Stride Length Estimation Using Ultra-Wide Band (UWB) Sensors Aided by Inertial Sensors

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Abstract

Accurate stride length estimation is crucial for gait analysis which has diverse applications in positioning and clinical domains. In positioning systems, particularly in pedestrian dead reckoning (PDR) and inertial navigation, precise stride length estimation directly influences the accuracy of trajectory reconstruction and displacement measurement. It plays a vital role in enabling reliable indoor localization in global navigation satellite system (GNSS) denied environments, such as in hospitals, airports, and shopping malls. This study presents a novel method for stride length estimation using Ultra-Wideband (UWB) sensors mounted on the shins of the user. UWB distance measurements, captured at 10 Hz, were smoothed and segmented into individual gait cycles using inertial data to detect heel strike and toe-off events. Since UWB measurements reflect stride length at the shin level, motion capture data was used to calibrate these measurements to actual foot-level stride lengths via a linear regression model. The model was trained on data from three separate experimental sessions and evaluated using root mean square error (RMSE), coefficient of determination (R^2), and paired t-tests. The calibrated UWB-based method demonstrated high agreement with motion capture reference data, achieving an RMSE of 0.057 m and R^2 of 0.897 on test data. Comparative analysis further showed a significant improvement over an IMU-only approach, with the UWB method yielding a lower mean error (0.036 m vs. 0.082 m). These findings support the viability of UWB sensors, when properly calibrated, as an effective and wearable solution for stride length estimation.

Keywords

Ultra-Wide Band, Stride Length Estimation, Foot mounted pedestrian positioning

1. Introduction

Stride length estimation is a crucial component of pedestrian positioning systems, enabling accurate trajectory reconstruction and improved localization. While most existing methods [1] use smartphone sensors, these may be impractical in scenarios such as fire rescue, military operations, or certain industrial settings. Foot-mounted systems offer an alternative by eliminating the need for handheld devices. These systems typically rely on strap-down inertial navigation, which estimates position by integrating accelerometer and gyroscope data. Stride length is computed as the Euclidean distance between successive initial contacts of the same foot, requiring precise gait segmentation and effective drift correction [2].

Zero velocity updates (ZUPT) are widely used to reset velocity during stance phases, reducing drift accumulation [3]. While effective, residual errors from sensor bias and noise can still impact position estimation over time [4]. To mitigate this, additional de-drifting methods based on acceleration or velocity constraints have been proposed, demonstrating improved stride estimation across varying speeds [5]. Step and Heading Systems (SHS) using biomechanical or regression models also exist [6], but suffer from overestimation due to cumulative drift and are often implemented using costly and noise-prone inertial sensors [7].

In this work, we propose a low-cost, drift-free alternative for stride length estimation using Ultra-Wideband (UWB) sensors. UWB enables accurate time-of-flight (ToF) distance measurements through

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short-duration radio pulses across a wide frequency spectrum. Its high temporal resolution, low power consumption, and robustness in non-line-of-sight (NLOS) conditions make it highly suitable for wearable applications in navigation, sports, and health monitoring. Unlike previous UWB-based methods that rely on fixed infrastructure [8], foot-mounted anchor arrays [7], or complex multi-unit setups [9, 10], we introduce a lightweight shin-mounted configuration. A single UWB anchor on one shin and a tag on the opposite shin measure inter-shin distance variations during gait, which are used to estimate stride length. This configuration reduces hardware requirements and avoids issues related to Fresnel effects and misalignment [10]. The main contributions of this study include: (1) development of a novel shin-mounted UWB-based stride estimation method, (2) experimental validation, and (3) comparative analysis with conventional INS-based approaches, demonstrating improved accuracy and practicality.

2. Stride length estimation using UWB

Human locomotion follows a cyclic sequence of movements, collectively referred to as the gait cycle [11]. This cycle is typically divided into distinct phases marked by key events such as heel strike (HS), foot flat (FF), mid-stance (MS), heel off (HO), toe off (TO), initial swing (IS), mid-swing (MS), and terminal swing (TS). In this study, a single gait cycle is defined as the interval between two successive heel strikes of the same foot, as illustrated in Fig. 1. Consistent with observations by Pradel et al. [12] and supported by our data, the inter-shin distance signal exhibits local maxima near the TO and HS events [13]. Based on this behavior, stride length is estimated by summing the two adjacent peak values corresponding to TO and the subsequent HS. Since the UWB sensors are mounted on the shins, the

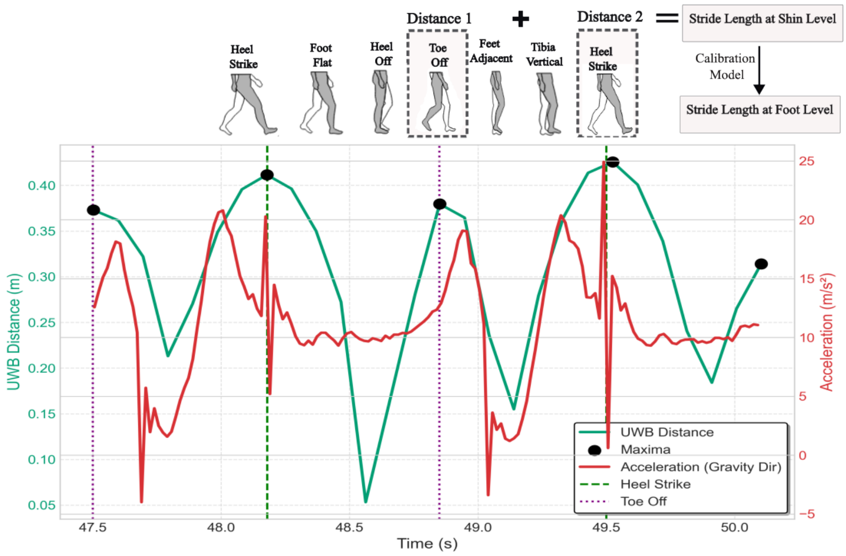

Figure 1: Illustration of a single gait cycle showing gait events (heel strike and toe-off) identified using IMU data, and corresponding UWB inter-shin distance signal. Maxima in the UWB signal are used to estimate step lengths, which are summed to compute stride length.

resulting measurements capture shin-level displacement rather than true foot-level stride lengths (refer to section 3.1. To address this discrepancy, a linear calibration model is applied to recover foot-level stride estimates using shin-level measurements 6.1.

3. Experimental Setup

3.1. Hardware and environment description

In this study, participants wore shoes equipped with a 9-axis Xsens DOT inertial measurement unit (IMU) mounted on the heel of the left foot [14]. The IMU's coordinate frame is defined such that the

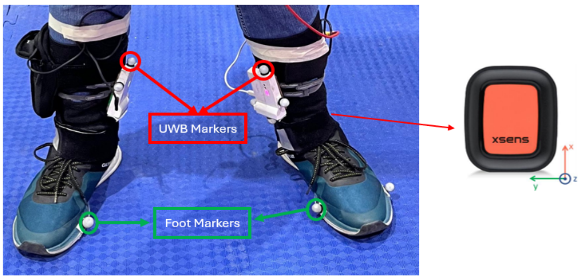

Figure 2: Decawave DWM 1001 UWB mounted on shin with reflective markers attached to UWB and Feet. Xsens IMU (shown in right) is mounted on the back of left foot.

X-axis is oriented opposite to gravity, the Z-axis points outward from the foot, and the Y-axis completes a right-handed system. The device recorded triaxial acceleration, angular velocity, and magnetic field data at a sampling rate of 60 Hz. Data were transmitted via Bluetooth to a smartphone running the Movella DOT app, which was used for data extraction. In parallel, Decawave DWM1001 Ultra-Wideband (UWB) modules were mounted on each shin to capture inter-shank distances at a sampling frequency of 10 Hz [15]. These modules comply with the IEEE 802.15.4-2011 UWB standard and perform distance measurements using single-sided two-way ranging (SS-TWR) based on time-of-flight (ToF) principles [16]. The UWB sensors were connected to a computer via wired interfaces to ensure reliable data logging and accurate timestamping for synchronization and analysis. To provide ground-truth kinematic data, a Qualisys optical motion capture (OMC) system with 16 cameras covering a 10 × 10 m capture volume was employed [17]. Twelve retroreflective markers were affixed to each participant: three on each UWB unit, two on the left foot, one on the IMU, and three on the right foot, as shown in Fig. 2. The OMC system operated at 100 Hz, with calibration performed prior to data collection. Marker trajectories were exported in .c3d and .tsv formats, with subsequent analysis conducted in Python using the .tsv files. Data collection began prior to walking and ended after task completion. OMC data were segmented into individual strides for comparative analysis with IMU and UWB data. Since the OMC system uses an East-North-Up (ENU) coordinate frame, while the strap-down inertial navigation system adopts a North-East-Down (NED) frame, a coordinate transformation was applied to ensure consistency between datasets.

4. Methodology

Stride length estimation in this work uses UWB ranging measurements along with inertial data, using OMC data as ground truth. The experimental setup is described in Section 3.1. Initially UWB data is preprocessed to reduce measurement noise and signal fluctuations (Section 4.1). All datasets are then temporally synchronized as explained in Section 4.2. Reference stride lengths are derived from high-resolution 3D positional data obtained using retroreflective markers attached to each foot, following the methodology in Section 4.3. Then gait event detection and stride length estimation (Section **??**) is performed by first identifying HS and TO events and then performing stride length estimation using both UWB and OMC data, as outlined in Section 4.4.

4.1. Preprocessing of raw UWB data

UWB sensors mounted on the shin record the Euclidean distance between the two sensor nodes at a sampling rate of 10 Hz. To mitigate the impact of measurement noise and minor signal fluctuations, the raw UWB signal is subjected to a preprocessing procedure described in Kumar et al. (2024) [18], which yields a continuous and denoised distance profile. Obtained UWB data has very distinctly identifiable minimas. These Minimas in the UWB interfoot distance signal are detected. Following minima detection, a second-degree Savitzky–Golay filter [19] is applied between each pair to smooth

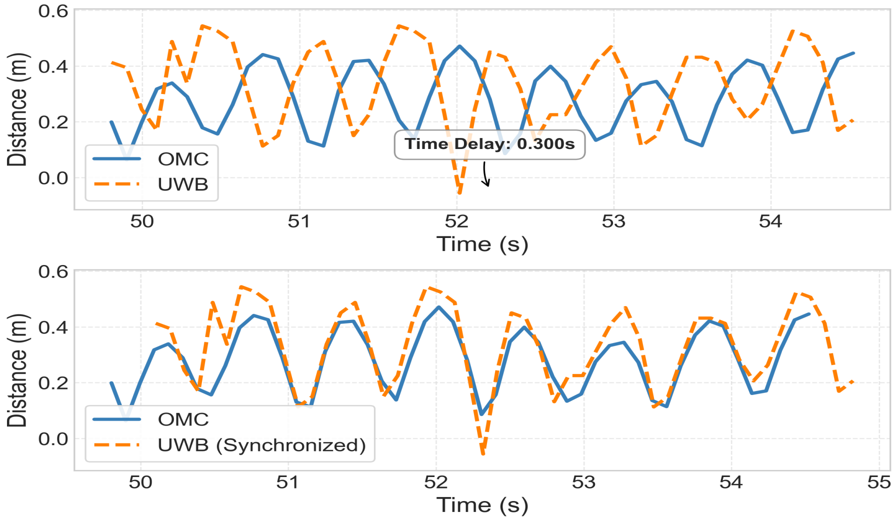

Figure 3: Comparison of UWB and OMC distance measurements before (top figure) and after (bottom figure) cross-correlation-based time synchronization.

the signal and suppress noise-induced maxima. Maxima detection is then performed (without inversion), retaining only one peak between each pair of minimas. This yields clean stride-related extrema for further analysis.

4.2. Time synchronization of datasets

4.2.1. Time Synchronization Between UWB and OMC Datasets

Due to independent acquisition systems, a temporal offset exists between the UWB and OMC datasets. The OMC system provides 3D marker positions at 100 Hz, while the UWB system records inter-shin distances at 10 Hz. To enable synchronization, a comparable signal is derived from the OMC data by computing the Euclidean distance between markers attached to the shin-mounted UWB units (see Fig. 2), as given by:

$$D_t = \sqrt{(x_L^t - x_R^t)^2 + (y_L^t - y_R^t)^2 + (z_L^t - z_R^t)^2} \tag{1}$$

where (x_L^t, y_L^t, z_L^t) and (x_R^t, y_R^t, z_R^t) represent the coordinates of the left and right UWB markers at time t, respectively. Prior to cross-correlation, the OMC data is downsampled to 10 Hz to match the UWB data. The temporal offset is determined using cross-correlation analysis [20]. An example of UWB-OMC time synchronization is shown in Fig 3.

4.2.2. Time Synchronization Between IMU and OMC Datasets

UWB signals alone cannot directly identify heel strike (HS) and toe-off (TO) events. Two approaches can address this limitation. The first uses prior knowledge of the user's initial step (e.g., left or right foot), enabling inference of HS and TO from the UWB trajectory. The second approach, more reliable, leverages foot-mounted IMU data to detect HS events, which often align with peaks in the UWB signal. This correlation allows accurate identification of both HS and TO events—provided the IMU and UWB data are time-synchronized. Since Xsens DOT IMUs are timestamped using the smartphone's clock, which is unsynchronized with the UWB system, synchronization is achieved via optical motion capture (OMC) data. A common event—the onset of walking—is used for alignment by analyzing vertical motion. The Z-axis heel marker position from OMC and gravity-aligned IMU acceleration are compared during an initial stationary phase. A threshold on the moving mean (window size WW) detects the first significant deviation, indicating the start of movement. The resulting temporal offset aligns the IMU and OMC data. An example of this synchronization is shown in Fig. 4.

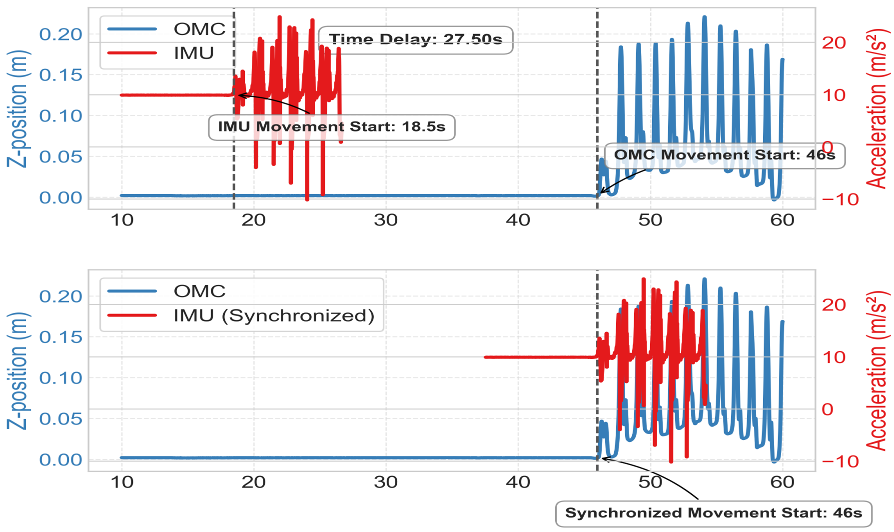

Figure 4: Event-based time synchronization between IMU and OMC using walking onset. **Top:** Signals before synchronization, showing misalignment between OMC Z-position and IMU gravity-aligned acceleration. **Bottom:** Aligned signals after synchronization based on the detected walking onset.

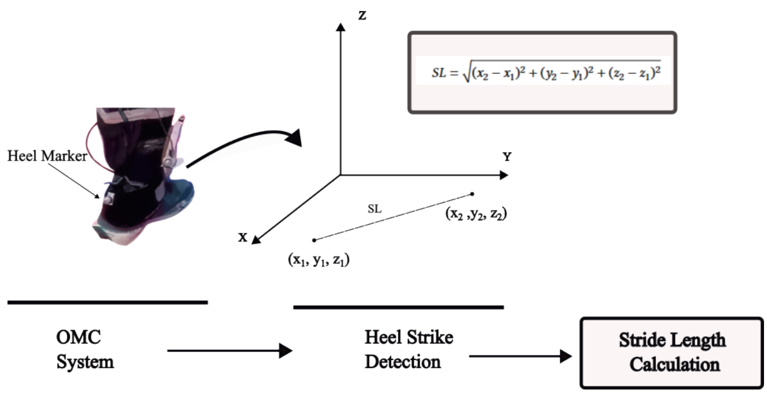

Figure 5: Illustration of ground truth stride length computation using the Optical Motion Capture (OMC) system. A heel marker is tracked across gait cycles. 3D Euclidean distance between consecutive heel marker positions provides stride length vector.

4.3. Generation of ground truth stride length

The OMC system is employed to generate ground truth stride length data. For stride length computation, the heel marker placed directly on the Xsens DOT sensor mounted at the heel was primarily utilized. Ground truth stride length is computed as the Euclidean distance between the 3D positions of the heel marker at successive heel strikes. The stride length SL is calculated using the following formula:

$$SL = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \tag{2}$$

where (x_1, y_1, z_1) and (x_2, y_2, z_2) denote the 3D coordinates of the heel marker at the initial and subsequent heel strike events, respectively. Heel strike events were manually annotated using files obtained from the OMC system. These files were visualized and processed using *Mokka*, an open-source, cross-platform software for biomechanical data analysis [21]. Within Mokka, marker trajectories were tracked frame-by-frame, and heel strike points were identified based on characteristic marker motion patterns. To ensure consistency, annotations were performed by a single trained reviewer, and consistency checks were conducted across random samples. The OMC system recorded marker positions at a sampling frequency of 100 Hz, providing high temporal resolution for gait event detection. The manually annotated heel strike events were subsequently utilized to calculate ground truth stride lengths for each gait cycle.

4.4. Gait Event Detection and Stride Length Estimation

Following signal preprocessing, gait event detection is performed using inertial measurement units (IMUs) attached to the feet. Heel strike (HS) and toe-off (TO) events are identified using the method proposed by Kumar et al. (2024) [18], and the corresponding timestamps are used to segment the gait cycles. These events also serve to segment the ultra-wideband (UWB) signal for stride-wise analysis.

Stride length is initially estimated at the shank level by summing the inter-sensor distances recorded at the TO of the current cycle and the HS of the subsequent cycle. As these UWB-derived measurements reflect movement at the shin rather than the foot, a calibration procedure is applied to align them with foot-level stride lengths obtained from a motion capture system. Specifically, a linear regression model is trained using paired data: UWB-based stride lengths as input and motion capture-based stride lengths as target output. The trained model is then used to calibrate the UWB estimates, and the performance of these calibrated stride lengths is evaluated against the ground truth.

5. Experiments

Using the hardware setup explained in section 3.1, three separate experiments were conducted with a single participant. In each experiment, participant is instructed to progressively increase their step length relative to the preceding trial. A rectangular trajectory is marked in the OMC area with a rectangular box marking the starting and ending point of the experiment. In each experiment the participant remains stationary for 1 minute inside the marked rectangular box after which they start walking along the rectangular trajectory. During each experiment, participant completed two full laps of the rectangular path. Only data collected while participant was inside the motion capture area is retained for analysis; any data recorded outside this region is excluded. Furthermore, only straight-line walking segments were considered for stride length analysis. Steps taken during turns were omitted to minimize the influence of directional changes on stride length estimation accuracy. Details regarding the number of steps analyzed, and the mean stride length per experiment are summarized in Table 1.

Table 1
Experimental Details

Experiments	**Parameters of Stride**	
	Number of Strides	***Mean Stride length (m)***
Experiment 1	57	0.95
Experiment 2	44	1.24
Experiment 3	42	1.24

6. Result and Discussion

6.1. Perfomance analysis of calibration model

To develop and evaluate the calibration model, stride length data from all three experimental sessions were partitioned into training (80%) and test (20%) sets. Stratified sampling was used to ensure that both sets reflected the full range of observed stride lengths, minimizing sampling bias and enhancing generalizability across diverse gait patterns. A linear regression model was trained using UWB-derived stride lengths measured at the shin as input and the corresponding foot-level stride lengths from the optical motion capture (OMC) system as ground truth. To ensure robustness and prevent overfitting, 5-fold cross-validation was applied to the training data for model parameter estimation.

Model performance was assessed on the independent test set using standard regression metrics. As shown in Fig. 6, the model achieved a root mean square error (RMSE) of 0.057 m and a coefficient of determination (R^2) of 0.897, indicating that the model explained approximately 89.7% of the variance in the OMC-based reference stride lengths. A paired t-test comparing predicted and ground truth stride lengths yielded p = 0.115, indicating no statistically significant difference and suggesting that prediction errors were random rather than systematic. Detailed results across individual experimental sessions

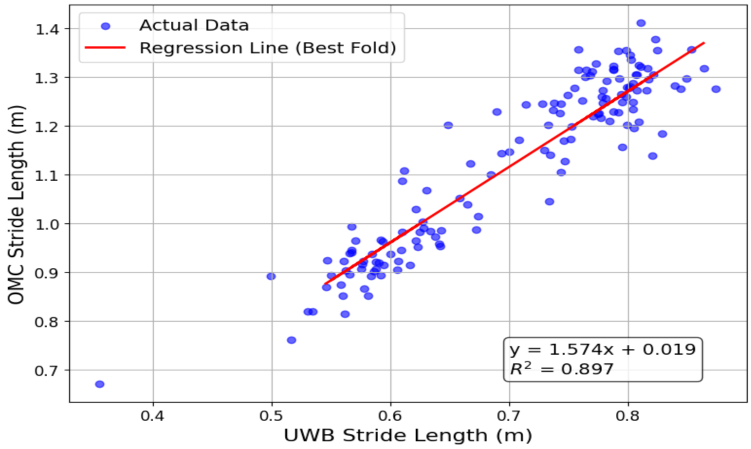

Figure 6: Linear regression calibration of UWB-based stride length against OMC ground truth, showing best-performing fold with regression line and equation.

are presented in Table 2. Experiment 1 and 3 exhibited moderate agreement, with RMSE values of 0.053 m and 0.073 m, and R^2 values of 0.392 and 0.515, respectively. Corresponding t-tests (p = 0.068 and p = 0.244) confirmed the absence of significant bias, although the reduced R^2 values suggest variability in model performance. In contrast, Experiment 2 showed a negative R^2 (−1.727), indicating poor trend capture despite a relatively low RMSE of 0.047 m. The high p-value (0.591) suggests that predictions were not significantly different from ground truth but lacked consistent directional agreement. Overall, these results demonstrate the effectiveness of the proposed UWB-to-foot-level calibration model, while highlighting the need for further investigation into inter-experiment variability to improve robustness under varied gait conditions.

Table 2
Performance of the UWB-to-OMC stride length calibration model

Experiment	RMSE (m)	R^2	t-statistic	p-value
Overall	0.057	0.897	-1.628	0.115
Experiment 1	0.053	0.392	-2.023	0.068
Experiment 2	0.047	-1.727	0.557	0.591
Experiment 3	0.073	0.515	-1.293	0.244

6.2. Comparison of proposed method against IMU based approach

To further evaluate the accuracy of the calibrated UWB-based stride length estimation, a comparative analysis was conducted against stride lengths derived from strap down inertial navigation approach used by Suzuki et al. [4]. For both methods, the error was computed as the absolute difference between the estimated stride lengths and the reference values obtained from the motion capture system. A box plot was generated to visualize the distribution of these errors across all samples (refer to Fig 7). The analysis revealed that the strap-down inertial navigation based approach exhibited a higher mean error of 0.082 m, whereas the calibrated UWB-based approach achieved a significantly lower mean error of 0.036 m. This substantial reduction in error highlights the effectiveness of the proposed calibration model in improving the accuracy of UWB-derived stride lengths. Moreover, the box plot demonstrated reduced variance in the UWB error distribution, indicating improved consistency and robustness of the UWB-based method when compared to the IMU-based approach. These findings suggest that, when appropriately calibrated, UWB sensors mounted on the shin can serve as a reliable alternative to conventional IMU-based gait analysis systems for stride length estimation.

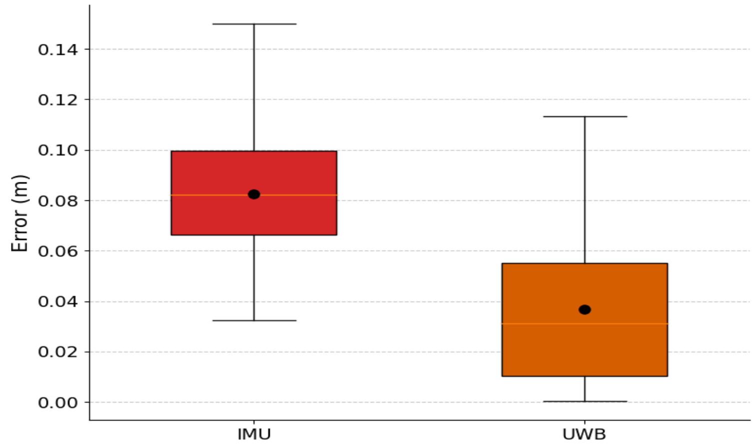

Figure 7: Error in stride length (IMU vs UWB)

7. Conclusions and Future Works

This study introduced a novel method for stride length estimation using shin-mounted Ultra-Wideband (UWB) sensors, integrated with inertial data for gait event detection and calibrated against motion capture data. A linear calibration model was developed to map UWB-derived stride lengths to foot-level reference values. Trained and validated on data from three experimental sessions, the model demonstrated strong performance with an RMSE of 0.057 m and R^2 of 0.897 on the test set. A paired t-test confirmed no significant difference between calibrated UWB estimates and motion capture ground truth, indicating high accuracy and consistency. Comparison with a conventional IMU-based method revealed a lower mean error for the UWB approach (0.036 m vs. 0.082 m), underscoring its potential as a robust alternative in GNSS-denied or constrained environments. Boxplot analyses further highlighted the reduced variability and improved reliability of the UWB-based estimates post-calibration. Future work will aim to generalize this method to diverse populations, including elderly and clinical cohorts with atypical gait. Additionally, the current linear calibration could be extended to nonlinear or machine learning-based models to better capture complex gait dynamics. Enhancements such as multi-sensor UWB configurations for stride symmetry analysis and real-time wearable implementation will also be explored to improve system scalability and practical deployment.

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Declaration on Generative AI

During the preparation of this work, the author(s) used X-GPT-4 and Gramby in order to: Grammar and spelling check. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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