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To cite this article: Changa Jun *et al* 2019 *IOP Conf. Ser.: Earth Environ. Sci.* **234** 012094

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A Weighted Bayesian Localization Algorithm Based on the Strongest AP Method

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Abstract. This paper presents a kind of using Wi-Fi location fingerprint to locate the interior regions of the weighted Bayesian algorithm based on the strongest AP method. The algorithm locates the regions with the strongest AP signal by voting according to the distribution rule of the online data, and then uses the weighted Bayesian algorithm to locate. The experimental scene is a typical "aisle" interior region, through the data measured and algorithm matching. The results show that compared with the Bayesian algorithm, the weighted Bayesian algorithm based on the strongest AP method has higher positioning precision and accuracy.

1.   Introduction

Nowadays, the outdoor positioning technology based on GPS[1] (Global Positioning System) has developed very well. However, with the increasing demand for indoor positioning, GPS signals are blocked by walls and other obstacles indoors and GPS cannot be used for indoor positioning. So different indoor positioning technology and methods have been produced. Positioning technologies commonly used include infrared, Bluetooth, radio frequency identification, Zigbee, Wi-Fi [2-6]. According to different measurement methods, there are positioning methods based on AOA (Angle of Arrival), TOA (Time of Arrival) and TDOA (Time Difference of Arrival)[7]. Since infrared, Bluetooth, RFID, Zigbee and other positioning technologies require additional equipment and high cost, and Wi-Fi positioning technology can solve this problem by using a large number of Wi-Fi networks and smart phone Wi-Fi receiving modules currently deployed indoors. Therefore, Wi-Fi positioning technology has become one of the most accepted positioning technologies in indoor positioning research due to its high transmission rate, low cost, wide coverage and other advantages [8-9]. Wi-Fi positioning technology is divided into propagation model method and fingerprint method [10]. The propagation model method needs to establish a wireless signal propagation model and the signal propagation characteristics are easily affected indoors. The fingerprint method refers to acquiring offline fingerprinting database first in offline phase, and then positioning and matching with data in offline fingerprinting database in online positioning phase. The fingerprint method needs a lot of data preprocessing. This article uses the location algorithm based on Wi-Fi location fingerprint. An improved algorithm based on the strongest AP method is proposed in [11]. The NN algorithm, KNN algorithm and WKNN algorithm are compared with the NN algorithm, the KNN algorithm and the WKNN algorithm based on the strongest AP method. The results show that the positioning accuracy of the improved algorithm based on the strongest AP method is higher than the original algorithm. [12] and [13] proposed a weighted Bayesian algorithm, the difference between the two algorithms is the weights are chosen differently, but the results are that the weighted Bayesian algorithm has higher positioning accuracy than the Bayesian algorithm; [14] proposed an indoor location fingerprint algorithm based on improved WKNN, in which the Euclidean distance was improved, the traditional Euclidean distance was changed to the weighted Euclidean distance, and the weight was determined

by variance. The results show that the positioning accuracy of the WKNN algorithm based on the weighted Euclidean distance is higher than the traditional WKNN algorithm.

This paper studies the location algorithm based on Wi-Fi location fingerprint. A weighted Bayesian algorithm based on the strongest AP method is proposed based on [11], [12], [13] and [14]. The experimental scene is a typical "aisle" interior region, through the data measured to verify and analyze the algorithm.

2.   Positioning System

2.1 Wi-Fi Location Fingerprint Database

Wi-Fi location fingerprint database M [15] is a database created after the positioning region is divided into several squares and the RSSI (Received Signal Strength Indication) is collected on all the squares. The RSSI value of the Wi-Fi data sent by the AP (Wireless Access Point) is collected and stored in the database as a fingerprint. The i-th element in the location fingerprint database is (1):

$$M_i = \left(L_i , \underbrace{\{fp_{ij} \mid j \in N\}}_{(fp_i \in fp)} \right) \quad i = 1, \ldots, m \tag{1}$$

Where M_i is the i-th element of the Wi-Fi location fingerprint database M, $L_i = (x_i, y_i)$ is the i-th location, fp_{ij} is the RSSI value of the j-th AP received at the i-th location, $fp_i = \{R_{i1}, R_{i2}, \ldots, R_{in}\}$ is the i-th fingerprint, and $fp = \{fp_1, fp_2, \ldots, fp_n\}$ is all the fingerprints.

2.2 Location Model Based on Location Fingerprint

Positioning algorithm based on location fingerprint [16] for positioning is divided into two phases: the first is the offline phase; the second is the online positioning phase. The location model of location fingerprint algorithm is shown in Figure 1:
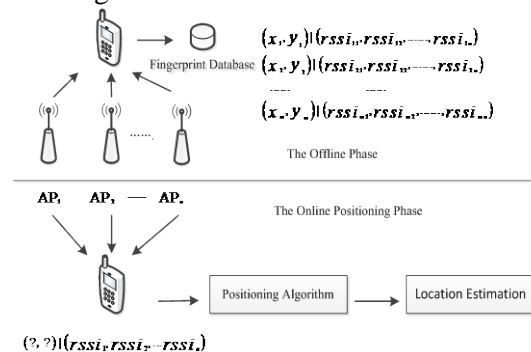

Figure 1 Location model based on location fingerprint

During the offline phase, the RSSI data sent by the existing APs needs to be collected by the test equipment at the collection points and then an offline fingerprint database M is established. During the online positioning phase, the RSSI data set R of each location to be determined needs to be measured online by a testing device. After matching the fingerprints fp in the database through the positioning algorithm, the corresponding matching fingerprints are found, and then the coordinates of the location to be determined are calculated through the positioning algorithm. Then, positioning process is over.

2.3 Positioning Algorithm

The weighted Bayesian algorithm based on the strongest AP method first locates a small region from the entire positioning region according to the strongest AP method and then uses the weighted Bayesian algorithm to positioning.

2.3.1   *The Bayesian Algorithm.* The principle of the Bayesian algorithm is to know the set $\boldsymbol{R}$ of online RSSI and find an unknown position L_i such that the probability of set $\boldsymbol{R}$ appears the most, then the positioning point is L_i and the positioning coordinate is L_i's coordinate (x_i, y_i). The goal is to solve the formula (2):

$$max\, P\left(\boldsymbol{L}_i \mid \boldsymbol{R}\right) \tag{2}$$

Formula (2) can be expressed as a Bayesian formula (3):

$$P\left(\boldsymbol{L}_i \mid \boldsymbol{R}\right) = \frac{P\left(\boldsymbol{R} \mid \boldsymbol{L}_i\right) * P\left(\boldsymbol{L}_i\right)}{P\left(\boldsymbol{R}\right)} \tag{3}$$

$P(\boldsymbol{R})$ is the probability of set $\boldsymbol{R}$, and the data request is constant for the user. $P(\boldsymbol{L}_i)$ represents the probability of location L_i appears, and we assume that the probability of location L_i is equal. Because the probabilities are only relatively large, $P(\boldsymbol{R})$、 $P(\boldsymbol{L}_i)$ can be neglected as a constant, so the solution target can be expressed as (4):

$$arg\, max\, P\left(\boldsymbol{L}_i \mid \boldsymbol{R}\right) = arg\, max\, P\left(\boldsymbol{R} \mid \boldsymbol{L}_i\right) \tag{4}$$

$max\, P\left(\boldsymbol{R} \mid \boldsymbol{L}_i\right)$ refers to finding a point L_i in the positioning region, so that the probability of the RSSI set $\boldsymbol{R}$ appears is the largest. Let R_j in $\boldsymbol{R}$ independent of each other.

$$P\left(\boldsymbol{R} \mid \boldsymbol{L}_i\right) = P\left(R_1, R_2, \ldots, R_n \mid \boldsymbol{L}_i\right) = \prod_{j=0}^{n} P\left(R_j \mid \boldsymbol{L}_i\right) \tag{5}$$

According to experience, the RSSI distribution of one AP corresponds to a Gaussian distribution curve [17], so let the RSSI distribution of any data acquisition point is Gaussian distribution.

$$P\left(R_j \mid \boldsymbol{L}_i\right) = \frac{1}{\sqrt{2\pi}\sigma}\, e^{-\frac{(\boldsymbol{R}-\mu)^2}{2\sigma^2}} \tag{6}$$

Where $\mu = \frac{1}{M}\sum_{j=1}^{M} R_j$; $\sigma = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}\left(R_j - \mu\right)^2}$, R_j is the actual RSSI of the location, M is the number of acquisitions, μ is the average RSSI value of the location, and σ is the standard deviation RSSI of the location. The final goal is formula (7):

$$arg\, max P\left(\boldsymbol{L}_i \mid \boldsymbol{R}\right) = arg\, max \prod_{j=0}^{n} \frac{1}{\sqrt{2\pi}\sigma}\, e^{-\frac{(\boldsymbol{R}-\mu)^2}{2\sigma^2}} \tag{7}$$

2.3.2   *The Weighted Bayesian Algorithm Based on The Strongest AP Method.* After establishing the fingerprint database M, the whole positioning region is divided into different small regions according to different locations' RSSI corresponds to the distribution of different APs, and the location fingerprint database of each small region is expressed as (8):

$$fp(i) = \begin{pmatrix} mac_i^1 & rssi_{min}^1 & rssi_{max}^1 \\ mac_i^2 & rssi_{min}^2 & rssi_{max}^2 \\ ------ & ------ & ------ \\ mac_i^n & rssi_{min}^n & rssi_{max}^n \end{pmatrix} \tag{8}$$

mac_i^1 is the MAC address of the first AP detected in the first small region, $rssi_{min}^1$ is the minimum RSSI of the first AP, $rssi_{max}^1$ is the maximum RSSI of the first AP, n is the total number of APs contained in the positioning region. In the online positioning phase, online data R is measured as shown in formula (9)

$$R = \begin{pmatrix} mac^1 & rssi^1 \\ mac^2 & rssi^2 \\ ------ & ------ \\ mac^n & rssi^n \end{pmatrix} \tag{9}$$

Where mac and $rssi$ are the MAC addresses and RSSI values of APs measured online by the location to be determined. In this paper, the RSSI value of n APs can always be received in the experimental area, so there is no case of RSSI cannot be detected.

Regional decision-making process based on the strongest AP method is shown in Figure 2:

As shown in Figure 2, when the region with the highest number of votes is unique, the area is located. If there are several regions with the highest and the same number of votes, the voting will continue in these regions until the region with the highest number of votes is selected.

After voting by the strongest AP method to the corresponding small region, we continue to locate by the weighted Bayesian algorithm. First of all, the difference between the weighted Bayesian algorithm and the Bayesian algorithm lies in that the probability is the weighted probability in the solution of the probability. Once again, the position coordinate of the target to be determined is K maximum probability points for weighted average. The weighted probability is solved as shown in (10):

$$arg\, P(L_i|R) = arg \prod_{j=0}^{n} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(R-\mu)^2}{2\sigma^2}} \cdot w_i^j \tag{10}$$
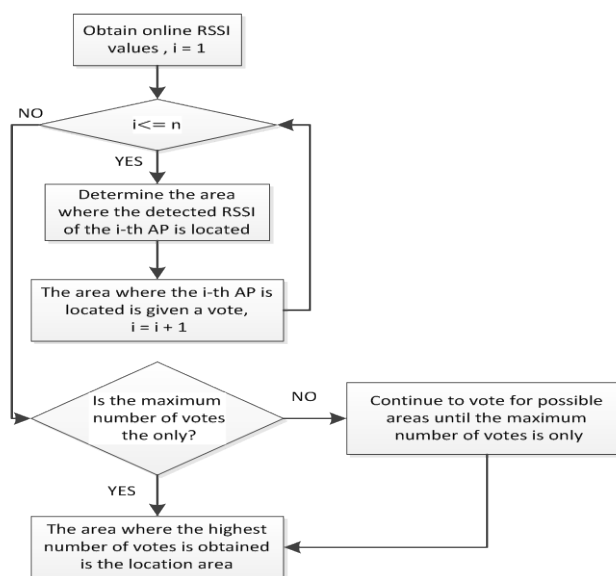

Figure 2 Voting process based on the strongest AP method

The definition of the other parameters in formula (10) is the same as in the Bayesian algorithm, where w_i^j is the probability weight, which is defined as shown in formula (11):

$$w_i^j = \frac{\frac{1}{{\sigma^2}_i^j + 1}}{\sum_{j=1}^{n} \frac{1}{{\sigma^2}_i^j + 1}} \tag{11}$$

In formula (11), ${\sigma^2}_i^j$ is the variance of the RSSI multiple measurement of the j-th AP at position i. Using the inverse of the variance as the coefficient, and normalizing the coefficients at the i-th fingerprint, then the probability weight w_i^j is obtained. Variance reflects the discreteness of the collected data, fingerprint points with large variance, RSSI value fluctuations are large, and the possibility of large differences between the collected data and the mean; fingerprint points with small variance, RSSI distribution is more concentrated, at any time RSSI will not be too far from the mean. When using the weighted probability to calculate the posterior probability, the reciprocal of the variance is added as a coefficient to the calculation of the posterior probability to reduce the RSSI of the AP with a large variance in the weight of the probability calculation, it can eliminate the influence of fluctuation of some RSSI values and improve the positioning accuracy.

After obtaining the probability $P(L_i|R)$ through the formula (10), it needs to be sorted and the first K maximum probabilities are selected, and the coordinate of the location to be determined by the weighted summation is calculated as (12):

$$(\hat{x}, \hat{y}) = \frac{\sum_{i=1}^{k} \left[P(L_i|R) * L_i \right]}{\sum_{i=1}^{k} P(L_i|R)} \tag{12}$$

Therefore, the flow chart of the weighted Bayesian algorithm based on the strongest AP method shown in Figure 3:
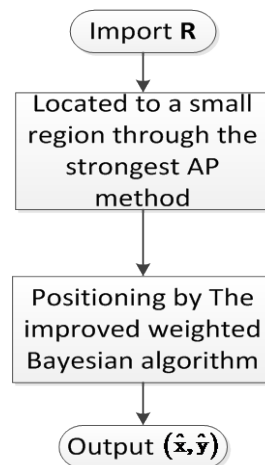

Figure 3 Flow chart of the improved algorithm

3. Experiment

3.1 Experimental Environment

The experiment was conducted at Information Institute of Yunnan University, where one of the aisles and one room were selected for testing. The specific environment shown in Figure 4:
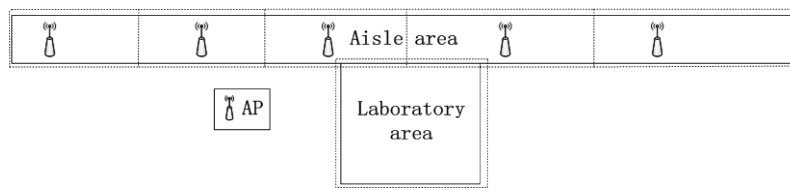
Figure 4 Map of the experimentation environment

Figure 4 is the map of the experimentation environment, consisting of a narrow aisle and a laboratory area with 5 APs randomly distributed in the aisles. After the establishment of the location fingerprint database, the overall positioning region is divided into six small regions. Five APs divide aisles into five regions, the laboratory is a single region, and divide the region according to the signal strength of RSSI value of 5 Aps, the regions have been given in Figure 4. Due to the irregular distribution of 5 Aps, the number of points in each small region may not be the same.
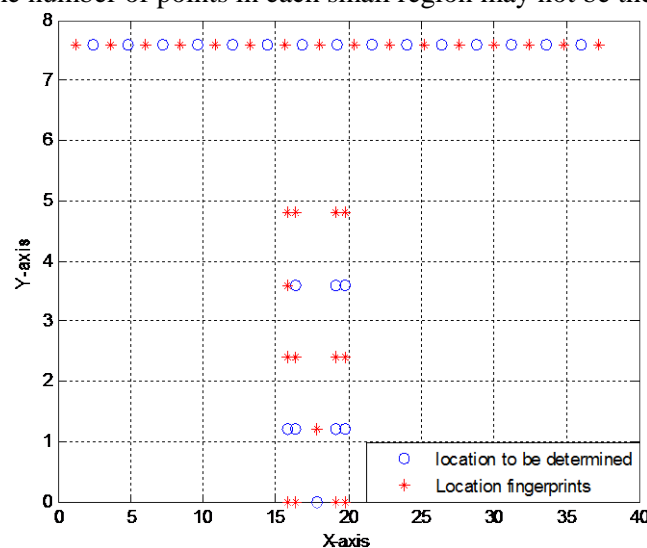

Figure 5 The distribution of location fingerprints and location to be determined

Figure 5 shows the distribution of location fingerprints and the location to be determined, with a total of 53 points, of which there are 30 location fingerprints and 23 points to be determined. The data collection points are well-defined center points in the positioning region, each with a size of $1.2m * 1.2m$. In the offline phase, data acquisition is carried out on 30 fingerprints using Wi-Fi data acquisition software, and the data is collected by the same mobile phone all the time. Each point is collected for 30 times and collected every 3 seconds. After the acquisition is complete, the obvious singular values are removed and the mean μ and standard deviation σ are taken as fingerprints.

3.2 Experimental results and analysis

In the online positioning phase, the RSSI data were collected five times in the same way at 23 points to be determined, taking the average value as the online verification data R. After obtaining the R, the strongest AP method is used to match all the $fp(i)$, and the small region matching the signal distribution is obtained after voting, and then the improved weighted Bayesian algorithm is used to continue positioning in a small region. Figure 6 shows comparison of the positioning error between the Bayesian algorithm and the weighted Bayesian algorithm based on the strongest AP method at each location to be determined. Figure 7 shows comparison of positioning accuracy in different positioning precision. Table 1 gives comparison of the positioning parameters of the two algorithms. Among them, the weighted Bayesian algorithm based on the strongest AP method takes K as 3 when positioning.
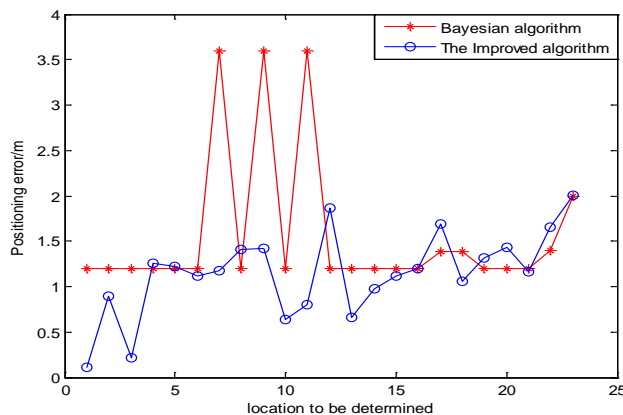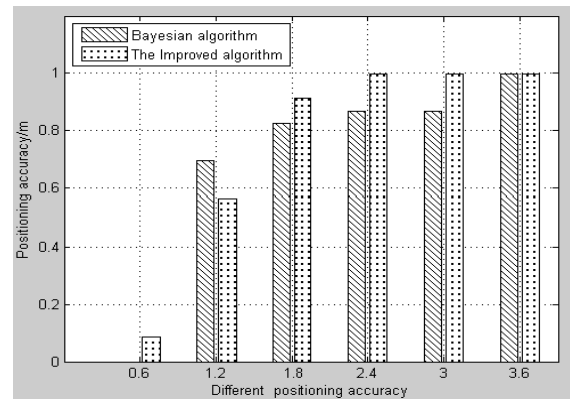
Figure 6 Comparison of positioning error

Figure 7 Comparison of positioning accuracy in different positioning precision

Table 1 Comparison of two positioning algorithms' parameters

Positioning error (m)	average value	minimum	maximum	variance
Bayesian algorithm	1.57	1.20	3.60	0.67
The improved algorithm	1.15	0.11	2.00	0.21

Figure 6 shows comparison of the positioning errors between the Bayesian algorithm and the weighted Bayesian algorithm based on the strongest AP method at each position to be determined. As can be seen from Figure 6, the positioning error of the weighted Bayesian algorithm based on the strongest AP method is lower than the Bayesian algorithm at most points to be determined, and the fluctuation range is small. However, the Bayesian algorithm has larger positioning error and larger fluctuation range.

Figure 7 shows comparison of positioning accuracy between the Bayesian algorithm and the weighted Bayesian algorithm based on the strongest AP method under different positioning precision. It can be seen from Fig. 7 that the weighted Bayesian algorithm based on the strongest AP method has a lower positioning accuracy than the Bayesian algorithm in addition to within 1.2m, the positioning accuracy of the weighted Bayesian algorithm based on the strongest AP method is higher than that of the Bayesian algorithm under other positioning precision, and its positioning precision is higher when the positioning accuracy is 100%.

Table 1 compares the positioning para- meters of the two algorithms. It can be seen that the weighted Bayesian algorithm based on the strongest AP method has lower average positioning error, minimum positioning error, maximum positioning error, and positioning error variance than the Bayesian algorithm.

4.   Conclusion

This paper proposes a weighted Bayesian algorithm based on the strongest AP method. The experimental results show that in the aisle interior region, the weighted Bayesian algorithm based on the strongest AP method has lower positioning error and higher positioning precision than the Bayesian algorithm, and the positioning accuracy within 2.4m can reach 100%, It shows that the improved algorithm proposed in this paper can improve the localization effect based on the original algorithm. The weighted Bayesian algorithm based on the strongest AP method proposed in this paper has a wide range of applications and can provide ideas and directions for the study of indoor scene positioning and navigation. In the future, we will make innovations in fingerprint database construction and data processing and continue to optimize algorithms.

5.   References

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