Extracting Spatio-Temporal Information from Inertial Body Sensor Networks for Gait Speed Estimation

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Abstract—**The fidelity of many inertial Body Sensor Network (BSN) applications depends on accurate spatio-temporal information retrieved from body-worn devices. However, there are many challenges caused by inherent sensor errors in inertial BSNs and the uncertainty of dynamic human motion in various situations, such as integration drift and mounting error. Spatial information is especially difficult to extract from inertial data.**

This paper presents practical methods to minimize errors caused by these challenges within the context of a case study – gait speed estimation – where both temporal and spatial information are crucial for accuracy. These methods include a practical calibration procedure for correcting mounting error in order to obtain more accurate spatial information and a refined human gait model for more accurate temporal information.

I. Introduction

In recent years, inertial Body Sensor Networks (BSNs) have emerged to facilitate numerous medical research and healthcare applications, providing continuous, non-invasive motion capture data in any location over an extended period. Gait analysis is one such application and is being applied in medical studies and clinical practice ranging from assessing fall risk in the elderly to improving orthopedic devices for children with cerebral palsy [1]. However, while simple temporal gait parameters such as step time and double stance time can be easily extracted from accelerometer and gyroscope data, parameters that depend on both temporal and spatial information are much more challenging to accurately assess due to integration drift (e.g., acceleration to velocity and position, rotational rate to angular displacement) and node placement uncertainty [2].

Gait speed is one such spatio-temporal parameter, as it includes both stride length and stride time. It is a particularly important parameter in geriatrics, as it is the number one predictor of mortality in adults over 65 years old, with differences of just a couple tenths of a meter per second predicting statistically significant outcome differences [3]. The most common method for gait speed estimation in medical research and clinical practice is to simply use a stopwatch and a tape measure. This typically provides good accuracy but is insufficient for applications that require more continuous and longitudinal data, especially given that speed and many other gait parameters can vary significantly day-to-day and even hour-to-hour in geriatric and gait impaired populations. It is therefore highly desirable to be able to estimate gait speed using inertial BSNs and to do so with a resolution of better than 0.1 m/s, but the abovementioned challenges have prevented significant progress towards this goal.

This paper addresses some of the fundamental challenges of extracting from inertial BSNs spatio-temporal information in general and gait speed in particular. The approach includes a new application independent method for *mounting calibration* using simple pre-defined movements and rotation matrices to ensure accurate spatial analysis regardless of how the BSN nodes are placed on-body. In addition, application specific methods are developed and applied that leverage knowledge of biomechanics and human gait – including temporal knowledge of gait phases – in order to *minimize integration drift* and to *better model stride length*. The combined use of the above results in gait speed estimates (performed on a treadmill) that are significantly more accurate than previous methods.

The rest of this paper is organized as follows. Section II reviews prevailing technologies and related work for gait speed estimation, including a simple pendulum gait model to explain the general method of gait speed estimation using inertial BSNs. In addition, methods leveraging known events in and the cyclic nature of gait are presented to overcome the challenges in cancelling integration drift. Section III proposes a practical method for reducing errors caused by inexact mounting. Section IV proposes a refined double pendulum model for gait speed estimation based on critical temporal information in human gait. Section V details the experiment setup. Section VI evaluates the results of using the proposed mounting calibration and gait model. Section VII summarizes the impact and limitations of the methods for obtaining accurate spatio-temporal information in the context of gait speed estimation.

II. Background and Related Work

A. Prevailing Technology

Whereas gait speed estimation is a seemingly trivial problem to solve, prevailing technologies have failed to provide the necessary accuracy and usability. The commercial personal training devices, such as Nike+® [4] and FitBit® [5], effectively count steps and then estimate gait speed using step length information obtained from a pre-defined calibration procedure. Since the step length can vary significantly at different gait speeds, the accuracy of these devices is questionable. GPS-based solutions, such as the Garmin Forerunner® [6], provide high accuracy but are limited to outdoor use and do not facilitate any other spatial or temporal gait information.

B. *Gait Speed Estimation using Inertial BSNs*

Most of the previous work using inertial sensors to estimate gait speed models human gait as an inverse pendulum [7] [8] [10]. [7] was the first to devise the method of using a single axis gyroscope to estimate stride length and gait speed. [8] and [9] proposed a more precise model by using both shank and thigh mounted inertial sensors. While the initial efforts in [7] seemed to provide an over-simplified model, the more refined model in [8] and [9] requires thigh nodes, which introduces more invasiveness to the wearer (an issue of both node location and number). In this paper, the invasiveness and mounting uncertainty of thigh-mounted nodes is avoided by the use of a refined gait model that only requires shank data. [10] explored using an accelerometer to obtain linear velocity by leveraging the gyroscope integrated angle information. Although integrating acceleration to obtain distance and velocity seems an intuitive approach, the accuracy is often worse because gravitational force is difficult to separate from inertial force and accelerometers are susceptible to linear mechanical noise. The dynamic characteristic of the shank's linear velocity presents an additional challenge to removing the noise and drift of accelerometers.

The simple compass gait model [7] in Figure 2. is implemented to extract spatio-temporal information for gait speed estimation. The gait speed is extracted by dividing the total traveled distance by total travelling time. Due to the cyclic nature of gait, the travelling distance can be obtained summing the stride length of each gait cycle. The method of segmenting the gait cycles is detailed in Section II D. The stride length can be estimated using the reference model [7] detailed in Section II.D.

C. *Gait Cycle Extraction*

Gait cycle extraction is critical to extract parameters such as gait phase, step time, and stride length, all of which are important for gait speed estimation. Based on the assumption that during the foot on ground event, the angular velocity should be near zero, a local maximum peak detection algorithm is selected for gait cycle extraction. (This portion of the gait cycle was chosen because it also supports integration drift cancelation, as detailed in Section II.E.) To suppress the ripples in the gyroscope signal, a zero-phase, 3rd order, Butterworth low-pass filter with a cutoff frequency of 3Hz is used. The cutoff frequency is determined empirically by inspecting the spectrum of the gyroscope signal, in which the main frequency components lie below 3Hz. The spike representing the Heel-Strike event is removed after the filtering, illuminating the foot-on-ground identified by the peak detection algorithm. Then the time point of foot-on-ground event is recorded and the original gyroscope signal is kept for later integration. This cycle extraction process is illustrated in Figure 1.

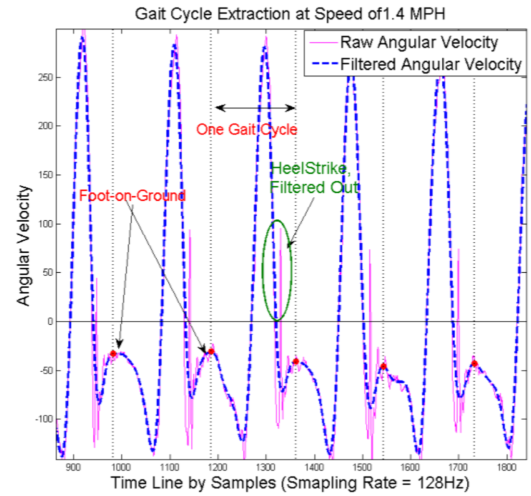


Figure 1. Gait cycle segmentation.

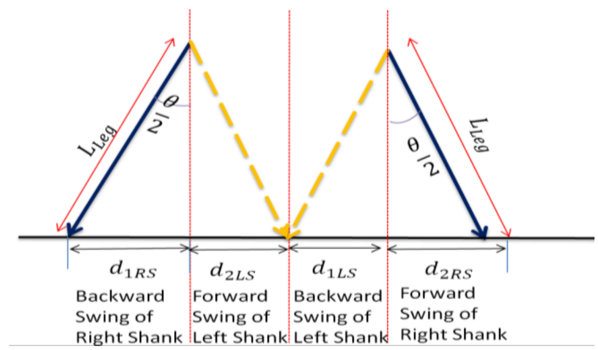


Figure 2. Reference Model [7], where L_{Leg} is the length of the leg, θ is the shank angle range of one gait cycle measured in degrees.

D. *Stride Length Computation*

Stride length can be computed utilizing the gait model illustrated in Figure 2. Since healthy human gait is relatively symmetric, the computation model can be applied to both shanks (assymetric models may have to be used for pathological gait). Here, the right shank is used as an example for computation:

$$\theta = \theta_{\max} + \theta_{\min} \tag{1}$$

$$d_{1RS} = d_{2RS} = \sin\left(\frac{\theta}{2}\right) \times L_{Leg} \tag{2}$$

The stride length of one gait cycle can be considered as:

$$Stride\_Length = d_{1RS} + d_{2LS} + d_{1LS} + d_{2RS} \tag{3}$$

The shank angle range is obtained by integrating the discrete angular velocity value measured from the rate gyroscope sensors:

$$\theta[n] = \theta[n-1] + \frac{\Delta}{2} \times (\omega[n-1] + \omega[n]), [8] \tag{4}$$

In Equation (4), ω is the angular velocity obtained from the rate gyroscope signal, Δ is the sampling period (1/128 s in this case), and $\theta[n]$ is the dynamic shank angle at time instant n. The swing range can then be found by differencing the maximum and minimum of the shank angle in one gait cycle.

E. Integration Drift Cancelation

Discrete integration as shown in Equation (4) introduces inevitable drift as a function of time due to gyroscope sensors' bias and random noise. Signal processing techniques such as high-pass filtering [12], complementary filtering, and Kalman filtering have been practiced for removing the drift. While these techniques are effective, they may also bring uncertainty in estimation of shank angle due to improper filtering parameters or fusing other source of information, i.e., accelerometer. In this work, the gait cycle information is leveraged to null the drift based on the evidence that at the foot-on-ground events the shank angle should be near zero. Since integration can be conducted in a small duration (one gait cycle in this case, no longer than 3 seconds), it is reasonable to assume the drift is accumulated due to constant bias over random noise that is linear over time. Therefore, at the initial and end instance of a gait cycle (foot-on-ground events), the angle integrated of these two instances can be reset to zero, hence eliminating the integration drift in a gait cycle:

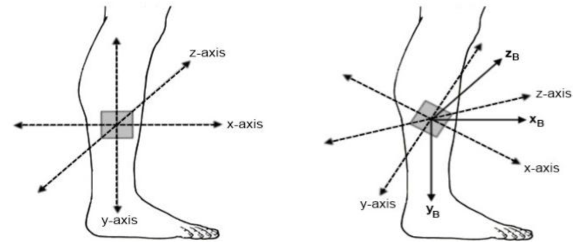
$$\begin{cases} Slope = \frac{\theta_{end} - \theta_{start}}{T_{end} - T_{start}} \\ \hat{\theta_i} = \theta_i - Slope \times i \end{cases} \quad (5)$$

where $Slope$ is the slope of the drift assumed linearly in one gait cycle, θ_{start} and θ_{end} denote the shank angle at the start and end point respectively of the gait cycle, T_{start} and T_{end} denote the timestamp at the start and end point respectively of this gait cycle, θ_i is the shank angle at time index i of this gait cycle, and $\hat{\theta}$ is the shank angle after drift cancellation at time index i of this gait cycle, as used to find the swing range.

III. MOUNTING CALIBRATION

[2] has characterized mounting error as a dominant source of error in inertial BSNs when applied to measuring knee joint angles. In the case of gait speed estimation, where shank angle is a critical piece of spatial information in obtaining stride length, a carelessly mounted inertial sensor node can cause a misinterpretation of the data, leading to a significant decrease in the accuracy of the estimation. In this application, it can cause the data to be interpreted with a reduced angular velocity, thereby underestimating gait speed. Mounting error exists when the sensor is not affixed to the body in the assumed orientation. Ideally the sensor coordinate frame should align with the body frame as shown in Figure 3.

In order to correct the error due to imperfect mounting, the orientation of the inertial frame (sensor coordinate frame) with respect to the body frame needs to be determined. To achieve this, two vectors are computed and then used to relate the two frames. These vectors, $\boldsymbol{y_B}$ and $\boldsymbol{z_B}$, are the y and z axes of the body frame represented by the coordinates of the inertial frame and can be determined by the pre-defined mounting calibration procedure detailed in the rest of this section. $\boldsymbol{x_B}$, the x-axis of the body frame, is determined as the cross product of $\boldsymbol{y_B}$ and $\boldsymbol{z_B}$.



(a) Ideal mounting (b) Non-ideal Mounting

Figure 3. Coordinate in Body Frame, x-axis is defined as the walking direction, y-axis is the direction of gravity, z-axis is pointing inward. The dotted axes represent the basis vectors for the inertial frame, and the solid vectors represent the basis vectors for the global frame.

To deterimine $\boldsymbol{y_B}$, the mounting calibration procedure requires the subject to stand straight with her/his leg vertical to ground. Thus the y-axis of body frame, which is also the direction of gravity in this posture can be represented in the inertial frame as:

$$\boldsymbol{y_B} = [a_x \quad a_y \quad a_z]^T \quad (6)$$

a_x, a_y, and a_z represent the readings from the x, y, and z axes of accelerometer respectively. This representation is based on the assumption that during standing straight posture, the gravity vector in the inertial frame is parallel to $\boldsymbol{y_B}$.

To determine the z-axis of the body frame in the inertial frame, it is necessary to rotate about the body frame's z-axis and find the axis of rotation in the inertial frame. In this mounting calibration procedure, the subject should lift his/her leg forward in the sagittal plane and hold the leg steady by resting it on a surface in order to isolating the gravitation force vector by minimizing the linear motion The reading from the accelerometers at this new position is recorded as:

$$\boldsymbol{g'} = [a'_x \quad a'_y \quad a'_z]^T \quad (7)$$

$\boldsymbol{z_B}$ is then determined as:

$$\boldsymbol{z_B} = \boldsymbol{y_B} \times \boldsymbol{g'} \quad (8)$$

The principle behind this procedure is that $\boldsymbol{z_B}$, the axis around which the gravity vector is rotated, is perpendicular to both $\boldsymbol{y_B}$ and $\boldsymbol{g'}$ and thus can be represented by their cross product. The greater the rotation of the gravity vector (i.e. the higher the leg is lifted), the more accurate this calibration will be. In addition, because $\boldsymbol{z_B}$ and $\boldsymbol{g'}$ are only orthogonal when the leg is lifted 90 degrees, it is necessary to normalize the vector $\boldsymbol{z_B}$.To determine $\boldsymbol{x_B}$:

$$\boldsymbol{x_B} = \boldsymbol{y_B} \times \boldsymbol{z_B} \quad (9)$$

With these three column vectors, $\boldsymbol{x_B}$, $\boldsymbol{y_B}$, and $\boldsymbol{z_B}$, it is possible to construct a rotation matrix to transform vectors in the inertial frame to their corresponding vectors in the body frame. This matrix is defined as:

$$\boldsymbol{R^{BI}} = [\boldsymbol{x_B} \quad \boldsymbol{y_B} \quad \boldsymbol{z_B}] \quad (10)$$

The two measurements used for determining gait speed are the measurements from the tri-axial accelerometer and the measurements from the tri-axial gyroscope. Both of these are taken in the reference frame of the sensor but need to be viewed from the reference frame of the body. In the inertial frame, the acceleration vector and the angular velocity vector are respectively represented:

$$\mathbf{a} = [a_x \quad a_y \quad a_z]^T \tag{11}$$

$$\boldsymbol{\omega} = [\omega_x \quad \omega_y \quad \omega_z]^T \tag{12}$$

The acceleration and angular velocity vectors in the body frame, $\mathbf{a_B}$ and $\boldsymbol{\omega}_\mathbf{B}$, are transformed by $\boldsymbol{R^{BI}}$:

$$\mathbf{a_B} = \boldsymbol{R^{BI}}\mathbf{a} \tag{13}$$

$$\boldsymbol{\omega}_\mathbf{B} = \boldsymbol{R^{BI}}\boldsymbol{\omega} \tag{14}$$

Therefore, by transforming all of the measurements taken in the inertial frame to measurements in the body frame, the mounting error is minimized.

To verify the mounting calibration algorithm, a pendulum model shown in Figure 4. was employed. A sensor node was affixed to the pendulum only rotating around the z-axis. The node was mounted with different controlled degrees of error around the y-axis. The angle rotated around the y-axis was then extracted from the rotation matrix produced by the algorithm.

Table 1 shows the effectiveness of the mounting calibration algorithm in measuring the mounting error. The average error between the angle measured using an inclinometer and the angle measured by the algorithm was 1.023°. Given the margin error of the inclinometer measurement, the results show that this method can accurately determine the spatial orientation of the sensor node with respect to the body frame.

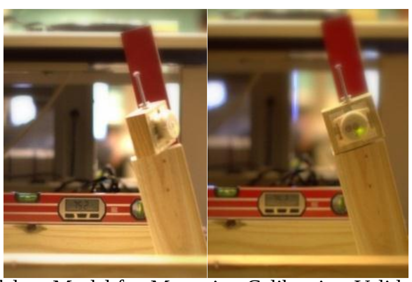


Figure 4. Pendulum Model for Mounting Calibration Validation.

TABLE 1. ANGLES MEASURED AT VARIOUS MOUNTING ERRORS.

Mounting Position Rotated Around Y-axis	**Measured by Proposed Algorithm**	**Measurement Error of Angle**
0°	-0.072°	0.072°
15°	16.286°	1.286°
30°	27.896°	2.104°
45°	43.954°	1.046°
60°	58.078°	1.922°
75°	74.737°	0.263°
90°	90.461°	0.461°

IV. REFINED HUMAN GAIT MODEL

To better examine the human gait model, the gait cycle is divided into 8 phases as shown in Figure 5. Research has shown that the angular velocity of the shank reaches its maximum when the leg is fully extended, and the angle of the shank reaches its maximum after this when the leg is flexed. These two events do not overlap in time as illustrated in Figure 5. and verified by the data in Figure 6. Thus using leg length and the maximum shank angle for computing step length during backward swing (the simplified pendulum model in Figure 2.) is imprecise. This discrepancy suggests a more refined compound pendulum model to compute step length as shown in Figure 7.

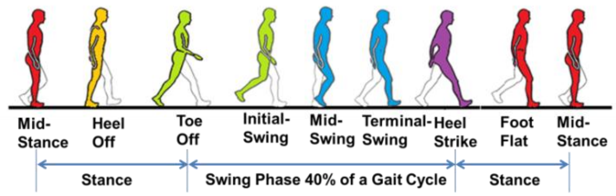


Figure 5. Human gait phases, adapted from [10]. This figure does not represent the actual percentages of a gait cycle spent in each phase.

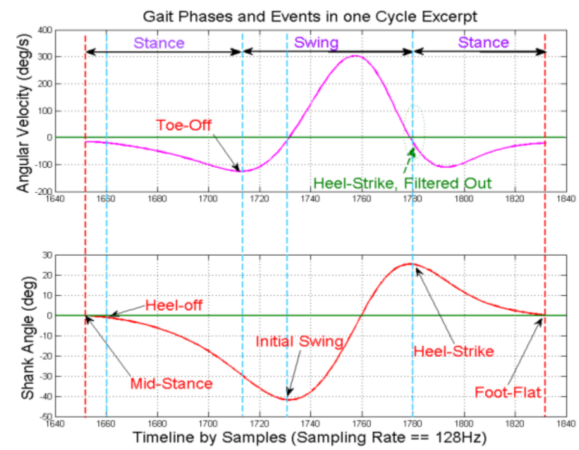


Figure 6. Comparison of angular velocity and shank angle in one gait cycle (counter-clockwise swing as positive in angular velocity).

In the refined model the legs are modeled as compound pendulums. The distance from the back leg to the center is now defined as:

$$d_{1RS} = \sin(\theta_{max}) \times L_{Shank} \tag{15}$$

$$d_{2RS} = \sin(\theta_{min}) \times L_{Leg} \tag{16}$$

where L_{Shank} is the shank length measured from knee joint to ankle joint, L_{Leg} is the leg length measured from hip joint to ankle joint, θ_{max} is the maximum shank angle at initial swing during backward swing, θ_{min} is the maximum shank angle at heel strike during forward swing. The stride length can be found by applying Equation (3).

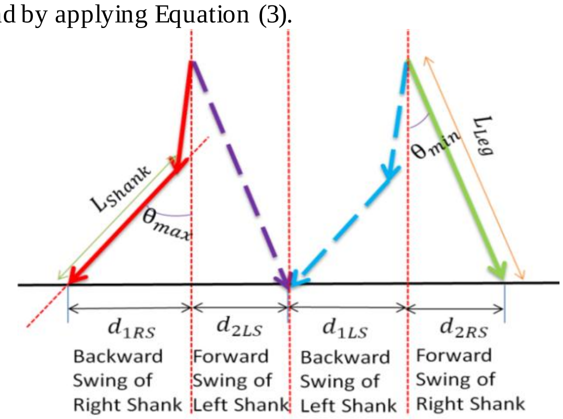


Figure 7. Proposed gait model.

As shown in Figure 7. , the step length calculation of our model differs from the model in [7]. One stride's length is defined as the sum of the step length of the right leg and the step length of the left leg in one gait cycle. The total distance travelled is the sum of the stride lengths of all cycles. Finally, the average gait speed is the distance travelled divided by the total time elapsed.

V. EXPERIMENT SETUP

The accuracy of the estimation was verified using a treadmill. Two walking trials at 1.2m/s on both ground and treadmill are studied to establish the assumption that the gait pattern of the sagittal plane gyroscope signal on treadmill do not differ from it on ground. Two healthy subjects, one female and one male, walked on the treadmill mounted with TEMPO inertial BSN nodes [11] on both shanks, as shown in Figure 8. An elastic Veclro® strap and racquet handle grip were used to maintain mounting position. In the mounting calibration procedure, the subjects were asked to stand still on the treadmill, raise their left leg and then their right leg, and hold them steady for 1 second in order to compensate for mounting error in post-processing. The subjects then were asked to walk on the treadmill at speeds ranging from 1 to 3 MPH with a 0.2 MPH increment for 45 seconds each. The data from the shank mounted sensors were recorded on a laptop and post processed in Matlab® for information retrieval and data analysis. Two trials were conducted for each subject, one with well-mounted nodes and another with poorly-mounted nodes.

Figure 8. TEMPO nodes mounted nonideally out of sagittal plane.

VI. RESULTS AND DISCUSSION

The RMSE is computed comparing treadmill speed, with a resolution of 0.2 MPH (0.09 m/s) from 1MPH to 3MPH, to the calculated gait speed. The accuracy of the proposed model was significantly higher than that of the reference model [7], which commonly overestimates gait speed. The largest RMSE was only 0.095m/s after mounting calibration as shown in Figure 9. With the data from the sessions with well-mounted sensors, we found that for a subject with symmetric gait, the gait speed estimated by single node on one shank does not differ much from each other. With correctly mounted sensor nodes, the two shank mounted solution does improve the accuracy, though not significantly.

The algorithm tends to overestimate at lower speeds and underestimate at higher speeds, which has also been found in [10]. Two sources of errors may lead to this: drift cancellation error and gait model error. On one hand, at low speeds, the longer gait cycle contains more integration drift, which cannot be eliminated completely by the linear drift cancelation function and leads to overestimation of the shank angle. Whereas at high speeds, the drift is overcorrected, decreasing the maximum shank angle in a gait cycle. On the other hand, the model also assumes the thigh angle is negligible during walking, i.e. it is vertical when the shank is at θ_{max}. However, at very low and high speeds, the thigh angle can be critical for controlling the step length. At very low speeds, the thigh tends to swing forward ahead of plumb line so as to maintain a very short step length on the treadmill, resulting in a step length that is shorter than predicted, and vice versa at high speeds. Thus, correction factors are needed to further reduce errors at very slow or fast walking speeds.

These observations also shed light on the errors seen on different subjects. It is observed the algorithm tends to overestimate the gait speed of the male subject. Since the male subject is taller, at a given speed he has a lower cadence and longer stride resulting in more drift and more forward thigh when the shank is at θ_{max}. It is, however, still possible to compensate for these inaccurate corrections with a scaling factor, since the slope of the estimated speed is fairly constant as shown in the figures below.

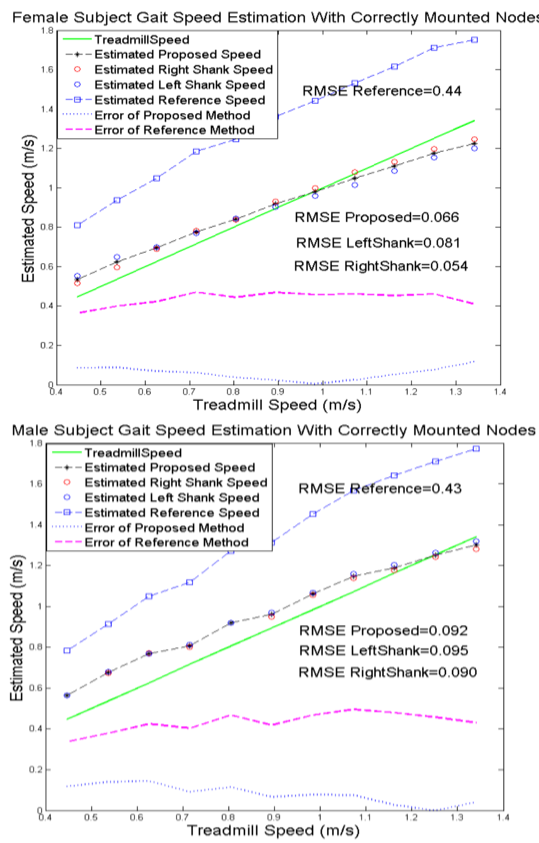


Figure 9. Gait speed estimation with correctly mounted nodes.

The female subject's data shows the effectiveness of mounting calibration in compensating for badly mounted nodes in gait speed estimation as shown in Figure 11. Without applying mounting calibration, the sensor nodes that were mounted approximately 20 degrees off of the sagittal plane have an increased RMSE of 0.24 m/s, while mounting calibration significantly reduces it to 0.073 m/s.

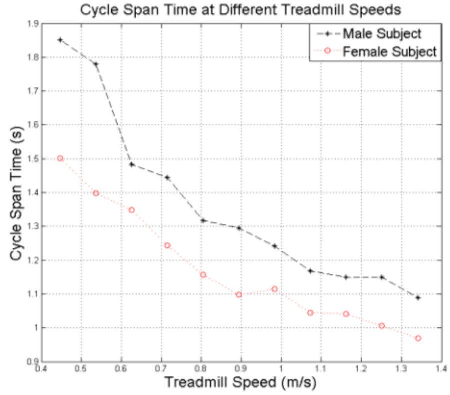
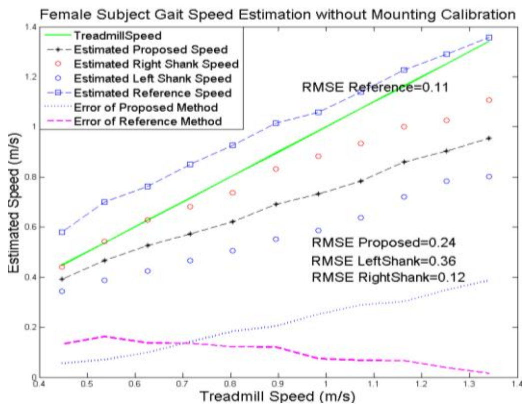
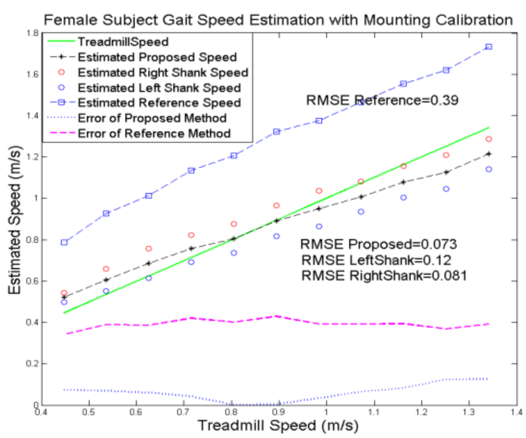


Figure 10. Gait cycle span of subject with different heights.



(a) Before mounting calibration with badly mounted nodes.



(b) After mounting calibration with badly mounted nodes.

Figure 11. Female subject mounting calibration with badly mounted nodes.

With badly mounted nodes at about 20 to 30 degrees rotated around the shank, the angular velocity sensed by the gyroscopes is attenuated from the actual angular velocity in the sagittal plane. So without compensating for bad mounting, the gait speed should be underestimated, as the proposed model does in Figure 11. Using mounting calibration, the attenuated angular velocity can be corrected. In compensating for mounting error, however, the reference model will overestimate the velocity even more as shown in Figure 11.

In addition, with mounting calibration, there still exists an asymmetry between the shank speeds. This is because the assumption that the body frame is equivalent to the global reference frame does not hold when out-of-plane motion occurs during walking. However, it does not affect the results here because of the symmetry of normal gait. Using both shanks allows one to average to the correct value as one should overestimate and the other should underestimate by nearly the same amount.

VII. CONCLCUSION AND FUTURE WORK

This paper explored the potential of accurately estimating gait speed using inertial sensors with high resolution. The proposed model achieved an RMSE of 0.095m/s, showing a significant improvement compared to the reference model [12]. The mounting calibration method effectively corrected the significant estimation error due to mounting uncertainty.

Work is underway to evaluate the estimation accuracy among various gaits, including both healthy and pathological gait at a greater range of speeds (including running), through experiments with more subjects. For healthy gait, a training set of data can be used to calibrate the algorithm for each individual subject. For certain types of pathological gait, including those with shuffling, a wide base, and out-of-plane motion, more refined gait models will be developed based on biomechanical knowledge.

ACKNOWLEDGMENTS

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