CROWDSOURCED WIFI FINGERPRINT LOCALIZATION IN URBAN CANYON

Ye Su, Liang Chen*, Xiaoyan Liu

State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430079, China

Commission WGIII/1

KEY WORDS: Crowdsourcing, Localization, WiFi, Fingerprint, Urban Canyon, RSSI (Received Signal Strength Indication), KWNN (K Weighted Nearest Neighbor)

ABSTRACT:

Although Global Navigation Satellite System (GNSS) has achieved success in outdoor localization, it does not often work well in urban canyon, which is due to the weak signals and the loss of satellites. WiFi technology is widely used at present, and the crowdsourced WiFi data has the advantages of rich sources and low cost. Therefore, utilizing the crowdsourced WiFi data for localization may effectively improve the deficiency of GNSS in the urban canyon. In this paper, we propose a novel method of crowdsourced WiFi fingerprint localization in urban canyon. Considering that the crowdsourced data is noisy, discontinuous and unstable, we carry out pre-processes for data refining, and grid-based statistical method for noise smoothing. Then in order to quickly locate the terminals in large-scale area, the AP coverage intersection method is proposed, in which the coverage range, centers and density of all APs are inferred, and the personal hotspots as well as the mobile APs are removed. To further enhance the positioning accuracy, the fine localization is carried out, which is based on the iterative KWNN algorithm. Extensive field tests are carried out in a typical urban canyon, results show that the average positioning error of our method is 16.82 m, which shows the effectiveness of the proposed method for crowdsourced positioning in urban canyon.

1. INTRODUCTION

With the rapid development of social economy and mobile communication network, smart devices have become popular, and various location-based mobile APPs provide lots of convenience to our daily life, such as AMap and Meituan. Undoubtedly, the location-based services (LBS) have the significance to our daily life (Chen and Chen 2017). Currently, outdoor positioning services mainly rely on Global Navigation Satellite System (GNSS) technology. However, GNSS often performs poorly in urban canyon, which is due to the weak signals, multipath transmission and the loss of satellites (Chen et al. 2021a). Therefore, it is urgent to develop a supplementary localization system in urban canyon(Wang et al. 2018).

Although a variety of localization methods have been proposed, which include UWB(Li et al. 2020), FM(Du et al. 2020), 5G (Chen et al. 2021b) etc, it is still challenging to use these schemes to achieve robust positioning in urban canyon environment. Considering that abundant WiFi access points (APs) can be well received in urban cities, it is thus promising to leverage the universally available WiFi infrastructure as GPS-free positioning scheme in urban canyon. The advantage is that, there is no additional cost for deploying the hardware with the method.

Fingerprinting is one of the most common methods for WiFi positioning. However, as is well known, it is time-consuming and labour-intensive to collect enormous amount of Wi-Fi RSSI (Received Signal Strength Indication) to build the database, especially in large-scale areas. Recently, crowdsourcing approach has been a promising solution to tackle this problem by obtaining a large amount of data from massive mobile users. In the literature, Jung et al. (Jung et al. 2016) use an unsupervised learning method to calibrate the localization model with unlabelled crowdsourced WiFi fingerprints and estimate the optimal position of fingerprints on an indoor map, under the constraint by the inner structure of the map, such as walls and partitions. Song et al. (Song and Wang 2017) propose a WLAN fingerprint indoor positioning method based on implicit crowdsourcing and semi-supervised learning. This method constructs database with a large number of unlabelled data and some labelled data, and estimate location through Co-Forest algorithm. Li et al. (Li et al. 2020) propose an enhanced crowdsourcing-based localization method, which integrates inertial, wireless and magnetic sensors. And it avoids the intervention of users and tuning of parameters, using crowdsourced sensor data to update simultaneously both the magnetic and wireless databases while positioning. It is noticed that, such techniques mentioned above have been developed for indoor positioning, where the number of APs is limited and the areas are relatively small, compared with the positioning in outdoor urban canyon scenarios. As to the research on crowdsourced outdoor localization, the WoLoc system (Wang et al. 2018) adopts a semi-supervised manifold learning technique to utilize all the labelled and unlabelled crowdsourced hotspot data and estimates the queried location. But their data is obtained by only three smartphones, and the user movements are only walking and bicycling, therefore, the quality of the data is relatively continuous and stable. It is the fact that, the quality of the crowdsourced data is much worse, since it is collected by different brands of mobile phones, and the motion patterns of collectors also vary. In addition, to save

* Liang Chen
Wuhan University, Luoyu Road. 129, 430079 Wuhan, China
e-mail: l.chen@whu.edu.cn

https://doi.org/10.5194/isprs-archives-XLVI-3-W1-2022-177-2022

the energy of phone battery, the collection frequency is low and unfixed. As a result, the crowdsourced data in reality is noisy, discontinuous and unstable, which brings great challenge to the localization research.

In this paper, we propose a novel crowdsourced WiFi fingerprint localization method used in urban canyon scenarios. To tackle the problem of noise and instability of crowdsourced data, we first filter out the data with low positioning accuracy in the pre-processing process. Then a grid statistical method is carried out to smooth the noise. For a quick localization in a large-scale urban canyon, the AP coverage intersection method is applied. To further improve the position accuracy, the iterative KWNN method is carried out.

The contributions of this work include the following aspects:

- A series of processes for refining the crowdsourced data are carried out, which includes removing abnormal records with low confidence of GPS accuracy and smoothing the noise using the grid-based statistical method.
- To quickly locate the terminals in the large-scale urban canyon, the AP coverage intersection method is proposed. In order to achieve this, an AP database is constructed, in which the coverage range, centers and density of all APs are inferred, and the personal hotspots as well as the mobile APs are removed.
- To further enhance the positioning accuracy, a fine localization is applied, which is based on the iterative KWNN algorithm.
- To validate the feasibility of our method, extensive field tests are conducted in a typical urban canyon scenario with 1.158 km in length and 0.574 km in width. Test results show that the average positioning error is 16.82 m, which indicates that our method is efficient.

2. CROWDSOURCED WIFI FINGERPRINT-BASED LOCALIZATION

To tackle the deficiency of GNSS in urban canyon, a whole crowdsourced WiFi fingerprint localization system is proposed for outdoor urban canyon environment. The system consists of three parts as shown in Figure 1, namely, the pre-processing of the crowdsourced data, the offline building database and the online localization.

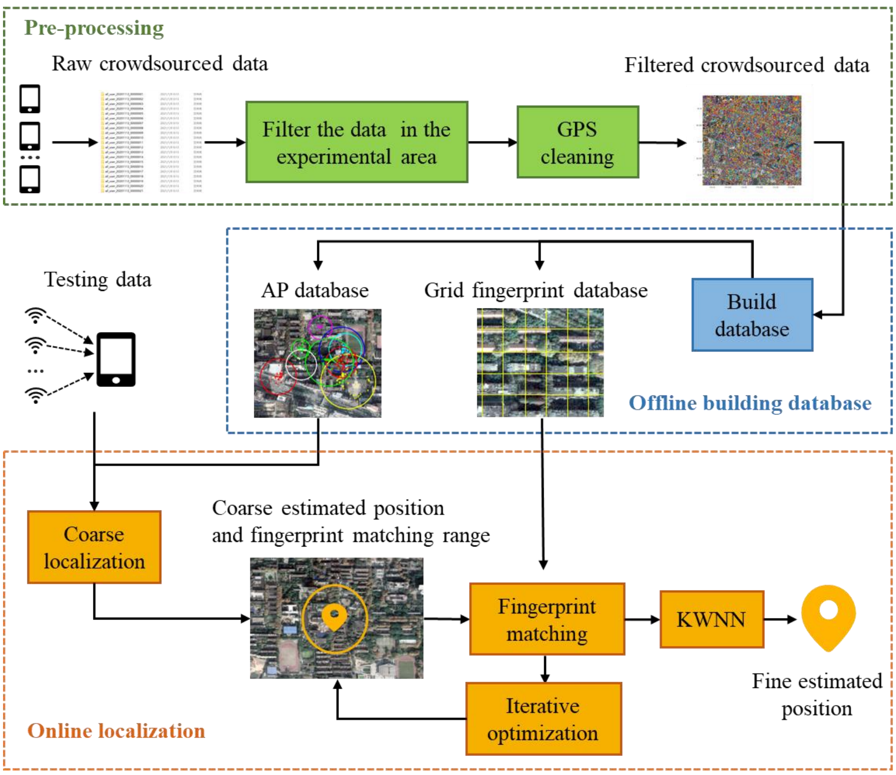

Figure 1. The architecture of crowdsourced WiFi fingerprint localization system

2.1 Pre-processing of Crowdsourced data

In reality, the crowdsourced data is noisy, unstable and of varying quality. In order to remove the data with inaccurate GPS coordinates, we carry out the pre-processing method.

The crowdsourced data consists of many elements as shown in Figure 2, including the scanning time, the location (latitude, longitude) of the collector, confidence range, and a set of information of the APs measured by the phone. What need to be explained is that the confidence range represents the accuracy of GPS, which ranges from 1 to 200. Basic Service Set Identifier (BSSID) is the Media Access Control (MAC) address of AP. And the number of APs received by each terminal is between 1 and 100.

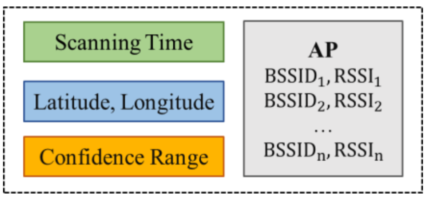

Figure 2. The elements contained in crowdsourced data

Firstly, we remove the data with a confidence range of GPS accuracy beyond 10 meters, in this way we can filter out lots of data with poor quality initially. To further eliminate the discontinuous data, we remove such abnormal data with huge distance changes in a short time interval (e.g. moving 50 m in 2 seconds) by analysing the GPS coordinates.

2.2 Database construction

2.2.1 Inference on the Coverage of APs

In order to quickly locate in the large-scale urban canyon, we use the AP coverage intersection method, which is described in detail in section 2.3.1. And to obtain the coverage of APs, we should infer the range and center of each AP first.

Firstly, we collect the information of all APs in the testing area and classify all the testing records according to their BSSID to obtain an AP database, and infer the centers, radii and density of all APs. In other words, an AP set covers all the coordinates of its receivers. Then we put the coordinates of the covered receivers into the corresponding AP set, and use the centroid localization method (Lv et al. 2019) to calculate the approximate location of AP, that is, take the average coordinates of all known receivers as the center of the specific AP:

$$(x, y) = \frac{1}{n}\sum_{i=1}^{n}(x_i, y_i) \tag{1}$$

Where (x, y) is the estimated center coordinates of AP, (x_i, y_i) is the known coordinates of the receiver i, n is the number of receivers that can hear the AP.

Then we calculate the average distance between all receiving points and the AP center, and take this as the coverage radius of AP:

$$R = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x-x_i)^2 + (y-y_i)^2} \tag{2}$$

However, there may have some personal hotspots and mobile APs in the AP database. Among them, the personal hotspots are temporary, and the mobile APs are unfixed, such as vehicle-mounted APs. These APs may adversely affect positioning, so we are supposed to eliminate them as much as possible.

It's noticed that the personal APs cover few receivers, so we can get rid of those APs heard by a small number of terminals. And the mobile APs cover receivers sparsely, so we can remove those APs with low density. The density can be calculated using (3)

$$D = \frac{n}{\pi R^2} \tag{3}$$

To sum up, we obtain an AP database shown in Figure 3, which contains the BSSIDs, the location of receivers, the AP centers, radii and density of WiFi APs.

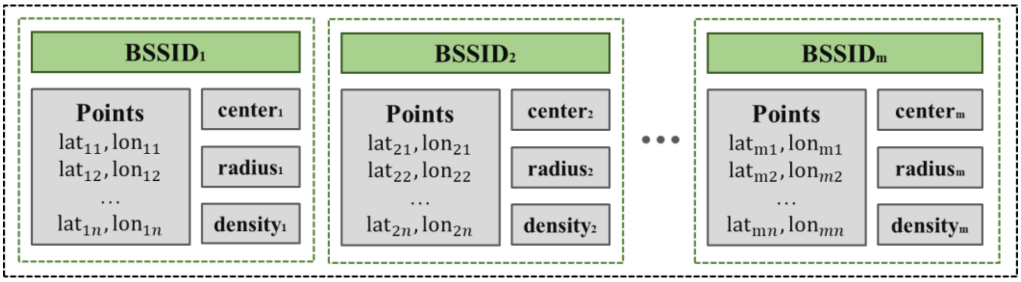

Figure 3. The structure of AP Database

2.2.2 Building Fingerprint Database Using Grid-Based Statistical Method

In order to smooth noise and compress the size of database, we construct a fingerprint database using grid-based statistical method.

Firstly, we divide the research area into several grids, then the records are placed into the corresponding grid according to their GPS coordinates. Each grid point can be called a fingerprint, and we make full use of data from the surrounding grids (upper left, upper right, lower left and lower right) to obtain more accurate RSSI measurements. In other words, the data in a grid is reused four times, except for the edge grids.

Specifically, all AP information of the four neighboring grids is classified by the BSSIDs, and we eliminate the personal hotspots and mobile APs according to the AP database. For each AP, it has several RSSI measurements since there are several records have heard it, so we calculate the mean value of all RSSI measurements. The process is shown in Figure 4. And we will discuss the validity of this approach in Section 3.2.2.

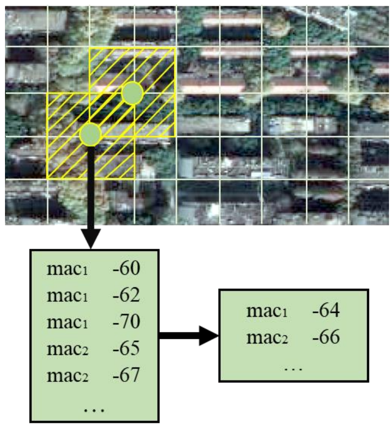

Figure 4. The method of building grid fingerprint database

2.3 Online Localization

In order to carry out real-time positioning in the large-scale urban canyon, a coarse-to-fine strategy is adopted during the online localization. The aim of the coarse localization is to quickly achieve an initial estimated position by AP coverage intersection, and the position is further refined by the step of fine localization.

2.3.1 Coarse Localization based on AP coverage intersection method

To save time and computing resources, we can quickly calculate the coarse estimated position and coverage radius according to the distribution parameters of APs obtained during the construction of AP database above, using the AP coverage intersection method as shown in Figure 5.

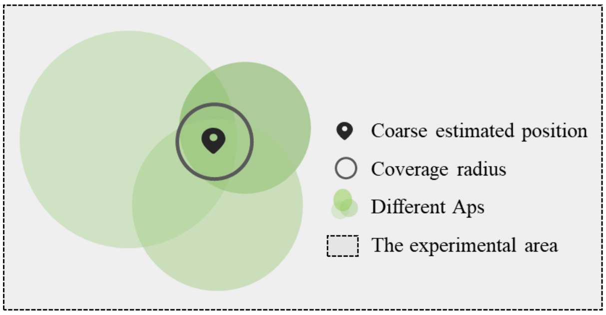

Figure 5. Coarse localization: the light grey rectangle represents the entire testing area, the different colored circles represent different APs, the black position is the coarse estimated position, and the black circle indicates the fingerprint matching area.

In AP coverage intersection method, we can obtain the coarse estimated position and the coverage radius of matching area through (4) and (5):

$$\frac{1}{R_c} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{R_i} \tag{4}$$

$$\frac{(x_c, y_c)}{R_c} = \frac{1}{n}\sum_{i=1}^{n}\frac{(x_i, y_i)}{R_i} \tag{5}$$

Where (x_i, y_i) is the center of AP_i, R_i is the coverage radius of AP_i, n indicates the number of APs heard by the testing record and existing in the AP database, (x_c, y_c) is the coarse estimated position, R_c is the coverage radius of the matching area.

As a result, we successfully limit the matching area to a small area, and greatly save the calculation time and improve the positioning efficiency.

2.3.2 Fine Localization based on iterative KWNN

To further improve the positioning accuracy, we carry out the fine localization. The initial fingerprint matching area is determined as a circular area according to the coarse estimated position and coverage radius obtained by coarse localization, with the coarse estimated position as the center and the coverage radius as the radius, all the fingerprints of the grid fingerprint database within this range should be matched.

During the process, we calculate the similarity between the fingerprints and the testing data using the cosine distance (Shuai et al. 2015).

$$S_u^f = sim(R^u, R^f) = \frac{\sum_{l=1}^{L_u^f} r_l^u r_l^f}{\sqrt{\sum_{l=1}^{L^u} (r_l^u)^2}\sqrt{\sum_{l=1}^{L^f} (r_l^f)^2}} \tag{6}$$

where L_u^f is the common AP set, r_l^u represents the RSSI value of AP_l measured by user, r_l^f represents the RSSI value of AP_l measured by fingerprint.

Since the APs they heard might not be exactly the same, we set the missing values as -120 dBm for APs appearing in fingerprint r_l^f while not in fingerprint r_l^u.

Then we get a set of candidate points, and use K Weighted Nearest Neighbor algorithm (KWNN) (Wei et al. 2016) to further refine the estimated position. We select the top K fingerprints with high similarity and use them to calculate the fine estimated position:

$$(x_f, y_f) = \{\sum_{i=1}^{K} x_i * \omega_i, \sum_{i=1}^{K} y_i * \omega_i,\} \tag{7}$$

Where (x_f, y_f) is the fine estimated position, (x_i, y_i) is the coordinates of candidate point i, we set $K = 20$ in practice, and ω_i is the weight of candidate point i calculated as follows:

$$\omega_i = \frac{S_i}{\sum_{i=1}^{K} S_i} \tag{8}$$

However, considering the case that, the position of user might be outside the fingerprint matching area as shown in Figure 6. Therefore, we adopt a method of iteratively updating the matching area.

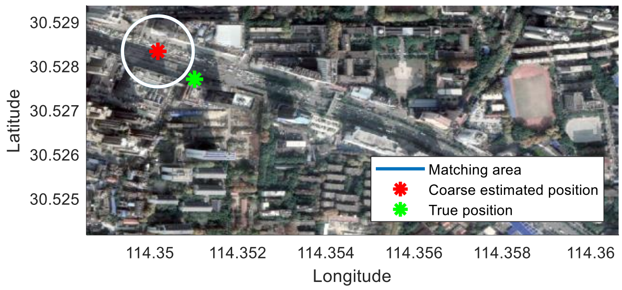

Figure 6. The possible condition of coarse localization

During the process, we perform several rounds of fingerprint matching, and update the center of matching area with the estimated position calculated in the last round. In addition, if the similarity of all candidate points is low (e.g. less than 0.9), the coverage radius will be lengthened to obtain more candidate points. The distance Δ_d between the estimated position calculated in this round and last round is obtained as follows:

$$\Delta_d = \sqrt{(x_f^n - x_f^{n-1})^2 + (y_f^n - y_f^{n-1})^2} \tag{9}$$

where (x_f^n, y_f^n) is the estimated position calculated in this round, (x_f^{n-1}, y_f^{n-1}) is the estimated position calculated in last round.

The loop will continue until Δ_d is less than ε_d or the number of loops reaches the maximum, and we set $\varepsilon_d = 1$ meter and set the maximum number of rounds is equal to 10. The process is shown in Figure 7.

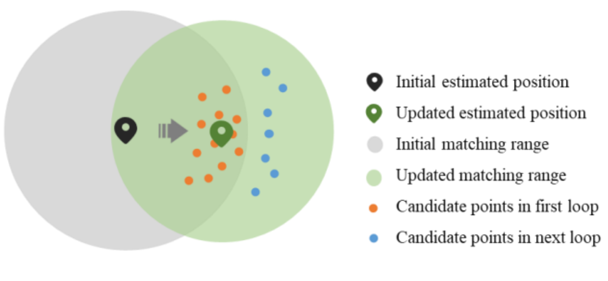

Figure 7. The process of iteratively updating the matching area

Algorithm 1: Fine localization

Input: The WiFi information received by user *testData*, the coarse estimated position (x_c, y_c), the radius of matching area R_c and the grid fingerprint database *DB*
Output: The fine estimated position (x_f, y_f)

// Initialize parameters
$n \leftarrow 0$, $R_f \leftarrow R_c$, $(x_f, y_f) \leftarrow (x_c, y_c)$
Define a point set *candiPoints* to store candidate points
While $n < 10$
  Extract the *fingerprints* in *DB* within the matching area with the center (x_c, y_c) and the radius R_c,, the number of *fingerprints* is *fingerNum*
  For $i = 1$ to *fingerNum* do
    Calculate S_u^f between *testData* and *fingerprints*(i)
    Add *fingerprints*(i) into *candiPoints*
  end // for
  Keep k fingerprints with high similarity in *candiPoints* and remove others with low similarity
  Calculate the estimated position (x_f^n, y_f^n) using KWNN
  If $\Delta_d < \varepsilon_d$ **then**
    Break // exit
  Elseif the highest similarity less than 0.9
    $R_f \leftarrow R_f + \Delta_r$
  Else
    $(x_f, y_f) \leftarrow (x_f^n, y_f^n)$
  End // if
End // while

3. EXPERIMENTS AND EVALUATION

3.1 Experiment Setting

The crowdsourced dataset is collected over 3 days by a large number of volunteers using different brands of mobile phones. The testing area is located on Luoyu Road in Wuhan, Hubei Province, which covers an area of about 0.67 square kilometers, as shown in Figure 8. There are many high-rise buildings and large shopping centers here, and it is a typical urban canyon environment, as shown in Figure 9. In this area, GNSS signals are weak but WiFi APs are abundant. The collected data includes GPS coordinates, GPS accuracy, and WiFi information, such as BSSIDs and RSSIs. The sampling frequency of the crowdsourced data is unfixed with the time interval ranging from seconds to minutes or even hours, which makes localization more difficult.

Figure 8. Satellite image of the testing area (1.158 km × 0.574 km)

The total number of data records is 223625. In each record, the number of hearable APs varies from 1 to 100. Figure 10 shows the GPS coordinates of the total data records. Different points represent different records, and the color of the points is randomly set. It can be seen that most of the collected data are concentrated on wide roads and a few are in narrow areas, which is in line with the trajectory of people's daily life.

Figure 9. Street view of the testing area

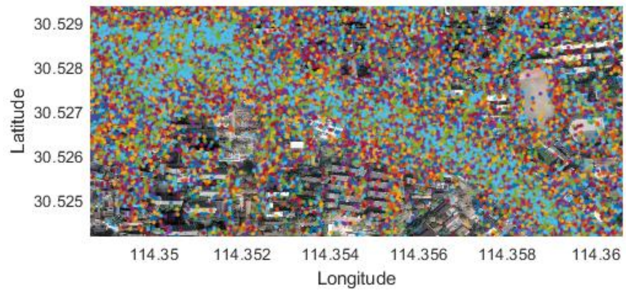

Figure 10. Location of the total data records

3.2 Performance Analysis

3.2.1 Pre-processing of Crowdsourced Data

To evaluate the effectiveness of the pre-processing module, we conduct a group of comparative tests: one group of the test is not pre-processed, and the other test is pre-processed. Figure 12 shows the results of comparative tests. As can be seen from Figure 12, compared with the test without pre-processing, the positioning error in 95% accuracy of the test with pre-processing is reduced by 42.72%. The reason may be that GPS is prone to failure in urban canyons, which makes the crowdsourced data contain a large number of wrong location references. Therefore, after removing abnormal records with a confidence range of more than 10 m, or records with large changes in distance in a short time interval, the positioning accuracy is significantly improved.

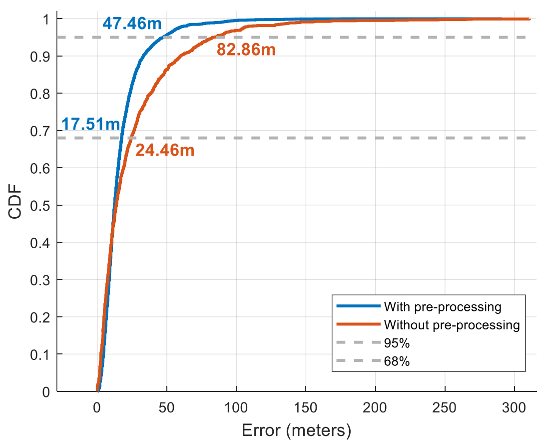

Figure 12. Error CDF of with/without pre-processing

3.2.2 Results of AP Database and Grid Database

During the process of building AP database, the APs whose number of receivers is less than 7 are eliminated, which are classified as the personal hotspots, while those APs are also eliminated if the hearable number is less than 0.002 normalized in one m^2, which are classified as the mobile APs.

After clearing a large number of the personal hotspots and mobile APs, the total number of APs in the testing area is 20208 and the AP density is about 30402 per km^2. Figure 11 shows the location of all APs, it can be seen that the APs density near the shopping center is high, while it is low in residential areas.

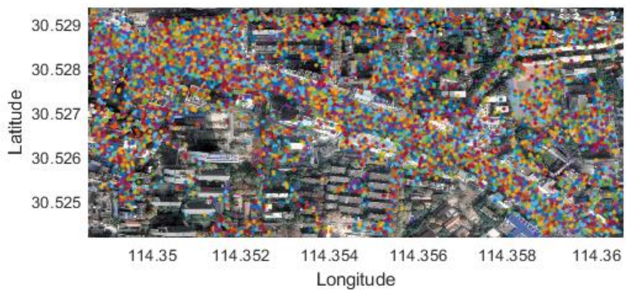

Figure 11. Approximate location of APs estimated by the centroid method described in section 2.2.1

As can be seen from Figure 13, compared with the test before removing the personal hotspots and mobile APs, the positioning accuracy in 95% of the test after removing the personal hotspots and mobile APs is increased by 10.54 m. The reason may be that the mobility of personal hotspots and mobile APs has an adverse effect on localization.

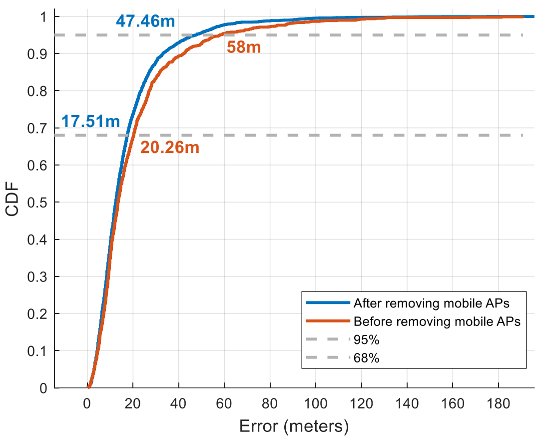

Figure 13. Accuracy comparison between after/before removing the personal hotspots and mobile APs.

To compare the influence of the grid length on positioning, the grid length is set as 2 m, 3 m, 4 m, and 5 m. As can be seen in Figure 14, the grid length does not have effect on the coarse positioning, which is due to the reason that, the coarse localization is only achieved by the AP coverage intersection. It also can be observed that the average error of fine positioning does not change dramatically with the grid length changes, and the grid length of 3 or 4 meters achieves the best positioning results. The reason may be that, when the grid size is small, each grid contains a small number of records, so there are not enough measurements for noise smoothing. And when the grid size is large, the fingerprints are so sparse that the positioning accuracy decreases.

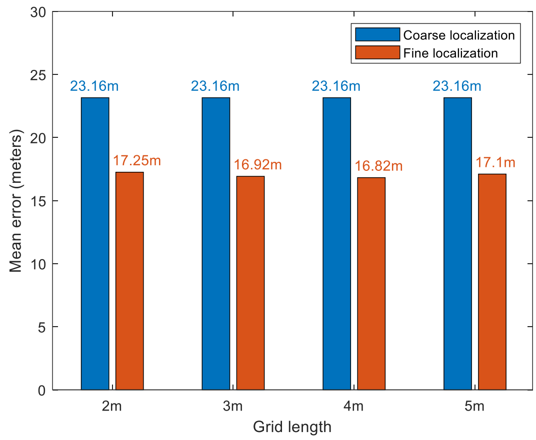

Figure 14. Accuracy comparison of different grid lengths

As mentioned in Section 2.2.2, a grid point contains the data from four neighbouring grids, i.e., upper left, upper right, lower left, and lower right. To further verify the effectiveness of the proposed method, we carry out two comparative tests using the same testing data, with the one using the data from the four neighboring grids, while with the other using the data from one grid, and set the grid center as the fingerprint coordinates as shown in Figure 15. Figure 16 shows that compared with the test using only one grid, the positioning accuracy in 95% of the test using four neighboring grids is enhanced by 2.02 m.

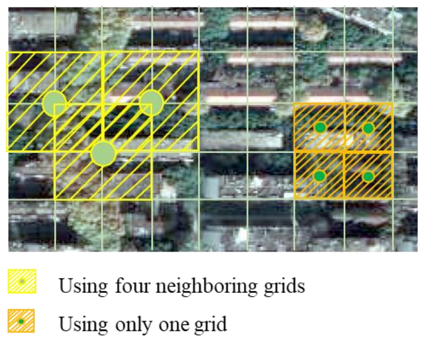

Figure 15. Two methods of constructing the grid fingerprint database

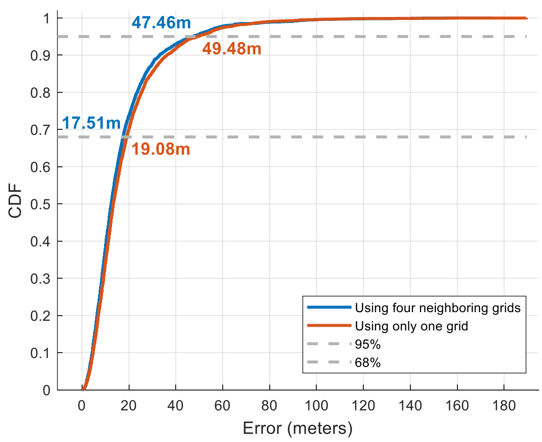

Figure 16. Accuracy comparison between using four neighboring grids and using only one grid

3.2.3 Online Localization

Figure 17 shows the distribution of the number of WiFi APs received by testing records, it can be found that most records can receive 21 to 40 APs. And many records can receive 100 APs, this is because one device can only record a maximum of 100 APs even though it can detect more than 100 APs.

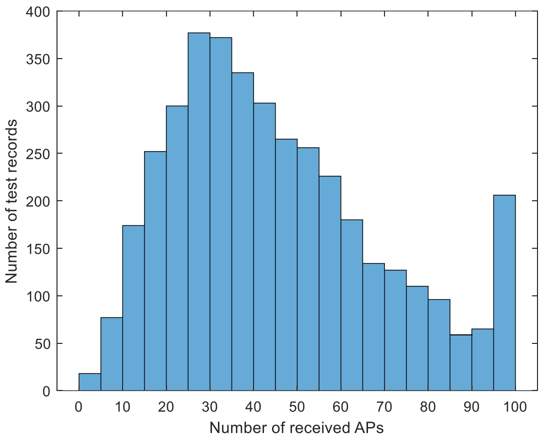

Figure 17. The number of WiFi APs received by testing data

To explore the relationship between the number of hearable APs and localization accuracy, we classify the positioning results into five categories, which are shown in Figure 18. It can be seen that the localization accuracy of the testing data receiving 1-20 APs is the lowest. The best positioning accuracy comes from the testing data of the category of 21-40 APs received. Since the large number of hearable APs will increase the energy consuming of the mobile phone, the tests results suggest that, the proposed localization method is able to trade-off between achieving high-precision localization and low power consumption.

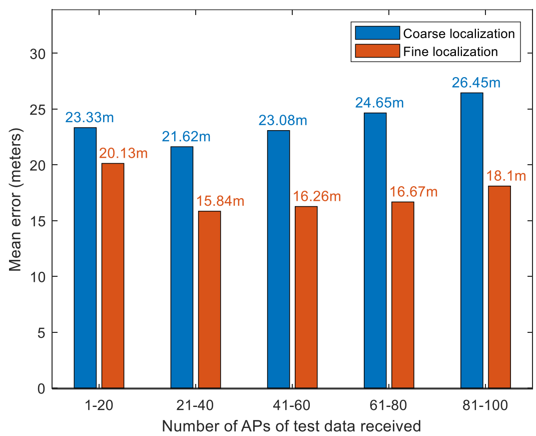

Figure 18. Error statistics of testing data receiving different numbers of APs

However, it can be noticed from Figure 18 that the positioning accuracy does not continue to increase with the number of APs received. Figure 19 shows the location of all test points, and Figure 20 shows the location of testing points receiving different numbers of APs. It can be observed that the testing points receiving 21-40 APs and 41-60 APs are evenly distributed in the testing area, while the testing data receiving 61-80 APs and 81-100 APs are mostly distributed in the ends of the road. And it can be seen from the Figure 8, the ends of the road are the areas where high-rise buildings intersect. The AP density in this area is high, but the high-rise buildings intersection will form a complete blind area of GPS, resulting in deviation of their position reference.

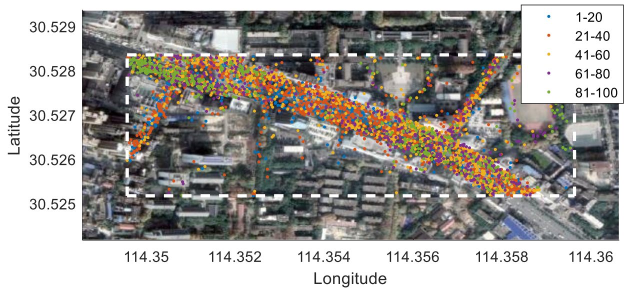

Figure 19. Location of testing data

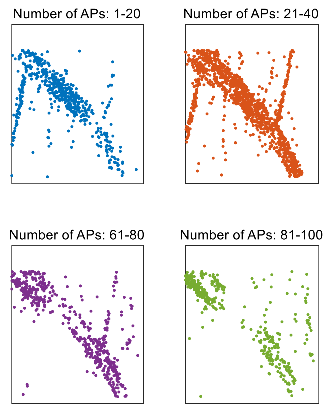

Figure 20. Location of testing data receiving different numbers of APs

Figure 21 shows the positioning accuracy of all testing points. In the figure, the mean value mu is equal to 16.82 m and the standard deviation is 16.14 m. The testing points with positioning error greater than 49.10 m are marked in red and the rest in green. It can be seen that most of the red points gather around the area with high-rise buildings.

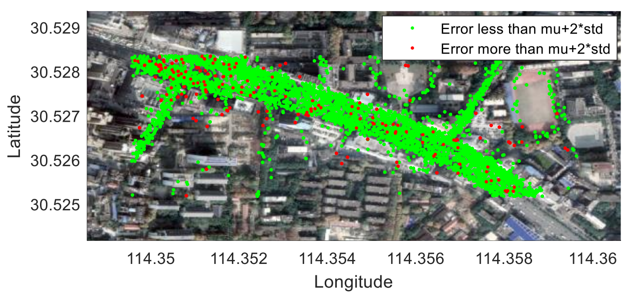

Figure 21. The statistics of the testing results

4. CONCLUSIONS

To solve the location problem in urban canyon, a novel crowdsourcing WiFi fingerprint location method is proposed in this paper. The method consists of three steps, namely, pre-processing, offline step for database building and online location.

To tackle the problem of noise and instability of crowdsourced data, we proposed a pre-processing method to remove abnormal records, and the test results showed that this method is able to effectively improve the positioning accuracy. In the step of database construction, we applied grid-based statistical method to smooth the noise and compress the size of database. To quickly locate in the large-scale urban canyon, we proposed the method of AP coverage intersection and built an AP database, then eliminated the personal hotspots as well as the mobile APs. To further improve the position accuracy, we carried out the fine localization, which is based on the iterative KWNN method.

The proposed method was verified by the tests results in a typical urban canyon. By applying the pre-processing method, the positioning accuracy was increased by 42.72%, compared with using the raw crowdsourced data directly. And by applying the process of removing the personal hotspots and mobile APs, the positioning accuracy was able to improve by 18.17%. In addition, in the process of fine positioning, with four neighboring grids to construct fingerprint database, the positioning accuracy was increased by 2.02 m. In general, the average positioning error of the proposed method was 16.82 m, which showed the effectiveness of the proposed method used in urban canyon.

5. ACKNOWLEDGMENT

This work is supported by National Natural Science Foundation of China under grant No. 42171417, Key Research and Development Program of Hubei Province under grant No. 2021BAA166, Special Fund of Hubei Luojia Laboratory under grant No. 220100008, and Special Research Fund of LIESMARS

REFERENCES

A. Toyama, K. Mitsugi, K. Matsuo & L. Barolli. 2020. Implementation of a Moving Omnidirectional Access Point Robot and a Position Detecting System. *Springer, Cham*

B. Li, K. Zhao & E. B. Sandoval. 2020. A UWB-Based Indoor Positioning System Employing Neural Networks. *Journal of Geovisualization and Spatial Analysis* 4

C. Du, B. Peng, Z. Zhang, W. Xue & M. Guan. 2020. KF-KNN: Low-Cost and High-Accurate FM-Based Indoor Localization Model via Fingerprint Technology. *IEEE Access* 8, 197523-197531

C. H. Cheng & S. J. Syu. 2019. Improving area positioning in ZigBee sensor networks using neural network algorithm. *Microsystem Technologies*

C. Song & J. Wang. 2017. WLAN Fingerprint Indoor Positioning Strategy Based on Implicit Crowdsourcing and Semi-Supervised Learning. *International Journal of Geo-Information* 6, 356

C. Wei, W. Weiping, L. Qun, C. Qiang & H. Hongtao. 2016. A Crowd-Sourcing Indoor Localization Algorithm via Optical Camera on a Smartphone Assisted by Wi-Fi Fingerprint RSSI. *Sensors* 16, 410

H. Shuai, Z. Cong, W. Meng & L. Cheng. 2015*Cosine similarity based fingerprinting algorithm in WLAN indoor positioning against device diversity*. Paper presented at the ICC 2015 - 2015 IEEE International Conference on Communications.

J. Wang, J. Luo, S. J. Pan & A. Sun. 2018. Learning-Based Outdoor Localization Exploiting Crowd-Labeled WiFi Hotspots. *Mobile Computing, IEEE Transactions on*

J. Zhang, X. Wang, Z. Yu, Y. Lyu & X. Wang. 2019. Robust RFID based 6-DoF Localization for Unmanned Aerial Vehicles. *IEEE Access* PP, 1

L. Chen, X. Lu, N. Shen, L. Wang, Y. Zhuang, Y. Su, D. Li & R. Chen. 2021. Signal acquisition of Luojia-1A low earth orbit navigation augmentation system with software defined receiver. *Geo-spatial Information Science*, 1-16. doi: 10.1080/10095020.2021.1964386

L. Chen, X. Zhou, F. Chen, L. L. Yang & R. Chen. 2021. Carrier Phase Ranging for Indoor Positioning with 5G NR Signals *IEEE Internet of Things Journal*, pp. 1–1, 2021, doi:10.1109/JIOT.2021.3125373

R. Chen & L. Chen. 2017. Indoor Positioning with Smartphones: The State-of-the-art and the Challenges. *Acta Geodaetica et Cartographic Sinica* 46, 1316-1326. doi: 10.11947

S. H. Jung, B. C. Moon & D. Han. 2016. Unsupervised Learning for Crowdsourced Indoor Localization in Wireless Networks. *IEEE Transactions on Mobile Computing*

W. Li, R. Chen, Y. Yu, Y. Wu & H. Zhou. 2021. Pedestrian Dead Reckoning with Novel Heading Estimation under Magnetic Interference and Multiple Smartphone Postures. *Measurement*, 109610

Y. Li, Z. He, Z. Gao, Y. Zhuang, C. Shi & N. El-Sheimy. 2020. Towards Robust Crowdsourcing-Based Localization: A Fingerprinting Accuracy Indicator Enhanced Wireless/Magnetic/Inertial Integration Approach

Y. Lv, Y. Liu & J. Hua. 2019. A Study on the Application of WSN Positioning Technology to Unattended Areas. *IEEE Access*, 1