An Indoor Navigation Algorithm Using Multi-dimensional Euclidean Distance and the Adaptive Particle Filter

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Abstract. The inertial navigation systems exhibit excellent short-term positioning accuracy, yet they are susceptible to cumulative errors over time. WiFi fingerprint localization avoids cumulative errors, but it is prone to mismatching issues. Therefore, a commonly used technique is the integration of an inertial navigation system and WiFi fingerprint matching.The particle filter employs dead reckoning (DR) for the state transfer equation, while utilizing the disparity between inertial navigation and WiFi fingerprint matching as the observation equation. Floor map information is introduced to detect whether particles cross the wall and if so, the weight is set to zero. For the particles that do not cross the wall, considering the distance between the current particles and the historical particles, an adaptive particle filter is proposed. The adaptive factor increases the weight of highly trusted particles and reduces the weight of untrusted particles. Another innovation is the introduction of a multidimensional Euclidean distance algorithm to reduce inconsistencies in WiFi fingerprint matching. The experimental results show that the proposed algorithm achieves high positioning accuracy.

Keywords: The inertial navigation system · WiFi fingerprint mathcing · The adaptive particle filter · Multi-dimensional Euclidean distance

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1 Introduction

A high level of positioning accuracy is currently achievable in open outdoor spaces through global satellite navigation systems. Examples include Baidu Maps and Google Maps, both of which offer navigation and location services for pedestrians and vehicles. In the indoor, tunnel, and other areas, due to the transmission of obstacle occlusion signal, the wireless signal attenuates greatly, so the scheme which using satellite navigation can not provide reliable positioning accuracy. Therefore, the study of indoor navigation solutions has aroused greater interest among researchers [1,2]. Smart phones have the advantages of high penetration and easy portability, Therefore, scholars have conducted extensive studies on indoor navigation utilizing smartphone platforms.

The inertial navigation system (INS) is an autonomous navigation system that operates independently without relying on external information or emitting energy externally. It can provide carrier position, attitude and speed information continuously and in real time. The main disadvantage of inertial navigation systems is the cumulative effect of positional errors. That is, as the elapsed time increases, the errors get bigger. The citation [3] indicates that the accumulated positional error in a two-dimensional plane is proportional to the cube of time. Aiming at the problem of cumulative error, many researchers have carried out in-depth research.The HDR and HDE algorithms [4,5] have been successful in mitigating cumulative errors during pedestrian movement in standard corridors. By incorporating map information, the study presented in references [6,7] employs a map-aided algorithm to mitigate the directional drift observed in inertial navigation. Another approach involves introducing the magnetic field and utilizing its north-pointing characteristic to correct the direction of the inertial navigation system (INS).

The utilization of WiFi wireless signals for positioning is widespread, with two typical indoor WiFi positioning technologies being the signal attenuation model and fingerprint matching model. The signal attenuation model requires prior knowledge of the anchor point's location, and based on the received channel state information[8], estimate the time to reach the direct or reach the Angle, and use the arrival time difference positioning method to estimate the user's position. The WiFi signal state fluctuates with time, and complex indoor environments, such as pedestrians walking or changes in the position of obstacles, are easy to affect the propagation model, resulting in deviations in parameter estimation and a decline in positioning accuracy.The WiFi fingerprint matching model typically consists of two stages: offline training and online positioning. In the off-line training stage, the received channel state information and the corresponding calibration coordinates are saved in the database, and the model is obtained after training. In the online positioning stage, the collected channel state information is used as the fingerprint and then matched with the state information in the database after the model estimation. Usually, the location marked by the fingerprint that is most similar to the fingerprint database is used as the pedestrian location. Because the channel state information of WiFi is easily polluted by environmental noise, it will inevitably cause the mismatch of fingerprints. Therefore, the reference [9] proposed a magnetic fingerprint matching method, which can reduce the location estimation error caused by the WiFi fingerprint mismatch phenomenon. Therefore, considering the complementary characteristics of the positioning errors of these two signal sources, an adaptive particle filter combining INS and WiFi is proposed. The main innovations of this paper are as follows

- To address the challenge of fingerprint mismatching, the multi-dimensional WiFi fingerprint is used instead of the traditional one-dimensional fingerprint, and the multi-dimensional Euclidean distance algorithm is proposed to compute the multi-dimensional WiFi fingerprint distance.
- To address the challenge of traditional particle filter weight updating, the improved particle filter uses adaptive factors to improve the high trusted particle weight and reduce the low trusted particle weight.
- Two cellularphone are used to carry out navigation experiments in two navigation areas, and the Observational results show that the average positioning accuracy is 1.84 m.

2 Framework Description

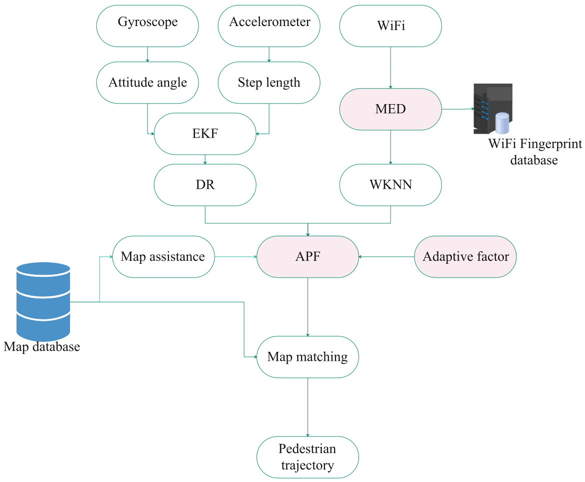

Fig. 1. Algorithm framework of MED and APF.

The smartphone's gyroscope and accelerometer are used to obtain the values of the smartphone's angular velocity and acceleration sensors in real time. Then the integration technology is used to obtain the attitude angle, and the gait technology is used to obtain the pedestrian's step length, so as to estimate the pedestrian's position based on the attitude angle and step length DR. The positioning process using the WiFi fingerprint positioning method can be divided into an offline channel state information fingerprint database construction stage and an online channel state information fingerprint matching stage. The reference point of the positioning area is calibrated through pre-placed anchor points, and then the fingerprint information of the reference point area is collected. The fingerprint data of two collection points are generated through interpolation technology, and a fingerprint database of the area is constructed. At the online stage, the distance between the MED to calculate the online collection of WIFI fingerprints and the fingerprints saved in the database.The weighted K-Nearest neighbor (WKNN) algorithm is used to further improve position performance by selecting the Kwifi matching results.The DR model is used as a state transmission equation for a particle filter. The difference between the distance result of the WiFi fingerprint and the inertial navigation result is used as an observation equation.A adaptive factor is proposed to increase the weight of high trust particles.Finally, MAP matching is used to further reduce estimated pedestrian position errors.The algorithm framework of the MED and APFs is shown in Figure 1.

2.1 DR module

EKF for Attitude Angle. When a pedestrian is moving, its vertical speed should be zero when its feet touch the ground. Therefore, an EKF filter is constructed to remove walking noise. The system model is as follows

$$X(k) = [Z(k), V_z(k), \text{Roll}(k), \text{Pitch}(k), \text{Yaw}(k)] \tag{1}$$

where $Z(k)$ and $V_z(k)$ represent vertical displacement and vertical velocity, respectively; $\text{Roll}(k), \text{Pitch}(k), \text{Yaw}(k)$ represent the attitude angle.

The vertical velocity and vertical displacement of the transition model is as follows

$$\begin{bmatrix} Z(k+1) \\ V_z(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix} \otimes \begin{bmatrix} Z(k+1) \\ V_z(k) \end{bmatrix} + \begin{bmatrix} 0 & 0 & \frac{T_s^2}{2} \\ 0 & 0 & T_s \end{bmatrix} \otimes \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{2}$$

where T_s represents the sampling interval, a_z, a_y, a_z represent tri-axis acceleration, respectively.

While the time moves to the moment where zero vertical velocity is detected by ZUPT, EKF is triggered. The vertical velocity is updated to zero. The algorithm flow chart for EKF is shown in Algorithm 1.

Attitude Angle. When the angular velocity is collected by the gyroscope, the increment of the three-axis angular velocity $[\Delta\theta_k^x, \Delta\theta_k^y, \Delta\theta_k^z]$ is calculated as follows [25]

$$\begin{aligned} \Delta\theta_k^x &= \omega_k^x * T_s \\ \Delta\theta_k^y &= \omega_k^y * T_s \\ \Delta\theta_k^z &= \omega_k^z * T_s \end{aligned} \tag{3}$$

Algorithm 1. The EKF module

Input: Accelerometers and gyroscopes collect acceleration and angular velocity
1. Extract the vertical acceleration from acceleration.
2. Estimate Zero Velocity Point using Vertical acceleration.
3. Compensate for acceleration and angular velocity errors.
4. Use acceleration to calculate the quaternion.
5. Obtain the attitude angle from the quaternion.
6. Filter noise using EKF.

where $[\omega_k^x, \omega_k^y, \omega_k^z]$ represents the angular velocity of the three axes respectively. T_s represents the sampling interval.

According to the reference [26], the quaternion vector is updated as follows

$$\mathbf{q}_{k+1} = \left[\mathbf{I} \cos\frac{\Delta\theta_k}{2} + \Delta\mathbf{\Theta} \frac{\sin\frac{\Delta\theta_k}{2}}{\Delta\theta_k} \right] \mathbf{q}_k \tag{4}$$

where $\mathbf{I}$ denotes a $3 * 3$ identity matrix. $\Delta\mathbf{\Theta}$ is calculated as follows

$$\Delta\mathbf{\Theta} = \begin{bmatrix} 0 & \Delta\theta_k^z & -\Delta\theta_k^y & \Delta\theta_k^x \\ -\Delta\theta_k^z & 0 & \Delta\theta_k^x & \Delta\theta_k^y \\ \Delta\theta_k^y & -\Delta\theta_k^x & 0 & \Delta\theta_k^z \\ -\Delta\theta_k^x & -\Delta\theta_k^y & -\Delta\theta_k^z & 0 \end{bmatrix} \tag{5}$$

After the quaternion are updated, the direction cosine matrix is calculated as follows

$$C_b^n = \begin{bmatrix} q_1^2 - q_2^2 - q_3^2 + q_4^2 & 2q_1q_2 - 2q_3q_4 & 2q_1q_3 + 2q_2q_4 \\ 2q_1q_2 + 2q_3q_4 & -q_1^2 + q_2^2 - q_3^2 + q_4^2 & 2q_2q_3 - 2q_1q_4 \\ 2q_1q_3 - 2q_2q_4 & 2q_2q_3 + 2q_1q_4 & -q_1^2 - q_2^2 + q_3^2 + q_4^2 \end{bmatrix} \tag{6}$$

After the direction cosine matrix are updated, the attitude angle is calculated as follows [25]

$$\begin{aligned} \vartheta &= \tan^{-1} \frac{-C_b^n(3,1)}{\sqrt{(C_b^n(3,2))^2 + (C_b^n(3,3))^2}} \\ \phi &= \tan^{-1} \frac{C_b^n(3,2)}{C_b^n(3,3)} \\ \psi &= \tan^{-1} \frac{C_b^n(2,1)}{C_b^n(1,1)} \end{aligned} \tag{7}$$

where ϑ, ϕ, ψ are called pitch, roll and yaw, respectively.

Step Length. Gait-based step length estimation has been successfully applied to low-end inertial sensors [27]. In the process of pedestrian walking, the vertical displacement is periodic, as shown in Figure 2.

The vertical displacement of pedestrians during walking is calculated as follows [28]

$$h(k) = -\int_{t1}^{t2} V_z(k) \tag{8}$$

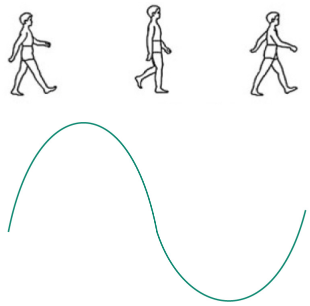

Fig. 2. Pedestrian walking posture.

where $h(k)$ and $V_z(k)$ denotes the vertical displacement and the vertical speed at the kth time.

According to the literature [28], the step length is calculated as follows

$$SL(k) = 2\sqrt{-2L\int_{t1}^{t2} V_z(k) - \left(\int_{t1}^{t2} V_z(k)\right)^2} \tag{9}$$

where L represents the leg length.

DR. Based on the step length, direction, and the position at the kth time, the pedestrian position at the $(k+1)th$ time is calculated as follows

$$\begin{bmatrix} x(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \end{bmatrix} + SL(k+1) \times \begin{bmatrix} \sin(\psi(k+1)) \\ \cos(\psi(k+1)) \end{bmatrix} \tag{10}$$

where $x(k)$ and $y(k)$ denote the position at the kth time.

2.2 MED for WiFi Matching

WiFi fingerprint matching is commonly used as a single point fingerprint matching [29]. Because WIFI fluctuates greatly, there is a "jump point" problem in single point matching. As shown in Figure 3, there is a "jump point" when estimating pedestrian position. Once the WiFi fingerprint is matched, use a triangle to mark the matching location. Obviously, the fourth triangle is far away from the other three triangles. The WiFi matching location of the fourth triangle is not reliable.

We propose a multi-dimensional fingerprint recognition algorithm to solve the jump point problem. In order to improve the algorithm matching stability, we add historical fingerprint information to reduce the impact of single fingerprint matching. $n$indicates the number of WiFi access points collected at the same time. The square represents the RSS of the access point. $k$indicates the kthtime for collecting WiFi fingerprints, as shown in Figure 4.

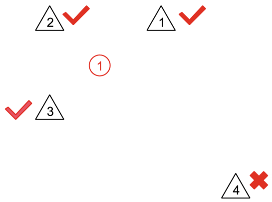

Fig. 3. A "jump point" for WiFi fingerprint matching.

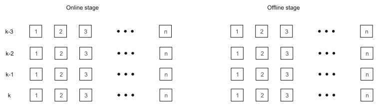

Fig. 4. The multi-dimensional WiFi fingerprint matching.

The traditional Euclidean distance is only suitable for one-dimensional WiFi fingerprints, so it is necessary to modify the traditional Euclidean distance, that is, MED. MED is calculated as follows

$$d = \sum_{i=k-3}^{k} \left[\sum_{j=1}^{n} (RSS(j) - RSS_{db}(j)) \right] \tag{11}$$

where $RSS(j)$ denotes the jth access point value in the online stage. $RSS_{db}(j)$ denotes the jth access point value in the offline stage. After calculating the fingerprint distance, WKNN is used to estimate the WiFi fingerprint matching position. For the detailed process, please refer to reference [19].

2.3 APF for Pedestrian Localization

System Equation for APF. Compared with Kalman filtering, particle filtering provides a different technique for nonlinear system state estimation[30]. Particle filtering is widely used in a variety of nonlinear and non-Gaussian system models because it is independent of the system model. The state equation and observation equation of particle filter are defined as follows

$$\mathbf{X}_k = f(\mathbf{X}_{k-1}) + \boldsymbol{\omega} \tag{12}$$

$$\mathbf{Z}_k = h\left(\mathbf{X}_k\right) + \boldsymbol{\nu} \tag{13}$$

where $f(\cdot)$ and $h(\cdot)$ represent known processes and observation equations, respectively; $\mathbf{X}_k$ and $\mathbf{Z}_k$ represent the process state and the observed state at the kth time, respectively; $\boldsymbol{\omega}$ and $\boldsymbol{\nu}$ represent process noise and observation noise, respectively.

The DR-based particle filtering process takes into account the errors of step size, direction and estimated position, and assumes that their noise follows Gaussian distribution and the mean is zero.

$$\mathbf{X}_k = f(\mathbf{X}_{k-1}) + \boldsymbol{\omega} = \begin{bmatrix} L_{k-1} \\ \theta_{k-1} \\ x_{k-1} \\ y_{k-1} \end{bmatrix} + \begin{bmatrix} \Delta L \\ \Delta\theta \\ L_k \cos(\theta_k) \\ L_k \sin(\theta_k) \end{bmatrix} + \boldsymbol{\omega} \tag{14}$$

where L_{k-1} and θ_{k-1} represent the step length and direction at $(k-1)th$ time. (x_{k-1}, y_{k-1}) represents the estimated position of pedestrians at $(k-1)th$ time; ΔL and $\Delta\theta$ represent pedestrian step length and direction change, respectively.

In the process of pedestrian walking, WiFi positioning system can provide positioning results. Combined with DR, the observation equation is defined as follows

$$\mathbf{Z}_k = h(\mathbf{X}_k) + \boldsymbol{\nu} = \begin{bmatrix} x_{DR} \\ y_{DR} \end{bmatrix} - \begin{bmatrix} x_{WIFI} \\ y_{WIFI} \end{bmatrix} + \boldsymbol{\nu} \tag{15}$$

where $[x_{DR}, y_{DR}]^T$ represents the positioning result of DR. $[x_{WIFI}, y_{WIFI}]^T$ represents the positioning result of WiFi fingerprint matching.

Particle Weight Technique. In order to deal with the difficulty of solving the posterior distribution of particle filter for nonlinear systems, it is more feasible to replace the analytical solution with the approximate solution. In order to solve the sampling problem of a posterior distribution, resampling technique can be adopted[31].

$$q(\mathbf{X}_{0:k} \mid \mathbf{Z}_{1:k}) = q(\mathbf{X}_{0:k-1} \mid \mathbf{Z}_{1:k-1})\, q(\mathbf{X}_k \mid \mathbf{X}_{0:k-1}, \mathbf{Z}_{1:k}) \tag{16}$$

The recursive formula for calculating the importance weight from each generation of particles is

$$\begin{aligned} \omega 1_k^i &= \frac{p(\mathbf{X}_{0:k} \mid \mathbf{Z}_{1:k})}{q(\mathbf{X}_{0:k} \mid \mathbf{Z}_{1:k})} \\ &\propto \omega 1_{k-1}^i \frac{p(\mathbf{Z}_k \mid \mathbf{X}_k)\, p(\mathbf{X}_k \mid \mathbf{X}_{k-1})}{q(\mathbf{X}_k \mid \mathbf{X}_{0:k-1}, \mathbf{Z}_{1:k})} \\ &\sim \frac{1}{(2\pi)^{m/2}|R|^{1/2}} \exp\left(\frac{-\left[Z^* - h(\mathbf{X}_{k,i}^-)\right]^{\mathrm{T}} R^{-1} \left[Z^* - h(\mathbf{X}_{k,i}^-)\right]}{2} \right) \end{aligned} \tag{17}$$

where $\mathbf{Z}^*$ represents the estimated observation; $\mathbf{X}_{k,i}^-$ represents the priori estimated state vector; m represents the vector dimension; R represents the observation noise.

During a move, the position of the next point in time is limited by the position of the previous point in time, as shown in Figure 5. Assume that the pedestrian is in the center of a circular area at time $(k-1)th$. Considering the limited step length of the pedestrian, the position of the pedestrian inside the circle at $kth$is more reliable, while the position outside the circle is less reliable. The particle weight is not only related to the WiFi fingerprint matching results, but also to the step size, so an adaptive factor is introduced to calculate the particle weight.

$$dist = \begin{bmatrix} x_{est} \\ y_{est} \end{bmatrix}_k - \begin{bmatrix} x_{est} \\ y_{est} \end{bmatrix}_{k-1} \tag{18}$$

$$\omega 2_k^i = \frac{1}{1 + e^{-dist}} \tag{19}$$

where $\begin{bmatrix} x_{est} \\ y_{est} \end{bmatrix}_k$ represents the estimated position at the kth time.

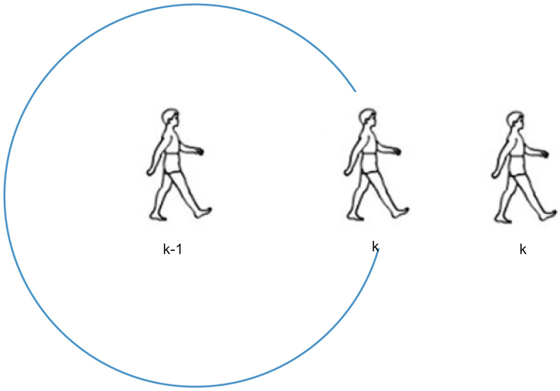

Fig. 5. Pedestrian walking position.

Combining the two-particle weight calculation methods, the new particle weight is calculated as follows

$$\omega = \omega 1 * \omega 2 \tag{20}$$

Map Assistance. In the offline phase, the floor structure map information is stored in the map database in advance. The online phase requires verification of the validity of the newly generated particles. If the particle passes through the wall, the weight is set to 0; If the particle does not pass through the wall, the original weight is used. The map-assisted algorithm can be referred to [21].

3 Experimental Results

3.1 Experimental Scene

In this experiment, we carried out the actual walking experiment in the office building. Participants walked from start to finish at a normal walking pace, holding a smartphone and measuring their true position with the help of a laser rangefinder. In the offline phase, the tester once again held a smartphone to walk from start to finish, using the smartphone's WiFi chip to collect the RSS value of the AP. Using the laser rangefinder and the corner of the building's hallway, we set up a WiFi fingerprint database. In order to conduct the experiment in the online phase, we asked pedestrians to collect the RSS values of AP in two office buildings at normal walking speed with smartphones in hand. The two office buildings are 123 metres and 138 metres walking distance respectively. We can download it from url https://github.com/Localization-IMU smartphones to collect data.

3.2 Acceleration and Gyroscope Data

The figure 6 is acceleration and angular velocity collected in the office building. The acceleration is approximately periodic. The stride size of the pedestrian is obtained by gait simulation. At the inflection point, the angular velocity increases significantly.

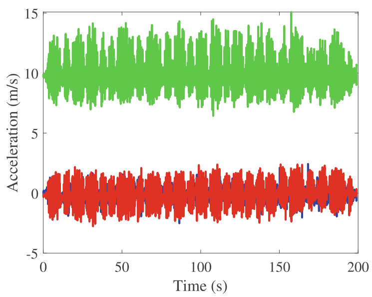

Fig. 6. Acceleration in the office building.

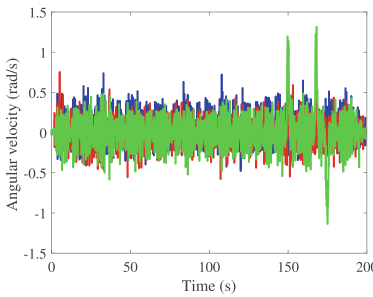

Fig. 7. Angular velocity in the office building .

3.3 The Office Building

The pedestrian was holding a cell phone, walk along a pre-set path in the office building. Figures 8 and 9 show the positioning locus and cumulative distribution function (CDF) of DR, WiFi, particle filter (PF) and MED + APF respectively. According to the data of table 1, the average deviations of DR, WiFi, PF and MED + APF are 8.03m, 1.98m, 3.45m and 1.51m respectively. The corresponding root-mean-square errors were 10.02 m, 2.43 m, 4.82m and 1.92m, respectively. In the initial stage, the positioning trajectory is on the Y-axis, and the positioning accuracy is high. With the passage of time, the track of walking location obviously deviates to the right, which leads to the increase of location error. We can observe that inertial navigation positioning (DR) has a cumulative error, and the longer the pedestrian walking time, the greater the error. In contrast, WiFi fingerprint matching does not have cumulative errors, but there may be fingerprint mismatch. Therefore, we use particle filtering (PF) to integrate DR

And WiFi technology to reduce positioning errors. In order to solve the problem of WiFi fingerprint mismatch and particle poverty, an algorithm called MED and an improved particle filter are introduced in this study. MED algorithm improves the accuracy of WiFi fingerprint matching by increasing the redundancy of fingerprint information. The improved particle filter increases the weight of reliable particles and reduces the weight of unreliable particles by considering the spatial position of pedestrians. The combined effect of these two algorithms significantly improves the accuracy of pedestrian location.

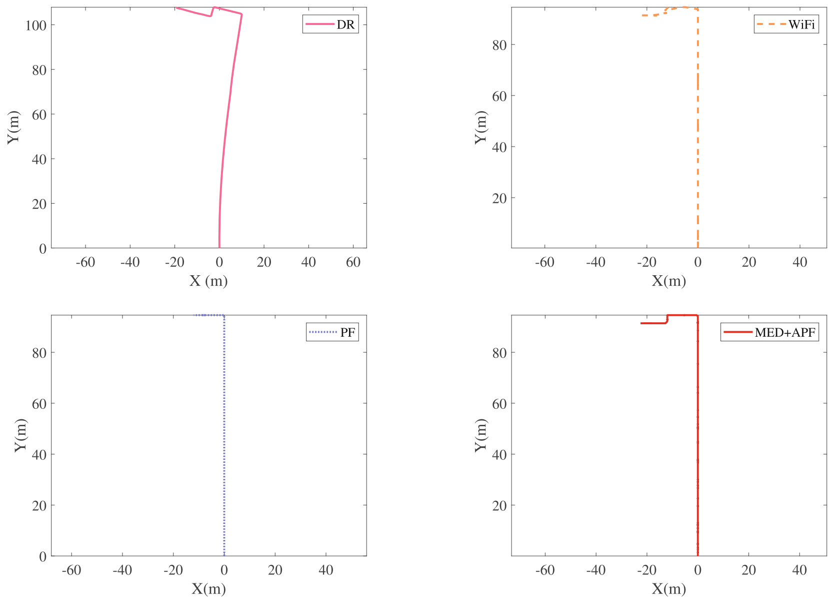

Fig. 8. Positioning trajectories with different strategies.

Table 1. Position errors of DR, WiFi, PF, and MED+APF.

Position error	Average error	Root mean square error
DR	8.03	10.02
WiFi	1.98	2.43
AVPF	3.45	4.82
MDE+APF	1.51	1.92

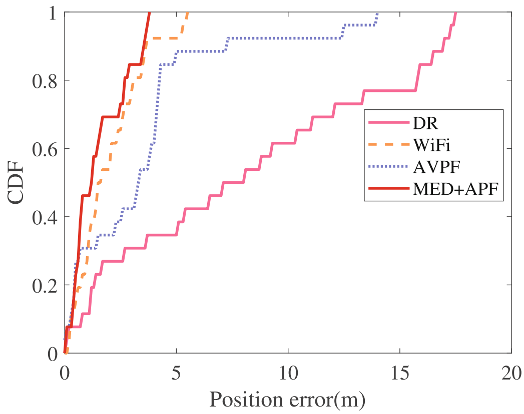

Fig. 9. CDF of errors.

4 Conclusions

Inertial navigation system is less affected by external interference and has high short-term positioning accuracy. However, its DR Error will accumulate over time, resulting in a large long-term positioning error. Unlike the WiFi fingerprint matching method, there is no cumulative error, but there may be problems with fingerprint mismatch. Under this background, this paper presents a MED method and an APF method. MED uses multi-dimensional WiFi fingerprint to reduce the occurrence of fingerprint mismatch. APF uses adaptive factors to increase the weight of high confidence particles and decrease the weight of low confidence particles. These two methods effectively reduce the indoor positioning error.

References

1. Martinez del Horno, M., García-Varea, I., Orozco Barbosa, L.: Calibration of Wi-Fi-based indoor tracking systems for Android-based smartphones. Remote Sens. **11**(9), 1072 (2019)
2. Sánchez-Rodríguez, D., Quintana-Suárez, M.A., Alonso-González, I., Ley-Bosch, C., Sánchez-Medina, J.J.: Fusion of channel state information and received signal strength for indoor localization using a single access point. Remote Sens. **2020**, 12 (1995)
3. Ali, A., El-Sheimy, N.: Low-cost MEMS-based pedestrian navigation technique for GPS-denied areas. J. Sensors **2013**, 1–11 (2013)
4. Borenstein, J., Ojeda, L., Kwanmuang, S.: Heuristic reduction of gyro drift. J. Navigation **62**, 41–58 (2009)
5. Borenstein, J., Ojeda, L.: Heuristic drift elimination for personnel tracking systems. J. Navigation **63**, 591–606 (2010)

6. Pinchin, J., Hide, C., Moore, T.: A particle filter approach to indoor navigation using a foot mounted inertial navigation system and heuristic heading information. In: 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1-10). IEEE (2012)
7. Zhao, W., Gao, J., Li, Z., Yao, Y.: An indoor positioning system based on map-aided KF-PF module. Geomat. Inf. Sci. Wuhan Univ. **43**, 806–812 (2018)
8. Zhuang, Y., Li, Y., Lan, H., Syed, Z., El-Sheimy, N.: Wireless access point localization using nonlinear least squares and multi-level quality control. IEEE Wirel. Commun. Le. **4**, 693–696 (2015)
9. Li, Y., Zhuang, Y., Lan, H., Zhang, P., Niu, X., El-Sheimy, N.: WiFi-aided magnetic matching for indoor navigation with consumer portable devices. Micromachines **6**, 747–764 (2015)
10. Zhang, L., Liu, Y., Sun, J.: A hybrid framework for mitigating heading drift for a wearable pedestrian navigation system through adaptive fusion of inertial and magnetic measurements. Appl. Sci. **2021**, 11 (1902)
11. Shi, S., Gao, T., Gao, D., Ding, Z., Zhang, Z.: Inertial navigation aid indoor navigation based on the establishment of accurate magnetic reference map. In: Journal of Physics: Conference Series (Vol. 1802, No. 4, p. 042022). IOP Publishing (2021)
12. Qin, F., Zuo, T., Wang, X.: CCpos: WiFi fingerprint indoor positioning system based on CDAE-CNN. Sensors **21**, 1114 (2021)
13. Karkar, A.G., Al-Maadeed, S., Kunhoth, J., Bouridane, A.: CamNav: a computer-vision indoor navigation system. J. Supercomput. **77**, 7737–7756 (2021)
14. Bao, H., Wong, W.-C.: A novel map-based dead-reckoning algorithm for indoor localization. J. Sens. Actuator Netw. **3**, 44–63 (2014)
15. Yu, C., El-Sheimy, N., Lan, H., Liu, Z.: Map-based indoor pedestrian navigation using an auxiliary particle filter. Micromachines **8**, 225 (2017)
16. Tian, Q., Salcic, Z., Wang, K.I.K., Pan, Y.: A hybrid indoor localization and navigation system with map matching for pedestrians using smartphones. Sensors **15**, 30759–30783 (2015)
17. Qian, J., Ma, J., Ying, R., Liu, P., Pei, L.: An improved indoor localization method using smartphone inertial sensors. In: International Conference on Indoor Positioning and Indoor Navigation (pp. 1-7). IEEE (2013).
18. Chen, P., Kuang, Y., Chen, X.: A UWB/improved PDR integration algorithm applied to dynamic indoor positioning for pedestrians. Sensors **17**, 2065 (2017)
19. Kang, W., Han, Y.: SmartPDR: smartphone-based pedestrian dead reckoning for indoor localization. IEEE Sens. J. **15**(5), 2906–2916 (2014)
20. Li, Y., Zhuang, Y., Lan, H., Zhang, P., Niu, X., El-Sheimy, N.: Self-contained indoor pedestrian navigation using smartphone sensors and magnetic features. IEEE Sens. J. **16**, 7173–7182 (2016)
21. Wang, J., Hu, A., Li, X., Wang, Y.: An improved PDR/magnetometer/floor map integration algorithm for ubiquitous positioning using the adaptive unscented Kalman filter. ISPRS Int. J. Geo-Inf. **4**, 2638–2659 (2015)
22. Li, Z., Liu, C., Gao, J., Li, X.: An improved WiFi/PDR integrated system using an adaptive and robust filter for indoor localization. ISPRS Int. J. Geo-Inf. **5**, 224 (2017)
23. Zhuang, Y., El-Sheimy, N.: Tightly-coupled integration of WiFi and MEMS sensors on handheld devices for indoor pedestrian navigation. IEEE Sens. J. **16**, 224–234 (2015)
24. Li, Z., Zhao, L., Qin, C., Wang, Y.: WiFi/PDR integrated navigation with robustly constrained Kalman filter. Meas. Sci. Technol. **31**, 084002 (2020)

25. Chen, J., Ou, G., Peng, A., Zheng, L., Shi, J.: An INS/floor-plan indoor localization system using the firefly particle filter. ISPRS Int. J. GEO-INF. **7**, 324 (2018)
26. Li, Y., Zhuang, Y., Lan, H., Niu, X., El-Sheimy, N.: A profile-matching method for wireless positioning. IEEE Commun. Lett. **20**, 2514–2517 (2016)
27. Yu, C., Lan, H., Gu, F., Yu, F., El-Sheimy, N.: A map/INS/Wi-Fi integrated system for indoor location-based service applications. Sensors **17**, 1272 (2017)
28. Chen, J., Ou, G., Peng, A., Zheng, L., Shi, J.: An INS/WiFi indoor localization system based on the Weighted Least Squares. Sensors **18**, 1458 (2018)
29. Deng, Z.A., Wang, G.F., Hu, Y., Wu, D.: Heading estimation for indoor pedestrian navigation using a smartphone in the pocket. Sensors **15**, 21518–21536 (2015)
30. Brajdic, A., Harle, R.: Walk detection and step counting on unconstrained smartphones. In: Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (pp. 225-234) (2013)
31. Zheng, L., Wu, Z., Zhou, W., Weng, S., Zheng, H.: A smartphone based hand-held indoor positioning system, pp. 639–650. Singapore, In Frontier Computing (2016)
32. Moghaddasi, S.S., Faraji, N.: A hybrid algorithm based on particle filter and genetic algorithm for target tracking. Expert Syst. Appl. **147**, 113188 (2020)
33. Chen, J., Ou, G., Peng, A., Zheng, L., Shi, J.: An INS/floor-plan indoor localization system using the firefly particle filter. ISPRS Int. J. GEO-INF. **7**, 324 (2018)