RAPID ESTABLISHMENT OF INDOOR WIFI POSITIONING DATABASE IN SHOPPING MALLS BASED ON WEARABLE NAVIGATION DEVICE (WEARTRACK)

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ABSTRACT:

Position information is an important attribute in Internet-of-things (IoT) applications. WiFi fingerprinting has been frequently used in shopping malls due to its low cost and the capability to provide accurate localization results in indoor environments with significant multipath signal occlusion. However, the popularization of WiFi fingerprinting in shopping malls still faces a challenge, that is, the database needs to be collected and updated regularly. Therefore, establishing and updating the wireless positioning database efficiently and reliably is the key to the promotion of indoor positioning in shopping malls. In this paper, we use the team's self-developed wearable navigation device (WearTrack) combined with post-processing to construct the database quickly and reliably. The procedure of database generation is organized and tested in a real shopping mall environment. Compared with the traditional database-generation method, the proposed method can improve the efficiency and maintain the robustness of database collection. Therefore, the method in this paper provides a feasible means for updating the positioning database in shopping malls.

1. MANUSCRIPT

Position information is an important attribute in Internet-of-things (IoT) applications. To acquire position data, it is necessary to use one or more types of positioning sensors (Mautz, 2012). One of the most widely-used positioning sensors is the low-cost wireless sensors (e.g., WiFi (Caso et al., 2016; Zou et al., 2017), BLE (Bluetooth Low Energy) (Faragher and Harle, 2015)). With these sensors, there are mainly two types of localization algorithms: geometric positioning (Schatzberg et al., 2014) and fingerprinting (Panyov et al., 2014) (i.e., database matching). Geometric positioning is affected by environmental factors such as indoor multipath and signal occlusion, which decrease its accuracy inside modern buildings. In contrast, the performance of fingerprinting does not suffer from such degradations; thus, fingerprinting has been frequently used for indoor wireless positioning.

At present, the WiFi wireless signal has been the main wireless positioning signal of fingerprint matching positioning technology in shopping malls. However, the popularization of WiFi fingerprinting in shopping malls still faces a challenge, that is, the database needs to be collected and updated regularly. The reason for this fact is that the distribution of WiFi signals may change due to various factors, such as the change in WiFi access points and the changes in the indoor environment, which will decrease the accuracy or even invalidate the database using (Li et al., 2020). Therefore, establishing and updating the wireless positioning database efficiently and reliably is the key to the promotion of indoor positioning in shopping malls.

The indoor fingerprinting (database matching) can be roughly divided into two parts: training (i.e., database generation) and prediction (i.e. localization via real-time signal strength measurements and database). Because the fingerprinting accuracy is directly affected by the quality of the database, it is key to build a high-precision database.

A basic wireless location database consists of two parts: reference points and wireless signal strength. The acquisition of the wireless signal strength (e.g., WiFi RSS (Received Signal Strength), BLE RSS) in the database is generally to cluster the signal strength measured by the same or similar reference points, implement outlier detection, and then calculate the statistics. Different from the RSS, the acquisition of the reference-point coordinates directly divided database generation methods into three categories: (1) Point-by-point collection method, which is the most commonly used method for database generation at present. The method selects reference points distributed in a grid pattern in the generated database area, and collects static wireless signal strengths in one or more directions at each reference point or collects dynamic wireless signal strengths by rotating in situ to complete the construction of the database. This method is simple and reliable, but using the method to construct a database requires more operations demand of the surveyor and need too much time and labor to finish it. (2) Dynamic collection method, which selects several landmark points in the database generation area, design the trajectory route passing through the landmark points, obtain the reference point and wireless positioning signal strength on a trajectory by integrating the landmark points and the assumption of the movement of the measurement personnel, compare the data on multiple dynamic trajectories through the reference, then fused the point positions to complete the construction of the database. This method is more efficient than point-by-point collection. However, the acquisition process needs to be completed according to the planned trajectory and has high demand of the surveyor whose operation determines the reliability of the data. (3) Crowdsourcing method, which uses the GNSS coordinates of users entering and exiting the room as landmark points, combines the dead reckoning results to generate reference points, and then completes the generation of the database. This method eliminates the requirement for human intervention and does not require additional collection work. However, due to the complexity of data sources, the reliability of this method is a challenge (Zhang et al., 2018). In this paper, we use the team's self-developed wearable navigation device (WearTrack) combined with post-processing to construct the database quickly, reliably, and easily. The above methods are compared in Table 1.

In this paper, the database generation and positioning process is organized and tested in a real shopping mall environment. Compared with the traditional indoor positioning database generation method, the proposed method uses the motion-tracking results provided by WearTrack to generate the coordinates of the reference points in the database, which can greatly improve the database collection efficiency. Meanwhile, based on the constraints of a small number of control points and the robust performance of WearTrack, the reliability of reference points in the generated database can be guaranteed. Therefore, the method in this paper provides a feasible means for updating the positioning database in shopping malls.

Table 1. Wireless Positioning Database Generation Method

Generation method	Reference point selection	advantage	Restrict
Point-by-point	Grid distribution	Simple; Reliable	Time-consuming Labor-consuming
Dynamic	Track selection	Quickly; Efficient	With movement restrictions, reliability depends on operation
Crowdsourcing	Track selection	Eliminate human intervention	Reliability challenges
This paper	Track selection	Quickly; Reliable; Easy to operate	Requires dedicated wearables few landmarks

This article is arranged as follows. Chapter 2 is the methodology, which specifically introduces the methods of WearTrack, post-processing of positioning results, IndoorTrack, data clustering, and database generation. Chapter 3 is the experimental procedure. Chapter 4 is the experimental results. Finally, Chapter 5 is the conclusion.

2. METHODOLOGY

To quickly and reliably generate the WiFi database in the mall, we propose a method based on the combination of the team's self-developed wearable navigation device (WearTrack) and the self-developed mobile app (IndoorTracker) in this paper.

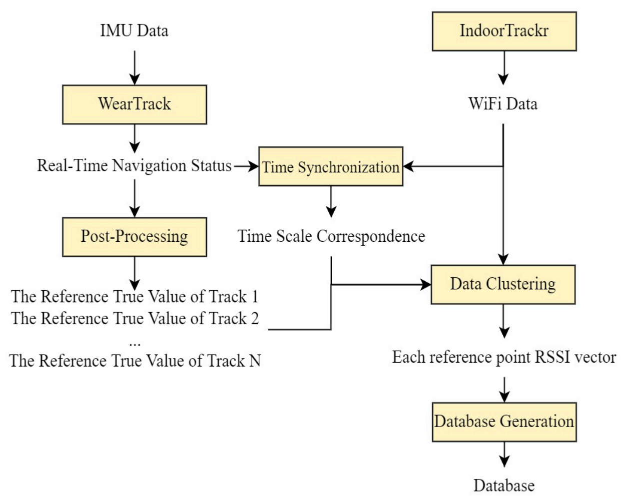


Figure 1. Overall Technical Route

We can obtain the user's real-time navigation status through the WearTrack and complete the generation of the reference true value of the navigation status through post-processing of the real-time navigation status data: the reference true value of track 1, the reference true value of track 2, ..., the reference true value of track n. Meantime, we obtain the shopping mall WiFi data on the users' movement trajectories through IndoorTracker and construct the corresponding relationship between the real-time navigation status and the WiFi data. Afterward, we combine the navigation state reference data, WiFi data, and the corresponding relationship of the time scale to complete the data clustering. Finally, we use the RSSI (Received Signal Strength Indicator) statistical value vector on each reference point to generate the database. We can realize the real-time positioning of moving positions based on the constructed indoor positioning database of shopping malls. The overall technical route is shown in Figure 1.

2.1 Wearable Real-time Positioning Device WearTrack

The WearTrack module was comprised of a low-cost MEMS (Micro-Electro-Mechanical System) IMU, a power module, a low-energy Bluetooth module, a data storage module, and a general multi-protocol system-on-chip.
The MEMS IMU includes a three-axis gyroscope and a three-axis accelerometer, which is convenient to obtain the real-time speed and attitude of the user, and then calculate the real-time position. The low-energy Bluetooth module is used for data communication and time synchronization between WearTrack and the smartphone. The module parameters of WearTrack are shown in Table 2.

Table 2. The Module Parameters of WearTrack

Parameter	Gyroscope	Accelerometer
Data rate	200HZ	200HZ
Dynamic range	2000°/s	16g
Bias instability	10°/h	0.2mg
White noise	$0.24°/\sqrt{h}$	$0.06m/s/\sqrt{h}$
Weight	≈50 g	
Size (no shell)	32×25×12 mm	

The WearTrack module obtains the acceleration and specific force during the real-time motion of the user through the three-axis acceleration and three-axis gyroscope and can obtain the real-time inertial navigation result through calculation. The use of calculation coordinate is the navigation coordinate system (ie, n-frame) which is the north-east-down (NED) geographic coordinate system, and the device coordinate system (ie, b-frame) which is located at the geometric center of the IMU in WearTrack and the x, y, and z axes are the fronts, right, and down axes, respectively (Niu et al., 2021). It is computed from the attitude quaternion updating equation as follows in (1) and (2).

$$q^n_{b,k} = q^n_{b,k-1} \otimes \left[\cos||0.5\phi_k|| \quad \frac{\sin||0.5\phi_k||}{||\phi_k||}(\phi_k)^T \right]^T \tag{1}$$

$$\phi_k \approx \alpha_k + \frac{1}{12}\alpha_{k-1} \times \alpha_k \tag{2}$$

where $\otimes$ is the quaternion product operator; $||\cdot||$ and $(\cdot)^T$ represent the magnitude function and the transpose function, respectively; $q^n_{b,k}$ is the attitude quaternion relating the b frame to the n frame at time tk ; $\alpha_k \approx \omega^b_k \Delta t$, with ω^b_k being the perceived angular rate; and Δt is the sampling interval. The corresponding attitude matrix can be obtained through the quaternion as shown in Equation 3.

$$C_b^n = \begin{pmatrix} q_1^2+q_2^2-q_3^2-q_4^2 & 2(q_2q_3-q_1q_4) & 2(q_2q_4+q_1q_3) \\ 2(q_2q_3+q_1q_4) & q_1^2-q_2^2+q_3^2-q_4^2 & 2(q_3q_4-q_1q_2) \\ 2(q_2q_4-q_1q_3) & 2(q_3q_4+q_1q_2) & q_1^2-q_2^2-q_3^2+q_4^2 \end{pmatrix} \quad (3)$$

Then combined with the existing attitude matrix and specific force calculation, the real-time speed and position of the movement are obtained, as shown in Equation 4 and 5:

$$v_k^n = v_{k-1}^n + \int_{t,k-1}^{t,k} C_b^n f^b dt + g^n \Delta t \quad (4)$$

$$r_k^n = r_{k-1}^n + 0.5(v_{k-1}^n + v_k^n)\Delta t \quad (5)$$

Where g is the acceleration of gravity.

To constrain the divergence of inertial navigation errors, the WearTrack performs the real-time zero velocity update (ZUPT), the zero angular velocity update (ZARU), the elevation constraint, straight-line constraints, etc. by judging the user's stance phase. Then, use the Kalman filter model to correct the error of the calculated real-time inertial navigation results which can obtain the accurate real-time navigation status, that is, the position, velocity, and attitude (Niu et al., 2021). The operation mode of WearTrack is shown in Figure 2:

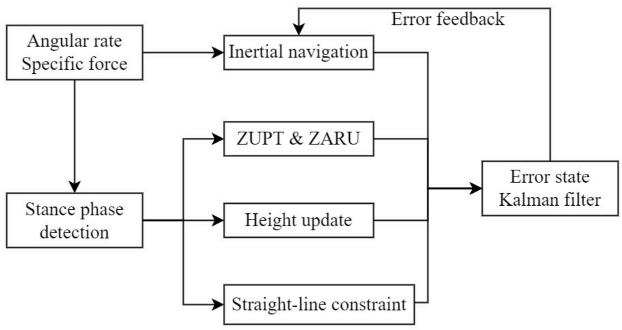


Figure 2. Operation Mode of WearTrack.

2.2 Post-Processing of Positioning Results

To improve the accuracy and reliability of the data to obtain the reference value of the navigation state, it is necessary to perform smooth operations on the past, current, and future navigation state observation information obtained through WearTrack. For linear and Gaussian systems, a commonly-used smoothing algorithm implemented within the KF framework is the Rauch-Tung-Striebel (RTS). Since WearTrack is modeled as a linear and Gaussian system, we use the RTS method to complete the post-processing of the navigation state information.

The RTS method calculates the state matrix $\hat{X}_k$ and covariance matrix P_k estimated by the Kalman filter model, as well as the predicted state matrix $\hat{X}_{k+1|k}$ and covariance matrix $P_{k+1|k}$, which can obtain the smoothed state matrix and covariance matrix (Niu et al., 2021). The specific process is as follows.

(1) Set initial parameters: $\hat{X}_{s|N} = \hat{X}_N$, $P_{s|N} = P_{s|N}$

(2) Traverse the loop calculation from N-1 to 1:

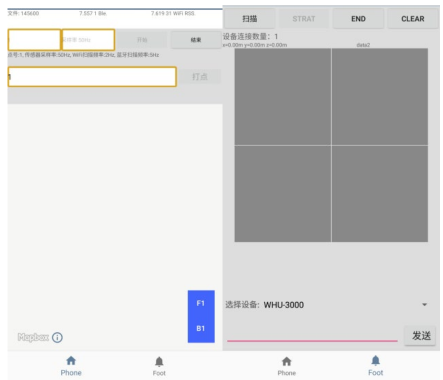
$$K_{s|k} = P_k \Phi_{k+1,k}^T P_{k+1|k}^{-1}, \hat{X}_{s|k} = \hat{X}_k + K_{s|k}\left(\hat{X}_{s|k+1} - \hat{X}_{k+1|k}\right),$$

$$P_{s|k} = P_k + K_{s|k}(P_{s|k+1} - P_{k+1|k})K_{s|k}^T$$

Through the above calculation, we can transform the real-time navigation state obtained by WearTrack into the reference value of the navigation state.

2.3 Smart Phone location APP IndoorTracker

Through the self-developed smartphone app (IndoorTracker), users can collect the WiFi signal strength at every moment of the location in real-time and store it in the smartphone memory which can be directly exported for subsequent use. The IndoorTracker only needs users to press a few buttons during use to complete the collection of relevant data. Figure 3 shows the operation interface of IndoorTracker.



(a) (b)

Figure 3. The Operation Interface of IndoorTracker, (a) Phone Page, (b) Foot Page

The "Phone" page is mainly used for the collection of mobile phone sensor files and the record of passing landmarks.
Through this page, we can start the collection of WiFi and inertial sensor data. The "Foot" page is mainly used for the binding of WearTrack devices, the acquisition of WearTrack data, and the real-time display of motion trajectories. Through this page, we can collect the IMU data. In addition, since the use of the self-developed IndoorTracker does not require any relevant professional knowledge, it is highly user-friendly in practical applications.

2.4 Time Synchronization

The WearTrack has a built-in low-cost sensor that can output the relative time corresponding to each IMU measurement value. Thus, there are two limitations: first, the lack of absolute time scale; second, the relative time scale will accumulate with the increase of use time. These two limitations will lead to time synchronization errors between the movement route information (real-time navigation status) obtained through WearTrack and the WiFi data collected through IndoorTracker. We can record and store the time-scale correspondence between WearTrack and IndoorTracker at each moment which is used for time synchronization when the database is generated.

2.5 Data Clustering

The accuracy of the positioning result is completely determined by the accuracy of the database construction, and the database accuracy is determined by the reference point and the RSS intensity of the reference point. The reference point in the database is fused by multiple navigation state reference trajectories. Because the reference value is relatively fixed with a precise coordinate value, the RSS value corresponding to the reference point determines the accuracy of the database and also determines the accuracy of positioning. The RSS value of the reference point is usually a final RSS value obtained by comprehensively considering the RSS values in the vicinity of the clustering reference point or all directions of the reference point.

The common RSS clustering methods include K-means clustering, agglomerative hierarchical clustering, etc. The

K-means clustering method is an unsupervised clustering method, which is relatively simple to implement and widely used. The K-means method is that for each reference point RSS, it is obtained by averaging the RSS values of the K points closest to the reference point. The agglomerative hierarchical clustering algorithm is a hierarchical clustering algorithm. For each reference point RSS, it is obtained by averaging the RSS values of the two closest location points to the reference point.

2.6 Database Generation

Calculate the number of each reference point and the number of RSS values in the RSSI vector, and output the data as a binary BIN file in the order of the number of reference points, the number of RSS values, the MAC address, the latitude, longitude, and elevation of all reference points, and the RSS vector of each reference point, to complete the construction of the database.

3. EXPERIMENTS AND RESULTS

The specific implementation of the proposed method is as follows. The first step is to obtain a map of the target area inside the shopping mall, followed by setting a small number of landmarks with known locations on the map. Afterward, a series of walking trajectories, which pass multiple landmarks, are designed to cover the target area. Next, a database collector wears WearTrack and starts IndoorTracker to collect motion information from WearTrack and WiFi information from the smartphone synchronously. During the data collection process, the timestamp is recorded in IndoorTracker when the collector passes a landmark. These timestamps and landmark locations will be used as the position constraints for forward-backward optimization of the WearTrack motion solution, so as to maintain its accuracy.

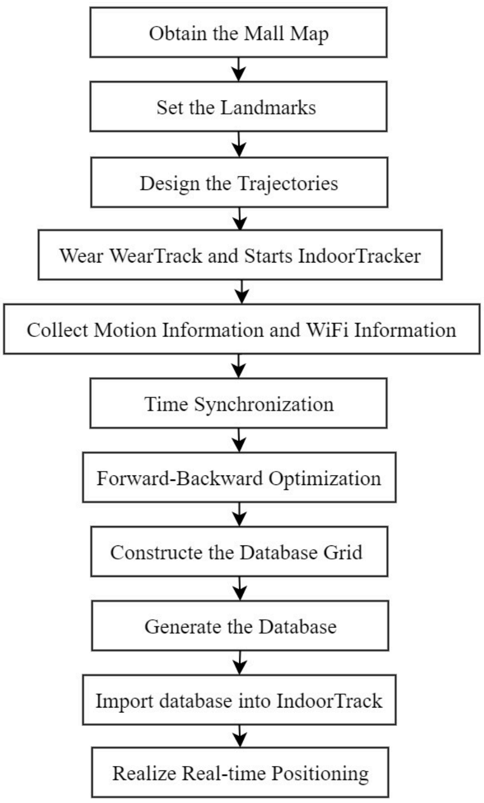


Figure 4. The Overall Process of the Test Process

After acquiring multiple test trajectories, such as those shown in Figure 6, use the bidirectional smoothing to convert the trajectories into the true value of the navigation state, which can obtain the corresponding reference point data. Then, use the development software to complete the time synchronization of the motion information (real-time navigation status) and the WiFi information and build the time scale corresponding relationship between the data. Afterward, complete the data clustering of the two types of data, and realize the construction of the database based on the clustered data. Finally, the generated database is imported into IndoorTracker to realize real-time positioning in the shopping mall. The process is shown in Figure 4.

3.1 Experimental Site, Landmarks, and Exercise Routes

The test site for this experiment was the 4th floor of a shopping mall near the school. The test site and test environment are shown in Figures 5 (a) and 5 (b). Then equally divide six points on the test field as the landmark points, as shown in Figure 5 (a).

(a)

(b)

Figure 5. Test Scenario, including (a) Mall Map & Landmarks (b) Mall Environment

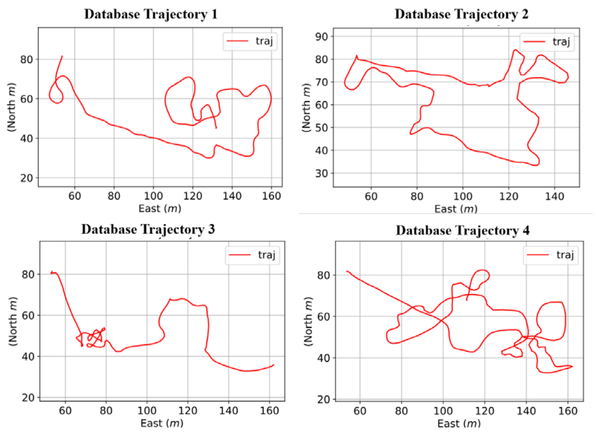
The coordinates of each landmark are shown in Table 3.

Table 3. The Coordinates of Each Landmark.

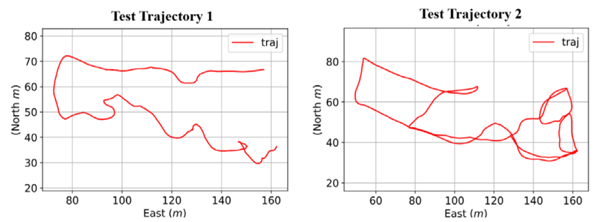
Landmarks num	Latitude	Longtitude
1	30°31'44.60"	114°21'00.47"
2	30°31'44.15"	114°21'02.46"
3	30°31'44.12"	114°21'04.34"
4	30°31'43.12"	114°21'04.53"
5	30°31'43.49"	114°21'01.35"
6	30°31'43.36"	114°21'03.27"

Based on the selected landmark points, plan the movement route and trajectory of the collected data. In this experiment, a total of 6 movement routes are planned, of which 1~4 are the movement routes for building the database, as shown in Figure

6 (a), of which 5~6 are the movement routes for testing the database, as shown in Figure6 (b)



(a)



(b)

Figure 6. The Movement Routes (a) Generate Database Routes (b) Test Database Routes

The specific roadmap is shown in Table 4.

Table 4. The Routes of Generating Database and Test Database

Num	Route	Route property
1	1->5->2->6->4	Generate Database
2	2->5->6->3->4->1	Generate Database
3	4->6->5->2->3	Generate Database
4	3->4->5->2->1->5->6->3->4->6	Generate Database
5	6->2->3->5->1	Test Database
6	1->2->6->5->1	Test Database

3.2 Test Equipment

After arriving at the experimental site, turn on the WearTrack device and fix it on the heel of the right foot. Meanwhile, hold the mobile phone and open the IndoorTracker app, as shown in Figure 7.

Figure 7. WearTrack and IndoorTracker

3.3 Data Collection

According to the planned route, go to the first landmark point and start data collection. Then, walk in the experimental site according to the planned route. When passing a landmark point, complete the dotting work. There is no clear regulation on the way of walking between landmarks, which can walk randomly. Finally, complete the final dotting at the final point. Repeat the above collection process to complete the collection of 4 database generation routes and 2 test testing routes.

3.4 Data Processing

Introduce the real-time navigation status data collected by WearTrack and the WiFi data collected by IndoorTracker in the database routes 1 to 4 to the computer, build the time scale corresponding relationship of the two types of data, and complete the time synchronization of the two types of data. According to the time when each motion track passes through the landmark point and the longitude, latitude, and elevation coordinates of the landmark, the real-time navigation status data is bi-directionally smoothed to obtain the reference real value data of the navigation status. Traverse the existing Wi-Fi data, and complete the summary of the Mac addresses in all Wi-Fi data. Based on the WiFi data and the Mac address, the Mac address is used as the registration data to complete the aggregation of the WiFi data at the same time. By fusing multiple navigation state reference trajectories, the reference point coordinates are obtained from them, as shown in Figure 8. The RSS value corresponding to each Mac address at the approximate location of each reference point is averaged and taken as the signal strength of the reference point, namely {reference point: RSSI vector}.

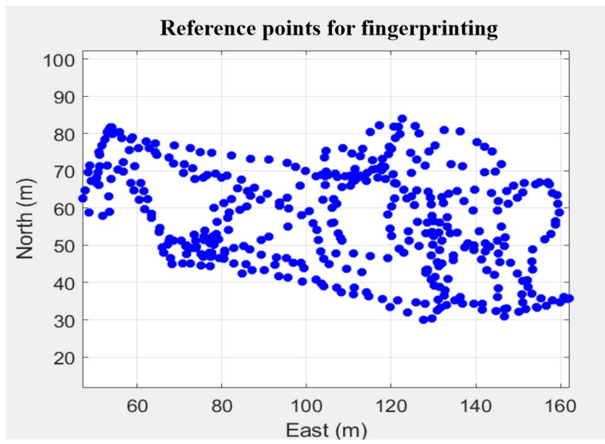


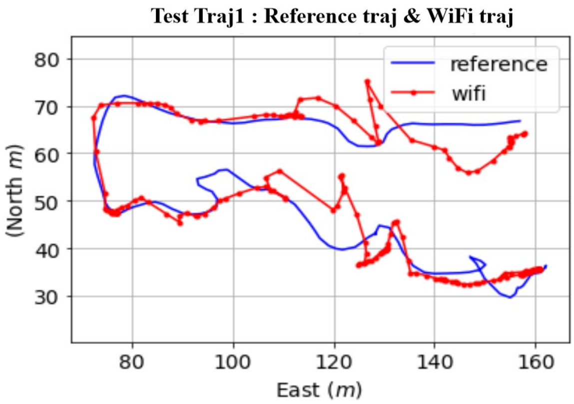
Figure 8. Display of Each Reference Point

3.5 Database Generation

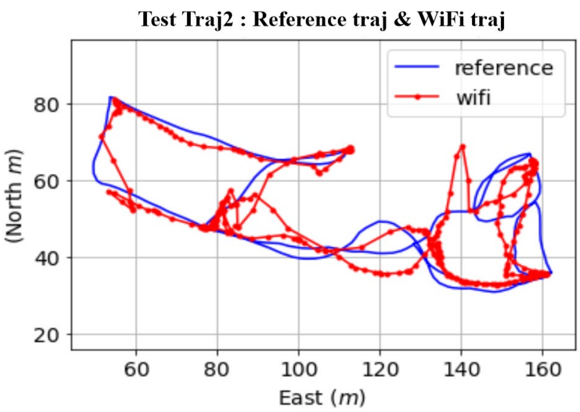
Complete the numerical conversion of the Mac addresses in the WiFi, calculate the number of each reference point and the number of RSS values in the RSSI vector. Output the data as a binary BIN file in the order of the number of reference points, the number of RSS values, the MAC address, the latitude, longitude, and elevation of all reference points, and the RSS vector of each reference point, to complete the construction of the database.

3.6 Positioning Result

To verify the availability of the generated database, import the real-time navigation status data collected by WearTrack in test routes 1 and 2 and the WiFi data collected by IndoorTracker in test routes 1 and 2 into the computer. Use the 3.4 methods to post-processing the real-time navigation status data collected by WearTrack, which will obtain the reference value of the navigation trajectory. At the same time, based on the database generated by using the 3.5 methods, use the fingerprint identification and positioning method (Haeberlen, 2004) to obtain the database matching motion trajectory, as shown in Figure 9.



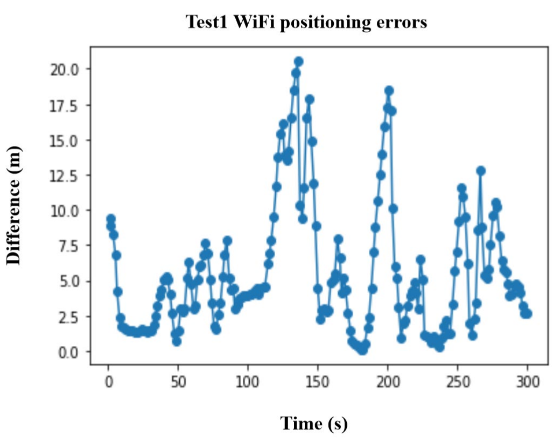
(a)



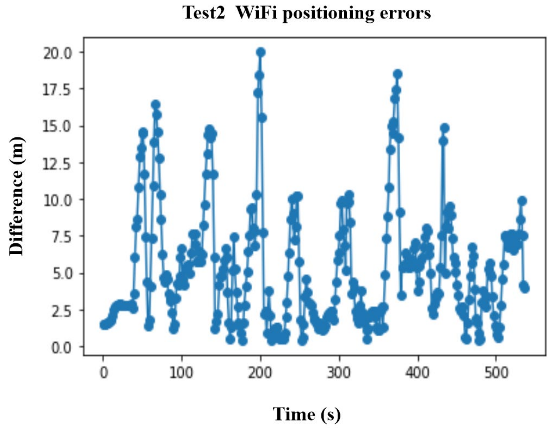
(b)

Figure 9. WiFi Positioning Results and Reference Truth. (a) and (b) are the data of testing routes 1 and 2 respectively

Perform the time-interpolation between the reference value and the real-time WiFi positioning value of the navigation track of the test track routes 1 and 2, and calculate the difference between the two positions as the positioning error time series and statistical results are shown in Figure 10 and Table 5, respectively.



(a)



(b)

Figure 10. The Time Series of the Difference between the WiFi Positioning Results and the Position Reference Truth. (a) and (b) are the Results of Experimental Routes 1 and 2 respectively

Table 5. The Statistical Value of Positioning Error

Traj	Mean (m)	STD (m)	RMS (m)	MAX (m)
1	5.53	4.49	7.13	20.54
2	5.251	3.970	6.58	19.97
Total	5.35	4.16	6.78	20.54

The area of the test site, the time spent in the experiment, and the positioning accuracy are shown in Table 6.

Table 6. Test Site Area, Experiment Time, Positioning Accuracy

Experimental Site Area	9576m^2
Time of Determining the Experimental Site, Landmarks, Routes	3min
Time of Wearing the acquisition device	2min
Time of Collecting Data	30min
Time of Processing Data	5min
Time of Generate Database	5min
Positioning Accuracy	6.78m

4 CONCLUSION

In this paper, we measured the database generation and positioning performance in the actual shopping mall environment. Compare the motion trajectory positioning generated by our method with the actual motion trajectory positioning, the STD value is 4.16 m, the RMS value is 6.78 m, and the maximum difference value is about 20.54 m. The positioning results are similar to the real results, but there are differences in some areas. We also can do some other restrictions to make the positioning results more accurate.

Compared with the traditional indoor positioning database generation method, the method in this paper uses the navigation results provided by WearTrack to generate the reference points to generate the database. The data acquisition time of this method is about 35 min and the database generation time is about 5 min, which can promote the database collection and generation efficiency higher than the traditional indoor positioning database generation and positioning method. On the other hand, The method which is based on the constraints of a small number of control points will guarantee the reliability of reference points in the database. Therefore, the method in this paper provides a feasible means for updating the mall database.

We will integrate and standardize the database generation process, evaluate the database accuracy and improve the database reliability in the future.

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