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Effective Fingerprint Extraction and Positioning Method Based on Crowdsourcing

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ABSTRACT At present, WiFi fingerprinting indoor positioning technology is a research hotspot, and the construction of a radio map based on crowdsourcing can significantly reduce the amount of labor required. However, when users collect fingerprint information using crowdsourcing data in practical applications, the received signal strength (RSS) information collected by user phones updates slowly and will remain the same for a certain distance and time. Therefore, crowdsourcing data is inaccurate, and a radio map thereby established will also lead to inaccurate indoor positioning. In order to address this issue, this paper proposes a method for extracting effective RSS information from crowdsourcing data in order to establish the radio map and achieve positioning. By analyzing the crowdsourcing data characteristics, effective RSS information is identified and extracted. Based on inertial sensors data, the position of effective RSS information is determined. The effective crowdsourcing data associated with the position is weighted and fused in order to establish the radio map. Aimed at the issue of the RSS collected by phones updating slowly, a combined positioning method for position calculation is proposed in order to achieve effective positioning. Experiments were conducted in a real environment to validate the algorithm, and the positioning accuracy could reach 1.5 m by using crowdsourcing data to construct the radio map and executing an indoor positioning algorithm, which is close to the accuracy achieved when using manual data collected by professionals at a certain distance and saves a great deal of labor.

INDEX TERMS Fingerprint, received signal strength, indoor positioning, crowdsourcing.

I. INTRODUCTION

With the increasing demand for location-based services [1]–[5], positioning technologies have become an indispensable aspect of contemporary science and technology. Shopping malls and smart home services can measure people's tendencies through location information. However, as buildings block satellite signals, global position system (GPS) cannot be used indoors. Therefore, researchers have realized indoor positioning by adding various hardware facilities, such as WiFi [6], Bluetooth [7], and Zigbee [8], or using mobile devices to record environmental features such as images [9], [10] and pedestrian dead reckoning (PDR) [11]. Owing to their extensive deployment and as they incur no additional costs, numerous WiFi-based indoor localization systems have been developed [12]–[14].

The majority of WiFi-based indoor localization systems construct a radio map in advance [12]. During the offline phase, reference points (RPs) are first selected, at a fixed distance from the area of interest. Thereafter, the received signal strength (RSS) of the surrounding access points (APs) at each RP is collected. Finally, WiFi information for all of the RPs is stored, and a radio map is established. A radio map can be created in two ways. One method is it may be constructed by professional staff, in which case the data are reliable and high levels of accuracy can be achieved. However, owing to the instability of WiFi systems and broad interest areas, the establishment of a radio map requires significant time and labor. The other method involves crowdsourcing, whereby users collect data as they engage in their daily activities. This does not involve assistance from professional staff.

As professional staff collect multiple sets of data at a fixed point, the descriptions of the fingerprint characteristics of each location could be improved. Crowdsourcing data is

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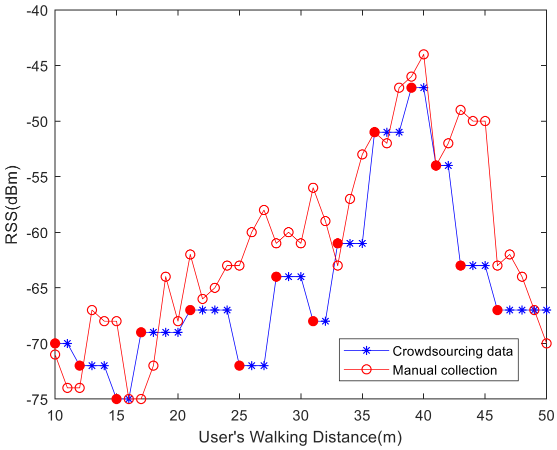


FIGURE 1. Comparison of data collected by crowdsourcing and manually.

RSS data collected during user walking. The user walks at a certain speed and the AP signal is updated for a certain period because the Wi-Fi module in the smartphone takes around 3-4 seconds to produce a new scan result [15], which is slower than the walking speed, resulting in the RSS data not corresponding to position changes. Therefore, fingerprints collected based on crowdsourcing cannot actually be applied to establish a radio map. Moreover, because pedestrians have not received professional training, significant interference and invalid data still exist in the crowdsourcing data. It is extremely challenging to extract high-quality fingerprints based on actual crowdsourcing data.

The RSS data collected manually and by means of crowdsourcing at a certain fixed AP are compared, as illustrated in Fig. 1. The data is filtered by a low-pass filter with a frequency of 3 Hz prior for analysis. The walking distance is calculated from the starting point of the corridor. The data collected manually at fixed points is sampled multiple times and the sampling time is long (for example, for every 1 m distance, the sampling time is 1 min and the sampling frequency is 1 Hz), so distinguishable fingerprint characteristics can be obtained for each fixed position. Crowdsourcing data are collected by the user while walking. The user walks at a certain speed and the RSS is updated for a certain period, which will result in the RSS data not corresponding to the pedestrian position change (as indicated in Fig. 1, within a 40 m distance, the RSS changes 14 times and the sampling frequency is 1 Hz). As most RSS collection software in mobile phone records Wi-Fi information at a fixed frequency like 1Hz, the RSS value will remain unchanged in several recording periods. Therefore, effective fingerprint features cannot be obtained for each fixed position. The effective RSS information is the updated RSS information when the user is walking, as shown in Fig. 1 by the red dots. The RSS information collected when RSS is not updated with position (blue dot) is not effective RSS information.

The construction of radio map is full of challenges. Although the traditional manual way can obtain high accuracy, the huge time and labor cost in it and the later update and maintenance is the bottleneck in the development of traditional way. For crowdsourcing way, the users who contributes the data are untrained, which lead to poor quality of the collected data, the RSS information not changing in real time with the position, and the mix of invalid data. Therefore, reasonable filtering and processing methods are needed to meet the requirements of radio map construction and autonomous maintenance.

The disadvantage of crowdsourcing data is that the RSS data collected on a single user trajectory does not correspond to the position change in real time; the advantage is that it is based on the characteristics of many users with massive amounts of data. Therefore, effective fingerprints can be extracted and fused in order to achieve similar effects to manual collection.

For the crowdsourcing data characteristics mentioned previously, this work identifies and extracts effective RSS data in the pedestrian trajectory. Then, using inertial sensors data, the position of effective RSS data is estimated. Finally, the effective crowdsourcing data at each position are fused in order to establish a radio map. By utilizing the advantages of crowdsourcing massive data, an effective radio map covering all interest areas is established, which is similar to manual collection. During the online phase, aimed at the issue of RSS data updating slowly, we correspondingly propose a combined positioning method suitable for user position calculation.

The main contributions of this paper are as follows.

- This paper proposes a method for establishing a radio map by extracting effective fingerprint (RSS) information from crowdsourcing data. In order to address the problem of the RSS data not corresponding to the real-time position change in crowdsourcing data, this work extracts effective RSS information and uses the inertial sensors data to estimate the effective RSS information positions. Finally, the location-related RSS data are weighted and fused in order to establish the radio map.
- To address the issue of the slow RSS updating rate, this paper proposes a combined positioning method suitable for position calculation. The WiFi and inertial sensors data used for combined positioning enable effective dead reckoning and achieve more accurate positioning results.

II. RELATED WORK

WiFi fingerprint-based positioning systems have been studied extensively. Microsoft Research [12] first developed an indoor localization system known as RADAR, which was a deterministic positioning model that located and tracked users from within buildings. Empirical measurements recorded the mean RSS values of each point within the region of interest. The current RSS was compared to the empirical value, with the most similar position returned as the result. Yossef and Agrawala [13] developed the Horus indoor localization system, which is a classic probabilistic positioning method by means of which the collected RSS values are stored in the form of Gaussian probability distributions, and

TABLE 1. Record format of collected data.

Mobile phone MAC address			XX:XX:XX:XX:XX:XX	
Time	WiFi information	Accelerometer	Gyroscope	Electronic compass
t_1	$\{mac_1, AP_1, RSS_1\}$ $\{mac_2, AP_2, RSS_2\}$ … $\{mac_{m1}, AP_{m1}, RSS_{m1}\}$	$acc_{1x}, acc_{1y}, acc_{1z}$	$gyr_{1x}, gyr_{1y}, gyr_{1z}$	$cp_{1n}, cp_{1x}, cp_{11y}$
t_2	$\{mac_1, AP_1, RSS_1\}$ $\{mac_2, AP_2, RSS_2\}$ … $\{mac_{m2}, AP_{m2}, RSS_{m2}\}$	$acc_{2x}, acc_{2y}, acc_{2z}$	$gyr_{2x}, gyr_{2y}, gyr_{2z}$	$cp_{2n}, cp_{2x}, cp_{2y}$
…	…	…	…	…
t_n	$\{mac_1, AP_1, RSS_1\}$ $\{mac_2, AP_2, RSS_2\}$ … $\{mac_{mn}, AP_{mn}, RSS_{mn}\}$	$acc_{nx}, acc_{ny}, acc_{nz}$	$gyr_{nx}, gyr_{ny}, gyr_{nz}$	$cp_{nn}, cp_{nx}, cp_{ny}$

the Bayesian method is used to match fingerprints during the online phase. A commonly used method of handling RSS signals involves extracting feature information related to locations. The positioning methods mentioned above require several days for professional data collection, which usually consumes additional labor.

When establishing a radio map by means of crowdsourcing, data collected via a mobile device must correspond to an actual physical space. Built-in sensors can detect a user walking state and estimate his or her location. Reference [16] uses an accelerometer to detect the user motion state. The system can gather radio signals continuously during a stationary period, greatly increasing the number of samples available; eventually, it achieves room-level positioning. As people walk through doors or up or down stairs, walking characteristics differ from normal conditions. For example, the walking direction changes considerably as a person walks through a door. These phenomena are reflected by sensor information. References [14], [17]–[19] use sensors to record special locations called landmarks and then estimate WiFi information in other locations by means of an accelerometer, and floor plans are used to construct radio maps. Wu *et al.* [20], [21] use both WiFi fingerprints and user movements, whereby fingerprint spaces are created from the spatial relations of WiFi fingerprints, and localization is achieved by matching logical to ground truth floor plans. The proposed system in [22] uses a propagation model to convert RSS of beacons to distance and estimate the weighted centroid (WC) of nearby beacons. The estimated WCs along with signal strength and rank of the nearby beacons are stored in the server database for localization instead of RSS from all the deployed beacons. Zhou *et al.* [23] outline the challenging issues to improve crowdsourcing-based indoor localization systems which shows that this is a topic worthy of in-depth study, and also provides some research directions for readers. Li *et al.* [24] propose an enhanced crowdsourcing-based localization method by integrating inertial, wireless, and magnetic sensors. Zhao *et al.* [25] propose a crowdsourcing and multisource fusion-based fingerprint sensing where motion sensors are used to construct the radio map by volunteers and pedestrian dead reckoning based on motion sensors equipped in smartphones is used for positioning. Lashkari *et al.* [26] study the level of user contribution in available crowd-powered techniques and propose a classification for crowd-powered indoor localization solutions to clarify which crowds-based approach is utilized in each indoor localization solution.

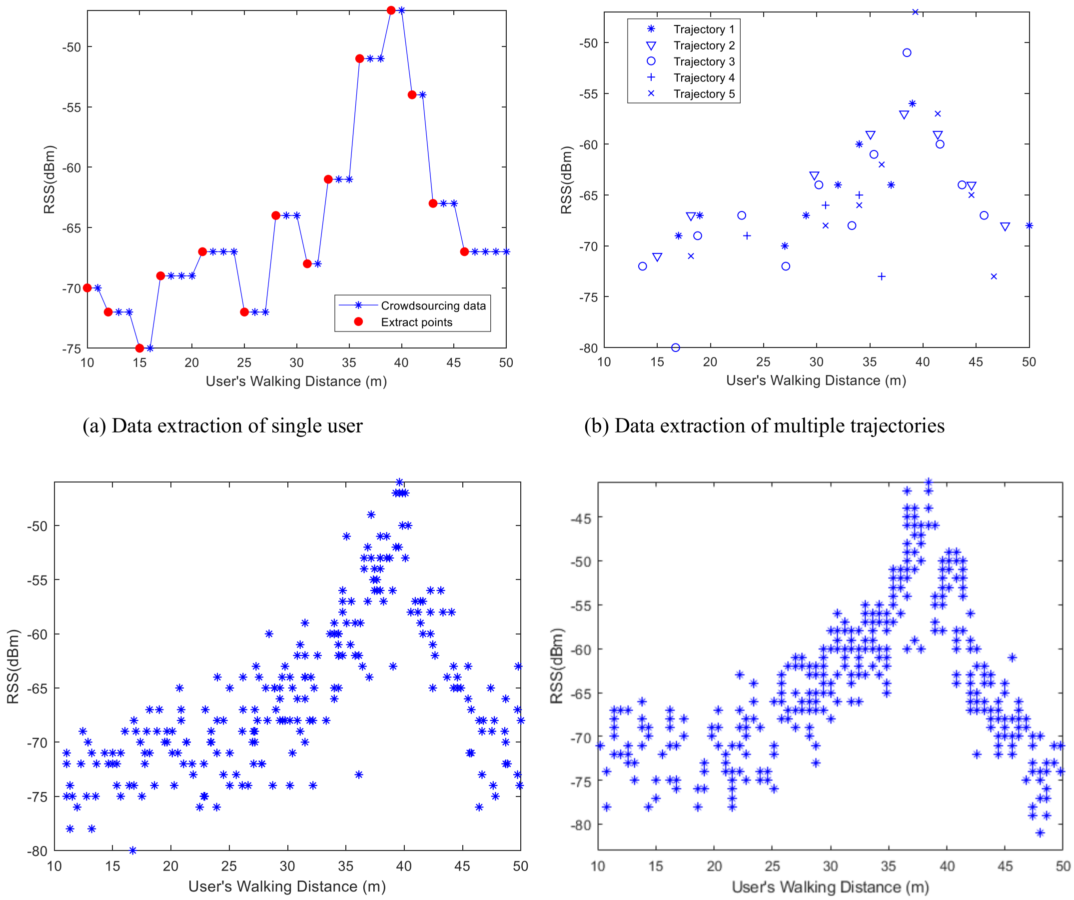
As users are not trained, a large amount of interference and invalid data still remain for the crowdsourcing data collected. It is very challenging to extract high-quality fingerprint features from actual pedestrian crowdsourcing data.

III. ARCHITECTURE OVERVIEW

A. CROWDSOURCING DATA COLLECTION

In this study, we collected information from the phone records of users' daily activities. By installing software on a phone to record WiFi and sensor information at a certain frequency, we acquire the media access control (MAC) address of a phone, the time, the WiFi MAC address and corresponding name, the WiFi RSS, the accelerometer value, gyroscope information, and electronic compass information, as illustrated in Table I.

1) The phone MAC address is used to distinguish different users.
2) Time: record the time at which each message is collected.
3) WiFi data refer to all AP names and corresponding RSSs, with each AP having its own MAC address, written as $\{\{mac_1, AP_1, RSS_1\}, \{mac_2, AP_2, RSS_2\}, \ldots, \{mac_m, AP_m, RSS_m\}\}$.
4) Accelerometer data: accelerometers can measure the mobile phone acceleration on the X, Y, and Z axes, which is written as $acc = \{acc_x, acc_y, acc_z\}$.
5) Gyroscope data: a gyroscope measures the angular velocities on three axes, which is written as $gyr = \{gyr_x, gyr_y, gyr_z\}$.
6) Electronic compass data: the three values returned by the electronic compass are $cp = \{cp_n, cp_x, cp_y\}$, where cp_n denotes the angle between the phone and real north of the earth, cp_x denotes the angle between the phone



(a) Data extraction of single user

(b) Data extraction of multiple trajectories

(c) Crowdsourcing data integration

(d) Data collected manually

FIGURE 2. Feature analysis of crowdsourcing data vs. manual data.

X-axis and horizontal plane, and cp_y denotes the angle between the phone Y-axis and horizontal plane. The information returned by the electronic compass is used to determine the change in the user walking direction, so we only consider cp_n for the following positioning.

B. FEATURE ANALYSIS OF CROWDSOURCING DATA

The RSS information collected by a single user during walking through an AP is illustrated in Fig. 2(a). It can be observed that the RSS is not updated for a period of time during the entire trajectory. It is because the user walks at a certain speed but the RSS is updated for a certain period, resulting in the RSS data not changing according to the pedestrian position. We extract the RSS change points; that is, when the acquired RSS of an AP changes, the corresponding RSS and geographical location are extracted, and the data that is continuously invariable during walking is removed.

If the effective RSS information in multiple user trajectories is extracted, as illustrated in Fig. 2(b), the effective RSS values obtained will gradually increase and eventually cover the entire positioning area.

As illustrated in Fig. 2(c), with all crowdsourcing data, the integrated signal values can cover the entire positioning area, and increased feature description values can be obtained at each position. Compared with the data collected manually, as illustrated in Fig. 2(d), we find that the distribution of fingerprint characteristics obtained by crowdsourcing collection is similar to that collected manually. The RSS will similarly change with the distance from the AP, and the statistical maximum values of the signal appear at the same position (approximately 40 m). This demonstrates that, by extracting and integrating the effective crowdsourcing data, we can solve the actual problem of the RSS not corresponding to the location owing to the slow updating of AP acquisition. Moreover, the entire corridor can be covered by extracting the effective RSS information in order to obtain fingerprint features, which is similar to manual acquisition at fixed points within the entire positioning space. Fig. 2(d) shows that the collected RSS value will fluctuate within a certain range. It is because of individual differences in crowdsourcing, such as the different shielding degree of the mobile phone during walking, different performance of the built-in antenna of the mobile phone, different environmental disturbance, and the AP source fluctuates itself. Even with the manual way, the RSS fluctuation in a certain position is still same as that with crowdsourcing way. Although the fluctuation exist, when the collected RSS signals are processed with specific methods, the clear RSS trend can be obtained, that is, the fluctuations of RSS will not affect the subsequent analysis.

Based on the above crowdsourced signal characteristics, we propose a method for extracting effective RSS information and establishing the radio map using crowdsourcing data. As crowdsourcing data contains multiple trajectories, this method uses the massive amount of RSS information contained therein to achieve similar results to those of manual collection.

C. FINGERPRINT POSITION DETERMINATION

In this section, we mainly estimate the position range of the effective RSS information extracted above. Indoor fixed landmarks (such as entrances and corridor corners) are identified using the sensor data combined with the indoor floor plan, following which the specific RSS information location is determined based on the landmarks (that is, PDR).

1) IDENTIFICATION OF FIXED LANDMARKS

Mobile phones can receive GPS signals when users are outdoors, but phones can barely receive GPS signals when a user enters a building, owing to building blockages. When a user enters or exits a building, the GPS signal strength changes considerably. Therefore, the point at which GPS signals change significantly can be denoted as the current user location at the gate. As only few entrances exist, we manually collect the WiFi information from each entrance in advance in order to distinguish the different entrances.

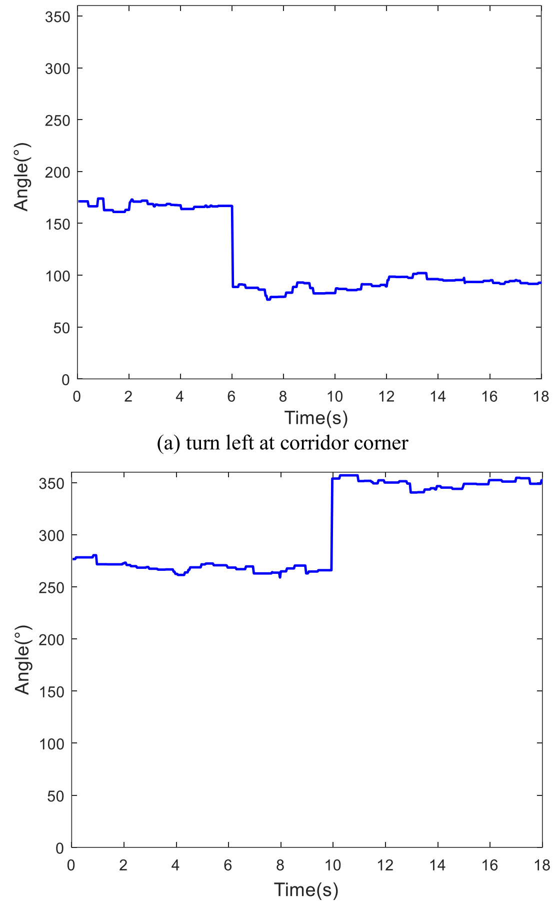
When users pass the corner, the electronic compass changes significantly with the walking direction. Figure 3 illustrates the electronic compass data changes when a user passes a corner.

It can be observed from Fig. 3 that when a user turns at the corner, the electronic compass data changes significantly. When a user walks normally through a corridor, the user walking direction does not change considerably. The X-axis value of the electronic compass will not change significantly and will exhibit small fluctuations, generally of only roughly between $-20°$ and $+20°$. The user original walking direction will change as he or she turns a corner, and the electronic compass value will change significantly, by roughly $90°$.

Therefore, the electronic compass data are used to identify the corner. We use Δcp to denote the electronic compass variation in two adjacent times t_1 and t_2, and record the RSS information at time t_2 as the fingerprint at the corner.

$$\Delta cp = cp_{t_2} - cp_{t_1} \tag{1}$$

It should be noted that, when users turn randomly, enter or exit a room, or intentionally make a turn at a corridor non-corner, the electronic compass will also reflect these changes; however, corner detection is not affected. As a corner is stationary, numerous repetitive turning actions will be detected within the same area by means of crowdsourcing. The occasional cornering behavior of individual users is a small probability event and not repetitive. Therefore, only sufficient trajectories demonstrate turning actions in the same place, from which corridor corners can be identified.



(a) turn left at corridor corner

(b) turn right at corridor corner

FIGURE 3. Changes in electronic compass data when turning.

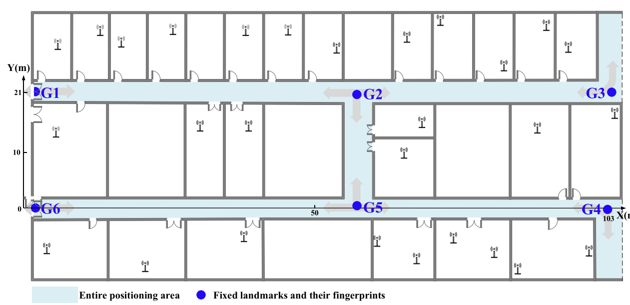


FIGURE 4. Positioning area, fixed landmarks and their fingerprints.

Moreover, if the user walks into the room from the corridor, the sensors will recognize features similar to a turn at the doorway. However, the user walking trajectory in the room following turning will be constrained, and they will not walk a far distance after the turn direction. In this manner, we can distinguish corridor corners from room doors.

As shown in Fig. 4, take the identification of landmark G2 as an example. In the crowdsourcing trajectory data, many turnings occur at G2. By judging the distance between the turning and the entrance of the building (G1 or G6), we can distinguish that the turning action occurs at G2, and extract the fingerprint there as a landmark. Among them, the building

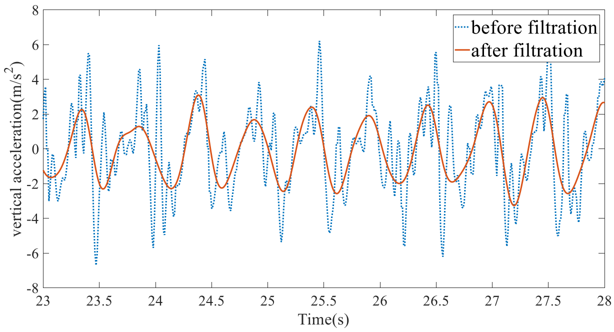


FIGURE 5. Comparison of vertical acceleration before and after filtering.

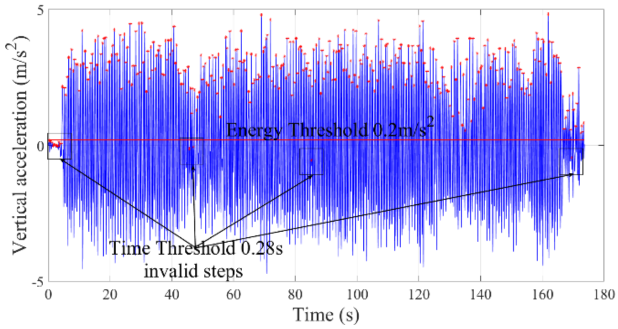


FIGURE 6. Effect of step frequency detection.

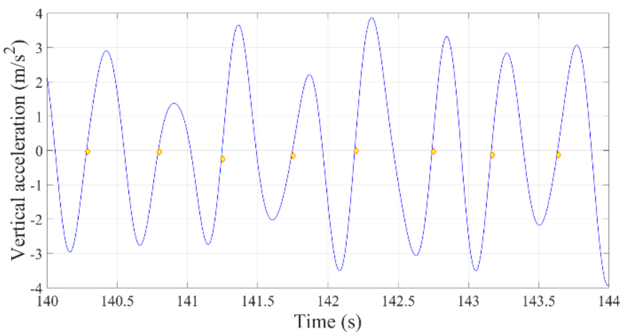


FIGURE 7. Result of zero crossing.

entrances (G1 and G6) are manually labeled as there are only a few entrances in one building. Other landmarks (like G2) are automatically identified based on crowdsourcing data. In principle, the identification of all fixed landmarks relies on the distance limitation relationship, that is, the distance between any two landmarks is certain. The fixed landmarks are identified based on the above principles, and labeled as G1 to G6 according to the pedestrian trajectory sequence. These fixed landmarks are used as starting or position updating points for each user trajectory in order to perform the following PDR.

2) PEDESTRIAN DEAD RECKONING

Based on the inertial sensor data, the user (pedestrian) step frequency and length are reckoned in order to obtain the specific pedestrian and collected RSS signal location information in the walking trajectory.

The acceleration signal collected by a handheld smartphone does not reflect the characteristics of the foot stance phase, but rather the movement law of the human body center of gravity, and exhibits an obvious periodicity. The signal to be detected is filtered by a low-pass filter with a frequency of 5 Hz prior to step frequency detection. This can eliminate the multi-peak phenomenon caused by body vibration, as illustrated in Fig. 5 for the comparison of the acceleration signal before and after filtering. This study uses the acceleration projected in the vertical direction for analysis and calculation. The acceleration is converted from the carrier (pedestrian) to the navigation (geography) coordinate system, and each step cycle is detected after the gravity (g) is subtracted from the vertical direction acceleration in the navigation coordinate system. In this study, step frequency detection is performed by using a peak detection method based on time and energy thresholds. The time threshold is used to reject peak points less than a specified time interval. The energy threshold is used to reject peak points with amplitudes less than a specified acceleration. As illustrated in Fig. 6, when a user walks normally, the time required for a step is between 0.2 and 0.8 s. If the minimum time threshold is set to 0.28 s, invalid steps can be eliminated. In order to avoid counting acceleration fluctuations caused by body shaking during walking into valid steps, where these fluctuations are small relative to the normal walking acceleration values, an energy threshold of 0.2 m/s^2 is used to eliminate invalid steps. The vertical direction acceleration after subtracting the g appears to fluctuate near zero. By determining that the acceleration value at the previous sampling time is less than or equal to zero and the value at the subsequent sampling moment is greater than zero, each step time can be obtained. The detected zero crossings are illustrated in Fig. 7. Finally, the step length (SL) is calculated by the nonlinear model Weinberg formula [27]:

$$SL = c * \sqrt[4]{a_{\max} - a_{\min}} \tag{2}$$

where a_{max} and a_{min} represent the maximum and minimum accelerations, respectively, in the vertical direction within a step; and c is a coefficient related to the individual, such as height and step frequency, which can be calculated by the distance and steps of the pedestrian through two known fixed landmarks. Therefore, according to different user characteristics, their c values are calculated and stored separately.

When the initial user position is known, the specific user position can be obtained by accumulation of the position vector, and the reckoning formula is expressed as follows:

$$\begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \end{bmatrix} + SL_k \tag{3}$$

where $(x_{k-1},\ y_{k-1})$ represents the position of k-1^{th} step (previous step), $(x_k,\ y_k)$ represents the position of k^{th} step (subsequent step), and SL_k is the length of k^{th} step.

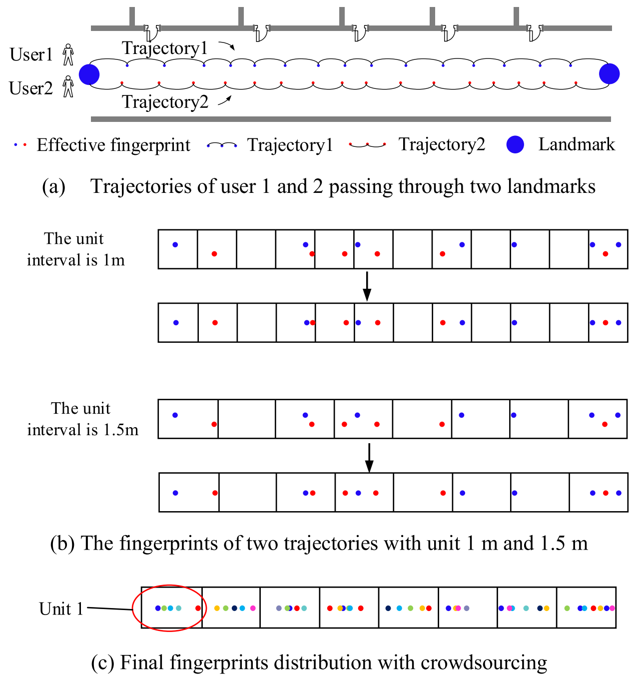


FIGURE 8. **Effective fingerprint extraction and collection.**

In this manner, the user position and trajectory information are deduced, and the position information of the RSS signal collected in the trajectory is obtained simultaneously.

D. FINGERPRINT ESTABLISHMENT RULES BASED ON CROWDSOURCING

1) FINGERPRINT COLLECTION IN THE UNIT SPACE

Based on the position determination method of RSS signal explained in the previous section, the effective fingerprint information is extracted and fused from crowdsourcing data. This study takes the trajectories of two users as an example and finally extends to multiple user trajectories. Trajectories 1 and 2 are the trails of user 1 and 2 passing through two landmarks respectively, as illustrated in Fig. 8(a). User 1 and 2 collected 17 and 18 effective fingerprints respectively, and the real-time user position corresponding to each fingerprint can be obtained. The effective fingerprint information is collected in a unit space according to position similarity. Figure 8(b) illustrates the results of collecting the effective fingerprint information of the two user trajectories by the unit space of 1 m and 1.5 m.

When the number of trajectories gradually increases, the effective fingerprints will cover the entire corridor, as illustrated in Fig. 8(c). Finally, all effective fingerprint information in each unit range is stored in order to fuse to a RP in the radio map.

For fingerprints from different trajectories, we determine the contribution weights of each fingerprint, according to the accuracy of each track point. The specific weight extraction and fingerprint fusion methods are performed in the following manner.

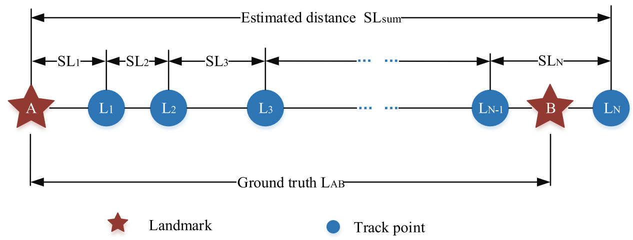


FIGURE 9. **Trajectory estimation between two fixed landmarks.**

2) FINGERPRINT WEIGHT EXTRACTION

For a certain user, some fixed landmarks are recognized during walking, and the distance between two landmarks is known. Based on this feature, we can evaluate the user trajectory accuracy.

As illustrated in Fig. 9, after the user recognizes landmark A, we can calculate the length of each step in the corridor direction, until the next fixed landmark is identified. We obtain the step length $SL_1, SL_2, \ldots, SL_N$ and the corresponding series of trajectory points $L_1, L_2, \ldots, L_N$ of each step. Moreover, we obtain the estimated distance SL_{sum}:

$$SL_{sum} = \sum_{i=1}^{N} SL_i \tag{4}$$

However, owing to the influence of various errors, there is a difference between the estimated distance SL_{sum} and the real distance L_{AB} between the identified fixed landmarks. We take L_{AB} as the actual distance walked by the user and use this difference to evaluate the trajectory estimation accuracy.

The inherent deviation of the coefficient c in the step length calculation formula (2) increases or decreases each step length estimation. As the coordinates of the next trajectory point are estimated from the position of the previous trajectory point, the accumulated error of the obtained trajectory point position will increase as the number of calculated steps increases. Assume that the real step length is defined as:

$$SL_i' = SL_i + \varepsilon_i \tag{5}$$

where SL_i' represents the real step length, SL_i represents the estimated step length, and ε_i represents the deviation between them. The step length reliability weight w_{s_i} is defined as:

$$w_{s_i} = \frac{SL_i' - |\varepsilon_i|}{SL_i'} \tag{6}$$

When walking to the l^{th} step, the position accuracy weight w_i of the trajectory point L_i is defined as:

$$w_i = \frac{\sum_{i=1}^{l} SL_i' - |\sum_{i=1}^{l} \varepsilon_i|}{\sum_{i=1}^{l} SL_i'} \tag{7}$$

where SL_i' represents the real step length of each step, $\sum_{i=1}^{l} SL_i'$ represents the current real position, and $\sum_{i=1}^{l} |\varepsilon_i|$ represents the absolute deviation between the current real position and estimated position. We incorporate formula (5) into formula (7) to obtain formula (8).

$$w_i = \frac{\sum_{i=1}^{l} SL_i + \sum_{i=1}^{l} \varepsilon_i - |\sum_{i=1}^{l} \varepsilon_i|}{\sum_{i=1}^{l} SL_i + \sum_{i=1}^{l} \varepsilon_i} = \frac{\sum_{i=1}^{l} SL_i + l\bar{\varepsilon} - |l\bar{\varepsilon}|}{\sum_{i=1}^{l} SL_i + l\bar{\varepsilon}}$$
$$= \begin{cases} \dfrac{\sum_{i=1}^{l} SL_i}{\sum_{i=1}^{l} SL_i + l\bar{\varepsilon}}, & \bar{\varepsilon} \geq 0 \\ \dfrac{\sum_{i=1}^{l} SL_i + 2l\bar{\varepsilon}}{\sum_{i=1}^{l} SL_i + l\bar{\varepsilon}}, & \bar{\varepsilon} < 0 \end{cases} \tag{8}$$

In the above equation, although the estimated deviation of each step cannot be determined, the average estimated deviation when N steps are walked between fixed landmarks A and B can be determined by equation (9). Therefore, the average deviation $\bar{\varepsilon}$ is used instead of the estimated deviation of each step.

$$\bar{\varepsilon} = \frac{L_{AB} - \sum_{i=1}^{N} SL_i}{N} \tag{9}$$

The position accuracy weight (w_i) can represent the position estimation accuracy of each trajectory point; that is, the position accuracy corresponding to each RSS signal collected. Moreover, the w_i will be used in the subsequent fingerprint fusion.

Every time a pedestrian passes a fixed landmark, the cumulative error of the PDR can be corrected by using the exact location of the landmark. For each time a pedestrian passes through two adjacent fixed landmarks (the distance is known), the difference of the actual distance between the two landmarks and the calculated distance of the pedestrian can be used to evaluate the accuracy of the calculated trajectory, so as to determine the accuracy weight of the fingerprint contributed by this pedestrian and trajectory.

3) FINGERPRINT FUSION RULES

Assume that the n APs' RSSs collected in a unit range are

$$\begin{aligned} &mac_1 : \{RSS_{11}, RSS_{12}, \ldots, RSS_{1m}\} \\ &mac_2 : \{RSS_{21}, RSS_{22}, \ldots, RSS_{2m}\} \\ &\qquad \cdots \\ &mac_n : \{RSS_{n1}, RSS_{n2}, \ldots, RSS_{nm}\} \end{aligned}$$

For all APs collected, the weighted average RSS value is calculated for each AP according to the MAC address. Taking mac_1 as an example, all effective RSS information for multiple users collected in a unit is $\{RSS_{11}, RSS_{12}, \ldots, RSS_{1m}\}$.

TABLE 2. The physical memory size of fingerprinting database.

Parameter	Typical RSS-based method	Proposed method
Avg. size of an RP	6,656 bytes	2,080 bytes
Size of fingerprinting database	978,432 bytes	305,760 bytes

The position accuracy of each effective signal RSS_{1i} is w_i. The mean value of AP_1 signal at this position is

$$\mu_{mac_1} = \frac{\sum_{i=1}^{m} w_i \cdot RSS_{1i}}{\sum_{i=1}^{m} w_i} \tag{10}$$

The standard deviation (STD) for the AP_1 is

$$\sigma_{mac_1} = \sqrt{\frac{\sum_{i=1}^{m} w_i \cdot \left(RSS_{1i} - \mu_{mac_1}\right)^2}{\sum_{i=1}^{m} w_i}} \tag{11}$$

It should be noted that certain user data are problematic, as user behavior or equipment anomalies occasionally appear during the actual data collection. It is necessary to remove unqualified data in order to develop more precise radio maps. For the RSS of a certain AP, when formula (12) is satisfied, we deem the information as abnormal.

$$\left|RSS_{1i} - \mu_{mac_1}\right| > 3 \cdot \sigma_{mac_1} \tag{12}$$

After removing the abnormal information, we recalculate the mean and STD of the APs.

Because an AP with a considerable RSS is stable and can effectively identify RP locations, we take the first j APs with stronger RSSs as a fingerprint feature for each unit in order to create a radio map. By selecting APs with stronger RSSs as valid data for constructing radio maps, rather than all APs collected, the radio map size can be reduced and accurate positioning can be achieved. The size of the physical memory occupied by the fingerprinting database is as presented in Table II. In our experiments, 28 APs are detected in the positioning area. The physical size of the fingerprinting database of the proposed method can be reduced by 68.75% compared to the typical method with collecting all APs. Thus, the final fingerprint of the i^{th} unit is: $F_i = \{(x_i, y_i)\{mac_1, \mu_1, \sigma_1\}\{mac_2, \mu_2, \sigma_2\}, \ldots, \{mac_j, \mu_j, \sigma_j\}\}$, where (x_i, y_i) is the coordinate of the i^{th} reference point and $\{mac_1, \mu_1, \sigma_1\}\{mac_2, \mu_2, \sigma_2\}, \ldots, \{mac_j, \mu_j, \sigma_j\}$ is its corresponding feature fingerprint.

In summary, we first divide the area into different unit intervals according to the user positioning accuracy requirements. Then, position extraction of the effective fingerprints is performed using all trajectory data. Finally, these fingerprints are assigned to corresponding units for fusion and feature extraction.

E. CROWDSOURCING-BASED COMBINED POSITIONING METHOD

For the localization phase, we have proposed a combined positioning method to achieve effective user positioning and tracking in response to the slow RSS updating. As the RSS information uploaded by the user during walking does not change with the position in real time, we use the combined positioning method of fingerprints and PDR to estimate the position effectively after judging the RSS information currently uploaded by the user.

1) FINGERPRINT POSITIONING

The radio map includes the RP coordinates and their fingerprint. The fingerprint information of each point contains the mean values and STDs of the AP signals collected at this point. The fingerprint data obtained by the users are $\{\{mac_1, RSS_1\}\{mac_2, RSS_2\}, \ldots, \{mac_n, RSS_n\}\}$. Firstly, the fingerprints are arranged according to the signal strength; then, the first j stronger RSSs are selected as $req\_rss = \{\{mac_1, RSS_1\}\{mac_2, RSS_2\}, \ldots, \{mac_j, RSS_j\}\}$.

After the user sends a positioning request, the current user fingerprint value is obtained. As the user walks, the RSS information is updated slowly. Here, we judge the effectiveness of the current information collected by the user. For the sequence of previously selected APs $req\_rss = \{\{mac_1, RSS_1\}\{mac_2, RSS_2\}, \ldots, \{mac_j, RSS_j\}\}$, we first compare the current signal strength with the previous moment. For the i^{th} AP collected at the k^{th} time, the MAC address is mac_i and the signal strength is RSS_k. When RSS_k satisfies formula (13), the current value RSS_k is considered as an effective value.

$$RSS_k \neq RSS_{k-1} \tag{13}$$

After judging the RSSs of the current j APs, we select effective information for positioning. Let the set of all reference points in a radio map be R. For each reference point r belonging to R, we store the joint probability distribution information for several APs. For the current m ($j \geq m$) effective fingerprint information collected by the user, which is $\{\{mac_1, RSS_1\}, \{mac_2, RSS_2\}, \ldots, \{mac_m, RSS_m\}\}$, we calculate the distribution probability at all RPs, and determine the highest probability location as the final result. According to the Bayesian theorem [13], for all $r \in R$ in the radio map, the joint distribution probability is

$$P(RSS/r) = \prod_{i=1}^{m} P(RSS_i/r) \tag{14}$$

In this study, the each AP RSS at each RP is fitted by a Gaussian distribution. The probability density function of the Gaussian distribution is

$$pdf(q) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(q-\mu)^2/(2\sigma^2)} \tag{15}$$

As these RSS_{i} collected are integers, $P(RSS_{\text{i}}/r)$ is defined as:

$$P(RSS_i/r) = \int_{rss_i-0.5}^{rss_i+0.5} pdf(q)dq \tag{16}$$

In summary, for the m effective fingerprint information sets$\{\{mac_1, RSS_1\}\{mac_2, RSS_2\}, \ldots, \{mac_m, RSS_m\}\}$ returned by the user, we firstly search the radio map and determine RPs with the same APs, regardless of their order. Then, we calculate the joint probability for these points according to formula (14). Finally, the highest probability RP is returned as the result. In this manner, the levels of computational complexity can be reduced significantly, and the calculation speed of the online stage can be improved in order to achieve rapid positioning.

2) POSITIONING BASED ON INERTIAL SENSORS

If all currently collected RSS information is not updated (all invalid), the inertial sensor information is used to estimate the current location. According to the last user fingerprint-based effective positioning result as the initial position, the current position is estimated by using PDR, as per section III.C.

IV. RESULTS ANALYSIS

This section focuses on the experimental results of the proposed algorithm when applied to a typical office building. The experiment was carried out in the corridor of an entire floor, where APs were freely distributed; therefore, the specific AP locations were not known. The entire floor area and corridor area were measured as 4600 m^2 and 411 m^2, respectively. The positioning area includes two entrances and four corners, as illustrated in Fig. 4.

The experiments were all conducted on Xiaomi Note phones (Android OS 6.0.1), equipped with a WiFi detection module, gyroscope, accelerometer, and electronic compass, among other features. The phone interface used is illustrated in Fig. 10.

A. FIXED LANDMARK RECOGNITION

Our main goal was to identify a corner during the fixed landmark identification stage. Therefore, this section thus mainly analyzes the gyroscope and electronic compass parameters for identifying walking direction changes.

Fig. 11 mainly describes the electronic compass data changes when the user is in different walking states. When a user walks normally, the angle changes are mainly concentrated in the vicinity of 0° and fluctuate between −20° and 20°. When a user turns left, the median value of the angle change is roughly −90°, while the fluctuation range varies from −110° to −70°. When a user turns right, the median value of the angle change is roughly 90°, and the fluctuation range varies from 70° to 115°. It is evident that the angle change values differ significantly between normal walking and turning movements.

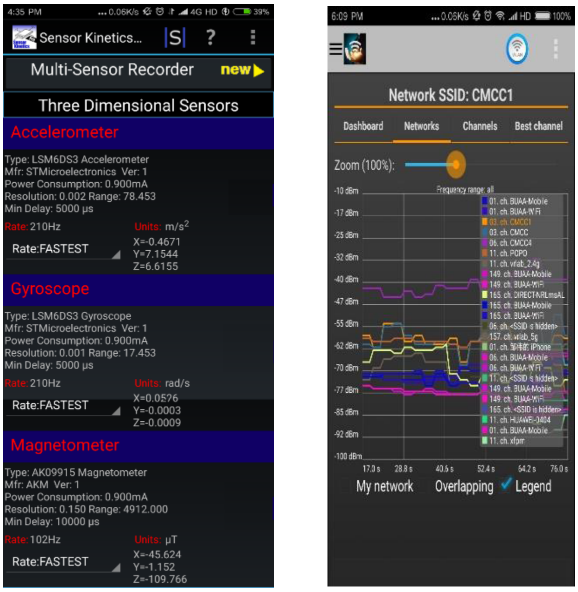


FIGURE 10. **Phone interface.**

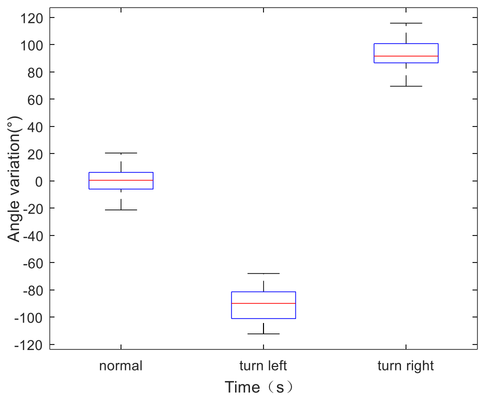
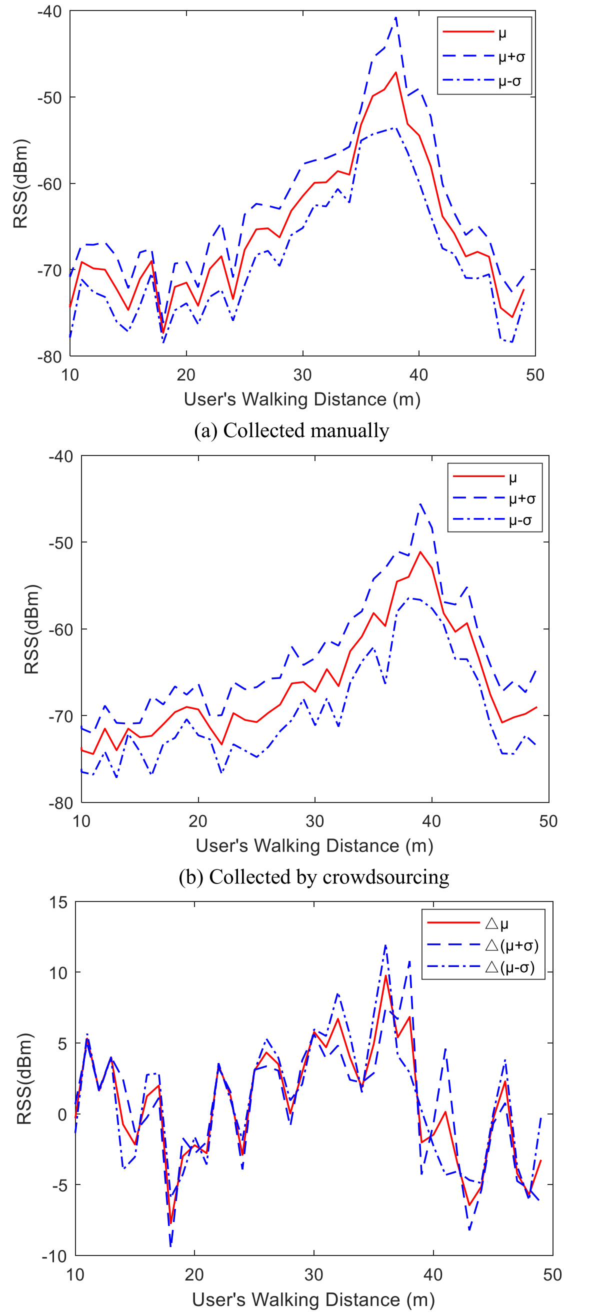


FIGURE 11. **Changes in electronic compass during normal walking and turning.**

From the electronic compass characteristics, we could accurately identify corridor corners and extract the corresponding fingerprints. A total of 649 trajectories were obtained, of which 283 were identified in the corridor corners.

B. FINGERPRINT COMPARISON

We compare the radio map data established by means of crowdsourcing and manually. We take a certain fixed AP as an example, with a RP distance of 1 m, and the signal distribution within a 40 m range in the radio map was observed. We stored the mean value (μ) and standard deviation (σ) of the RSS in the radio map to characterize each reference point signal fluctuation. As illustrated in Fig. 12, we first observed the distribution of the received signal mean value. As the position changes, the signal mean value will first increase and then decrease, and the change trend is obvious. The distribution trend of the signal mean value obtained based on crowdsourcing is close to that of the manual collection.



(a) Collected manually

(b) Collected by crowdsourcing

(c) Difference between the manually measured and the crowdsourced one

FIGURE 12. **Characteristics of a certain AP signal.**

Signal fluctuations at each reference point are characterized by the standard deviation. The signal fluctuations within the range of one-fold standard deviation for the two methods are basically similar. The point-to-point difference of μ, $\mu + \sigma$ and $\mu - \sigma$ between manually measured and crowdsourced data (i.e. $\Delta\mu$, $\Delta(\mu+\sigma)$ and $\Delta(\mu-\sigma)$) is shown in Fig. 12(c). The average value of $\Delta\mu$ is 3.47 dBm, the maximum value is 9.76 dBm and the minimum value is 0.02 dBm. It means the average mismatch between the manually measured and the crowdsourced data is little. The crowdsourced method is similar to the manual one in establishment of fingerprint map.

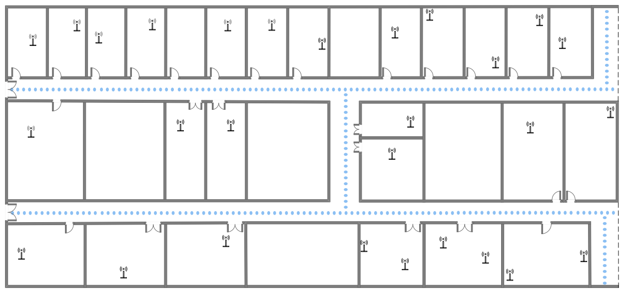


FIGURE 13. Fingerprints distribution in entire positioning area.

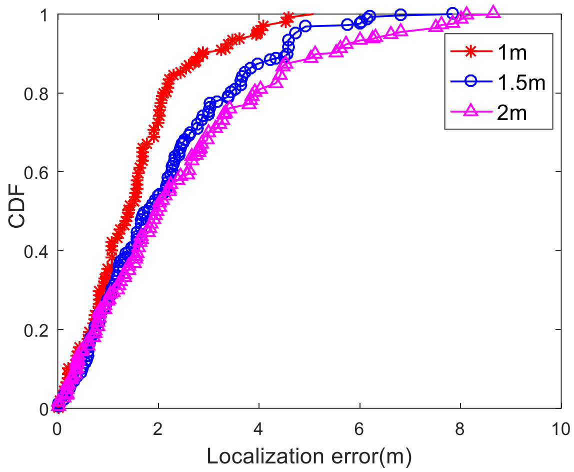


FIGURE 14. Comparison of fingerprint positioning performance at different reference point densities.

C. PERFORMANCE OF RADIO MAP

In order to verify the radio map performance, we selected a series of test points from the interest area to conduct an online accuracy test. The test point data include real physical coordinates and WiFi data. The real physical coordinates of the test point is (x_t, y_t) and the calculated coordinates generated from radio map matching is (x_r, y_r). The localization error Err is expressed as

$$Err = \sqrt{(x_t - x_r)^2 + (y_t - y_r)^2} \tag{17}$$

We established a radio map with unit intervals of 1, 1.5, and 2 m, respectively. Take 1.5 m intervals as an example, the fingerprints distribution in the entire positioning area is shown in Fig. 13. In total, 225 test points were used for online positioning, and the cumulative distribution function (CDF) of the localization errors are illustrated in Fig. 14, which is shown by Crowdsourcing(Horus) method. When the intervals were set to 1, 1.5, and 2 m, the positioning accuracies of 80% of test points were 2.08, 3.45, and 3.91 m, respectively. In general, a smaller unit interval of the interest area after fusing and extracting fingerprints according to the unit interval results in a higher level of positioning accuracy. In practical applications, the unit interval is selected based on the positioning accuracy requirements.

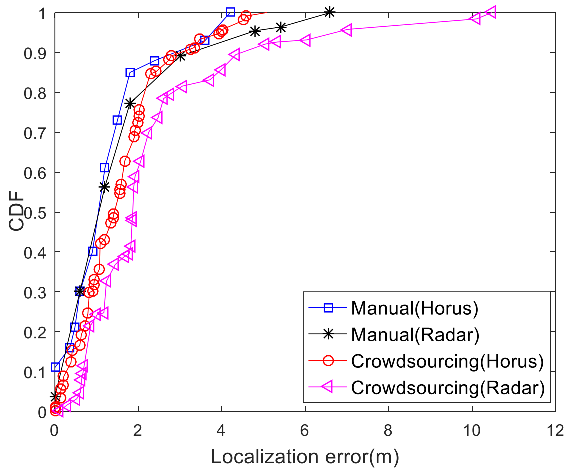


FIGURE 15. Error CDFs of radio maps constructed by different methods.

TABLE 3. Average localization error of different algorithms.

Number	Algorithm	Average localization error (m)
1	Manual (Horus) (1 m)	0.828
2	Manual (RADAR) (1 m)	1.800
3	Crowdsourcing (Horus) (1 m)	1.556
4	Crowdsourcing (RADAR) (1 m)	2.436

In order to verify the effectiveness of the proposed method, it is compared to traditional manual collection methods for establishing a radio map. For the same experimental area, RPs were selected for every 1 m, and 60 data points were collected for each point to establish a radio map.

Furthermore, we compare the classic RADAR and Horus methods with the crowdsourced method, with a density of 1 m, to measure the positioning accuracy levels.

Fig. 15 illustrates the localization error CDFs for the four methods. The level of positioning accuracy achieved from the manual collection is higher, and the precision levels obtained from the Horus method are superior to those obtained from the RADAR method. Four APs with higher signal strengths were used to establish a radio map using the Horus method, while the RADAR method used all APs collected at the RP.

In Table III, we compare the average localization errors of the different methods. When the RP density is 1 m, the average localization errors of the manual (Horus) and crowdsourcing (Horus) are 0.828 and 1.556 m, respectively. Although the positioning accuracy of the crowdsourcing method is not as high as that of the manual method, it significantly decreases labor costs while satisfying precision requirements.

The experiments are also performed in various buildings and the experimental results are almost same. The positioning accuracy based on the fingerprint database of crowdsourcing method is slightly lower than that of manual collection method. The crowdsourcing method with the proposed effective fingerprint extraction way could be a better substituted means to manual collection method.

V. CONCLUSION

In this paper, we have proposed a method for extracting effective RSS information from crowdsourcing data in order to construct a radio map and positioning. By identifying and extracting effective RSS in crowdsourcing information, and using inertial sensor information to determine the location, we evaluated the position results and established fingerprint extraction rules to construct a radio map. The experiments demonstrated that the positioning accuracy obtained by the radio map established based on crowdsourcing is close to that of manual collection, and effective positioning can be achieved.

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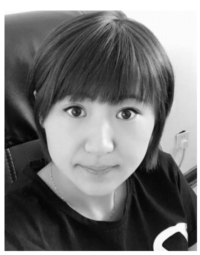

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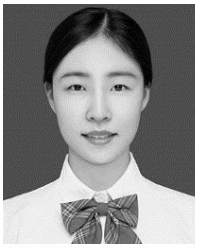

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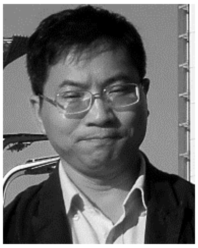

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