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Functional Rotation Axis Based Approach for Estimating Hip Joint Angles Using Wearable Inertial Sensors: Comparison to Existing Methods

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FUNCTIONAL ROTATION AXIS BASED APPROACH FOR ESTIMATING HIP JOINT ANGLES USING WEARABLE INERTIAL SENSORS: COMPARISON TO EXISTING METHODS

A Thesis Presented

by

Lukas Adamowicz

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Abstract

Wearable sensors are at the heart of the digital health revolution. Integral to the use of these sensors for monitoring conditions impacting balance and mobility are accurate estimates of joint angles. To this end a simple and novel method of estimating hip joint angles from small wearable magnetic and inertial sensors is proposed and its performance is established relative to optical motion capture in a sample of human subjects. Improving upon previous work, this approach does not require precise sensor placement or specific calibration motions, thereby easing deployment outside of the research laboratory. Specific innovations include the determination of sensor to segment rotations based on functionally determined joint centers, and the development of a novel filtering algorithm for estimating the relative orientation of adjacent body segments. Hip joint angles and range of motion determined from the proposed approach and an existing method are compared to those from an optical motion capture system during walking at a variety of speeds and tasks designed to exercise the hip through its full range of motion. Results show that the proposed approach estimates flexion/extension angle more accurately (RMSE from 7.08° to 7.29°) than the existing method (RMSE from 11.64° to 14.33°), with similar performance for the other anatomical axes. Agreement of each method with optical motion capture is further characterized by considering correlation and regression analyses. Mean ranges of motion for the proposed method are not largely different from those reported by motion capture, and showed similar values to the existing method. Results indicate that this algorithm provides a promising approach for estimating hip joint angles using wearable inertial sensors, and would allow for use outside of constrained research laboratories.
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Chapter 1: Introduction

1.1 Background

Joint angle estimates are emerging as important metrics for the analysis of human health and performance. They may soon play key roles in the diagnosis and treatment of a variety of conditions impacting mobility. For example, significantly altered gait kinematics and ranges of motion have been observed in multiple disorders, including musculoskeletal disorders such as osteoarthritis (OA)[1], and neurological disorders such as multiple sclerosis (MS) [2], Parkinson’s disease (PD) [3], and stroke [4], indicating that these measures may be important for early identification and prescription of preventative interventions. Similarly, hip range of motion was recently shown to be statistically correlated with measures of lower limb motor impairment, such as time to complete a 25-foot walk test, the expanded disability status scale, and self-assessed MS walking scale [5] in persons with MS. Joint angle estimates and ranges of motion are also increasingly being used for athlete performance monitoring and in tracking rehabilitation from injury[6]. For example, significantly improved outcomes following anterior cruciate ligament surgery were observed when rehabilitation steps and timeframes were based upon kinematic and kinetic measures of knee function[7].

Figure 1.1: Example motion capture walkway camera setup [8].
However, advancement in the use of joint angles for the analysis of human health and performance is largely inhibited by the limitations of current measurement modalities employed in both clinical and research contexts.

1.2 Stereophotogrammetry for Estimating Joint Angles in Research

The accepted standard for joint angle estimation is stereophotogrammetry (optical motion capture - OMC). This approach uses reflective markers observed by an infrared camera array [9], such as in Figure 1.1. The reflective markers are typically placed on anatomical landmarks of the body segments of interest. The subject then performs activities in a capture volume, defined by where markers can be seen by at least two cameras. The marker positions are then computed in space, and for the model based approach, fit to a subject-scaled cadaver-based model. Relative orientations between segments are then estimated, from which joint angles are obtained. [10]

OMC suffers from several limitations. These include a finite capture volume, high cost, complexity of the setup, limited ability to move the setup to different locations, and the need for little or tight-fitting clothing to prevent marker occlusion. Additionally, the markers require trained personnel to place in the correct locations. This placement also takes a significant amount of time due to the difficulty of finding the locations as well as the large number of markers required. The high cost, setup complexity, and the requirement of trained personnel limit the availability of OMC to research institutions, while the finite capture volume, poor mobility, and marker occlusion severely limit the types and settings of activities that can be observed.

Multiple studies have been done in an effort to quantify the intra- and inter-observer results for OMC. Coefficient of multiple correlation (intra-observer) values
ranged between 0.567 and 0.959 for hip joint angles measured over multiple days[11]. Other studies with both intra- and inter-observer found large ranges of results, with coefficients of multiple determination as low as 0.280 and 0.351 for intra- and inter-observer differences respectively [12] and intraclass correlation coefficients (ICCs) from 0.66 and 0.72 for intra- and inter-observer sessions [13]. Systematic measurement error due to marker re-application was also quantified to be about 3.8° for both intra- and inter-observers between testing sessions[12]. One study with two subjects, but 6 experiment repetitions for intra-observer and 6 different experimenters for inter-observer, observed marker 3D placement varied by as much as 21.0 and 24.8mm for the hip and 17.9 and 18.6mm for the thigh from intra- and inter-observer placements. These findings led to hip angle precision between 2.5 and 5.3° and 5.0 and 5.6° for intra- and inter-observer sessions [14]. Difference in determination of the anatomical landmarks for marker placement therefore results in a large component of the poor repeatability of OMC, especially with marker placement by different observers.

Nevertheless, OMC remains the gold standard research method for capturing human movement, and especially joint angles.

1.3 Goniometers for Estimating Joint Angles in Clinical Practice

While OMC is often used for quantifying joint angles in research, the associated time and costs preclude its use in clinical contexts. Clinically, joint angles and more specifically static joint range of motion (ROM) are quantified using a handheld goniometer. Goniometers are typically comprised of two arms attached at a common point (Figure 1.2) and angles are manually read and reported. Angles are determined by reading corresponding angle marks around the rotation point of the goniometer arms. There
are multiple disadvantages to this technique, including difficulty in aligning the arms with anatomical landmarks and segment long axes, difficulty in moving patients into the correct positions while also maintaining the alignment of the goniometer, and large variability in the intra- and inter-observer reliability of the method. While studies have reported moderate to good intra-observer ICCs of 0.86 to 0.97 [15] and 0.84 to 0.95[16] for three degrees of freedom and 0.51 and 0.54 [17] for hip extension, inter-observer ICC values ranged from 0.16 to 0.55 [18] for three degrees of freedom and 0.30 to 0.65[17] for hip extension. This wide range of reliability and especially poor between observer correlation, as well as their application to ROMs only during highly constrained and specific motions provides evidence that new methods are needed to assess joint angles in unconstrained settings.

Figure 1.2: A short arm goniometer used for measuring joint angles [18].
1.4 Wearable Sensors for Estimating Joint Angles in Research and Clinical Practice

The financial, activity type, and required personnel limitations of OMC, and the reliability limitations of goniometers indicate that alternative methods are needed for measuring joint kinematics. With the recent advances in micro-electromechanical systems (MEMS), inertial measurement units (IMUs) are being utilized with increasing frequency in biomechanics to estimate joint angles [19]–[34].

IMUs, such as the examples in Figure 1.3, are typically comprised of an accelerometer and a gyroscope, which measure linear acceleration and angular velocity respectively. Some IMUs also contain a magnetometer, which measures the local magnetic field, and are referred to as magnetic and inertial measurement units (MIMU). While IMUs can provide orientation estimates, MIMUs provide this orientation estimate...
relative to magnetic north and gravity under the assumption of no significant local magnetic fields effecting the values measured by the magnetometer. The data can then be used in several different ways to obtain estimates of segmental or joint angles. Generally inertial data is extracted from the sensors in the IMU/MIMUs (accelerometer and gyroscope, and potentially magnetometer), and fused together to estimate the relative orientation of adjacent body segments.

Figure 1.4 shows the general structure of methods used for estimating joint angles. From the raw data, the relative orientation of the sensors is estimated. This can be done relative to gravity, the magnetic field, or other sensors typically through applying known constraints on sensor-to-sensor relative behavior. The appropriate data is then mapped to the anatomical axes of interest. With rotation and acceleration data about the anatomical axes, the joint angles can then be estimated. This is usually done alongside any drift correction methods. The output of these two steps are the joint angles.

![Diagram](image)

*Figure 1.4: General steps for joint angle estimation.*

The difficulties arise in mapping the sensor reference frames to the segment reference frames, and compensating for drift - the accumulation of error in the estimate over time due to bias and approximations in integration and other calculations. With some methods of joint angle estimation, drift is a concern that has to be addressed. Several methods have been used to mitigate drift: using strap down integration [19],
kinematic constraint driven updates to global reference frame estimates \cite{24},
zero-velocity updates and random drift models \cite{25, 26}, Kalman and particle filters
\cite{30, 31}, and complementary filters \cite{22, 23}.

Analysis of the literature reveals a variety of methods for quantifying body segment
and joint angles with wearable IMUs and/or MIMUs. Specifically, the articles have
focused on estimating segment orientation relative to a global coordinate system
\cite{29–33}, shoulder and elbow angles \cite{25–27}, knee angles \cite{19, 22–24, 34}, and hip
angles \cite{19, 38–42}.

1.5 Previous Work
Several previous works have focused on estimation of segment angles and comparison
to OMC \cite{28, 29}. Average absolute root mean square deviation/error (RMSD/RMSE) between MIMU and OMC was found to be less than $4.0^\circ$, $3.7^\circ$, and $4.4^\circ$
for all measured body segments (head, upper trunk, pelvis, thigh, shank, foot) for sit-
to-stand (STS), walk, and turn, respectively\cite{28}. Additionally, the findings indicated
an increase in mean RMSD as the angular velocity of the activity increased. As such,
the ability of an algorithm to handle highly dynamic motions is an important con-
sideration. Pelvic segmental angles were compared between MIMU and OMC in the
frontal and sagittal planes\cite{29}. The frontal plane had RMSE values of $2.68^\circ$, $4.44^\circ$, and $3.05^\circ$ for walking, STS, and block step-up, respectively. The sagittal plane had
reported RMSE values of $2.70^\circ$, $8.89^\circ$, and $6.61^\circ$ for walking, STS, and block step-up,
respectively. These studies however provide little information about the duration of
the activities and any effects of drift due to longer data collection periods. Addi-
tionally, while segment orientation angles can be important, they do not capture the
motion of joints.
Obtaining results useful in clinical or diagnostic settings generally requires joint angles as opposed to segmental angles. This is due to the extra information joint angles provide, namely orientation relative to another body segment and ranges of motion that are constrained. This allows for comparison to standard ranges or previous baselines accounting for any relative postural changes that are not represented in segment angles.

Some previous work on joint angles has focused on upper-limb joints such as the shoulder or elbow, with validation either on human subjects or robotic arms and coordinate measurement machines. Using biomechanical models of joint-connected links employed in an unscented Kalman filter (non-linear state estimation algorithm) with validation on human subjects using OMC, RMSE values of less than 6.5° were found for the elbow, with values less than 5.5° observed for the shoulder. Pearson’s correlation coefficients were also reported to be above 0.95 for both elbow and shoulder [25].

In a later modification of the previous method, modeling of drift and zero-velocity updates were added to the algorithm, however validation was completed on a robotic arm. RMSE values less than 5.9° were observed for all mimicked shoulder and elbow rotations during three rotation speeds, except for ‘shoulder’ internal-external rotation (IER) in which 7.8° RMSE was observed during slow rotations [26]. The main limitation for this study was the use of the robotic arm, which while useful for algorithm validation, provides little information regarding performance on human subjects. Validation on humans would likely see worse performance due to STA and other sensor motion relative to the underlying bones. Additionally, zero-velocity updates require assumptions about sensors being static and degradation of performance is possible under highly dynamic motions that contain few still periods.
Knee angle estimation has also been explored previously. Validating against a hand-rotated coordinate measurement machine (CMM), an algorithm using zero-velocity updates and sensor orientation estimates exploiting hinge joint kinematic constraints found RMSE values of 3.46°, 2.48°, and 1.69° for flexion-extension (FE), ad/abduction (AA), and IER respectively [24]. Pearson’s correlation coefficients were also all above 0.94 and regression slopes were all within 0.02 from 1.0. The limitations including validating on a non-human device, zero-velocity updates, and assumptions about the joint acting as a hinge, all of which limit applicability to humans, joints that are not quasi-1D, and highly dynamic motions. Additional work for the knee reported on a 1D algorithm that was employed on a human subject with a normal and prosthetic leg. Angle estimates from acceleration and angular velocity were fused in a complementary filter to mitigate drift and noise. RMSE values for the knee FE axis were 3.30° on the normal human knee, and lower for the prosthetic knee [22]. The primary limitations being the implementation on a 1D hinge joint, though a framework for extension to 3D joints was provided, and the validation on a single subject.
Figure 1.5 shows the complementary filter used in the previous study for the knee flexion extension angle during gait[22]. The angle from the accelerometer $\alpha_{acc}$ is a high frequency noise effected estimate of the joint angle based on the raw acceleration. The angle from the gyroscope $\alpha_{gyro}$ is a low frequency noise (drift) effected estimate of the joint angle based on the integrated angular velocity. Fusing the two estimates together provides an estimate that is more accurate on both time scales.

Previous work for hip angle estimation has all involved human subjects performing different activities. One such study confined the algorithm to cycling and assumed the thigh’s motion was similar to that of a pendulum, with observed RMSE values of $0.8^\circ$ to $11.6^\circ$ for the hip [38] when compared to OMC. The main limitation to this study was the use of OMC to obtain the sensor to anatomical segment orientations. This, however, is not a feasible solution generally, as it maintains reliance on OMC systems. The need for this sensor to segment alignment is acknowledged in the paper as a gap in the literature. Additionally, the applicability of the algorithm presented to non-cycling motions is unclear.
Comparison of a commercial full-body inertial sensor system with proprietary algorithms to OMC during manual material handling tasks showed good performance, with less than 7.5° RMSE for all three hip angles [39]. However, no information about how dynamic the motions are, the assumptions being made by the algorithm, or how many of the sensors are required for estimating one joint’s angles, was provided. While the data collection lasted for 32 minutes, frequent static standing periods were included. This, combined with the lack of algorithm information raises concerns regarding generalizability to broader ranges of activities.

Comparison of another commercial IMU system with manufacturer’s algorithms to OMC reported results of 9.6° and 27.6° RMSE during 20-stride walking and running bouts respectively [40]. Similar to the previous study, no information was available regarding the algorithms used by the inertial system, and consequently any assumptions made by the algorithm are unknown.

One study comparing lower body IMU-based estimates of joint angles to OMC during walking, squatting, and jumping reported mean RMSE values of less than 2.29° for cluster based OMC\(^1\) and less than 5.60° for anatomical landmark based\(^2\) OMC during a 6-minute walk trial [41]. During squatting and jumping, mean RMSE values were all less than 2.28° during cluster based, and less than 8.27° for skin marker based OMC for both left and right hips [42]. However, the sensor to segment orientations are determined by the OMC system, mitigating a large portion of the differences that exist between IMU-based and OMC joint angle estimates. Therefore it is unclear how well this method would work when using inertial sensor based methods of estimating sensor to segment alignment. This reliance on OMC additionally does not allow the

\(^1\) Using cluster to segment orientations to determine joint angles.
\(^2\) Using segment frames defined by markers directly on the skin.
inertial sensor system to be used as a stand-alone measure of joint angles, and leaves room for improvement.

Using repeated functional calibration motions under the assumption they were aligned with primary rotation axes along with strap-down integration for drift correction, a study targeted at alpine skiing found mean errors (sample-by-sample difference) less than $10.7^\circ$ for left hip angles [19]. Trunk rotation, squats, left and right hip AA, and static standing functional calibration motions were performed between each of four skiing treadmill trials. The requirement of several calibration activities and assumptions regarding the primary rotation axes of the activities makes this method harder to implement for untrained clinicians. Additionally, the specific nature of the target activity makes performance during normal daily activities unknown.

1.6 Objective

The objectives of this study can be broken into three categories: first, to develop a novel wearable inertial sensor based method of 3D hip joint angle computation that addresses previous limitations, second, to validate the developed method against OMC, and third, to implement an existing method to provide a performance comparison against the proposed method.

These three objectives are specified as the following:

1. The novel proposed method will use functionally defined joints and axes, without using OMC data. The method will use minimally constrained and a minimal number of calibration motions, in addition to being open source. This directly addresses limitations in the previous literature, namely validation of proprietary systems [39], [40], using OMC data in the algorithms [41], [42] and requiring numerous constrained calibration motions [19]. Addressing these limitations
will allow for better clinical and research deployment of inertial sensor based approaches for hip angle estimation.

2. The proposed method will be validated against the current gold standard, OMC. Validation will occur on human subjects, which has not always been the case for joint angle methods [24], [26]. Additionally, activities of daily living will be used in order to understand how the proposed method performs on activities that would typically be performed in clinical and research settings, which again was not always the case in previous work which used non-daily living activities [19], [38].

3. An existing method will be implemented and compared against OMC to provide a performance comparison for the proposed method. This will help establish the performance of the proposed method in the existing method space.

Validation for the second and third objective will be achieved through exploring the differences in estimated joint angles between the proposed and OMC methods, and the existing and OMC methods. Correlations between IMU and OMC methods will be computed. Additionally, ROM values will be computed and reported due to their clinical significance.
Chapter 2: Methods

2.1 Measurement Protocol

Eleven subjects (N=8 male, N=3 female, 22.5 ± 3.4 years old; Inclusion: 18-50 years old, able to perform daily activities without difficulty; Exclusion: diagnosis of a balance or mobility impairment, inability to complete the in-lab activities of daily living without assistance, opioid dependent). All study activities were approved by the University of Vermont Institutional Review Board (CHRBSS: 18-0518) and subjects gave written informed consent before participating in the study.

Subjects were instrumented with wearable IMU and MIMU sensors and reflective markers for OMC. Two calibration trials were performed, a static standing and a star calibration motion (see Appendix A.1). Following the calibration trials, calibration only markers were removed before subjects completed a series of activities including standard functional assessments (e.g. standing-sitting transitions) as well as simulated activities of daily living (e.g. walking, lying down). The full list of activities performed is in Appendix A.2. Herein we consider the star calibration, multispeed overground walk, and forwards and backwards walking on a treadmill. The star calibration was included for its range of motion in all three axes of rotation, while the multispeed overground walking and forward treadmill walking were included to have two walking trials across different speeds. The treadmill backwards walking was included due to the slightly different motion required.

2.2 Motion Capture System

The OMC system consisted of 18 infrared cameras and one video camera (VICON Motion Systems) covering two overlapping capture volumes (a force plate walkway and treadmill). A minimum of 12 cameras covered each capture volume. System
sampling frequency was set at 100Hz for all trials. Subjects had markers placed on body segments and segment anatomical landmarks, using markers necessary to create anatomical references frames as in Table 2.1 and adding markers as used in [43] (full marker set described in Appendix B.1). Additional markers were attached as part of a different study and were only considered during joint center computation. Marker clusters were attached to inertial sensors as described in Section 2.3.
Certain markers, typically medial markers, were only present in the calibration trials, and were removed afterwards to facilitate ease of movement and mitigate markers being knocked off of the subject (denoted in Appendix B.1). Left and right marker placements were symmetric except for one marker on the left shank which was not
present to aid left and right side recognition in the OMC software. The full marker set, including calibration only markers and marker clusters, is shown in Figure 2.1 (see Appendix B.1 for a complete list of marker locations).

*Table 2.1: Description of anatomical reference frames for the pelvis and thighs*[^1], [^2].

<table>
<thead>
<tr>
<th>Pelvis</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>Midpoint between left and right ASIS</td>
</tr>
<tr>
<td>Z-axis</td>
<td>From left ASIS to right ASIS</td>
</tr>
<tr>
<td>X-axis</td>
<td>Perpendicular to z-axis in the plane defined by the midpoint of the left and right PSIS and the left ASIS and right ASIS.</td>
</tr>
<tr>
<td>Y-axis</td>
<td>Perpendicular to the x-axis and z-axis pointing upwards.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Thigh</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>Midpoint between lateral (LEP) and medial (MEP) femur epicondyles.</td>
</tr>
<tr>
<td>y-axis</td>
<td>From midpoint of LEP and MEP to the hip joint center.</td>
</tr>
<tr>
<td>z-axis</td>
<td>Perpendicular to y-axis and in the plane defined by the LEP, MEP and hip joint center.</td>
</tr>
<tr>
<td>x-axis</td>
<td>Perpendicular to the y-axis and z-axis pointing forwards.</td>
</tr>
</tbody>
</table>

[^1]: [44], [45]
[^2]: [45]
Functional joint centers were computed using a least squares geometric fit method, which determines the best center of rotation of the markers on a specific segment [46]. An additional bias correction optimization was included as well to compensate for any STA in the marker locations [47]. Segment anatomical frames were defined as in Table 2.1 during the static calibration trial, and constant cluster frame to anatomical frame rotations were computed. The cluster to segment rotations allowed computation of the segment anatomical frames when not all of the required markers were present during non-calibration trials. Hip joint angles were computed as suggested in the ISB standards [44]. The angle range correction from [48] for FE angles was also applied, and the same derivation was used to obtain a correction for IER angles. Specifically, hip joint coordinates \((e_1, e_2, e_3)\) are defined such that \(e_1\) is aligned with the Z-axis of the pelvis, \(e_3\) is aligned with the y-axis of the thigh, and \(e_2\) is perpendicular to each \((e_2 = e_3 \times e_1)\). Hip joint angles are then defined per
\[ \alpha = \arctan 2 (\eta_\alpha \| X \times e_2 \|_2, X \cdot e_2) \quad (2.1) \]
\[ \eta_\alpha = \frac{(X \times e_2) \cdot Z}{\| (X \times e_2) \cdot Z \|} \]
\[ \gamma = \arctan 2 (\eta_\gamma \| x \times e_2 \|_2, x \cdot e_2) \quad (2.2) \]
\[ \eta_\gamma = \begin{cases} 
  \text{right} & ((x \times e_2) \cdot -y) [\| (x \times e_2) \cdot -y \|]^{-1} \\
  \text{left} & ((x \times e_2) \cdot y) [\| (x \times e_2) \cdot y \|]^{-1}
\end{cases} \]
\[ \beta = \begin{cases} 
  \text{right} & -\frac{\pi}{2} + \arccos(e_1 \cdot e_3) \\
  \text{left} & \frac{\pi}{2} - \arccos(e_1 \cdot e_3)
\end{cases} \quad (2.3) \]

Where \( \alpha \) is the FE angle, \( \gamma \) is the IER angle, \( \beta \) is the AA angle, and \( \| \cdot \|_2 \) is the vector 2-norm. \( \eta \) is a correction that ensures the sign conventions are maintained.

### 2.3 Wearable Inertial Sensors

Eight MIMU sensors (Opal v2, APDM, Inc. ‘Opal’) were each seated in plastic clips and attached to feet, shanks, thighs, the lumbar, and sternum, as in Figure 2.3, via double sided adhesive tape and velcro straps to prevent slipping against the skin.
Figure 2.3: Opal sensor locations on the subjects.

Opal sensors were placed in the manufacturer suggested locations (see Appendix B.2) on each body segment. However, the orientation and location of the sensors is not required to be consistent for the proposed algorithm to work. Sensors may be placed anywhere and in any orientation on the body segment they are attached to. The Opals were time synchronized with each other, and trials were synchronized with the OMC system via an electronic trigger. Acceleration, angular velocity, and magnetic field were recorded from each sensor at a sampling frequency of $128 \text{Hz}$. The plastic clips allowed rigid attachment of three reflective markers to the sensor, as shown in Figure 2.4.
Figure 2.4: Sensor clip with three reflective markers attached.

An additional set of 8 IMUs and 4 combined accelerometer and electromyograph sensors (BioStamp nPoint, MC10, Inc.) were placed on the subject, though they are not considered for this study.

2.3.1 Reference IMU Method

A reference method based on wearable IMU sensor estimates of joint angles was implemented (‘Fasel method’). The Fasel method was chosen due to available and open source algorithms, in addition to the method not using OMC data. Finally, the method was initially validated during alpine skiing, and this study can then additionally serve as a validation of the method during activities of daily living. The algorithms from [19], [20] were used and ported from the available MATLAB scripts \(^1\) to Python, validating against the sample data provided. This method requires a series of functional calibration activities that are used to determine anatomical axes.

\(^1\)https://codeocean.com/capsule/1305245/tree/v1
These activities are left and right hip adduction, squatting, trunk rotations, and standing. Corresponding activities used were left and right lateral treadmill walking, air squatting, and the standing trial. Trunk rotations were omitted as the algorithm corrects the estimated axis to be aligned with gravity during the standing trial. Angles were estimated in the same way as for OMC.

Briefly, the Fasel algorithm works by first estimating the rotation axes from specific calibration activities designed to primarily activate those rotation axes. Once those axes have been obtained, various assumptions about the symmetry of the subject are employed to correct initial angle estimates, and ensure left and right side symmetry in angles during static standing. Following the symmetry corrections, the joint centers are computed, and drift is estimated and corrected for using various sensors adjacent to the sensor being corrected. Best performance is achieved when all lower body sensors and the sternum sensor are used for drift correction, resulting in optimal performance with six sensors (shanks, thighs, pelvis, sternum or mid/upper back).

2.3.2 MIMU Method

A novel method (‘Functional method’) was developed to estimate hip angles. Functionally obtained joint center locations were employed to create the anatomical axes corresponding to those found in the OMC method. Angles were then computed via the same method as in OMC.

Data Preprocessing

Accelerations for each sensor were scaled to ensure that the mean magnitude during static standing was equivalent to the local gravitational acceleration. Additionally,
measured angular velocity, acceleration, and magnetometer readings were low-pass zero-phase filtered with a 15Hz cutoff frequency. Angular acceleration was calculated from angular velocity using a second order approach per

\[ \dot{\omega}_i^k = \frac{\omega_i^{k+1} - \omega_i^{k-1}}{2\Delta t} \]  

(2.4)

Where \( \dot{\omega}_i^k \) is the angular acceleration of the \( ith \) sensor at time point \( k \), \( \omega \) is the measured angular velocity, and \( \Delta t \) was the time difference between adjacent samples. After calculation, angular acceleration was low-pass zero-phase filtered with a cutoff frequency of 12Hz.

Orientation

Sensor orientations were calculated relative to adjacent sensors (ex. left thigh to pelvis) using a novel approach. First, vectors collinear with gravity for each sensor were estimated using the IMU-only algorithm \( (\beta = 0.041) \) in [49] (code adopted from and validated against a MATLAB implementation with sample data \(^2\)). This works by fusing estimates of the orientation from the accelerometer and gyroscope readings. A partial rotation from distal (sensor 2) to proximal sensor (sensor 1) frames can then be calculated based on Equation 2.5. The global reference frame uses the convention of gravity being aligned with the z-axis. Time indices are left off for clarity unless different time points are used in the same equation.

\(^2\text{http://x-io.co.uk/open-source-imu-and-ahrs-algorithms/}\)
\[ z_1 = \frac{1}{2} R_z z_2 \quad (2.5) \]

Where \( z_i \) is the gravity collinear vector in the \( i \text{th} \) sensor’s local frame, and \( \frac{1}{2} R_z \) is a partial rotation from sensor 2’s frame to sensor 1’s frame, where this partial frame is denoted by I. The rotation is only partial because it does not account for any rotation of the sensor local frames around the gravity axis. Generally, the rotation between two vectors \( v \) and \( w \) can be found per

\[ \theta = \cos^{-1} \left( \frac{v \cdot w}{||v||_2 ||w||_2} \right) \quad (2.6) \]
\[ u = \frac{v \times w}{||v \times w||_2} \quad (2.7) \]
\[ w R = \cos(\theta) I_3 + \sin(\theta) u^x + (1 - \cos(\theta)) uu^T \quad (2.8) \]

Where \( || \cdot ||_2 \) is the 2-norm of a vector, \( u^x \) is the skew-symmetric matrix representation of a vector (i.e. \( v \times w = v^x w \)). \( u \) and \( \theta \) comprise the axis-angle representation of a rotation.

To obtain the second correction rotation, the magnetometer readings were used. In order to not modify the rotation from aligning the gravity axes, the magnetometer readings in the direction of these vectors are removed per

\[ h_{i,xy} = h_i - (h_i \cdot z_i) z_i \quad (2.9) \]
Where $h_{i,xy}$ is the $ith$ sensor’s magnetic reading in the x-y plane, $h_i$ is the $ith$ sensor’s magnetometer reading. The gravity based rotation was then applied to $h_{2,xy}$, and a rotation was obtained to $h_{1,xy}$ as per

$$h_{1,xy} = \frac{1}{2}R_z h_{2,xy} \quad (2.10)$$

$$h_{1,xy} = \frac{1}{1}R_m h_{1,xy} \quad (2.11)$$

The two rotation matrices were combined to yield an estimate of the rotation from sensor 2 to sensor 1,

$$\frac{1}{2}R = \frac{1}{1}R_m \frac{1}{2}R_z \quad (2.12)$$

This rotation was computed for each time point, and provided a measurement for an unscented Kalman Filter (UKF). An UKF is an optimal state estimation algorithm that uses a physical model of a process to predict the future state of interest, with the general process as shown in Figure 2.5. The unscented refers to the use of the unscented transform, which allows non-linear model equations to be used.

![Figure 2.5: Flowchart of an iteration of the UKF.](image)

Briefly, the UKF iterates over every sample in time, first finding the sigma points
and weights per

\[
\chi = \begin{bmatrix} x & x+U & x-U \end{bmatrix}
\]
(2.13)

\[
U = \sqrt{(n + \lambda)P}
\]
(2.14)

\[
\lambda = \alpha^2(n + \kappa) - n
\]
(2.15)

\[
W = \begin{bmatrix} \frac{\lambda}{n+\lambda} & \frac{1}{2(n+\lambda)} & \ldots & \frac{1}{2(n+\lambda)} \end{bmatrix}
\]
(2.16)

Where \(x\) is the state vector, \(U\) is a square root matrix found via Cholesky decomposition, \(P\) is the state covariance matrix, and \(\alpha\) and \(\kappa\) are state distribution parameters, set here to 0.001 and 3.0 respectively [50]. Predictions of the states and estimates of the measured values are then obtained by using the state update and measurement estimation equations on the sigma point, and passing the results through the unscented transform, as per

\[
\hat{\chi}^k = F(\chi^{k-1})
\]
(2.17)

\[
\hat{\zeta}^k = H(\hat{\chi}^k)
\]
(2.18)

\[
\hat{x}^k = \hat{\chi}^k W
\]
(2.19)

\[
P_x = W(\chi^k - \hat{x}^k)(\hat{\chi}^k - \hat{x}^k)^T + Q
\]
(2.20)

\[
\hat{m}^k = \hat{\zeta}^k W
\]
(2.21)

\[
P_m = W(\zeta^k - \hat{m}^k)(\hat{\zeta}^k - \hat{m}^k)^T + M
\]
(2.22)

Where \(\hat{s}\) denotes an estimate of \(s\), \(x\) is the state vector, \(m\) is the measurement
vector, $F$ is the state update function, $H$ is the measurement estimation function, $Q$ is the process covariance (measure of the trust in the state prediction), and $M$ is the measurement covariance (measure of the trust in the measurement estimation). Then, the final estimate of the state is computed per

$$P_{xm} = W(\hat{x}^k - \hat{x}^k)(\hat{z}^k - \hat{m}^k)^T$$

(2.23)

$$K = P_{xm} P_m^{-1}$$

(2.24)

$$x^k = \hat{x}^k + K(m^k - \hat{m}^k)$$

(2.25)

$$P^k = P_x - KP_m K^T$$

(2.26)

Where $K$ is the Kalman gain. The process is then repeated for the next time point and so on until the final time has been reached.

The UKF fused the gravity and magnetometer based measurement (Equation 2.12) with a prediction from integrating relative angular velocity. The state vector was a quaternion representing the rotation from the second to first sensor’s frames (e.g. thigh to pelvis). The state update equations for the UKF are then defined as

$$\omega_{rel}^k = \omega_2^k - \left[\frac{1}{2}R(x^{k-1})\right]^T \omega_1^k$$

(2.27)

$$q_{\omega}^k = \left[0 \omega_{rel}^k\right]$$

$$\dot{x}^k = 0.5 \left(x^{k-1} \otimes q_{\omega}^k\right)$$

(2.28)

$$x^k = x^{k-1} + \Delta t \dot{x}^k$$

(2.29)
Where $\dot{x}$ is the state vector derivative and $\otimes$ is the quaternion product. While the time update step is first order, this has been used before in previous orientation estimation algorithms [49] and should be sufficient due to the high sampling frequency (128 Hz). Since the measurement is directly estimated via gravity and magnetic field ($\frac{1}{2}R$ can be expressed as a quaternion) vectors, the measurement estimation is simply the state vector (e.g. $H(x) = x$). The dynamics of the activity were taken into account through adapting the measurement covariance parameter of the UKF. An estimate of the motion dynamic level was obtained by adding the differences between the measured acceleration and local gravitational acceleration, and applied to the measurement covariance as per

$$
\delta = |(||a_1||_2 - g)| + |(||a_2||_2 - g)| \tag{2.30}
$$

$$M = I_4 \delta \mu \tag{2.31}
$$

Where $a_i$ is the acceleration measured by the $i$th sensor, $g$ is the constant gravitational acceleration, $M$ is the measurement covariance matrix, $I_4$ is the $4 \times 4$ identity matrix, and $\mu$ is a chosen scale factor, set to 0.1. Only the acceleration was used to modify $M$ as any magnetic disturbances were assumed to be observed by both sensors, and therefore rotations between the two sensors should not vary with magnetic disturbances. The effect of relaxing this assumption could be considered in future work.
Joint Centers and Anatomical Frames

Joint center locations were estimated using the Symmetrical Acceleration Center (SAC) method in [51]. Given two adjacent segments with sensors on each, that are linked via a common joint, the acceleration of the joint center has to be the same, when resolved from either sensor’s measurements, to within some relative rotation between frames. Mathematically, this is defined per

\[
\ddot{a}_i^k = a_i^k - W_i^k r_i
\]

\[
W_i = \omega_i^x \omega_i^x + \dot{\omega}_i^x
\]

\[
a_1^k - W_1^k r_1 = \frac{1}{2} R^k \left[ a_2^k - W_2^k r_2 \right]
\]

(2.32)

Where \( \ddot{a} \) is the acceleration at the joint center and \( \omega^x \) is the skew symmetric matrix representation of \( \omega \) the angular velocity vector (i.e. \( \omega \times r = \omega^x r \)). With some manipulation, Equation 2.32 can be rearranged into an indeterminate linear system. However, since multiple time points are available, an overdetermined linear system can be obtained as in Equation 2.33, to which a least-squares solution exists.

\[
\begin{bmatrix}
K_1^1 & -\frac{1}{2} R_1^1 K_2^1 \\
\vdots & \vdots \\
K_1^N & -\frac{1}{2} R_N^1 K_2^N
\end{bmatrix}
\begin{bmatrix}
r_1 \\
r_2
\end{bmatrix}
= \begin{bmatrix}
\frac{1}{2} R_1^1 a_1^1 \\
\vdots \\
\frac{1}{2} R_N^1 a_2^N
\end{bmatrix}
\]

(2.33)

Where the superscripts indicate the time index. A minimum of 1400 points are used, determined by the largest accelerations measured by sensors 1 and 2.
While the hip experiences enough 3D rotation for a good location estimation, the pseudo-1D nature and limited AA and IER ranges of the knee can result in the estimated location lying anywhere along the knee FE axis. A correction for this location error relies upon an estimate of the knee FE axis found via enforcing the following kinematic constraint:

\[ ||\omega^k_1 \times j_1||_2 - ||\omega^k_2 \times j_2||_2 = 0 \] (2.34)

Where \( j_i \) is the rotation axis in the \( i \text{th} \) sensor’s reference frame. The rotation axes can be found via a least squares minimization algorithm such as gradient descent or as in [22], [23]. Once the axes have been obtained, the knee joint centers can be corrected per

\[ r_i = \hat{r}_i - j_i \frac{(\hat{r}_1 \cdot j_1) + (\hat{r}_2 \cdot j_2)}{2} \] (2.35)

Where \( \hat{r}_i \) is the initial estimate of the knee joint center in the \( i \text{th} \) sensors frame obtained from Equation 2.33. For the knee this would be the shank and thigh sensors. This process shifts the joint center location close to the sensors, and results in a better estimate.

Once the joint centers had been calculated, the pelvis and thigh fixed axes were calculated following the conventions for axes direction in [44]. The pelvis and thigh anatomical frames were then formed using a static standing trial as follows:

1. Rotate the fixed axes into common frames (ex left thigh fixed axis from left
thigh sensor frame to pelvis sensor frame).

2. Create the left and right hip joint coordinate systems as in [44].

\[ e_1 = \text{Pelvis fixed axis.} \]
\[ e_3 = \text{Left/right thigh fixed axis.} \]
\[ e_2 = e_3 \times e_1 \]

3. The pelvis anatomical frame from the hip joint coordinate systems as:

\[ Z = e_1 \]
\[ X = \frac{1}{2} (e_{2,\text{left}} + e_{2,\text{right}}) \]
\[ Y = z \times x \]

4. The thigh anatomical frame from the hip joint coordinate system as:

\[ y = e_3 \]
\[ x = e_{2,\text{left/right}} \]
\[ z = x \times y \]

The anatomical frames and axes were created during the most still period of the static calibration trial, and remained constant relative to their respective sensors (e.g. left thigh anatomical frame is constant in left thigh sensor frame). Hip joint angles were then calculated by rotating the thigh anatomical frames into the pelvis frame at each time point, and computing the angles in the same way as the Fasel and OMC methods (i.e. see Equations 2.1, 2.3, 2.2).
2.4 Validation

Joint angle differences from Functional to OMC and Fasel to OMC were calculated using root mean squared error (RMSE). Angles from the Functional and Fasel methods were downsampled to 100Hz to match those from OMC. RMSE values per trial were computed as in Equation 2.36.

\[
RMSE_\theta = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (\theta^k_{\text{inertial}} - \theta^k_{\text{ref}})^2}
\] (2.36)

Where \(N\) was the number of samples in that trial, \(\theta^k_{\text{inertial}}\) was any of the FE, AA, or IER angles estimated from the Functional or Fasel algorithms at time \(k\), and \(\theta^k_{\text{ref}}\) was the corresponding angle estimate from the reference OMC method. RMSE values can then be averaged per subject (\(RMSE_{\theta}^{\text{subj}}\)) or averaged per trial type (\(RMSE_{\theta}^{\text{trial}}\)). Functional method RMSE values were compared to those of the Fasel method in order to compare to one of the only existing methods for estimating hip angles with wearable sensors.

Regression analysis was performed between Functional and OMC and Fasel and OMC results. After downampling, Functional and Fasel results were plotted against OMC results, and a linear regression fit was applied. This yielded slope, intercept and Pearson correlation coefficient \(r\). Slope gives an indication of how well the angle estimate tracks the reference angle, \(r\) provides information on the how well the estimated angles align with OMC results, and intercept provides a measure of the bias of the resulting angles.

ROM is a useful clinical metric for assessing and diagnosing diseases [2], [3] and
rehabilitation [7]. Range of motion (ROM) of each joint angle were also compared between methods. For trials over 30s long, the ROM is calculated for the angles after the first 20s of the trial, to avoid any start-up perturbations not associated with the trial activity. This restriction is removed for trials under 30s in length, and the ROM over the whole trial is used. ROM error (ROME) is calculated as the trial by trial difference between IMU estimated ROM and OMC ROM, with the mean and SD take of the absolute value of ROME.

Run times were also observed for both the Functional and Fasel methods for different similar sections of the algorithms. The algorithms were broken up into an initial phase, where any parameters and values needed for angle estimation of individual trials were computed, and a trial processing phase, where all the individual trials were processed. Total processing time per approximate number of seconds of data processed (PTPS) was also estimated, based on an approximate 730s worth of data processed through both algorithms. Total time for the whole algorithm was also recorded. All processing was done on the same laptop (Lenovo Y50-70) with an Intel i7-4720HQ 2.60GHz processor.

Means and standard deviations (SDs) of statistics were reported for each method (Functional vs. OMC, Fasel vs. OMC), trial type (star calibration, multispeed over-ground walking, force plate walks, fast treadmill walking, and backwards treadmill walking), and angle (FE, AA, IER).
Chapter 3: Results & Discussion

3.1 Results

Proposed method results showed similar or better alignment with OMC than the Fasel method during multiple different types of trials and motions. FE typically showed the most improvement over the Fasel method, with AA and IER typically being comparable to Fasel method results, as shown in Figure 3.1.

![Figure 3.1: RMSE values for all angles and trials from the proposed and Fasel methods.](image)

Figure 3.1 highlights that the entire inter-quartile range (IQR) of FE angles from the proposed method is below the IQR of the FE angles from the Fasel method, evidence of the better performance of the proposed method. IQRs for AA and IER angles from both methods are overlapping, indicating comparable performance of the two methods.

Figure 3.2 shows several sample cycles of gait during fast walking on a treadmill for a typical example. Both FE and IER functional angles exhibit close agreement with the OMC estimate, and while the Fasel results track the angle well, have a larger
offset. AA angles for both methods track more poorly, with similar trends in peaks and troughs, but less agreement to the full trend of the reference angle.

Figure 3.2: Subset of a sample treadmill fast walking trial for the right hip, showing the Functional, Fasel, and reference OMC system resultant FE, AA, and IER angles.

Figure 3.3 shows sample regression plots for the treadmill fast walk trial for the right hip angles. The good agreement between Functional and reference methods can be observed, with slopes and $R^2$ ($r = \sqrt{R^2}$) values that are close to 1. The circular pattern for Ad/Abduction in Figure 3.3b is due to the cyclic nature of the angles as they are closer and farther away from the OMC estimate of the angles. This indicates more poor tracking of the AA angle, which is also reflected in the lower $r = 0.78$ ($R^2 = 0.604$) value.
Table 3.1 contains the results from the star calibration trial. The Functional method had half the RMSE compared to the Fasel method as well as lower SD, with $7.08 \pm 3.48^\circ$ and $13.75 \pm 5.27^\circ$ respectively. Slopes were comparable between methods, though Functional intercepts were slightly closer to 0 but large SDs were present for both methods. Comparable ROME values were observed between both methods for FE, though AA and IER showed lower values for the Functional method ($3.54 \pm 2.87^\circ$ to $6.69 \pm 4.94^\circ$ and $5.09 \pm 3.66^\circ$ to $7.14 \pm 5.17^\circ$), though SDs overlap for all angles.
Table 3.1: Star calibration mean (SD) of statistics for all subjects and left and right hip angles.

<table>
<thead>
<tr>
<th>Method</th>
<th>Angle</th>
<th>RMSE [°]</th>
<th>Slope</th>
<th>Intercept [°]</th>
<th>r</th>
<th>IMU ROM [°]</th>
<th>MC ROM [°]</th>
<th>ROME [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional</td>
<td>FE</td>
<td>7.08(3.48)</td>
<td>1.03(0.08)</td>
<td>-1.39(7.19)</td>
<td>0.98(0.03)</td>
<td>91.09(36.03)</td>
<td>81.79(25.52)</td>
<td>12.57(11.16)</td>
</tr>
<tr>
<td></td>
<td>AA</td>
<td>5.63(2.65)</td>
<td>0.94(0.10)</td>
<td>-2.66(4.60)</td>
<td>0.95(0.03)</td>
<td>49.43(17.03)</td>
<td>49.19(15.50)</td>
<td>3.54(2.87)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>8.32(4.88)</td>
<td>1.10(0.18)</td>
<td>-0.50(8.65)</td>
<td>0.91(0.06)</td>
<td>39.55(12.47)</td>
<td>36.14(10.94)</td>
<td>5.09(3.66)</td>
</tr>
<tr>
<td>Fasel</td>
<td>FE</td>
<td>13.75(5.27)</td>
<td>1.04(0.07)</td>
<td>-3.87(13.35)</td>
<td>0.98(0.03)</td>
<td>90.60(35.80)</td>
<td>81.79(25.52)</td>
<td>12.75(10.86)</td>
</tr>
<tr>
<td></td>
<td>AA</td>
<td>5.92(2.96)</td>
<td>0.97(0.18)</td>
<td>-2.84(3.52)</td>
<td>0.91(0.05)</td>
<td>50.37(17.29)</td>
<td>49.19(15.50)</td>
<td>6.69(4.94)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>8.46(3.48)</td>
<td>0.95(0.27)</td>
<td>-3.08(6.85)</td>
<td>0.84(0.14)</td>
<td>40.81(13.39)</td>
<td>36.14(10.94)</td>
<td>7.14(5.17)</td>
</tr>
</tbody>
</table>
Multispeed overground walking showed a similar trend in Table 3.2. FE RMSE was lower, 7.29 ± 6.25° compared to 11.64 ± 4.94° for the Functional method. AA and IER both had similar RMSE values, 5.44 ± 2.28° to 4.61 ± 2.43° and 9.13 ± 5.29° to 8.45 ± 4.87° respectively. Slopes, intercepts, and r values were all similar between both methods. Mean ROME was comparable between the two methods, with values between 5.68° and 11.50° for the Functional method and between 6.10° and 9.18° for the Fasel method.
Table 3.2: Multispeed overground walking mean (SD) of statistics for all subjects and left and right hip angles.

<table>
<thead>
<tr>
<th>Method</th>
<th>Angle</th>
<th>RMSE [°]</th>
<th>Slope</th>
<th>Intercept [°]</th>
<th>r</th>
<th>IMU ROM [°]</th>
<th>MC ROM [°]</th>
<th>ROME [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Functional</td>
<td>FE</td>
<td>7.29(6.25)</td>
<td>1.01(0.04)</td>
<td>-5.17(7.93)</td>
<td>0.99(0.00)</td>
<td>70.03(9.09)</td>
<td>65.86(8.16)</td>
<td>5.68(3.98)</td>
</tr>
<tr>
<td></td>
<td>AA</td>
<td>5.44(2.28)</td>
<td>0.93(0.08)</td>
<td>-2.41(4.97)</td>
<td>0.87(0.05)</td>
<td>28.92(4.66)</td>
<td>30.61(7.90)</td>
<td>4.13(6.18)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>9.13(5.29)</td>
<td>0.90(0.13)</td>
<td>-1.07(8.45)</td>
<td>0.73(0.11)</td>
<td>50.38(8.11)</td>
<td>41.03(8.99)</td>
<td>11.50(7.41)</td>
</tr>
<tr>
<td>Fasel</td>
<td>FE</td>
<td>11.64(4.94)</td>
<td>0.99(0.04)</td>
<td>-6.52(10.64)</td>
<td>0.99(0.00)</td>
<td>68.33(8.72)</td>
<td>67.46(11.68)</td>
<td>6.10(9.39)</td>
</tr>
<tr>
<td></td>
<td>AA</td>
<td>4.61(2.43)</td>
<td>0.89(0.17)</td>
<td>-2.90(3.52)</td>
<td>0.83(0.08)</td>
<td>29.54(5.61)</td>
<td>30.73(8.39)</td>
<td>5.17(7.16)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>8.45(4.87)</td>
<td>0.87(0.11)</td>
<td>-2.13(8.13)</td>
<td>0.87(0.06)</td>
<td>40.60(7.73)</td>
<td>44.91(22.06)</td>
<td>9.18(16.67)</td>
</tr>
</tbody>
</table>
Results from fast walking on a treadmill showed the same pattern as previous trials for RMSE values. Table 3.3 lists approximately half the RMSE for FE - $7.16 \pm 6.18^\circ$ compared to $14.33 \pm 6.45^\circ$, and similar values for AA and IER. Slopes were similar across both methods, with a larger difference for IER angles with slopes of $0.87 \pm 0.21$ compared to $0.80 \pm 0.19$ for Functional and Fasel methods respectively. However the relatively larger SDs indicate that the values are not necessarily that different. ROME values for all three angles were comparable between methods, with the Functional values ranging from $1.99^\circ$ to $3.22^\circ$ and Fasel values ranging from $2.99^\circ$ to $4.42^\circ$. 
Table 3.3: Treadmill walk fast mean (SD) of statistics for all subjects and left and right hip angles.

<table>
<thead>
<tr>
<th>Method</th>
<th>Angle</th>
<th>RMSE [°]</th>
<th>Slope</th>
<th>Intercept [°]</th>
<th>r</th>
<th>IMU ROM [°]</th>
<th>MC ROM [°]</th>
<th>ROME [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE</td>
<td>7.16(6.18)</td>
<td>1.01(0.04)</td>
<td>-4.86(8.04)</td>
<td>0.99(0.00)</td>
<td>48.00(4.39)</td>
<td>46.86(4.00)</td>
<td>1.99(2.12)</td>
</tr>
<tr>
<td>Functional</td>
<td>AA</td>
<td>5.61(2.51)</td>
<td>0.91(0.12)</td>
<td>-0.56(5.03)</td>
<td>0.83(0.13)</td>
<td>19.77(3.59)</td>
<td>19.37(3.99)</td>
<td>2.80(2.44)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>10.04(5.92)</td>
<td>0.87(0.21)</td>
<td>-7.05(8.03)</td>
<td>0.81(0.13)</td>
<td>24.00(4.66)</td>
<td>23.45(3.72)</td>
<td>3.22(2.26)</td>
</tr>
<tr>
<td></td>
<td>FE</td>
<td>14.33(6.45)</td>
<td>0.98(0.04)</td>
<td>-9.32(12.28)</td>
<td>0.99(0.01)</td>
<td>48.61(4.95)</td>
<td>46.86(4.00)</td>
<td>2.99(2.28)</td>
</tr>
<tr>
<td>Fasel</td>
<td>AA</td>
<td>5.36(3.47)</td>
<td>0.95(0.14)</td>
<td>-2.96(4.62)</td>
<td>0.84(0.13)</td>
<td>21.84(4.62)</td>
<td>19.37(3.99)</td>
<td>4.42(3.67)</td>
</tr>
<tr>
<td></td>
<td>IER</td>
<td>10.85(5.42)</td>
<td>0.80(0.19)</td>
<td>6.20(8.98)</td>
<td>0.73(0.15)</td>
<td>25.39(5.44)</td>
<td>23.45(3.72)</td>
<td>4.12(3.71)</td>
</tr>
</tbody>
</table>
Table 3.4 lists the results from backwards walking on the treadmill. RMSE was again better for the Functional method FE angle (7.24 ± 6.37° to 12.52 ± 5.08°), similar for AA, and slightly better for IER (9.21 ± 5.08° to 11.42 ± 6.61°). Slopes and \( r \) values were all similar between methods. Intercepts from the Functional method were better (−5.91 ± 7.67° to −8.35 ± 10.55°, 2.87 ± 9.58° to 8.26 ± 9.28° for FE and IER respectively), except for AA which was similar. ROME values were comparable between methods again, with values ranging between 2.53° to 2.77° for the Functional method and values between 2.93° and 4.76° for the Fasel method.
Table 3.4: Treadmill walk backwards mean (SD) of statistics for all subjects and left and right hip angles.

<table>
<thead>
<tr>
<th>Method</th>
<th>Angle</th>
<th>RMSE [°]</th>
<th>Slope</th>
<th>Intercept [°]</th>
<th>r</th>
<th>IMU ROM [°]</th>
<th>MC ROM [°]</th>
<th>ROME [°]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FE</td>
<td></td>
<td>7.24(6.37)</td>
<td>1.02(0.05)</td>
<td>-5.91(7.67)</td>
<td>0.98(0.01)</td>
<td>36.38(4.83)</td>
<td>34.89(5.05)</td>
<td>2.53(2.48)</td>
</tr>
<tr>
<td>Functional AA</td>
<td>5.04(3.12)</td>
<td>0.95(0.08)</td>
<td>-2.88(5.04)</td>
<td>0.95(0.02)</td>
<td>11.88(2.73)</td>
<td>13.83(4.13)</td>
<td>2.77(3.97)</td>
<td></td>
</tr>
<tr>
<td>IER</td>
<td></td>
<td>9.21(5.08)</td>
<td>0.79(0.19)</td>
<td>2.87(9.58)</td>
<td>0.78(0.14)</td>
<td>21.09(3.13)</td>
<td>22.03(5.58)</td>
<td>2.47(3.29)</td>
</tr>
<tr>
<td>FE</td>
<td></td>
<td>12.52(5.08)</td>
<td>0.99(0.07)</td>
<td>-8.35(10.55)</td>
<td>0.97(0.02)</td>
<td>35.70(4.36)</td>
<td>34.89(5.05)</td>
<td>2.93(2.42)</td>
</tr>
<tr>
<td>Fasel AA</td>
<td>5.32(4.64)</td>
<td>0.97(0.19)</td>
<td>-3.01(6.13)</td>
<td>0.82(0.14)</td>
<td>16.36(3.78)</td>
<td>13.83(4.13)</td>
<td>4.26(2.84)</td>
<td></td>
</tr>
<tr>
<td>IER</td>
<td></td>
<td>11.42(6.61)</td>
<td>0.91(0.20)</td>
<td>8.26(9.28)</td>
<td>0.75(0.15)</td>
<td>24.16(4.94)</td>
<td>22.03(5.58)</td>
<td>4.76(4.55)</td>
</tr>
</tbody>
</table>
Table 3.5 lists the run times for the Functional and Fasel methods for various similar parts of the algorithms. The Functional method over two times faster than the Fasel method, which an average total processing time of $332 \pm 15.7\,s$ compared to $873 \pm 79.8\,s$. PTPS is also substantially lower, with an average of $0.456 \pm 0.0216\,s$ for the Functional and $1.19 \pm 0.109\,s$ for the Fasel method.

<table>
<thead>
<tr>
<th>Method</th>
<th>Total [s]</th>
<th>PTPS</th>
<th>Initial [s]</th>
<th>Process all trials [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional</td>
<td>332(15.7)</td>
<td>0.456(0.0216)</td>
<td>38.3(6.40)</td>
<td>294.41(12.4)</td>
</tr>
<tr>
<td>Fasel</td>
<td>873(79.8)</td>
<td>1.19(0.109)</td>
<td>355(76.0)</td>
<td>520(26.6)</td>
</tr>
</tbody>
</table>

3.2 Discussion

In this study, a simple and novel method for estimating full three-dimensional hip joint angles is presented. The method requires minimal calibration motions, does not rely on assumptions about sensor placement, and is validated on human subjects. Hip angles were validated against a reference OMC system, and an additional comparison between an existing hip angle method and OMC was computed.

Comparison to the reference OMC system showed mean RMSE values ranging from $5.04^\circ$ to $5.63^\circ$ for AA, $7.08^\circ$ to $7.29^\circ$ for FE, and $8.32^\circ$ to $10.04^\circ$ for IER across all explored trials. Slopes and $r$ values all indicated good to excellent agreement of angle trends for all activities, with mean slope ranging from 0.79 to 1.10 (1 is best), mean $r$ values between 0.73 and 0.99, and SD $r$ values all below 0.15. ROME values for all trials were below $6.0^\circ$, except for FE during the star calibration ($12.13^\circ$) and IER during the multispeed overground walking ($11.50^\circ$).

Existing inertial sensor methods for estimating hip kinematics with available algorithms are not common. The only method (Fasel method) found in the literature
with an algorithm description that had the fewest constraints, originally intended for analysis of alpine skiing biomechanics, was implemented to provide a performance comparison. As evidenced in Tables 3.1, 3.2, 3.3, and 3.4, performance of the proposed method was largely comparable or better than this existing approach. Functional method mean FE RMSE values (range 7.08° to 7.29° compared to 11.64° to 14.33°) were lower for all trials examined, and mean AA RMSE (range 5.04° to 5.63° compared to 4.61° to 5.92°) and IER RMSE (range 8.32° to 10.04° compared to 8.45° to 11.42°) values were comparable for all trials. ROME was comparable or better between methods for all trials (range 1.99° to 12.57° compared to 2.93° to 12.75°).

Reported results for the original study showed the largest mean sample-to-sample difference occurred in FE (−10.7 ± 4.3°) while AA and IER showed lower values (−3.3 ± 4.1° and 0.5 ± 4.8° respectively) for the left hip. Mean sample-to-sample differences can present differently than RMSE however, exemplified by Functional method mean sample-to-sample differences of 4.98 ± 7.90° for FE, 2.22 ± 4.86° for AA, and 1.45 ± 9.25° for IER for multispeed overground walking trial, which are similar or better to the results reported in [19] for skiing. In comparison, the Fasel method mean sample-to-sample differences for multispeed overground walking were 6.63 ± 10.65°, 2.51 ± 3.35°, and 2.51 ± 9.04° for FE, AA, and IER respectively. Similar mean correlation values to those observed in this study were reported (0.974, 0.896, and 0.977 for FE, AA, and IER) [19]. Several differences between this study and the study in [19] may have resulted in the disparities in results. Calibration motions were repeated in between every trial recorded, totaling five calibration procedures recorded. Performing this many calibration motions however limits the ability of algorithms to be deployed under conditions where trained personnel can observe and
ensure that calibration motions are performed correctly. As the calibration motions are designed to primarily activate only one axis at a time, correct realization of these motions is important for acceptable results. While a specific star calibration motion was used in this study, any motion that achieves sufficient rotation about all axes for the hip and knee should provide acceptable results.

The Fasel method additionally requires more sensors than the Functional method presented in this paper. Symmetric standing posture assumptions are made for the left and right legs, as well as corrections of knee angle during standing which require sensors on the shanks. Additionally, the best drift correction was observed with sensors on the upper trunk, which means that the ideal solution requires six sensors with this approach. Conversely, the Functional method would require only three permanent sensors and one temporary sensor to provide the same functionality. The temporary sensor only has to be moved between left and right lower legs during the dynamic calibration motion, and is not necessary thereafter.

The Functional method was also simpler in design and implementation than the Fasel method. Large differences in run time were observed between the two methods, with the Functional method running in about 40% of the time required for the Fasel method. This difference is significant, especially if real-time implementations are ever required, as the PTPS for the Functional method is below 1 (0.456 while the Functional method is above 1.0 (1.19)).

Drift in the proposed method was explored during the fast walking on the treadmill by calculating the slope of the absolute mean error between proposed and OMC angles relative to time. Computed slopes for all subjects and sides were tested using a one-sample T-test under the null hypothesis that the mean of the slopes equaled zero.
None of the angles (FE, AA, IER) provided sufficient evidence to reject the null hypothesis \( (p-values 0.63, 0.12, 0.12 \text{ respectively}) \), indicating that there was no discernible drift during the minute long trial.

Other previous works have implemented both one and three-dimensional joint angle estimation algorithms with varying results. Two of these have validated against a robotic arm [26] or coordinate measurement machine (CMM) [24]. The studies reported less than 7.8° RMSE [26] and 3.46° RMSE for all 3D angles. While these values are mostly better than observed in this study, the robotic arm and CMM have no STA which can add significant differences in angles [52], [53]. As such, these levels of performance likely will not generalize to measurements made on human subjects.

Another method for estimating knee FE angle was tested on a single transfemoral amputee subject with a prosthesis on one leg. Due to the tiny subject pool, results should be interpreted with care, however reported RMSE values for the non-prosthesis leg were less than 3.30° during normal gait. This was matched during the current study for one subject, with mean RMSE values of 3.07°, 1.89°, and 3.69° for FE, AA, and IER respectively during multispeed overground walking and treadmill fast walking. Prosthesis RMSE values were lower, as expected with the lack of STA to effect sensor to bone relative positions. Additionally, this method was only implemented under a 1D hinge-joint assumption, which may be valid for the knee, but certainly does not apply to the hip. These levels of performance for human subjects and non-human machines, indicate that for the hip, which experiences larger activity in the non-FE axes, the proposed algorithm provides comparable performance to established literature.

Previous hip angle comparisons of IMU systems using proprietary algorithms to OMC showed a range of RMSE values for hip angles. One study reported values less
than 7.5° [39] during manual material handling tasks. Another study using a different IMU system reported 9.6° and 27.6° RMSE for walking and running on a treadmill respectively. The manual material handling and walking RMSE values are comparable to those found in this study. However, no information was provided regarding the algorithms employed by the sensor systems, and the significant performance decrease from walking to running raises concerns regarding the utility of the systems. Additionally, the proprietary nature of the algorithms would not allow other sensor systems to be used with the algorithms, which is not a limitation imposed by the proposed method presented in this study.

Other comparisons have used novel algorithms during walking, squatting, and jumping. Two OMC methods for estimating joint angles were employed, one based on rigid clusters that were attached to the sensors, and the second using individual markers directly on the skin. The IMU based algorithm reported RMSE values less than 2.29° for cluster based and less than 5.60 for skin marker based OMC comparisons during a 6-minute walk trial [41]. During the squatting and jumping, RMSE values were all less than 2.28° and 8.27° for cluster and skin based markers respectively [42]. While the results initially appear better, the OMC system was used to provide the sensor to body segment orientations. This links the two system’s results, and has been shown to have a significant influence on the results obtained [39].

Previous literature in disorders effecting gait provides evidence that the proposed method could be used for diagnosis. In persons with OA, mean peak hip extension in the stance phase during walking was reported as 8.4±7.0° compared to 14.2±8.7° for healthy controls [1], a 5.8° difference in means. In another study on persons with MS, hip ROM during stance was reported as 35.58 ± 4.91° during walking compared to
39.26±3.84° for healthy controls [2], a 3.68° difference in mean ROM. People afflicted by PD showed the biggest difference to healthy control, with sagittal plane (similar to FE) ROM values of 47.6±4.1°, 33.2±8.5°, and 41.5±5.1° for healthy controls, PD patients off Levadopa (PD treatment drug), and PD patients on Levadopa respectively [3]. For the proposed method, FE ROME was 1.99 ± 2.12° during treadmill fast walking, indicating that the proposed method has the resolution necessary to observed these differences in healthy or afflicted populations.

While OMC was the gold standard measure used in this study, other methods of estimating angles have been used. Goniometers are used clinically to measure ROM on subjects, however multiple studies have shown variable reliability and re-testability. Inter-observer ICC (intra-class correlation coefficient) values range from 0.30 to 0.65 [17] for hip extention and 0.16 to 0.55 [18] for across FE, AA, and IER angles. One study reported limits of agreement (LOA) between goniometers and an electromagnetic tracking system for hip ROM, with values of −18.92 ± 12.57° for hip flexion[16], which is substantially higher than those observed from comparing the proposed method to OMC. Additionally, goniometers are only suited for static ROM measurements due to the manual aligning with anatomical landmarks, and require a trained clinician to align and perform the movements to achieve the necessary FE, AA, and IER specific motions.

The other reported methods for obtaining human biomechanics involve some form of radioscopy or x-ray fluoroscopy. While these methods are the most accurate, the setup and small field of view limit the applicability. These systems have been used previously to quantify the effect of STA on skin marker based estimates of knee joint angles. Large RMSE values were observed, with RMSE values ranging from 2.4° to
8.3° [52] and rotational errors of up to 12°[53]. Additionally, AA and IER average RMSE values were significantly larger than the observed ROM, with RMSE/ROM values as high as 181.3% [52]. These differences indicate that future work exploring the difference between the proposed method and x-ray fluoroscopy should be completed, as the proposed method may do a better job of capturing the underlying bone motion. Nevertheless, OMC is used extensively in both clinical and research contexts, thus the comparison presented herein is critical for understanding the performance of the proposed approach.

Future work should involve a comparison against fluoroscopic methods in an effort to further quantify the error in wearable sensor based methods and provide further determination on their utility in both laboratory and unconstrained settings. Another aspect that could be improved upon is the estimation of joint center locations during activities of daily living, obviating the need for the short star calibration trial used herein. This would allow for better deployment of this method to populations with mobility and ROM impairments that might not allow them to complete the star calibration or similar motion. Finally, quantitatively measuring the repeatability of the proposed method would be necessary for application to longitudinal studies or those looking for changes in kinematics over time. While previous studies have not grouped by gender [39], [40], [42], [54], this should be explored in the future, due to potential differences in STA or sacrum sensor placement due to waist geometry.

Limitations of this study include the limited age range of subjects, with little to no representation of subjects over the age of 25, as well as the small subject pool. While typical for similar studies (N=11 in [19]) a larger subject pool would allow for stronger conclusions to be drawn from the results. Furthermore, the testing on
healthy subjects does not indicate how well the algorithms will perform on individuals with mobility impairments, though the only significant change should be in the joint center estimation through the star calibration trial. Additionally, while effort was made to ensure that subjects were instrumented for OMC by the same person in the same way, marker placement was done by two people, potentially introducing some variability between subjects in the initial creation of anatomical reference frames. Finally, while the sensor assigned to the pelvis is placed in the manufacturer’s recommended location, which is also used in previous studies [19], [41], [42], it is not directly on the pelvis which could result in some rotations from the spine affecting results.
Chapter 4: Conclusion

A wearable magnetic and inertial sensor based method for estimating 3D hip joint angles was proposed and validated against OMC on human subjects. Novel aspects of the algorithm include no assumptions about sensor orientation and no specialized calibration motions as well as new orientation estimations. An additional comparison to the performance of an existing method was also implemented. Results were typically comparable or better than the existing method, in addition to being simpler and faster to run. RMSE for the proposed method compared to OMC ranged between $7.04^\circ$ and $7.96^\circ$ for FE, $5.34^\circ$ and $6.07^\circ$ for AA, and $8.29^\circ$ to $10.06^\circ$ for IER, compared to between $11.64^\circ$ and $14.33^\circ$, $4.61^\circ$ and $5.92^\circ$, and $8.46^\circ$ to $11.42^\circ$ for an existing method comparison to OMC for FE, AA, and IER respectively. All regression analysis mean slopes and Pearson’s correlation coefficients were between 0.79 and 1.10 and 0.84 to 0.99 respectively for the proposed method. ROME was below $5^\circ$ for all angles in the star calibration, treadmill fast walking, and treadmill backwards walking except for FE during the star calibration ($12.13^\circ$). Overall, these results are comparable to and improve upon existing methods for estimation of hip joint angles.
Bibliography


Appendix A: Study Activities

A.1 Star Calibration

A star calibration consists of the following sequence of events:

1. Start standing still, pick a leg to start with. Pick the chosen leg off the ground and do not set back down until motions have been completed. A support may be used to prevent loss of balance.

2. Extend chosen leg at $0^\circ$ from the sagittal plane in the forwards direction and bring back.

3. Repeat step 2 for angles of $45^\circ$, $90^\circ$, $135^\circ$, and $180^\circ$.

4. Extend chosen leg at $180^\circ$ from the sagittal plane in the forwards direction and rotate through to $0^\circ$ before bringing back to not extended.

5. Bring thigh up to approximately horizontal and perform 3-5 knee flexion-extension motions.

6. Perform 3-5 passes of random rotation of the foot about the ankle joint.

7. Return chosen leg to the ground, switch legs, and repeat steps 2-6.
(a) Top down view of the angles the leg is extended at during the star calibration, through step 3.

(b) Side view of the star calibration extension of step 2.

(c) Side view of the star calibration knee flexion-extensions of step 5.

(d) Side view of the star calibration random ankle rotations of step 6.

Figure A.1: Star calibration motions.
## A.2 Full activity list

*Table A.1: Full list of activities performed for the study, their duration, and if they were performed with OMC. * indicates performed as a calibration trial.*

<table>
<thead>
<tr>
<th>Activity</th>
<th>Duration (s)</th>
<th>OMC [yes/no]</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static Standing</td>
<td>3</td>
<td>yes*</td>
<td></td>
</tr>
<tr>
<td>Star Calibration</td>
<td>untimed</td>
<td>yes*</td>
<td></td>
</tr>
<tr>
<td>45° Static Lean</td>
<td>10</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Stand</td>
<td>60</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Stand to Sit</td>
<td>untimed</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Sit</td>
<td>60</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Sit to Stand</td>
<td>untimed</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Squat</td>
<td>60</td>
<td>yes</td>
<td>Static pose</td>
</tr>
<tr>
<td>Calf Raises</td>
<td>untimed</td>
<td>yes</td>
<td>x10</td>
</tr>
<tr>
<td>Air Squats</td>
<td>untimed</td>
<td>yes</td>
<td>x5</td>
</tr>
<tr>
<td>Multispeed Overground Walking</td>
<td>60</td>
<td>yes</td>
<td>Continuous speed increase</td>
</tr>
<tr>
<td>10x Force Plate Walk</td>
<td>untimed</td>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>Treadmill walk slow</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill walk normal</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill walk fast</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill walk laterally left</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill walk laterally right</td>
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<td>yes</td>
<td>Self-selected pace</td>
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<tr>
<td>Treadmill walk backwards</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill run slow</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill run comfortable</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Treadmill run fast</td>
<td>60</td>
<td>yes</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Lie Prone</td>
<td>60</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Lie Supine</td>
<td>60</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Lie Left</td>
<td>60</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Lie Right</td>
<td>60</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Stair Ascent</td>
<td>untimed</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Stair Descent</td>
<td>untimed</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Crutches walk injured left</td>
<td>60</td>
<td>no</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Crutches walk injured right</td>
<td>60</td>
<td>no</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Hallway walk slow</td>
<td>60</td>
<td>no</td>
<td>Self-selected pace</td>
</tr>
<tr>
<td>Hallway walk normal</td>
<td>60</td>
<td>no</td>
<td>Self-selected pace</td>
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<tr>
<td>Hallway walk fast</td>
<td>60</td>
<td>no</td>
<td>Self-selected pace</td>
</tr>
</tbody>
</table>
## Appendix B: Instrumentation

### B.1 Motion Capture

Table B.1: List of OMC reflective markers, and descriptions for their placement.

<table>
<thead>
<tr>
<th>Name</th>
<th>Location Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>sternum cluster 1</td>
<td>Sternum MIMU cluster marker 1</td>
</tr>
<tr>
<td>sternum cluster 2</td>
<td>Sternum MIMU cluster marker 2</td>
</tr>
<tr>
<td>sternum cluster 3</td>
<td>Sternum MIMU cluster marker 3</td>
</tr>
<tr>
<td>(left/right) axis</td>
<td>Left/right anterior superior iliac spine</td>
</tr>
<tr>
<td>(left/right) pxis</td>
<td>Left/right posterior superior iliac spine</td>
</tr>
<tr>
<td>sacrum cluster 1</td>
<td>Sacrum MIMU cluster marker 1</td>
</tr>
<tr>
<td>sacrum cluster 2</td>
<td>Sacrum MIMU cluster marker 2</td>
</tr>
<tr>
<td>sacrum cluster 3</td>
<td>Sacrum MIMU cluster marker 3</td>
</tr>
<tr>
<td>(left/right) trochanter</td>
<td>Left/right greater trochanter</td>
</tr>
<tr>
<td>(left/right) anterior thigh 50</td>
<td>Approximately 50% from knee and hip on anterior surface</td>
</tr>
<tr>
<td>(left/right) lateral thigh 30</td>
<td>Approximately 50% from knee and hip on lateral surface</td>
</tr>
<tr>
<td>(left/right) anterior thigh 25</td>
<td>Approximately 25% from knee to hip on anterior surface on top of IMU</td>
</tr>
<tr>
<td>(left/right) lateral thigh 25</td>
<td>Approximately 25% from knee to hip on lateral surface</td>
</tr>
<tr>
<td>(left/right) anterior thigh 15</td>
<td>Approximately 15% from knee to hip on anterior surface</td>
</tr>
<tr>
<td>(left/right) lat femoral epicondyle</td>
<td>Lateral femoral epicondyle</td>
</tr>
<tr>
<td>(left/right) med femoral epicondyle†</td>
<td>Medial femoral epicondyle</td>
</tr>
<tr>
<td>(left/right) thigh cluster 1</td>
<td>Left/right thigh MIMU cluster marker 1</td>
</tr>
<tr>
<td>(left/right) thigh cluster 2</td>
<td>Left/right thigh MIMU cluster marker 2</td>
</tr>
<tr>
<td>(left/right) thigh cluster 3</td>
<td>Left/right thigh MIMU cluster marker 3</td>
</tr>
<tr>
<td>(left/right) anterior shank 30</td>
<td>Approximately 30% from ankle to knee on the anterior surface</td>
</tr>
<tr>
<td>right lateral distal shank</td>
<td>Approximately 25% from ankle to knee on the lateral surface on top of IMU</td>
</tr>
<tr>
<td>(left/right) lateral malleolus</td>
<td>Left/right lateral malleolus</td>
</tr>
<tr>
<td>(left/right) medial malleolus†</td>
<td>Left/right medial malleolus</td>
</tr>
<tr>
<td>(left/right) shank cluster 1</td>
<td>Left/right shank MUMU cluster 1</td>
</tr>
<tr>
<td>(left/right) shank cluster 2</td>
<td>Left/right shank MUMU cluster 2</td>
</tr>
<tr>
<td>(left/right) shank cluster 3</td>
<td>Left/right shank MUMU cluster 3</td>
</tr>
<tr>
<td>(left/right) heel</td>
<td>Left/right heel, same height as second metatarsal marker</td>
</tr>
<tr>
<td>(left/right) metatarsal 2</td>
<td>Left/right second metatarsal</td>
</tr>
<tr>
<td>(left/right) metatarsal 5†</td>
<td>Left/right fifth metatarsal</td>
</tr>
<tr>
<td>(left/right) metatarsal 1†</td>
<td>Left/right first metatarsal</td>
</tr>
<tr>
<td>(left/right) toe tip†</td>
<td>Left/right tip of toes</td>
</tr>
<tr>
<td>(left/right) foot cluster 1</td>
<td>Left/right foot MUMU cluster 1</td>
</tr>
<tr>
<td>(left/right) foot cluster 2</td>
<td>Left/right foot MUMU cluster 2</td>
</tr>
<tr>
<td>(left/right) foot cluster 3</td>
<td>Left/right foot MUMU cluster 3</td>
</tr>
</tbody>
</table>

† Calibration only marker
### B.2 MIMU Sensors

_Table B.2: Placement of MIMU sensors._

<table>
<thead>
<tr>
<th>Name</th>
<th>Location Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sternum</td>
<td>On the chest approximately 2cm below the suprasternal notch</td>
</tr>
<tr>
<td>Lumbar</td>
<td>On the lumbar at approximately L4</td>
</tr>
<tr>
<td>Left/right thigh</td>
<td>On the iliotibial band between the 25% and 50% lateral reflective markers</td>
</tr>
<tr>
<td>Left/right shank</td>
<td>Medially on the tibial surface below the tibial tuberosity</td>
</tr>
<tr>
<td>Left/right foot</td>
<td>On the superior surface of the foot above the arch</td>
</tr>
</tbody>
</table>