Lightweight Indoor Trajectory Localization via Multi-step Fusion of Wi-Fi Fingerprinting and PDR

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Abstract

Indoor localization in complex environments is challenged by signal instability, environmental occlusion, and cumulative motion-estimation errors. To address these issues, this study proposes a fusion localization method that combines Wi-Fi fingerprint trajectories and pedestrian dead reckoning (PDR) trajectories in a library scene. A dual-device collaborative acquisition scheme is adopted, in which an ESP32-C5 board collects Wi-Fi data and a smartphone collects inertial and attitude data. Weighted K-nearest neighbor (WKNN) is used for Wi-Fi fingerprint positioning, while PDR trajectory propagation is derived from linear acceleration and a roll-derived directional signal for stepwise propagation. On this basis, a 9-dimensional augmented multi-step extended Kalman filter is constructed to fuse Wi-Fi and PDR information. Experiments were conducted in two walking scenarios, namely a U-shaped trajectory and an L-shaped trajectory, within the same library environment. Results show that the proposed fusion method consistently improves overall trajectory fitting and demonstrates good applicability under different trajectory geometries. Although the improvement in local point-to-point errors remains scenario-dependent, the proposed framework effectively combines Wi-Fi absolute position constraints with continuous PDR motion information, thereby improving trajectory localization performance in complex indoor environments.

1. Introduction

With the continuous development of digital services, smart buildings, and location-aware technologies, indoor positioning has become an increasingly important topic in location-based services. Unlike outdoor environments, indoor spaces are characterized by building obstructions, complex layouts, dynamic changes in people and objects, and significant signal interference, all of which pose substantial challenges to positioning accuracy, real-time performance, and stability. Meanwhile, the growing demand for navigation, guidance, and spatial services in libraries, hospitals, shopping malls, and warehouses has further promoted the development of low-cost and reliable indoor positioning methods (Li et al., 2024; Bahl and Padmanabhan, 2000).

Among smartphone-based indoor positioning approaches, Wi-Fi-based positioning and pedestrian dead reckoning (PDR) are two widely used solutions. Wi-Fi positioning can leverage existing access point infrastructure and has been widely applied for indoor absolute localization because of its wide coverage, relatively low deployment cost, and ease of implementation (Bahl and Padmanabhan, 2000; Dai et al., 2023). Within Wi-Fi fingerprint positioning, deterministic nearest-neighbor methods such as NN, KNN, and WKNN remain popular because of their simple implementation and practical effectiveness (Xia et al., 2017; Wang et al., 2019; Oh, 2018). The classical RADAR system demonstrated the feasibility of nearest-neighbor matching in signal space (Bahl and Padmanabhan, 2000), and more recent studies have shown that WKNN remains effective for improving localization robustness in complex indoor environments (Wang et al., 2024). In contrast, PDR relies on built-in smartphone sensors to continuously estimate walking motion and heading, providing infrastructure-free trajectory continuity (Li et al., 2024; Chen et al., 2011).

However, both approaches have clear limitations in real indoor environments. Wi-Fi fingerprint positioning is sensitive to multipath propagation, occlusion, temporal signal variability, and environmental dynamics, which can degrade matching stability and localization accuracy (Turgut and Gorgulu Kakisim, 2024; Yang, 2024; Fan and Sun, 2024; Ayub et al., 2025). PDR provides better continuity, but accumulated heading and step-length errors can lead to substantial trajectory drift over time (Zhu et al., 2023; Yan et al., 2021). To exploit their complementary strengths, previous studies have integrated Wi-Fi observations with inertial motion estimation using extended Kalman filters, unscented Kalman filters, and particle filters, showing that multi-source fusion can improve positioning accuracy and trajectory stability (Deng et al., 2016; Chen et al., 2018; Chen et al., 2022). For example, Deng et al. (2016) fused Wi-Fi, smartphone sensors, and landmarks for continuous indoor localization; Chen et al. (2018) proposed an INS/Wi-Fi hybrid localization system; and Chen et al. (2022) further improved PDR/Wi-Fi fusion using a federated particle filter.

Despite these advances, several practical issues remain. According to the official Android documentation, Wi-Fi scan requests may be throttled when requested too frequently, and returned results may correspond to previous scans rather than the latest ones, which reduces the stability of real-time observations on a single smartphone (Android Developers, n.d.). In complex library environments, bookshelf occlusion, corridor constraints, and multipath effects further limit the smoothness and stability of Wi-Fi fingerprint positioning, while PDR alone still accumulates drift. In addition, many existing fusion methods rely on relatively low-dimensional state representations and make limited use of short-term historical motion information, leaving room for improvement in start-up periods, turns, and abnormal-observation handling (Deng et al., 2016; Chen et al., 2018; Chen et al., 2022).

To address these issues mentioned above, this study addresses three main research questions:
(1) How can a dual-device collaborative acquisition scheme alleviate the limitations of real-time Wi-Fi scanning on smartphones in a complex library environment?
(2) How can WKNN-based Wi-Fi fingerprint positioning and PDR-based trajectory propagation be effectively integrated within a 9-dimensional augmented multi-step extended Kalman filter framework?
(3) To what extent can the proposed framework improve trajectory fitting and positional consistency under different walking trajectory scenarios in the same library environment?

The main contributions of this study are threefold. First, a dual-device data acquisition and alignment workflow is established for real walking scenarios, improving the availability of online Wi-Fi observations while retaining the low-cost characteristics of the system. Second, a 9-dimensional multi-step extended Kalman filtering method based on augmented modeling of positions and motion-direction variables at three consecutive time steps is proposed to enhance the continuity and robustness of short-term trajectory prediction. Third, comparative experiments in two trajectory scenarios within a university library, namely a U-shaped path (Scenario 1) and an L-shaped path (Scenario 2), show that the proposed method consistently improves overall trajectory fitting and demonstrates good applicability under different trajectory geometries. These results indicate that the framework can effectively combine Wi-Fi absolute positioning with continuous PDR motion information to improve indoor trajectory localization performance in complex environments.

2. Methodology

To address the instability of single-method indoor localization and the limitation of real-time smartphone Wi-Fi scanning, this study builds upon an existing open-source Wi-Fi/PDR/EKF indoor fusion framework[1] and introduces targeted improvements for practical trajectory localization in a library environment. Specifically, an ESP32-C5 board is used for Wi-Fi acquisition, while a smartphone is used to collect inertial and attitude data. The overall methodological framework consists of four stages: data acquisition and preprocessing, standalone positioning, fusion localization, and error evaluation. First, the Wi-Fi and inertial data collected by the two devices are preprocessed and temporally aligned. Second, standalone Wi-Fi fingerprint positioning and PDR trajectory propagation are conducted. Third, the resulting Wi-Fi and PDR trajectories are fused using the proposed 9-dimensional augmented multi-step EKF. Finally, the fused trajectories are evaluated against the corresponding ground-truth trajectories.

2.1 Data Acquisition and Preprocessing

Two walking trajectories were designed in the library scene for localization analysis, namely a U-shaped trajectory (Scenario 1) and an L-shaped trajectory (Scenario 2). A dual-device acquisition scheme was adopted, in which Wi-Fi observations were collected for fingerprint positioning and linear-acceleration, gravity, and attitude data were collected for PDR trajectory propagation. Data collection included an offline stage for fingerprint database construction and an online stage for trajectory acquisition. Ground-truth positions were obtained from ground markers and manual measurements.

For Wi-Fi preprocessing, the offline fingerprint dataset and the online trajectory datasets were first organized separately, and only the APs appearing in both the offline and online data were retained to construct a unified feature space for subsequent fingerprint matching. The raw scan records were then reorganized by scan event to provide standardized Wi-Fi observations. For inertial preprocessing, linear acceleration, gravity, and attitude records collected by phyphox were merged into a unified time series after timestamp reconstruction.

Because Wi-Fi and PDR-related sensor data were acquired by different devices, the two streams were aligned using relative time and nearest-neighbor matching. The alignment tolerance was set to reduce the influence of asynchronous acquisition.

2.2 WKNN-Based Wi-Fi Fingerprint Positioning

After preprocessing, only the APs appearing in both the offline fingerprint dataset and the online trajectory datasets were retained to construct a unified Wi-Fi feature space. For each online scan, the RSS observation was matched to the fingerprint database in RSS space, and the top-K most similar reference points were selected for position estimation. To obtain a more stable Wi-Fi observation for subsequent fusion, WKNN was adopted:

$$\hat{p}_{WKNN} = \frac{\sum_{i \in N_K} w_i \, p_i}{\sum_{i \in N_K} w_i}, w_i = \frac{1}{d_i + \varepsilon} \tag{2.1}$$

where $\hat{p}_{WKNN}$ denotes the estimated Wi-Fi position, p_i denotes the coordinate of the i-th neighboring reference point, d_i denotes the RSS-space distance between the online observation and the corresponding fingerprint, and ε is a small constant introduced to avoid division by zero.

In the implementation, the online observation sequence was organized by scan event, and only one Wi-Fi positioning result was generated for each scan to avoid repeatedly using the same Wi-Fi observation in the positioning process. Considering its simple implementation, low computational cost, and compatibility with the subsequent fusion framework, WKNN was adopted in the final Wi-Fi positioning module, and its outputs were used as the Wi-Fi observation inputs for the subsequent fusion process.

2.3 PDR Trajectory Estimation Based on Inertial Data

This study used smartphone linear acceleration and attitude data to perform pedestrian trajectory propagation. Considering that the experiments were conducted in a corridor-constrained library environment, where pedestrian motion was relatively steady, a lightweight PDR method based on peak-based step detection, directional-signal smoothing, and a fixed step-length model was adopted. This design does not require additional training and provides continuous relative displacement input for the subsequent fusion process.

Step events were detected from the linear-acceleration sequence using a peak-detection strategy. Because the default phyphox settings led to large step-counting errors, the peak threshold and minimum peak distance were calibrated using 20 additional walking datasets with manually recorded ground-truth step counts. A two-dimensional grid search combined with leave-one-out cross-validation (LOOCV) was adopted for parameter selection, yielding a peak threshold of 1.56 and a minimum peak distance of 77 samples. To reduce false detections caused by the

[1] https://github.com/salmoshu/IndoorFusionNav

stationary phase at the beginning of recording, only peaks detected after the first 1.0 s were retained.

For direction estimation during PDR propagation, the roll-channel attitude output from the smartphone was used as a surrogate directional signal under the fixed phone-holding condition of this experiment, rather than as a general absolute heading measurement. The resulting directional sequence was first unwrapped to remove angular discontinuities and then smoothed using a moving average with a window length of 7. Because the smartphone coordinate system did not fully coincide with the floor-plan coordinate system, a constant direction offset was applied for correction:

$$\theta_k = \tilde{\phi}_k + \beta, \beta = -90° \tag{2.2}$$

where θ_k denotes the corrected propagation-direction variable used for trajectory propagation. In this study, θ_k is referenced to the north direction (i.e., the positive y-axis of the floor-plan coordinate system).

In the trajectory propagation stage, a fixed step length of 0.6 m was adopted. This choice was made because the experiments involved a single participant walking under relatively stable corridor conditions, where gait variation was limited. The position at step k was updated as

$$x_k = x_{k-1} + L\,sin\,\theta_k\,, y_k = y_{k-1} + L\,cos\,\theta_k \tag{2.3}$$

where x_k and y_k denote the two-dimensional coordinates at step k, L denotes the fixed step length, and θ_k denotes the corrected propagation-direction variable rather than a general absolute heading angle. Under this definition, $\theta_k = 0°$ corresponds to motion along the positive y-direction, and the step displacement is therefore decomposed as $\Delta x = L\sin\,\theta_k$ and $\Delta y = L\cos\,\theta_k$. Through step detection, direction-signal estimation, and position updating, a stepwise PDR trajectory was obtained.

2.4 Multi-Step EKF Fusion Localization Based on a 9-Dimensional Augmented State

To jointly exploit the absolute position observations provided by Wi-Fi and the continuous motion information provided by PDR, this study adopts a multi-step extended Kalman filter (EKF) based on an augmented state design. Unlike a conventional current-state filter that models only the pedestrian position at the current step, the proposed method explicitly retains the positions and motion-direction variables at three consecutive time steps. This design allows the filter to preserve short-term motion history during fusion, which helps improve trajectory continuity and robustness when Wi-Fi observations are sparse or unstable.

Because the Wi-Fi positioning results and the PDR trajectory are generated from different processing pipelines and have different sampling frequencies, temporal association is required before fusion updates. In this study, PDR step events are treated as the basic temporal unit for EKF updates, and nearest-neighbor time matching is used to associate the temporally closest Wi-Fi observation with each PDR step event. A Wi-Fi observation is considered valid only when

$$|\, t_k^{pdr} - t_j^{wifi} \,| \leq \tau \tag{2.4}$$

where t_k^{pdr} denotes the timestamp of the k-th PDR step event, t_j^{wifi} denotes the timestamp of a candidate Wi-Fi observation, and τ denotes the temporal alignment tolerance. In this study, the temporal alignment tolerance was set to 180 ms.

The key idea of the proposed method is to augment the state by jointly retaining three consecutive motion states, namely the states at steps $k-2$, $k-1$, and k. Each step contains three variables: the two-dimensional position (x, y) and the motion-direction angle ϕ. Therefore, the total state dimension is $3 \times 3 = 9$. The augmented state vector at step k is defined as

$$X_k = [x_{k-2}, y_{k-2}, \phi_{k-2}, x_{k-1}, y_{k-1}, \phi_{k-1}, x_k, y_k, \phi_k]^T \tag{2.5}$$

where x_k and y_k denote the two-dimensional coordinates at step k, and ϕ_k denotes the corresponding motion-direction angle used internally in the EKF. Compared with a conventional filter that only estimates the current state, this augmented design explicitly preserves short-term historical motion information, making the fusion process less sensitive to local Wi-Fi fluctuations and more stable during turns and short-term disturbances.

In the prediction stage, the EKF does not directly reuse the propagation-direction variable defined in the PDR propagation model. Instead, the motion-direction angle is reconstructed from adjacent PDR displacement increments. Let

$$\Delta x_k^{pdr} = x_k^{pdr} - x_{k-1}^{pdr}, \Delta y_k^{pdr} = y_k^{pdr} - y_{k-1}^{pdr} \tag{2.6}$$

denote the stepwise displacement derived from the PDR trajectory. Then, the motion-direction angle and its increment are computed as

$$\phi_k = atan2\left(\Delta y_k^{pdr}, \Delta x_k^{pdr}\right), \Delta\phi_k = wrap(\phi_k - \phi_{k-1}) \tag{2.7}$$

Accordingly, the current predicted motion state is updated as

$$\begin{aligned} \phi_{k+1} &= wrap(\phi_k + \Delta\phi_k), \\ x_{k+1} &= x_k + L\,cos\,\phi_{k+1}, \\ y_{k+1} &= y_k + L\,sin\,\phi_{k+1} \end{aligned} \tag{2.8}$$

where L denotes the fixed step length and was set to 0.6 m in this study. Here, ϕ is referenced to the positive x-axis of the floor-plan coordinate system. Accordingly, the augmented state shifts forward by one step, so that the oldest state is discarded and the newly predicted state is appended. In this way, the filter simultaneously preserves the short-term motion history and the current predicted state during fusion.

In the observation update stage, Wi-Fi provides two-dimensional absolute position observations, which are used to correct only the current position components of the augmented state. To suppress the influence of abnormal Wi-Fi observations, a residual-gating strategy is introduced before the EKF update. Let z_k denote the Wi-Fi observation and $X_{k|k-1}$ denote the predicted state. The observation is accepted only when

$$\rho_k = \| z_k - HX_{k|k-1} \|_2, \rho_k \leq r_{\max} \tag{2.9}$$

where ρ_k denotes the residual norm and $r_{\max}$ denotes the residual threshold. If the residual exceeds the threshold, the Wi-

Fi observation is rejected and only the predicted state is retained. In this study, the residual threshold in the normal stage was set to 4.0 m, while a looser threshold of 6.0 m was used in the start-up stage.

Because the PDR trajectory is less stable during the initial steps, stronger Wi-Fi constraints were applied in the start-up stage. The number of start-up steps was set to $N_{start} = 3$, and a smaller observation-noise setting was used during this stage to increase the influence of valid Wi-Fi observations on early-state correction. Standard EKF prediction and correction were then used for state propagation and observation update. For brevity, the full Jacobian and covariance update equations are omitted here, since the main contribution of this study lies in the augmented three-step state design and the residual-gated fusion strategy rather than in the standard EKF formulation.

3. Evaluation

3.1 Experimental Setup and Evaluation Metrics

To evaluate the effectiveness of the proposed method, we conducted a set of experiments in a university library covering approximately 10.5 m × 9 m. Figure 1 shows the layout of the experimental area. The environment contains bookshelves and corridors and exhibits typical characteristics of complex indoor spaces, including occlusion, multipath propagation, and path constraints. Two walking scenarios were considered in this study, namely Scenario 1 with a U-shaped trajectory and Scenario 2 with an L-shaped trajectory. The compared methods included standalone Wi-Fi fingerprint positioning, standalone PDR trajectory propagation, and the proposed 9-dimensional augmented multi-step EKF fusion method.

Figure 1. Layout of the experimental area in the university library

A dual-device collaborative acquisition scheme was adopted. An ESP32-C5 development board was used as an independent Wi-Fi acquisition terminal, while a smartphone running the phyphox application was used to collect linear acceleration, gravity, and attitude data for PDR. Data collection consisted of two stages. In the offline stage, 56 reference points were deployed in the experimental area with a spacing of 1.5 m. At each reference point, Wi-Fi data were collected continuously for 30 s and repeated four times to construct the offline fingerprint database. In the online stage, Wi-Fi and linear-acceleration, gravity, and attitude data were acquired in parallel along the predefined trajectories. The ground-truth trajectories were obtained through ground markers and manual measurements for subsequent error analysis.

In the final implementation, Wi-Fi positioning was based on WKNN fingerprint matching, PDR was derived from step detection and roll-derived directional-signal estimation, and fusion was performed using the proposed 9-dimensional augmented multi-step EKF. The same fusion parameter setting was used in both Scenario 1 and Scenario 2 to ensure a consistent evaluation, and the main fusion parameter settings are summarized in Table 1.

Table 1. Key fusion parameter settings

Parameter	Description	Value
$\boldsymbol{\sigma_{wifi}}$	Standard deviation of Wi-Fi observation noise	7.0
$\boldsymbol{\sigma_{pdr}}$	Standard deviation of PDR position process noise	0.25
$\boldsymbol{r_{max}}$	Wi-Fi residual threshold in the normal stage	4.0 m
$\boldsymbol{\tau}$	Temporal alignment tolerance between Wi-Fi and PDR	180 ms
L	Fixed step length used in fusion prediction	0.6 m
$\boldsymbol{N_{start}}$	Number of start-up steps with stronger Wi-Fi trust	3

Two error metrics were used for evaluation: (1) trajectory-to-polyline error, defined as the shortest distance from each estimated point to the ground-truth reference polyline, which reflects the overall trajectory fitting quality; and (2) point-to-point error, computed by interpolating the ground-truth trajectory according to the PDR step count and then calculating the Euclidean distance between each estimated point and the corresponding reference point, which reflects positional consistency along the trajectory. For both metrics, the count, mean error, RMSE, and maximum error were calculated. To further indicate the actual participation of Wi-Fi observations in the fusion process, the number of accepted Wi-Fi updates and the Wi-Fi usage ratio were also reported as auxiliary statistics.

3.2 Performance Comparison of Wi-Fi, PDR, and Fusion Methods in Two Scenarios

Tables 2 and 3 present the quantitative comparison of the three methods under the two evaluation metrics across the two walking scenarios, providing the basis for the subsequent analysis.

Table 2. Comparison of trajectory-to-polyline error in Scenario 1 (U-shaped) and Scenario 2 (L-shaped)

Scenario	Method	Count	Mean (m)	RMSE (m)	Max (m)
Scenario 1 (U-shaped)	Wi-Fi	52	1.3545	1.5249	2.5000
	PDR	26	0.9258	1.0133	1.7354
	EKF-9D (ours)	26	0.4794	0.5975	1.2374
Scenario 2 (L-shaped)	Wi-Fi	33	1.4307	1.5410	2.5000
	PDR	16	0.4770	0.5455	0.9735
	EKF-9D (ours)	16	0.2738	0.3402	0.5736

Table 3. Comparison of point-to-point error in Scenario 1 (U-shaped) and Scenario 2 (L-shaped)

Scenario	Method	Count	Mean (m)	RMSE (m)	Max (m)
Scenario 1 (U-shaped)	Wi-Fi	7	3.6462	4.0481	7.0622
	PDR	26	1.2499	1.3239	2.1059
	EKF-9D (ours)	26	0.9184	0.9854	1.5276
Scenario 2 (L-shaped)	Wi-Fi	4	2.7601	2.8704	3.6160
	PDR	16	0.6063	0.6496	1.0982
	EKF-9D (ours)	16	0.6697	0.8393	1.7212

Overall, the proposed fusion method achieved the best trajectory-to-polyline performance in both scenarios, indicating that it provided the strongest overall path-fitting capability among the three methods. For point-to-point error, the fusion method achieved the best performance in Scenario 1, while in Scenario 2 the standalone PDR method obtained a lower mean error and RMSE than the proposed fusion method. This suggests that the proposed framework consistently improved global trajectory fitting, whereas its stepwise positional consistency still showed scenario-dependent variation.

In Scenario 1, the proposed fusion method showed clear advantages over both standalone Wi-Fi and standalone PDR. For trajectory-to-polyline error, it achieved the lowest mean error, RMSE, and maximum error, namely 0.4794 m, 0.5975 m, and 1.2374 m, respectively. A similar trend was observed for the point-to-point metric, where the corresponding mean error, RMSE, and maximum error were 0.9184 m, 0.9854 m, and 1.5276 m. These results suggest that, along the U-shaped trajectory, the fusion framework was able to combine Wi-Fi absolute constraints with continuous PDR propagation, thereby improving both global trajectory fitting and positional consistency along the walking path.

A different pattern can be observed in Scenario 2. Although the fusion method still delivered the best trajectory-to-polyline performance, with a mean error of 0.2738 m, an RMSE of 0.3402 m, and a maximum error of 0.5736 m, its advantage was less pronounced under the point-to-point metric. In this case, standalone PDR yielded a lower mean error and RMSE (0.6063 m and 0.6496 m) than the proposed fusion method (0.6697 m and 0.8393 m). This indicates that, while the fused trajectory was globally closer to the reference path, its stepwise correspondence with the interpolated reference points was not consistently better than that of standalone PDR in the L-shaped scenario.

From the perspective of method characteristics, standalone Wi-Fi positioning could provide absolute position observations, but its trajectory points remained highly scattered and yielded the largest errors in both scenarios, especially under the point-to-point metric. By contrast, standalone PDR showed better continuity and generally lower point-to-point error than Wi-Fi, but still suffered from drift accumulation during trajectory propagation. The proposed fusion method alleviated the instability of Wi-Fi observations while correcting part of the accumulated PDR drift, which led to the best trajectory-to-polyline performance in both scenarios and the best overall balance of accuracy and continuity in Scenario 1.

It should also be noted that the numbers of valid evaluation points were not identical across the three methods. In both scenarios, the point-to-point error of Wi-Fi was calculated from only a small number of valid observations successfully aligned with PDR step events, whereas both PDR and fusion were evaluated on all step-event points. This difference indicates that, although Wi-Fi could provide absolute position observations, its effective participation at the step-event level remained limited. Nevertheless, the accepted Wi-Fi updates in the fusion process still provided useful absolute corrections, as reflected by the auxiliary statistics reported in Table 4.

Table 4. Auxiliary Wi-Fi participation statistics in the fusion process

Scenario	Accepted Wi-Fi updates	Wi-Fi usage ratio	Rejected Wi-Fi updates
Scenario 1 (U-shaped)	5	0.7143	2
Scenario 2 (L-shaped)	4	1.0000	0

3.3 Trajectory Visualization Analysis

Figure 2 and Figure 3 show the trajectory comparisons in Scenario 1 and Scenario 2, respectively. In both scenarios, the three methods exhibit clearly different spatial characteristics. Standalone Wi-Fi positioning shows the strongest spatial dispersion, with scattered positioning points and obvious cross-segment jumps. Standalone PDR preserves trajectory continuity more effectively, but still suffers from accumulated drift during trajectory propagation. By contrast, the proposed fusion method provides a better balance between path fidelity and motion continuity, producing trajectories that are visually closer to the ground-truth path.

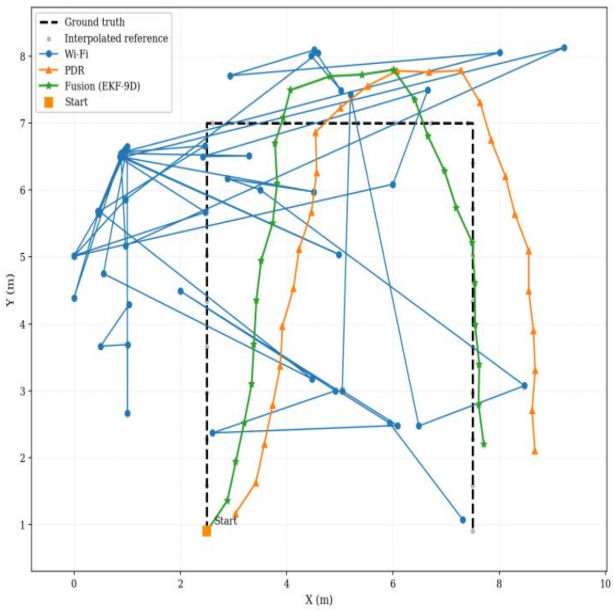

Figure 2. Trajectory comparison in Scenario 1

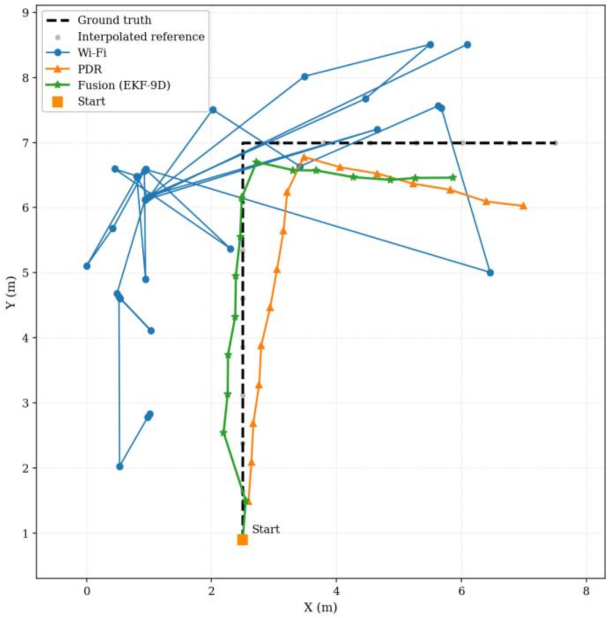

Figure 3. Trajectory comparison in Scenario 2

In Figure 2, corresponding to Scenario 1, the standalone Wi-Fi trajectory is widely dispersed and deviates substantially from the reference path, indicating strong sensitivity to signal fluctuations, multipath propagation, and bookshelf-induced occlusion in the library environment. The standalone PDR trajectory retains the overall U-shaped geometry, but still exhibits a systematic offset from the ground-truth path because of accumulated direction-estimation and step-length errors. The fused trajectory remains much closer to the reference path, effectively suppressing both the large spatial dispersion of Wi-Fi and the long-term drift of PDR. This visual pattern is consistent with the quantitative results in Section 3.2, where the fusion method achieved the best performance under both trajectory-to-polyline and point-to-point metrics.

As shown in Figure 3 for Scenario 2, the overall visual characteristics remain broadly similar to those in Scenario 1, but the relative behavior of PDR and the proposed fusion method becomes more subtle. Standalone Wi-Fi still shows obvious scattering and limited temporal consistency. Standalone PDR follows the overall L-shaped path with relatively good continuity and remains close to the reference path over most segments. The fused trajectory is globally closer to the ground-truth path than both standalone Wi-Fi and standalone PDR, especially in terms of overall path fitting. However, some local deviations can still be observed in parts of the trajectory, which is consistent with the quantitative results that the fusion method achieved the best trajectory-to-polyline performance, while standalone PDR produced lower point-to-point error.

Overall, the trajectory visualizations further support the interpretation of the quantitative results. The proposed fusion method consistently improves the global fitting of the estimated trajectory to the reference path in both scenarios. Its advantage in stepwise positional consistency is more evident in Scenario 1, whereas in Scenario 2 the standalone PDR trajectory remains more competitive under the point-to-point metric. These observations suggest that the proposed EKF-based fusion framework is particularly effective in enhancing overall path consistency, while its local point-to-point behavior still depends on the trajectory geometry and the actual availability of effective Wi-Fi updates.

3.4 Discussion and Limitations

Taken together, the results in the two scenarios indicate that the main advantage of the proposed method lies in its ability to improve overall trajectory fitting by combining smooth PDR-based motion propagation with effective Wi-Fi absolute position corrections. In both Scenario 1 and Scenario 2, the proposed fusion framework achieved the lowest trajectory-to-polyline error, showing that the augmented multi-step EKF can effectively constrain the estimated trajectory toward the reference path while preserving motion continuity.

At the same time, the results also suggest that the improvement brought by fusion is not identical under all evaluation metrics. In Scenario 1, the fusion method outperformed both standalone Wi-Fi and standalone PDR under both trajectory-to-polyline and point-to-point metrics, indicating a clear advantage in both global path fitting and stepwise positional consistency. In Scenario 2, however, although the fusion method still achieved the best trajectory-to-polyline performance, standalone PDR produced lower point-to-point error. This difference suggests that the proposed framework is particularly effective in improving global path consistency, whereas its benefit for stepwise correspondence may still depend on trajectory geometry, local update conditions, and the actual interaction between PDR propagation and Wi-Fi corrections.

The comparative results also highlight the complementary characteristics of the three methods. Standalone Wi-Fi can provide absolute position observations, but its results remain highly scattered and temporally inconsistent, especially under step-level evaluation. Standalone PDR provides better continuity, but accumulated drift still causes deviation from the reference path. The proposed fusion method can alleviate the instability of Wi-Fi observations while correcting part of the long-term drift of PDR, thereby producing a trajectory that is globally more consistent with the ground-truth path.

Despite the promising results, some limitations should also be noted. First, the current evaluation was conducted only in a single library scene, although two trajectory scenarios with different geometries were included. Therefore, the generalizability of the proposed method to other indoor environments still requires further validation. Second, all experiments were carried out by a single participant, and the PDR module adopted a fixed step-length model, so the influence of inter-subject gait variation was not systematically investigated. In addition, the propagation-direction signal used in the PDR module was derived under a fixed phone-holding condition and should not be interpreted as a general absolute heading estimate; therefore, its robustness under different device postures and carrying modes still requires further investigation. Third, after temporal alignment between Wi-Fi observations and PDR step events, the number of effective Wi-Fi updates remained limited, which may constrain the frequency of absolute position correction. Finally, although the proposed fusion framework showed clear advantages in overall trajectory fitting, its stepwise improvement was not uniformly superior across all scenarios, indicating that further work is still needed to enhance local point-to-point consistency under different path geometries and observation conditions.

4. Conclusion and Future Work

This study proposes an indoor fusion localization method that combines Wi-Fi fingerprint trajectories and PDR trajectories to address the limited stability of standalone Wi-Fi positioning, the

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accumulated drift of standalone PDR, and the constraints of real-time Wi-Fi acquisition on smartphones in complex library environments. By adopting a dual-device collaborative acquisition scheme and a multi-step fusion framework, the proposed method effectively integrates Wi-Fi absolute position constraints with continuous PDR motion information.

Experimental results in two trajectory scenarios within the same library environment show that the proposed fusion method can consistently improve overall trajectory fitting and demonstrate good applicability under different trajectory geometries. Although its improvement in local point-to-point consistency still shows some scenario-dependent variation, the proposed framework can effectively combine Wi-Fi absolute position constraints with continuous PDR motion information, thereby improving trajectory localization performance in complex indoor environments.

It should be noted that the current experiments were conducted in a single library scene and with a single participant, while the PDR module adopted a fixed step-length model. In addition, the propagation-direction signal used in the PDR module was derived under a fixed phone-holding condition and therefore still requires further validation under different device postures and carrying modes. Therefore, the applicability of the proposed method to more indoor environments, more participants, and different gait conditions still requires further investigation. Future work will extend the evaluation to more scenes and more trajectories, and will further explore more adaptive step-length modeling and improved local correction mechanisms to enhance fusion-based indoor localization performance in complex environments.

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