankle joint estimation benefitted the most from tuning. This is likely due to the foot IMUs experiencing the strongest effect of ferromagnetic distortions due to underground metals and force plates. We further suggest a good practice for future studies and applications to appropriately tune their selected sensor fusion algorithm to reduce distortions and other sources of noise in the applied environment.

No difference in joint kinematics estimation was found across different sensor fusion algorithms. While EKF has been shown to outperform complementary-typed filters in various applications (Nazarahari and Rouhani, 2021; Nazarahari and Rouhani, 2021; Slade, et. al., 2021), our results, however, suggested that complementary filters (e.g., Madgwick or Mahony) can be as good as EKF in estimating lower-body kinematics given proper parameters. This indicated a mutual agreement with (Al Borno, et. al., 2022). However, we did not find any strong evidence showing using the biomechanical model from the OpenSense software would bring additional benefits in mitigating drift and magnetic disturbances to improve the kinematics estimation. Notice that the authors from (Al Borno, et. al., 2022) did not perform this comparison between using and without using OpenSense in their study. We anticipated that the magnetometer was very helpful in correcting sensor drift in sensor fusion algorithms. Future studies could compare estimation using OpenSense and not using OpenSense in environments with high magnetic disturbances to further confirm this. Lastly, due to the increasing error at the final trial, we suggested that the built-in filter supported by Xsens may not be tuned for long-duration data collection. As the research community has initiated data collection with longer periods, everyone should be cautious of this before using orientations from the Xsens built-in filter for further analyses.

Sensor misplacement severely impacted the estimation results. Due to the misplacement of the thigh sensor, the hip and knee angle estimation errors increased. This is especially prevalent in the hip angles since the misplacement was aligned with the calibration orientation (i.e., the thigh sensor was parallel with the pelvis sensor). While biomechanical constraints from OpenSense reduced the estimation error of the hip angles, it increased the error in estimated knee and ankle angles. Since data from the misplaced sensor were not involved in the calculation of the ankle kinematics, the ankle angles remained the same for inverse kinematics without using OpenSense. However, this was not the case when using OpenSense where the estimated ankle angle became less accurate. This is because the OpenSense optimization process takes into account data from all sensors to perform inverse kinematics. We suggest changing the weights of each sensor data may help reduce the estimation error of the knee and ankle angles but increase the error of the estimated hip angle. Using a biomechanical model may not bring significant benefits in the context of sensor misplacement.

Skin/soft-tissue motion artifacts barely affected joint kinematics estimation with sensors tightly wrapped to body segments. It is worth noticing that due to the tight wrap of Coban in our experiment, the motion artifacts on the sensors might have been significantly minimized. The results, therefore, are more likely to represent the effects of minor misplacements instead of motion artifacts. Based on our observation, we suggested a simple and low-cost solution to eliminate or reduce motion artifacts by wrapping the sensor tightly to the body segment.

Three major limitations should be acknowledged to appropriately apply our findings for future studies. First, only four participants recruited on campus were included in our study. It is worth noticing that results are relatively consistent across subjects for several analyses. An example of this is the adverse impacts of the thigh sensor misplacement on the estimation accuracy of the hip angle. However, a larger and more diverse sample size may be necessary for other analyses to derive more solid and generalizable conclusions. Another limitation of this study is its sole focus on the sit-to-stand task. Due to the inferior quality of the marker-based motion capture data, the overground walking and forward jumping tasks were discarded. Inclusion of more tasks, especially the highly dynamic ones, would provide greater insights into the applicability of each sensor fusion method, for example, which method should be used for which task. Last but not least, future work should further investigate how biomechanical modeling may affect skin or soft-tissue motion artifacts, which was not fully addressed in this study.

Despite the limitations, this study provides useful information for the biomechanics-research community working on joint kinematics estimation. Here, we present five lessons learned from our work:

(1) Tuning of sensor fusion methods can be generalized to different subjects, periods of data recordings, and populations.

(2) Complementary filters can be as good as Kalman filters. Depending on the application and available resources, one may choose a desired filter for joint kinematics estimation (e.g., real-time or not, low versus high computational resources).

(3) Biomechanical models may not bring significant benefit to the estimation of lower-body kinematics.

(4) Sensor misplacements severely affected joint kinematics estimation. While biomechanical modeling could help improve a specific angle, estimation accuracy on the other angles may be sacrificed.

(5) Tight wrapping of sensors on body segments would considerably mitigate skin or soft-tissue motion artifacts.

While the first three need more data to confirm, the last two messages can be highly reliable due to the consistency we observed across all subjects. We hope these lesions will benefit future studies to improve the quality of joint kinematics estimation and soon make this technology widely adopted in clinical applications.

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