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Multi-sensor Modelling for Temporal Gait Analysis: Evaluating IMU and UWB-Based Approaches

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Abstract

Wearable sensors are essential for gait analysis outside of traditional laboratory environments. However, selection of the right sensor technology involves several trade-offs. Inertial Measurement Units (IMUs) offer high temporal resolution which are ideal for detecting gait events but they suffer from drift. Ultra-Wideband (UWB) provides stable spatial data, but are less precise for detecting event timing. This paper presents a comparative study of three distinct foot-mounted sensor methodologies for heel strike detection and cadence estimation: (1) IMU-Only approach, (2) UWB-Only approach, and (3) a multi-sensor IMU+UWB fusion approach. Each method is evaluated against a camera-based ground truth system using data from four subjects. Results show the IMU-Only method is inconsistent, with moderate event precision (Avg. F1: 0.798), temporal accuracy (Avg. MAE: 47.99 ms), and subject-dependent cadence accuracy (Avg. Acc: 89.59%). The UWB-Only method provides robust event detection (Avg. F1: 0.811) with similar temporal error (Avg. MAE: 49.0 ms) but is exceptionally accurate for cadence estimation (Avg. Acc: 96.94%). The IMU+UWB fusion approach achieves the highest event precision (Avg. Precision: 0.835) and the best temporal accuracy (Avg. MAE: 46.51 ms), while also maintaining robust cadence accuracy (Avg. Acc: 95.62%). In conclusion, while the UWB-Only method is ideal for cadence-only applications, the IMU+UWB fusion approach provides the best overall balance of high event precision, superior temporal accuracy, and reliable cadence estimation.

1. Introduction

Human gait analysis is an essential tool in biomechanics and clinical research, providing critical insights for diagnosing movement disorders, monitoring rehabilitation, and improving athletic performance (Chambers and Sutherland, 2002, Prajapati et al., 2021). In gait analysis, parameters are generally classified into temporal, spatial, and kinematic domains (Whittle, 2014). Temporal parameters describe the timing aspects of walking, including stride time, step time, stance time, swing time, and double support duration. Spatial parameters quantify the geometric characteristics of motion, such as step length, stride length, step width, and walking speed. Kinematic parameters capture the dynamic motion of body segments and joints, including joint angles, angular velocities, and linear accelerations of the lower limbs. Among these, accurate detection of gait events particularly heel strike and toe-off and estimation of cadence form the basis for computing higher-level gait metrics such as stride length, walking speed, and stance-to-swing ratios. Thus, while heel strike detection and cadence estimation are among the most critical parameters for quantifying gait behavior, a comprehensive gait analysis must incorporate both spatial and temporal characteristics to fully capture gait performance and variability fully.

While traditional motion capture systems are the 'gold standard' for accurate gait measurement (Spanos et al., 2023), their expensive, complex setups confine them to controlled laboratories, making them unsuitable for everyday monitoring (Xin, 2023). Therefore, there is a need for more flexible and affordable alternatives. The rapid advancement of wearable sensor technologies has led to major progress in this area. These sensors make it possible to measure and analyze gait in real-world conditions, outside of laboratories (Hutabarat et al., 2021). Wearable technology has opened new opportunities for long-term gait monitoring, helping clinicians and researchers capture how people naturally walk in their daily lives.

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For gait analysis, foot-mounted sensor systems are widely preferred over placements on the trunk, limbs, or smartphones because they provide the most direct and accurate measurements of gait-specific events and parameters. The feet are the only body segments that cyclically contact the ground during locomotion, making them ideal for capturing gait dynamics. Their motion profiles comprising acceleration, angular velocity, and inter-foot distance offer clear signals for identifying critical gait events such as heel strike (HS) and toe-off (TO) (Sabatini et al., 2005). Moreover, foot-mounted systems enable precise estimation of spatial parameters like step length and stride length, since they directly capture the displacement of each foot relative to the ground and the contralateral foot (Díez et al., 2018, Anderson et al., 2019). This proximity minimizes interference from upper-body motion and reduces the complexity of kinematic modeling required for other placements.

Among these systems, Inertial Measurement Units (IMUs) are widely adopted for capturing detailed motion dynamics (Hannink et al., 2016, Lin et al., 2021). IMUs combine accelerometers and gyroscopes to record high-frequency acceleration and angular velocity data, which effectively reveal rapid transitions in gait cycles and allow accurate detection of HS and TO events (Sabatini et al., 2005). Recent IMU-based studies show strong performance in identifying heel strike, with Bayesian recognition methods achieving 92.83% accuracy for heel strike detection (Martinez-Hernandez et al., 2017). One related study utilized a single IMU mounted on the shank, detecting heel strikes by analyzing the local maxima and minima of the acceleration and angular velocity signals (Han et al., 2019). This approach demonstrated high temporal accuracy, achieving a mean

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absolute error (MAE) of approximately 20 ms when validated against a force-sensitive resistor (FSR) system. Figure 1 illustrates the typical IMU signal shown by red curve. HS event can be clearly identified from the signal by the sharp peak that occurs at the start of each gait cycle. However, IMUs may accumulate drift or misclassify events if signal noise or motion artifacts are present (Ensink, 2025).

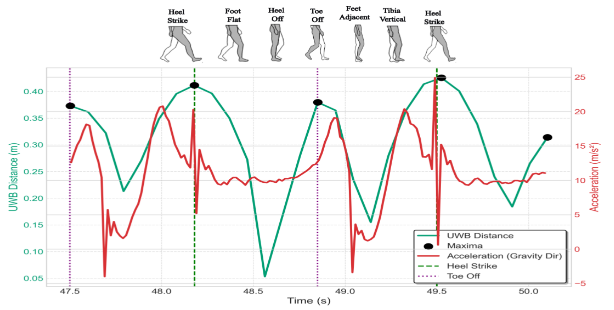

Figure 1. An illustration showing IMU and UWB signal against gait events (Adapted from (Kumar et al., 2025))

In contrast, Ultra-Wideband (UWB) systems provide highly accurate inter-foot distance measurements with minimal error (Díez et al., 2018, Kumar et al., 2022, Kumar et al., 2024, Kumar et al., 2025). When mounted on the feet, UWB sensors can reliably compute stride and step parameters (Park et al., 2023, Anderson et al., 2019). However, their lower sampling rate make them less suitable for capturing fast temporal events such as HS or TO. For cadence estimation it could provide drift free and stable results for longer durations as inter-foot distance measurements do not suffer from integration drift (Park et al., 2023). The authors in (Anderson et al., 2019) developed a foot-mounted UWB-only system and validated it against a GAITRite mat for cadence estimation. They achieved a mean absolute error (MAE) for cadence of 0.442 steps/min. This high temporal accuracy demonstrates the potential of UWB to reliably estimate rhythmic parameters like cadence with minimal error. Figure 1 illustrates typical UWB signals obtained from foot-mounted sensors during walking using green curve. While IMU signals exhibit sharp peaks corresponding to gait events, UWB signals show smooth periodic variations that accurately reflect spatial displacement. Thus, IMUs provide temporal precision, whereas UWBs offer spatial stability—and their complementary nature makes a combined IMU–UWB system particularly effective for comprehensive gait analysis (He et al., 2023, Almassri et al., 2022, Wu et al., 2019).

The primary aim of this paper is to systematically investigate and compare the performance of different foot-mounted sensing configurations for temporal gait parameters analysis in real-world environment. In particular, the study focuses on understanding how single sensor systems, based on either inertial or UWB sensing, perform relative to a combined multi-sensor fusion approach. Main contributions of this paper are: 1) A comparative evaluation is performed between IMU-based and UWB-based foot-mounted sensing systems to assess their effectiveness in performing temporal gait analysis for heel strike timing and cadence. 2) Evaluation of a sensor fusion framework that combines the IMU's high temporal resolution with the UWB's spatial accuracy to achieve improved precision and robustness in temporal gait analysis. 3) A quantitative validation is conducted against a ground-truth camera-based system, providing clear evidence of benefits of sensor fusion and offering insights into the complementary characteristics and trade-offs between single-sensor and multi-sensor approaches.

The remainder of this paper is structured as follows. Section 2 describes the experimental setup, sensor configuration, and data acquisition procedures used in this study. Section 3 details the methodologies employed for heel strike detection, cadence estimation, and sensor fusion. Section 4 presents the experimental results and comparative analysis of the three approaches—IMU-only, UWB-only, and fused IMU–UWB systems—against the ground-truth data and also provides a discussion of the findings, highlighting the performance trade-offs and complementary characteristics of the sensing modalities. Finally, Section 5 concludes the paper and outlines potential directions for future research.

2. Experimental Setup

The experimental setup used in this study follows the same sensor configuration described in (Kumar et al., 2024). An Intel Real Sense L515 LiDAR camera (Verheyde, 2019) is positioned in front of a treadmill to capture depth and motion data of the participant. Each subject is equipped with two types of wearable sensors: one DecaWave DWM 1001 UWB module (Qorvo, 2020) (unit cost ≈ 30 USD) mounted on the shin of each foot in the forward facing direction, and one Xsens DOT IMU (Alcala et al., 2021) (unit cost ≈ 200 USD) affixed to the heel of the left foot. The sensor axes is oriented such that the X-axis pointed upward (along gravity), the Z-axis outward from the heel, and the Y-axis laterally outward from the left foot forming a right-handed coordinate system. The experimental setup is shown in figure 2.

Figure 2. Subject is equipped with DWM1001 UWB sensors with ArUco Markers attached on top of them. Xsens DOT IMU is placed on the heel of the left foot. Ground truth is collected using the Intel Realsense LiDAR Camera.

To enable inter-foot ranging, one UWB device operated as an anchor and the other as a tag. The tag is connected to a computer via USB for data acquisition at 10 Hz, while the anchor is powered by a portable powerbank. Data is collected from the UWB sensors using UART shell mode, providing real-time distance measurement at 10 Hz. The IMU is connected via Bluetooth to a smartphone running the Movella DOT application, which streamed acceleration and angular velocity data at 60 Hz. Using this setup, gait data is collected from four participants walking on the treadmill at a constant speed of 0.8 km/h. Each recording session consists of alternating stationary and walking phases: the subject first remained stationary to maintain a constant inter-foot distance (stationary pose), followed by 30 seconds of walking, and then returned to the stationary pose. This cycle is repeated five times to ensure sufficient data for both calibration and synchronization between IMU and UWB measurements.

3. Proposed Methodology

A complete processing pipeline for the comparative study is shown in Figure 3. First, the sensor-specific preprocessing methods (Sections 3.1 and 3.2) are described. Procedures for data synchronization is described briefly in section 3.3. Following this, the specific algorithms used for heel strike detection within each of the three approaches are detailed in section 3.4. Section 3.5 concludes the methodology with the approach used for cadence calculation.

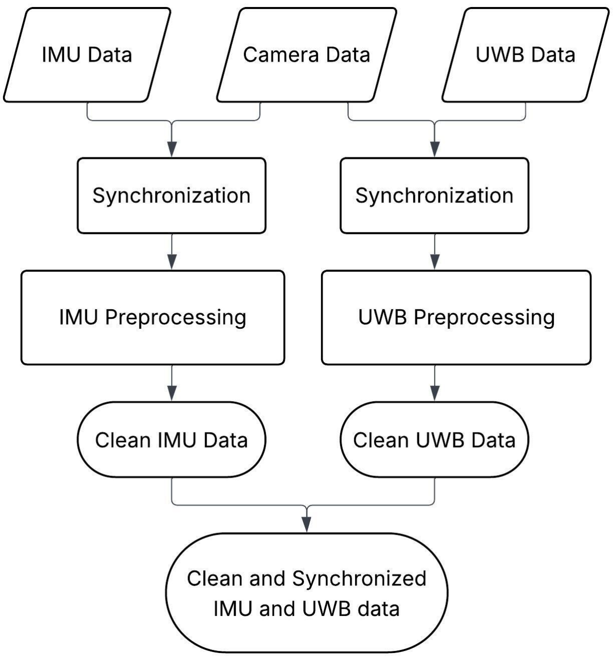

Figure 3. Flowchart describing the proposed methodology

3.1 UWB Preprocessing:

According to Figure 1, the raw UWB inter-foot distance signal should have a periodic structure, with each gait cycle producing an alternating sequence of distinctive maxima and minima that correspond to the relative motion of the feet. However, because of measurement noise, multipath, non-line-of-sight (NLOS) and sensor-level perturbations, the unprocessed UWB signal displayed in Figure 4 does not clearly express this periodic pattern. In order to convert the raw signal into a smooth, physiologically interpretable waveform while maintaining the cyclical gait characteristics, a specialized preprocessing pipeline is needed. This processing pipeline is adapted from the methodology presented by (Kumar et al., 2024). As shown in figure 4, the process first involves detecting all local minima in the UWB distance signal. These minima are then classified as occurring during stationary periods or active walking based on the local neighbourhood based evaluation. The absolute difference between the minima point and the neighbourhood points serve as the decision criterion. Following this classification, a Savitzky-Golay filter (Press and Teukolsky, 1990) is applied to smooth the UWB signal, but only in the segments between the minima identified as “active walking”. Local maxima (peaks) are then detected within these smoothed segments, as they represent the moments of maximum foot separation during walking. The obtained maxima points are then considered for further analysis of the dataset for heel strike detection and cadence estimation. This processing pipeline is adapted from the methodology presented by (Kumar et al., 2024). This preprocessing yields a clean signal and a set of UWB-based minima and maxima that are used as inputs for the subsequent UWB-Only and IMU wih UWB Fusion event detection algorithms.

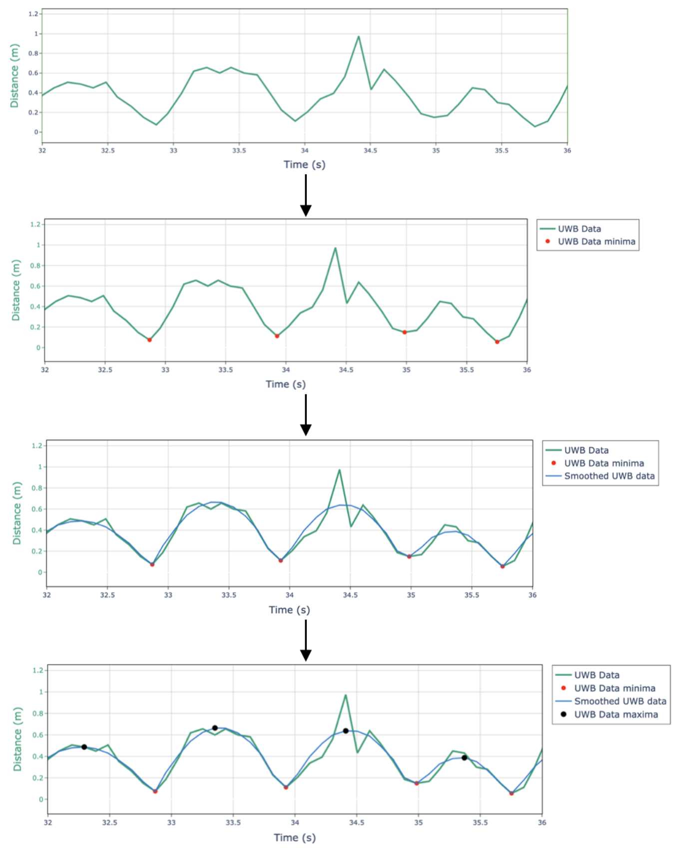

Figure 4. Steps involved in UWB pre-processing.

3.2 IMU Preprocessing:

Raw IMU data is noisy and contain small fluctuations that can interfere with event detection. In this study, only accelerometer data in X-direction (pointing towards gravity direction at rest) is considered for IMU ony approach. To address the small fluctuations occuring in the data it is pre-processed using a zero-phase butterworth low-pass filter (Butterworth et al., 1930). This filter smooths the signal by removing high-frequency noise while preserving the important underlying pattern of the walking motion. The resulting clean signal provides a much clearer representation of the impacts (as shown in figure 5).

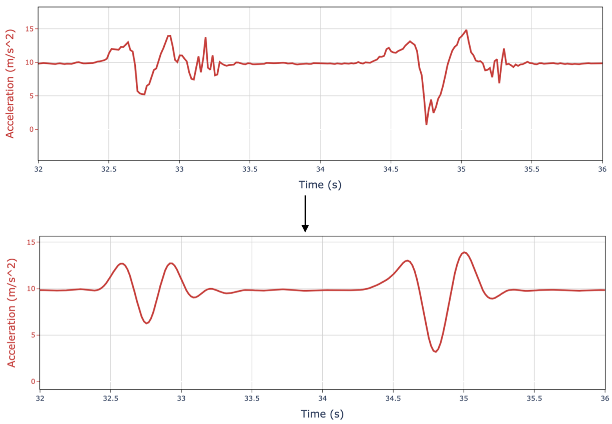

Figure 5. IMU Preprocessing using a low-pass filter.

3.3 Data Synchronization:

A critical step before analysis is the synchronization of all sensor data streams. Since the IMU, UWB, and Camera systems operate on independent clocks, a manual synchronization procedure is performed relative to the camera's timeline, which serves as the ground truth. This alignment is applied specifically as required by each methodology. For the IMU data stream, alignment with the camera data is achieved by identifying a reliable synchronization feature. As shown in figure 1, acceleration signal along gravity direction exhibits a clear and distinct peak at heel strike event. This feature is used to calculate the constant time offset ($\Delta t_{IMU-Cam}$) between the ground truth data and accelerometer data. For the UWB data, the stream is aligned with the camera data by applying a separate time offset ($\Delta t_{UWB-Cam}$), which is calculated by matching the first local distance maxima to the ground truth heel strike labels generated manually. This targeted synchronization ensures that each methodology is accurately compared against the ground truth data.

3.4 Heel Strike Detection:

This section explains the process of heel strike event detection for three distinct algorithms discussed one by one.

3.4.1 IMU Only Approach: This method uses the clean and preprocessed accelerometer data along X-direction. First, candidate detection is performed by applying a peak detection algorithm to the filtered acceleration signal to identify all local maxima. This algorithm identifies candidates based on several key parameters such as height, prominence and distance. The height parameter sets the minimum vertical amplitude (in m/s^2) that a signal point must reach to be considered a peak, which is used to filter out low-amplitude signal noise. Prominence measures how much a peak stands out from the surrounding signal (the vertical distance from its summit to its lowest contour line containing no higher peaks); this is highly effective at distinguishing true heel strike impacts from minor vibrations. Finally, distance sets the minimum required horizontal separation (in samples, corresponding to time) between adjacent peaks, which enforces a physiologically realistic separation between steps. Due to the high inter-subject variability in gait dynamics, the specific values for these parameters required subject-specific empirical tuning against the ground truth data to achieve optimal baseline performance. While a formal sensitivity analysis of these parameters is outside the scope of this initial study, this reliance on manual, individual calibration highlights an inherent limitation of static threshold-based algorithms, further motivating the need for adaptive multi-sensor fusion. For this analysis, the parameters are intentionally set to be highly sensitive (e.g., lower height/prominence thresholds) to achieve a high recall. This ensures that all potential heel strike peaks are captured in the initial "candidate events" set, even if it means including some false positives, which are then handled by the subsequent filtering step.

After candidate detection a sequential Cluster Filtering is applied to remove detected false positives. As observed in the signal in Figure 1, the true heel strike is the last peak in a small cluster of peaks. A heuristic "last-of-cluster" filter is applied, which groups consecutive peaks into "clusters" based on a minimum time gap. It then discards all peaks within a cluster except for the very last one. The timestamps of this final, filtered set of peaks constitute the detected heel strike events. The complete methodology for heel strike detection using IMU is shown in figure 6.

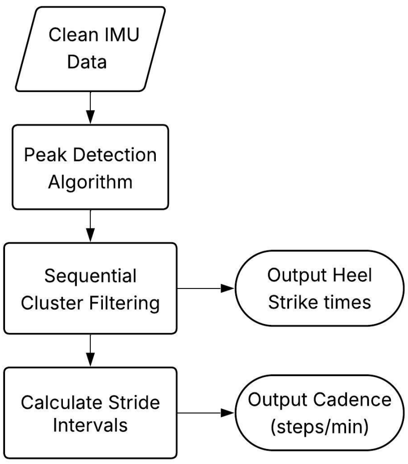

Figure 6. Flowchart for heel strike detection using IMU Only approach.

3.4.2 UWB Only Approach: This method uses the preprocessed UWB inter-foot distance data. The heel strike detection process begins with candidate detection, where the local maxima (peaks) identified during the UWB Signal Preprocessing step (Section 3.1) serve as the initial candidates. These peaks represent the moments of maximum foot separation and approximate the timing of heel strikes for both feet in an alternating sequence. Following this, segmented alternate peak selection is applied to assign these alternating peaks to the correct foot (right vs. left). For each active walking segment, the candidate peaks are split into two subsets: "Alt1" (even-indexed peaks) and "Alt2" (odd-indexed peaks). Both subsets are compared against the camera's ground truth labels for a single foot (e.g., the Right Foot). The subset that achieves the higher F1-Score in this comparison is designated as the "Right Foot" heel strikes, and the other subset is assigned as the "Left Foot". This process is repeated for all walking segments to accurately separate the events for each foot. The timestamps of the assigned subset for the foot under analysis constitute the final detected heel strike events. This step can be omitted if it is known from which leg the person starts walking in each walk segment. Therefore, the corresponding foot can be identified for each alternate peak. The complete flowchart for heel strike detection using UWB only approach is shown in figure 7.

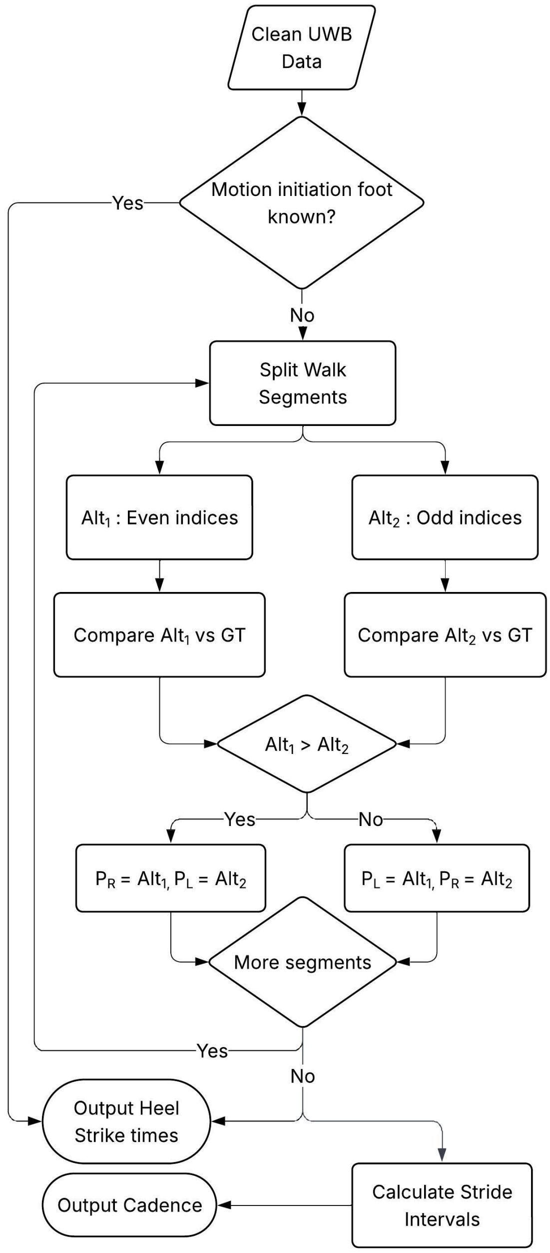

Figure 7. Flowchart for heel strike detection using UWB Only approach.

3.4.3 IMU and UWB Fusion Approach

This method uses both sensor data after preprocessing and synchronization. The detection process begins with generating labels for stance phase (walking phase between heel strike and toe off event when the foot is assumed to be in stationary phase) as described by (Kumar et al., 2024). In brief, this method analyzes the standard deviation of the IMU's vertical acceleration signal within search windows defined by the maximas obtained from UWB preprocessing. If the standard deviation within a given window falls below a predetermined threshold, the entire duration corresponding to that window is classified as a stance phase (labeled '1'); otherwise, it is a swing phase (labeled '0'). Following this, event identification is performed. A heel strike event is defined as the onset of the stance phase, which the algorithm identifies by locating every transition from 0 (swing) to 1 (stance) in the labelled IMU signal. The timestamps of these swing-to-stance transitions constitute the final detected heel strike events. The flowchart for heel strike detection using IMU and UWB fusion approach is shown in figure 8.

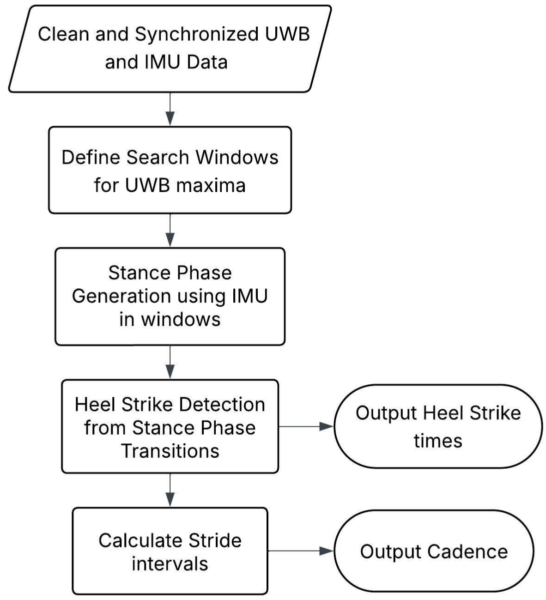

Figure 8. Flowchart for heel strike detection using combined IMU and UWB fusion approach

3.5 Cadence Calculation:

For all three approaches, cadence (in steps per minute) is calculated using the final list of detected heel strike timestamps (t_{HS}) for a single foot. Cadence is the number of steps that would be taken in one minute. The mean stride time (Δt_{stride}^{mean}) in seconds is then calculated by averaging all of these individual stride intervals. A stride interval (Δt_{stride}) is defined as the time duration between two consecutive heel strikes of the same foot. Since one stride interval represents one step for that foot, the cadence is equal to $60/\Delta t_{stride}$.

4. Results and Discussion

This section presents the quantitative results obtained from applying the three methodologies (IMU-Only, UWB-Only, and IMU and UWB Fusion) to the data collected from four subjects. Performance is evaluated for heel strike detection and cadence estimation, using the camera-based system as the ground truth. The results presented are typically averaged across the four subjects. The findings highlight the distinct trade-offs inherent in each sensing modality and approach. While a sample of four subjects (N=4) is too small for tests like ANOVA, analyzing the hundreds of individual steps proves our method is statistically reliable. The data shows the fusion approach consistently reduces errors, regardless of individual walking differences.

4.1 Heel Strike Detection

The accuracy of detecting heel strike events for one foot using IMU-Only, UWB-Only, and IMU+UWB Fusion approach is presented in figure 9. Performance is measured using Precision, Recall, F1-Score, and Mean Absolute Error (MAE) in timing relative to ground truth heel strike events which are shown in each individual plot.

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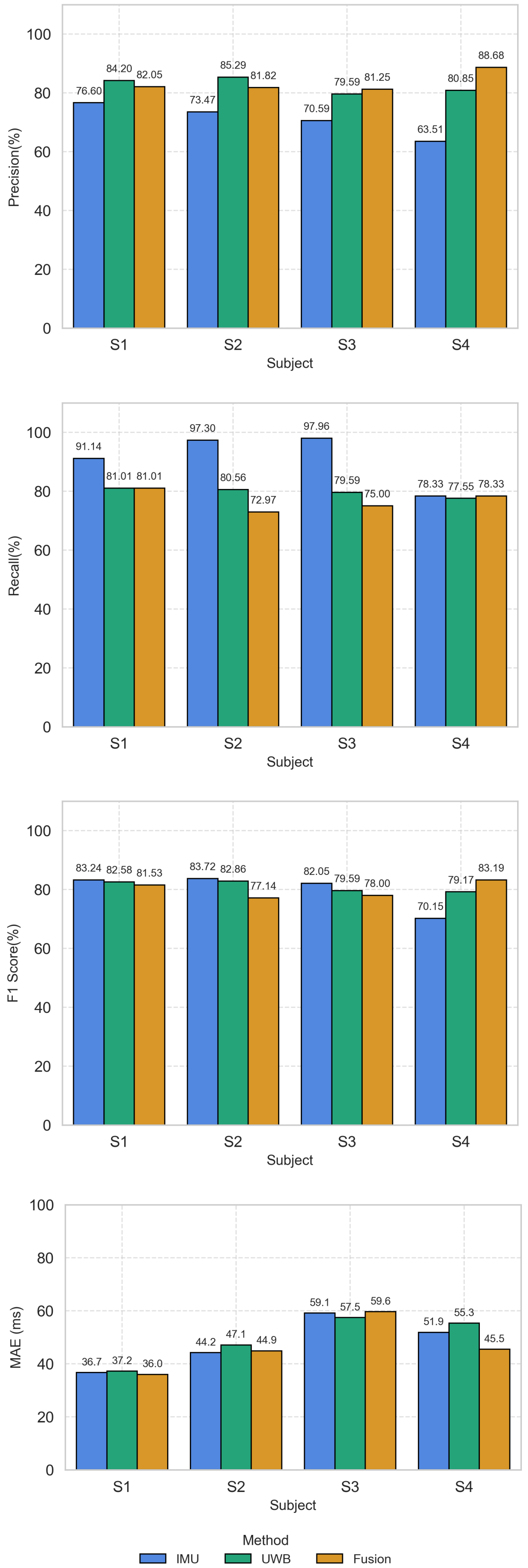

Figure 9. Comparison of heel strike detection performance (Precision, Recall, F1 score and MAE) across IMU-only (blue), UWB-only (green), and Fusion methods (yellow) for four participants.

The **IMU-Only** approach is characterized by an exceptionally high average recall (91.18%) but it provides more modest average precision (71.04%) compared to the other methods. This trade-off is a direct consequence of the detection algorithm. The peak detection parameters were intentionally tuned for high sensitivity to capture all possible gait-related peaks, ensuring that very few true heel strikes were missed (high recall). However, this sensitivity also caused the algorithm to detect minor, non-gait-related signal artifacts (e.g., pre-impact vibrations, foot-flat jitters) as candidate events. While the sequential cluster filter was designed to remove these, it was not perfectly effective, resulting in a high number of false positives constrained the overall precision. Furthermore, this method’s performance was highly subject-dependent. As seen with Subject 3 in Figure 9, the F1-Score (70.15%) was markedly lower than for other subjects. High inter-subject variability was most evident in the IMU-only method’s failure on Subject 3. This participant’s shuffling gait and soft-soled footwear severely dampened the physical heel-strike impact, making the acceleration peaks too weak for reliable detection. However, the fusion approach successfully compensated for this missing signal by using UWB spatial constraints to verify the stance phase. This recovery demonstrates how the multi-sensor method effectively neutralizes subject-dependent variability.

In contrast, the **UWB-Only** approach in Figure 9 provided the most balanced performance, achieving the highest average F1-Score (81.05%) of the three methods. Its strength lies in its precision (82.48%), which is significantly higher than the IMU-Only approach. This is because the signal smoothing and peak detection are based on the inter-foot distance, a strong, cyclical biometric. The Savitzky-Golay filter effectively removes high-frequency noise, preventing the algorithm from being “fooled” by spurious signal jitters. However, this reliance on smoothing a relatively low-frequency signal (10 Hz) is also its main drawback. The lower recall (79.68%) suggests that the smoothing process can occasionally “flatten” or merge more subtle, true heel strike peaks, causing them to be missed. This smoothing also explains the method’s higher temporal error (MAE of 49.27 ms). The algorithm is excellent at detecting the rhythm of the steps but is less precise at pinpointing the exact instant of the event, as the smoothed peak may be slightly shifted in time from the true heel strike.

The **IMU+UWB Fusion** method (in Figure 9) emerged as the most precise and temporally accurate, achieving the highest average precision (83.45%) and the lowest average MAE (46.505 ms). This performance is due to its “double-check” logic, which leverages the strengths of both sensors. The UWB signal first identifies a “search window” where a stance phase is likely, and the IMU must then confirm this window by exhibiting low signal variance (i.e., stability). This dual-criteria system is exceptionally effective at rejecting false positives from both sensors, hence the high precision. This high precision, however, comes at the cost of the lowest average recall (76.83%). The proposed fusion algorithm adopts this conservative strategy to intentionally prioritize precision over recall. This trade-off is critical in gait analysis because false positives (detecting non-existent steps) introduce additive noise that permanently skews cadence calculations. In contrast, an occasional missed step (causing lower recall) is a manageable error structure that is easier to identify and handle in downstream post-processing. A true heel strike is rejected if either sensor fails its check. For instance, a gait irregularity (like a shuffle) can cause the UWB to misalign its “search window”, thus missing the event entirely. Alternatively, a particularly hard heel strike can cause high-impact vibrations in the IMU, which the algorithm mistakes for “swinging” (high signal variance) and therefore incorrectly rejects the true stance phase.

4.2 Cadence Estimation

The cadence estimation results shown in Figure 10 reveal a different aspect of performance. Here, the focus shifts from the precise timing of individual events to the overall rhythm and count of the steps over the trial duration.

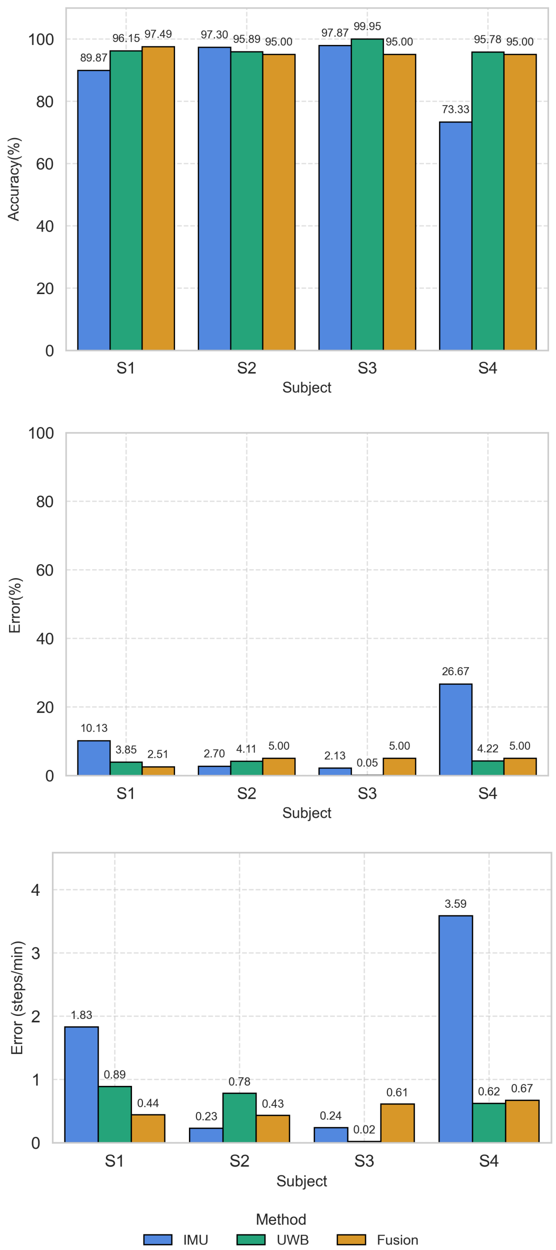

Figure 10. Comparison of cadence estimation performance (Accuracy and Error) across IMU-only (blue), UWB-only (green), and Fusion methods (yellow) for four participants.

The **IMU-Only** approach (shown by blue in Figure 10) shows a clear dependency on gait style. While it performed very well for Subjects 1 and 2 (over 97% accuracy), its performance for Subject 3 dropped dramatically to 73.33%. This instability is a direct result of the poor F1-Score in the event detection for that subject (refer to Figure 9), where the algorithm’s reliance on acceleration peaks failed. The high average error (1.47 steps/min) indicates that this method is not reliable for cadence estimation across different users.

The **UWB-Only** approach (shown by green in Figure 10) was the standout performer for cadence estimation, achieving the highest average accuracy (96.94%) and the average error of 0.58 steps/min. This is a significant finding that even though the method had a higher MAE for event timing, its ability to capture the fundamental rhythm of walking is exceptionally robust. The UWB signal’s strong, cyclical pattern of inter-foot distance is less affected by individual gait styles than the IMU’s acceleration, making it a more reliable source for cadence. The **IMU and UWB Fusion** method (shown in orange in Figure 10) also performed extremely well, with an average accuracy of 95.62% and the lowest average error (0.54 steps/min) that was statistically comparable to the UWB-Only method. Crucially, it was highly consistent across all subjects, completely overcoming the reliability issues of the IMU-Only approach (which failed on Subject 3). This demonstrates that by using the robust swing-to-stance transition as the event marker, the fusion method provides a very reliable count of total steps, resulting in a highly accurate cadence calculation.

While there is a hardware overhead introduced in case of IMU+UWB approach, its computational cost and implementation effort remain distinctly low. The algorithm uses efficient thresholding instead of heavy filtering that makes it highly suitable for near real-time wearable sensors. Most importantly, the primary gain is system reliability. By preventing complete failure modes (such as the breakdown of IMU-only approach for Subject 3), the fusion framework guarantees robust performance. This consistency fully justifies the extra hardware overhead.

5. Conclusions and Future work

This study presented a comparative evaluation of three gait analysis techniques utilizing different sensor modalities (IMU, UWB and fusion of IMU and UWB) against a camera-based ground truth. The experimental results demonstrate the inherent trade-off between spatial and temporal sensing modalities. Although the IMU-only approach shows a high degree of responsiveness to motion dynamics, it suffers from severe subject-dependent variability, leading to catastrophic single-sensor failures (e.g., Subject 3) and reduced event precision. In contrast, the UWB-only approach provides long-term stability and superior cadence accuracy (96.94%). The highest heel strike precision (83.45%) and consistently high cadence accuracy (95.62%) were attained by the proposed IMU and UWB fusion framework. By successfully integrating the high temporal resolution of the IMU with the drift-free spatial accuracy of the UWB, the fusion logic intentionally prioritizes precision over recall to prevent false positives from skewing cadence calculations.

Overall, the findings show that modality-specific limitations severely compromise single-sensor systems in unsupervised settings. The IMU and UWB fusion strategy offers the most balanced and dependable solution. Crucially, the system’s ability to maintain robustness and prevent data loss across diverse walking styles fully justifies the hardware overhead of the dual-sensor setup, making it ideal for thorough gait characterization in real-world scenarios.

Future research will concentrate on expanding the fusion framework to include more gait parameters, such as walking asymmetry, stance-to-swing ratio, and stride length. Deep learning-based approaches will also be explored to enhance automatic feature extraction and enable adaptive sensor fusion, effectively eliminating the current reliance on subject-specific empirical parameter tuning. Although the small cohort (N=4) limits statistical generalizability, it sufficiently validated the methodology's robustness; future work will expand to larger, diverse populations to confirm broader clinical performance. Finally, to enable completely autonomous gait monitoring in unrestricted environments, future efforts will focus on optimizing the current near real-time, lightweight embedded implementation for fully wireless, low-power wearable deployment.

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