Smartphone-Based Attitude-Unconstrained Pedestrian Dead Reckoning System with Positioning Adjustment using Wi-Fi Fingerprinting*

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Abstract

With people nowadays spending an increasing amount of time indoors, smartphone-based indoor positioning technology holds significant practical value. However, existing Pedestrian Dead Reckoning (PDR) algorithms typically require smartphones to maintain specific attitudes, severely limiting their practicality. Attitude changes affect both heading estimation accuracy and step detection performance, leading to positioning errors. Current research addressing attitude constraints primarily focuses on optimizing individual modules rather than providing comprehensive system solutions. This paper proposes a complete attitude-unconstrained smartphone PDR system integrated with Wi-Fi positioning technology. The system encompasses three core modules: (1) Step detection employing multi-sensor fusion technology with cross-sensor axis combinations; (2) Heading estimation adopting frequency-domain analysis to align the smartphone coordinate system with the actual walking direction through angle traversal and coordinate transformation; (3) Step length estimation using an enhanced Weinberg model based on biomechanical characteristics, comprehensively considering height, acceleration variations, and step frequency factors. The PDR results are subsequently adjusted using an adaptive weighted fusion mechanism integrating Wi-Fi fingerprinting. The complete proposed tracking solution is demonstrated through real-world experiments with average positioning errors of 0.66m and 1.1m, for pocket and reading modes respectively.

Keywords

Pedestrian Dead Reckoning, Indoor Positioning, Smartphone, Attitude-Unconstrained, Multi-sensor Fusion

1. Introduction

Pedestrian localization and tracking have attracted considerable attention due to their importance in search and rescue, emergency services, and location-based applications. With eight billion smartphones predicted to be in use by 2028 [1], these ubiquitous devices provide unprecedented opportunities for indoor positioning solutions in settings without GPS, where people spend more than 87% of their time. Pedestrian Dead Reckoning (PDR) [2] has emerged as a promising indoor positioning solution due to its non-reliance on specific infrastructure. Nevertheless, a significant drawback of the PDR systems is their requirement that devices maintain particular attitudes while in use. This constraint significantly impacts practical deployment, as users naturally change device orientations when placing phones in pockets, or bags, or performing activities while walking. Existing algorithms assume a fixed coordinate system relationship between device and user movements, which leads to the attitude dependency problem affecting all three main PDR components, i.e., step detection, heading estimation and step length estimation. This assumption is a major obstacle preventing PDR from being widely used in practical applications. The present research proposes a comprehensive, attitude-unconstrained PDR system integrated with Wi-Fi positioning technology [3], aiming to decrease attitude dependencies among PDR components and eliminate the impact of attitude variations on positioning accuracy. While

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integrating Wi-Fi fingerprinting introduces some infrastructure dependency, it provides crucial benefits including cumulative error correction and absolute positioning reference, which are invaluable for preserving PDR's continuous tracking advantage.

The remainder of this paper is organized as follows: section 2 reviews related work; section 3 presents the proposed system architecture and methodology; section 4 describes the experimental setup and performance evaluation; section 5 concludes this work.

2. Related Work

Pedestrian Dead Reckoning (PDR) systems have been extensively studied for indoor localization due to their independence from external infrastructure. However, smartphone carrying positions and device orientations significantly impact PDR performance, as different phone orientations introduce substantial challenges to accurate positioning [4]. The authors in [5], demonstrated that orientation changes can cause shifts in the acceleration signal dominant axis, leading to significant performance degradation in traditional single-axis detection methods. Research has shown that heading estimation modules are most sensitive to orientation changes, followed by step detection, while step length estimation exhibits relative robustness [6].

Various approaches have been proposed to improve step detection robustness against orientation variations. Traditional signal processing techniques include threshold detection, double threshold detection, and peak detection methods [7], [8]. Furthermore, the heading estimation represents the most challenging component for achieving orientation independence in PDR systems, primarily due to the misalignment between the smartphone device heading and the pedestrian walking direction. Traditional approaches assume a constant offset angle between device and user heading, but when devices are placed in pockets or different positions, the offset angle varies with body movement, causing this assumption to fail. In [9], the pocket placement problem was addressed by developing rotation matrix and principal component analysis methods that consider dynamic coordinate system changes, projecting acceleration signals into reference coordinate systems to extract the actual walking directions without being affected by device orientation. The step length estimation demonstrates better robustness to device orientation changes compared to other PDR components. The Weinberg model relies primarily on acceleration magnitude differences and step frequency information, maintaining stable accuracy across different device placements [7]. Multi-pattern step detection algorithms have achieved high accuracy across different walking patterns using smartphone sensors [10].

The PDR systems inherently suffer from cumulative errors caused by sensor noise, bias drift in low-cost MEMS sensors, and the integration of inertial measurements over time, leading to positioning accuracy degradation during extended operation. To overcome cumulative errors, researchers have explored fusion methods combining PDR with other positioning technologies. Extended Kalman filter-based approaches fuse WiFi fingerprinting with PDR using adaptive measurement noise estimation [11]. Bluetooth technology and PDR fusion frameworks achieve meter-level positioning accuracy through intelligent parameter adaptation based on RSS measurements [12]. In addition, multi-modal systems combining Wi-Fi, Bluetooth, and PDR demonstrate superior localization performance using unscented Kalman filters [13]. Recent factor graph models with local attention mechanisms show enhanced interference resistance in multi-sensor fusion systems [14].

3. Methodology

PDR is an infrastructure-free technology primarily used for navigation. It is essential to estimate pedestrian positions accurately over time without imposing predetermined limitations on smartphone placement. In order to obtain a reliable indoor positioning that can adjust to changes in posture, the integration of Wi-Fi fingerprinting with the suggested posture-unconstrained PDR localization method is required.

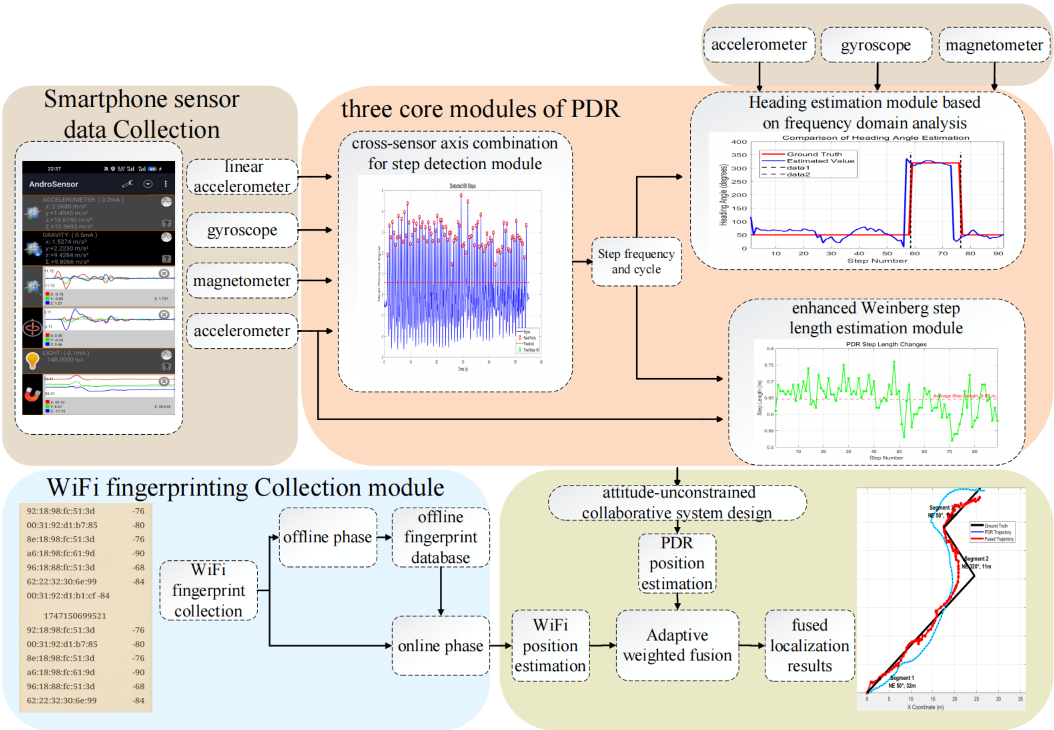


Figure 1: Proposed system flowchart

Figure 1 illustrates the overall framework of the proposed system, which comprises of two collaborative localization methods: the PDR for relative positioning and Wi-Fi fingerprinting for absolute positioning correction. In particular, the PDR system includes three core modules: step detection, heading estimation, and step length estimation. These modules process smartphone sensor data, i.e., accelerometer, linear accelerometer, gyroscope, and magnetometer. The system employs cross-sensor axis combination for step detection to obtain the step frequency and step cycle, which are then input to the heading estimation and step length estimation modules. All modules demonstrate robust performance against posture variations. The Wi-Fi component operates in both offline and online phases for fingerprint database construction and real-time position estimation, respectively. An adaptive weighted fusion mechanism integrates PDR relative positioning with Wi-Fi absolute positioning to achieve accurate localization with minimal computational overhead.

3.1. Multi-Sensor Axes Fusion for Step Detection

The step detection is based on the multi-sensor axes fusion method proposed in [15]. In particular, the following four sensors, i.e., accelerometer (A), linear accelerometer (L), gyroscope (G) and magnetometer (M) are combined in four different 3-sensor fusion groups: ALG, ALM, LGM, and MAG. By decomposing each sensor into its X, Y, Z axes components, each fusion group results in 9 different data-streams resulting in 84 possible combinations per group. The optimal combination is selected by calculating:

$$M_{\text{fusion}}(t) = \sqrt{S_1^2(t) + S_2^2(t) + S_3^2(t)}, \tag{1}$$

where S_1, S_2, S_3 are the three selected axis component measurements. Subsequently, adaptive threshold peak detection is performed based on the combined signal's standard deviation.

3.2. Attitude-Unconstrained Heading Estimation

The traditional PDR heading estimation requires fixed smartphone orientation, limiting practical applicability. Users frequently change device positions, i.e., handheld and pocket, causing misalignment between device heading and actual movement direction. The present work adopts the constraint-free heading estimation method proposed in [16], which utilizes the frequency domain characteristics of acceleration signals during human locomotion, and identifies the optimal coordinate system alignment. In particular, through coordinate system rotation transformation, the smartphone's carrier coordinate system is realigned so that one axis aligns with the person's actual forward direction. The following three steps are used to implement the algorithm:

1. *Multi-axes Rotation Optimization*: Follow the sequence to perform three-axes rotation traversal to identify the optimal smartphone coordinate system:

- For $\theta_x \in [0°, 90°]$: Rotate around X-axis, identify step frequency maximum peak
- For $\theta_y \in [0°, 90°]$: Apply θ_x, rotate around Y-axis, repeat analysis
- For $\theta_z \in [0°, 90°]$: Apply θ_x, θ_y, rotate around Z-axis, calculate frequency ratio

The binary search method used in the original paper may converge to a local optimal search value, therefore this paper adopts a grid search method for full-angle range exploration, ensuring finding the globally optimal solution that meets the optimization objective.

2. *Coordinate Transformation and Filtering*: Through the multi-axes rotation optimization in step 1, the system sequentially searches for angles that maximize step frequency characteristics along *X*, *Y*, and Z axes, ultimately obtaining the optimal rotation angle combination (θ, γ, ψ). The determination of these three angles indicates finding the optimal coordinate system configuration that aligns one smartphone axis with the user's actual walking direction. After rotation, a low-pass filter is applied to the forward direction, while band-pass filters are used for the lateral and vertical direction.

3. *Geographic Projection and Heading Calculation*: A direction cosine matrix is derived from Quaternion Extended Kalman Filter-based Attitude and Heading Reference System (QEKF-AHRS) attitude estimation using the rotated and filtered sensor data, i.e., accelerometer, gyroscope, and magnetometer, composed of Euler angles that describe the smartphone's orientation relative to the Earth's reference frame. This provides the transformation from the aligned body coordinate system to the geographic coordinate system, i.e., East-North-Up coordinate system.

3.3. Enhanced Step Length Estimation

The Weinberg model is a classical step length estimation method proposed by Weinberg et al. [7], that estimates pedestrian step length by establishing a nonlinear relationship between step length and the magnitude of vertical acceleration variations. This model has been widely adopted due to its simplicity, effectiveness, and thorough validation, along with its certain degree of robustness to device orientation changes, making it a fundamental model suitable for scenarios involving device attitude variations. The traditional Weinberg model establishes the relationship between step length and acceleration variations as follows:

$$SL = K \times \sqrt[4]{(a_{\max} - a_{\min})}, \tag{2}$$

where SL denotes the estimated step length, K represents a calibration constant typically associated with pedestrian height, and $a_{\max}$ and $a_{\min}$ correspond to the maximum and minimum acceleration signal values respectively, within a single gait cycle. The present study deploys an enhanced Weinberg model that builds upon this fundamental approach by introducing a multi-factor adjustment mechanism to improve robustness to device attitude variations while maintaining computational efficiency. In particular, the framework initially establishes a foundation step length based on pedestrian height as follows:

$$\text{Base\_SL} = \alpha \times H, \tag{3}$$

where $\alpha = 0.34$ serves as the base calibration coefficient. Subsequently, the model incorporates a comprehensive multi-factor adjustment mechanism as follows:

$$SL = \text{Base\_SL} \times F_{\text{accel}} \times F_{\text{freq}}, \tag{4}$$

where F_{accel} represents the acceleration adjustment factor, derived through normalization of acceleration differentials estimated by:

$$F_{\text{accel}} = 0.85 + 0.3 \times \frac{\text{Accel\_diff} - \text{Accel\_diff}_{\text{min}}}{\text{Accel\_diff}_{\text{max}} - \text{Accel\_diff}_{\text{min}}}, \tag{5}$$

while F_{freq} represents the step frequency adjustment factor, set to 0.95 when step frequency is below 90% of the average step frequency, set to 1.05 when above 110%, and set to 1.0 otherwise. The effective gain $K_{effective} = \alpha \times F_{accel} \times F_{freq}$ is determined through dynamic adjustment, with a gain range of approximately 0.27-0.41.

The system establishes a base step length based on height (0.34 $\times$ height), and estimates the acceleration adjustment factor through the normalization (0.85 + 0.3 $\times$ normalized difference), and obtains the final step length by multiplying the base step length with the two adjustment factors. Finally, to ensure the rationality of the estimated step length, boundary constraints are implemented as follows:

$$\text{min\_SL} \leq SL \leq \text{max\_SL} \tag{6}$$

3.4. WiFi Fingerprinting Integration

The Wi-Fi fingerprinting module employs an adaptive Weighted k-NN (WKNN) algorithm that assigns weights based on the detection frequency of the Media Access Control (MAC) addresses across fingerprint sampling locations. The detection frequency is calculated as the ratio of sampling locations where each MAC address is detected to the total number of fingerprint sampling locations. Specifically, characteristic MAC addresses with detection frequencies below 20% are assigned 3.0 times weight due to their high location specificity, regional MAC addresses with frequencies between 20%-60% receive 1.5 times weight, while common MAC addresses with frequencies exceeding 60% are given 1.0 times weight. The weighted distance is estimated as follows:

$$d = \sqrt{\sum_i w_i \times (\text{RSS}_{\text{online},i} - \text{RSS}_{\text{fp},i})^2}, \tag{7}$$

where $RSS_{online,i}$ represents the real-time signal strength of the i-th WiFi access point, $RSS_{fp,i}$ denotes the pre-stored signal strength of the same access point in the fingerprint database, and w_i is the adaptive weight assigned to each access point based on its spatial coverage rate. Based on distance distribution, characteristic MAC density, signal variance and matching quality, multi-strategy fusion dynamically determines the k-value ($3 \leq k \leq 8$). Final positioning adopts k-nearest neighbor weighted average, combining distance-based weights ($1/d^2$) and matching quality weights.

Finally, the adaptive weighted fusion is applied, which is estimated as follows:

$$P_f = \alpha \cdot P_{PDR} + (1 - \alpha) \cdot P_{WiFi}, \tag{8}$$

where P_f represents the fused position estimation, P_{PDR} represents the PDR position estimation, P_{WiFi} represents the WiFi position estimation, and α represents the adaptive fusion weighting coefficient. The weighting coefficient α is dynamically determined based on the Euclidean distance $d = ||P_{PDR} - P_{WiFi}||^2$ between PDR and WiFi position estimations, with values of 0.95, 0.75, 0.65, and 0.55 corresponding to distance ranges of >20m, 10-20m, 5-10m, and <5m respectively.

4. Experiments and Results

Experiments were conducted in a Z-shaped corridor at the Cyprus University of Technology, providing a representative indoor environment with consistent flooring, uniform lighting, and magnetic interference

(a) Experimental site (b) Pocket Mode (c) Reading Mode

Figure 2: Experimental site, pocket and reading mode

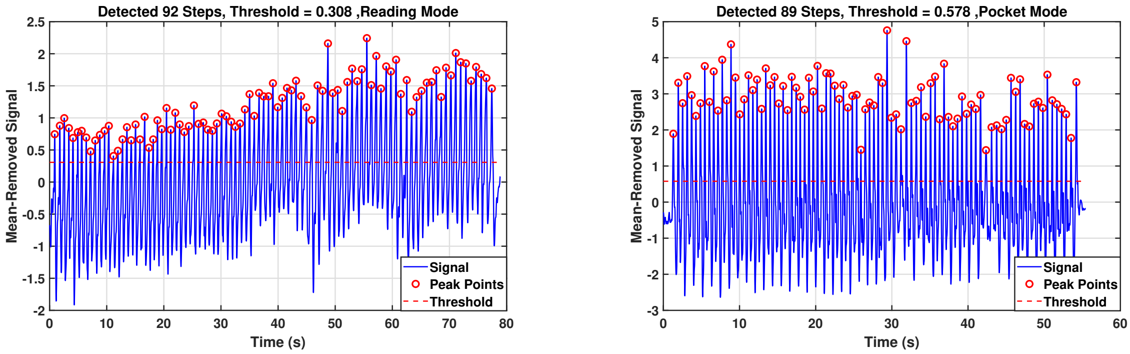
from electronic devices. The test path consisted of three segments: 32 meters in the direction of 50° east of North, 11 meters in the direction of 320° west of north, and 11 meters in the direction of 50° east of north, totaling 54 meters with two significant directional changes to evaluate the performance of the attitude-unconstrained PDR system under dynamic conditions.

The data acquisition was performed by using a OnePlus 10 Pro smartphone equipped with integrated MEMS sensors, i.e., tri-axial accelerometer, gyroscope, and magnetometer. Sensor data were captured by utilizing the AndroSensor application at a sampling frequency of 100Hz. The experiments employed two smartphone carrying modes: pocket mode (device placed in trouser pocket) and reading mode (handheld with screen facing the user). The experimental site and the carrying modes are shown in Figures 2a, 2b and 2c respectively. Additionally, the experiments required prior collection of offline Wi-Fi fingerprint data and establishment of a fingerprint database. Experiments were conducted with participants walking at normal speeds (approximately 1.2-1.5 m/s). The Wi-Fi fingerprint database was constructed approximately 10 hours prior to the online positioning experiments. Wi-Fi fingerprints were collected at 2-meter intervals along the trajectory, with 1-meter intervals near endpoints. Considering the temporal variations in signal strength, multiple 20-30 second stationary Received Signal Strength Indicator (RSSI) measurements were collected at each reference point during different time periods to establish the offline database. Sensor data required for PDR and online Wi-Fi fingerprint data were collected to prepare for subsequent algorithm processing.

Figure 3a and Figure 3b demonstrate the step detection results. Step detection using the Accel_X-Accel_Y-Lin_Acc_Z configuration correctly identified 92 steps in reading mode and 89 steps in pocket mode under the same configuration, both matching the actual step counts. The adaptive threshold effectively handled amplitude variations, with approximately 0.3 for reading mode and 0.6 for pocket mode, demonstrating excellent adaptability to non-stationary walking signals. Meanwhile, the detected peaks (red circles) were consistently distributed throughout the time series, showing robust stride recognition capability. Using the enhanced Weinberg model, Figure 4b shows step length variations in pocket mode ranged from 0.52-0.76 meters with an average of 0.65 meters, while as shown in Figure 4a, reading mode showed shorter step lengths of 0.48-0.67 meters with an average of 0.57 meters.

As shown in Figure 5a and Figure 5b, the heading estimation concluded in average errors of 22.74°in pocket mode and 16.91°in reading mode, with reading mode demonstrating better accuracy. Although the errors were somewhat larger than those in [16], possibly due to differences in experimental environments, equipment, and optimal parameter selection, the method accurately captured the overall heading change trends, demonstrating the robustness of the approach.

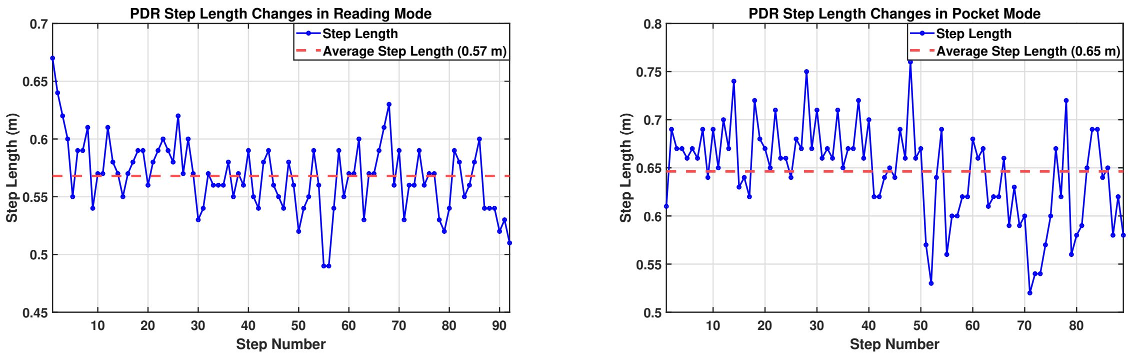
The experiments employed Sequential Importance Resampling (SIR) particle filter [17] for comparison. The adaptive weighted fusion method achieved optimal performance in both modes of this experiment. As shown in Figure 6a and Figure 7a, in reading mode, adaptive weighted fusion achieved a mean error of 1.10m, median error of 0.84m, and 95th percentile error of 2.82m, while SIR particle filter achieved 1.52m, 1.55m, and 3.07m respectively. Pure attitude-unconstrained PDR exhibited errors of 2.51m, 2.43m, and 4.29m, while standalone WiFi positioning showed poor performance with 95th percentile error of 3.99m.



(a) Reading mode

(b) Pocket mode

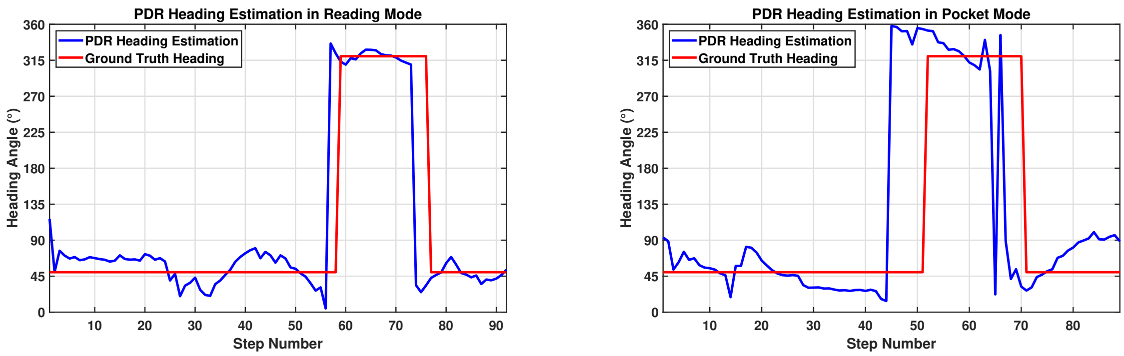
Figure 3: The step detection results



(a) Reading mode

(b) Pocket mode

Figure 4: Step length estimation results

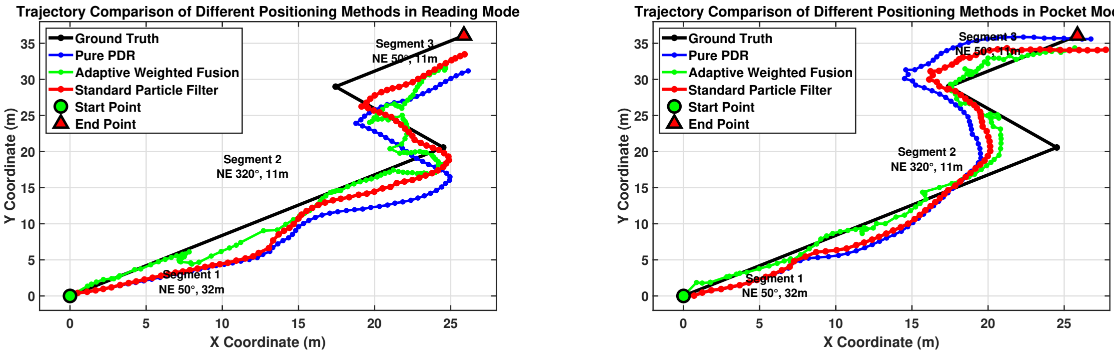


(a) Reading mode

(b) Pocket mode

Figure 5: Heading estimation results

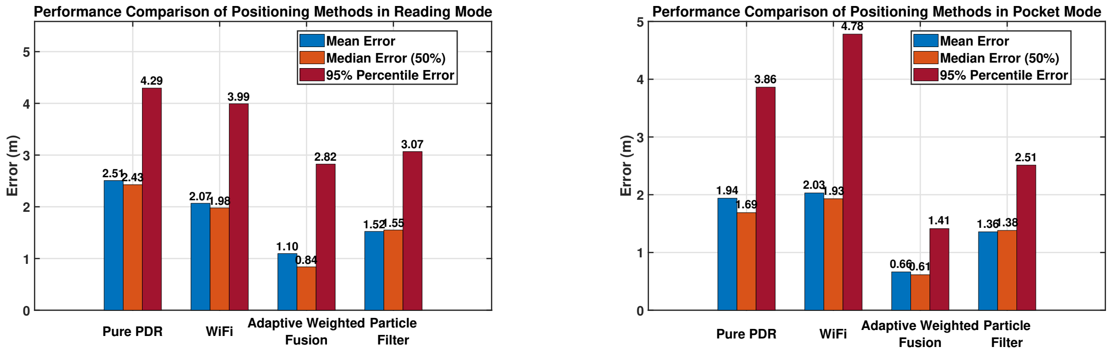
As illustrated in Figure 6b and Figure 7b, the pocket mode, adaptive weighted fusion demonstrated superior performance with mean error of 0.66m, median error of 0.61m, and 95th percentile error of 1.41m. SIR particle filter achieved 1.36m, 1.38m, and 2.51m respectively, while pure PDR exhibited 1.94m, 1.69m, and 3.86m. Standalone Wi-Fi positioning showed poor stability with 95th percentile error of 4.78m. Compared to pure PDR, adaptive weighted fusion achieved improvements of 56-66% in mean error, 48-65% in median error, and 24-63% in 95th percentile error across both modes.



(a) Reading mode

(b) Pocket mode

Figure 6: Positioning Results



(a) Reading mode

(b) Pocket mode

Figure 7: Performance comparison

5. Conclusions

In this paper we propose a comprehensive, attitude-unconstrained PDR system integrated with Wi-Fi fingerprinting technology, aiming to decrease attitude dependencies among PDR components and eliminate the impact of attitude variations on positioning accuracy. Our preliminary experimental results indicate that the proposed attitude-unconstrained PDR system demonstrates good robustness and positioning accuracy across different carrying modes, with significantly enhanced performance when combined with WiFi fusion technology. In this setting, the adaptive weighted fusion method outperformed both pure PDR and SIR particle filter approaches in both pocket and reading modes, demonstrating the effectiveness and practicality of the integrated positioning system.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] F. Laricchia, Smartphones - statistics and facts, https://www.statista.com/topics/840/smartphones/, 2024. Accessed: 2024/03/04.

[2] X. Hou, J. Bergmann, Pedestrian dead reckoning with wearable sensors: A systematic review, IEEE Sensors Journal 21 (2021) 143–152. doi:10.1109/JSEN.2020.3014955.

[3] H. Liu, H. Darabi, P. Banerjee, J. Liu, Survey of wireless indoor positioning techniques and systems, IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37 (2007) 1067–1080.

[4] Q. Tian, Z. Salcic, K. I.-K. Wang, Y. Pan, A multi-mode dead reckoning system for pedestrian tracking using smartphones, IEEE Sensors Journal 16 (2016) 2079–2093. doi:10.1109/JSEN.2015.2510364.

[5] H. Zhang, W. Yuan, Q. Shen, T. Li, H. Chang, A handheld inertial pedestrian navigation system with accurate step modes and device poses recognition, IEEE Sensors Journal 15 (2015) 1421–1429. doi:10.1109/JSEN.2014.2363157.

[6] T. Michel, H. Fourati, P. Genevès, N. Layaïda, A comparative analysis of attitude estimation for pedestrian navigation with smartphones, in: 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2015, pp. 1–10. doi:10.1109/IPIN.2015.7346767.

[7] N.-H. Ho, P. H. Truong, G.-M. Jeong, Step-detection and adaptive step-length estimation for pedestrian dead-reckoning at various walking speeds using a smartphone, Sensors 16 (2016). URL: https://www.mdpi.com/1424-8220/16/9/1423. doi:10.3390/s16091423.

[8] M. Khedr, N. El-Sheimy, A smartphone step counter using imu and magnetometer for navigation and health monitoring applications, Sensors 17 (2017). URL: https://www.mdpi.com/1424-8220/17/11/2573. doi:10.3390/s17112573.

[9] Z.-A. Deng, G. Wang, Y. Hu, D. Wu, Heading estimation for indoor pedestrian navigation using a smartphone in the pocket, Sensors 15 (2015) 21518–21536. URL: https://www.mdpi.com/1424-8220/15/9/21518. doi:10.3390/s150921518.

[10] Y. Yao, L. Pan, W. Fen, X. Xu, X. Liang, X. Xu, A robust step detection and stride length estimation for pedestrian dead reckoning using a smartphone, IEEE Sensors Journal 20 (2020) 9685–9697. doi:10.1109/JSEN.2020.2989865.

[11] Z.-A. Deng, G. Wang, D. Qin, Z. Na, Y. Cui, J. Chen, Continuous indoor positioning fusing wifi, smartphone sensors and landmarks, Sensors 16 (2016). URL: https://www.mdpi.com/1424-8220/16/9/1427. doi:10.3390/s16091427.

[12] X. Li, J. Wang, C. Liu, A bluetooth/pdr integration algorithm for an indoor positioning system, Sensors 15 (2015) 24862–24885. URL: https://www.mdpi.com/1424-8220/15/10/24862. doi:10.3390/s151024862.

[13] Y. Zhu, X. Luo, S. Guan, Z. Wang, Indoor positioning method based on wifi/bluetooth and pdr fusion positioning, in: 2021 13th International Conference on Advanced Computational Intelligence (ICACI), 2021, pp. 233–238. doi:10.1109/ICACI52617.2021.9435887.

[14] J. Liu, Z. Yang, S. Zlatanova, S. Li, B. Yu, Indoor localization methods for smartphones with multi-source sensors fusion: Tasks, challenges, strategies, and perspectives, Sensors 25 (2025). URL: https://www.mdpi.com/1424-8220/25/6/1806. doi:10.3390/s25061806.

[15] C. Isaia, M. P. Michaelides, Step counting by optimum fusion of IMU sensor measurements, in: Proceedings of the Work-in-Progress Papers at the 14th International Conference on Indoor Positioning and Indoor Navigation, IPIN-WiP 2024, 2024, pp. 1–9. URL: https://github.com/conisaia/Step-Counting-by-Optimum-Fusion-of-IMU-Sensor-Measurements, [Online]. Available: https://github.com/conisaia/Step-Counting-by-Optimum-Fusion-of-IMU-Sensor-Measurements.

[16] D. Liu, L. Pei, J. Qian, L. Wang, P. Liu, Z. Dong, S. Xie, W. Wei, A novel heading estimation algorithm for pedestrian using a smartphone without attitude constraints, in: 2016 Fourth International Conference on Ubiquitous Positioning, Indoor Navigation and Location Based Services (UPINLBS), 2016, pp. 29–37. doi:10.1109/UPINLBS.2016.7809947.

[17] W. Wu, Y. Xu, Z. Li, J. Lai, A multi-source fusion positioning system based on mdaw-pf algorithm and pdr, International Journal of Computational Intelligence Systems 18 (2025) 34. URL: https://doi.org/10.1007/s44196-025-00749-z. doi:10.1007/s44196-025-00749-z.