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Bluetooth Indoor Positioning Based on RSSI and Kalman Filter

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Abstract In recent years, indoor positioning is becoming more and more important. Satellites can position only in the outdoor environment, which is unable to achieve precise positioning in the indoor environment. At present, the indoor positioning is mainly based on wireless signals, such as WiFi, RFID, Zigbee, Bluetooth etc. The cost and power consumption of using WiFi, RFID and Zigbee to realize the indoor positioning is very high and the deployment of WiFi, RFID and Zigbee is inconvenient. In this paper,indoor positioning is based on Bluetooth ibeacon, which is Bluetooth 4.0 standard. The power consumption and the cost of Bluetooth 4.0 is lower than others. In addition, Bluetooth has spread widely in the distance. This paper proposes a new indoor location method, which uses the method of learning to train the Bluetooth signal propagation model in the museum environment and uses the method of weighted least square and four-border positioning to estimate the location of the target object. The experimental result shows that the method is stable and good robustness. The positioning accuracy meets the requirements of the indoor positioning.

Keywords Indoor positioning · Bluetooth ibeacon · Museum · Propagation model

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1 Introduction

At present, the indoor positioning is applied in many fields. Such as the cultural objects information to push, the navigation in the shopping center, the products information and advertising to push, etc. Outdoor positioning development is faster and faster, of which the accuracy is becoming more and more high, but indoor positioning system develops slowly, because of the signal refraction, obstacles block and so on [1]. How to accurately determine the location of the object is an important problem of indoor positioning field. Now outdoor positioning accuracy has reached the centimeter level, but indoor positioning accuracy is lower. How to position accurately in the indoor environment is an urgent problem to solve [2].

The traditional positioning method is not suitable for indoor positioning, because in the indoor environment the receiver can't receive the satellite signal. Although the GPS and inertial navigation can navigate, the cost is high. Now a lot of technologies have been used in indoor positioning: WiFi [3], Bluetooth [4], ZigBee [5], RFID [6], UWB [7], Ultrasound [8], Infrared Signal [9], the Computer Vision [10], the Magnetic field [11], Optical localization [12], and so on. According to the latest Bluetooth protocol—IEEE 802.15.1, Bluetooth has many advantages: low power consumption, low cost, high availability and high precision. The positioning system in the paper uses Bluetooth technology to position. According to the Bluetooth 4.0 standard, the positioning distance can reach 100 m. A Bluetooth beacon can work 1–2 years relying on button battery. Mobiles open Bluetooth and nearly spend few electricity. Bluetooth beacons send data packets by radio broadcast in a while, and the data packets can contain the current position of geographic coordinates (longitude latitude)or any other information (such as cultural objects information, etc.), in addition to the beacon ID information. After provisioning the content of data packets and making the Bluetooth ibeacon in the positioning area (such as a large museum, shopping malls, amusement park, shopping center, etc.), the user can use mobile phones to determine their position. In addition, all smart phones and wearable devices have Bluetooth module, which makes the Bluetooth have a unique advantage in the indoor positioning. Bluetooth has higher precision and saves more energy than WiFi. Compared with ZigBee and RFID, the Bluetooth is deployed more conveniently. And Compared with UWB, Ultrasound, Infrared signal, the Computer vision, Magnetic field and Optical localization, the Bluetooth cost more lower and more easily to achieve [13].

Indoor positioning algorithms based on Bluetooth can be mainly divided into two categories: geometric methods and the algorithms based on RSSI. This paper is based on the RSSI methods. The RSSI method is mainly to acquire Bluetooth access point signal strength (RSS) and determines the positioning area [14, 15]. Wang [16] combines the RSSI and trilateral positioning, and then uses wireless transmission model to convert the Bluetooth signal strength into distance. This method can only use signal strength value, without considering the signal in the obstacles and the attenuation in the air, which makes the accuracy have great error. Hallberg [17] proposes two positioning methods. One is direct to program in the Bluetooth and the other is the indirect method, which does not need to program in the Bluetooth. The first method has high accuracy, but it needs a good Bluetooth hardware as the support. The cost of second method is very low and poor precision, whose error is 10 m. Fernandez [18] proposes to use RSSI information to improve the positioning accuracy. Almaula [19] proposes a trilateration method which is based on Bluetooth. Because the positioning method is simple and only uses the Bluetooth transmission model and trilateral positioning, the positioning results only preliminary estimate the positioning area and is unable to realize positioning accurately. Meanwhile, the result of positioning is not very accurate.

Kotanen [20] uses the extended Kalman filter to process the Bluetooth signal and then gets a distance. This method can obtain the accurate distance only on the base of the precise signal strength. But in the experiment, it doesn't get a real distance. Spratt [21] is proposed a method which is based on the wireless link information of short distance transmission method. This method needs study the Access Points location information and make use of the geometry or the method of numerical to get distance. Altini [22] is proposed a method to the distribution of the Bluetooth signal characteristics and through neural network training to calculate the actual location. The method is via mobile devices to receive the RSSI and then uses neural network to learn the Bluetooth beacon positioning location. Finally it estimates the location of the target object. Bargh [23] and Machaj [24] propose a method which is location fingerprinting method. This method has high accuracy, but they need to collect many fingerprint information. It can be realized in small indoor environment and is not easy to realize in big indoor environment. Pei [25] combines the fingerprint and RSSI to realize localization. Firstly, the fingerprint model was established based on Weibull function and at the same time combines Bayes histogram maximum likelihood algorithm. Under static and dynamic environment, it extracts the 11589 RSSI sampling points. In a static environment, the positioning accuracy can reach meter levels. Compared with other methods, the locating precision improves twenty percent. It already meets the needs of indoor positioning. But the whole positioning process is more complex and not easy to realize. Meanwhile fingerprint database needs a long time to training.

Cruz [26] proposes a method which uses Bluetooth technology to position and navigate indoor. This method uses KNN algorithm to estimate the positioning area of the target object. Firstly, the mobile devices read RSSI. Then this method deposits the data of coordinates of each Bluetooth beacon and RSSI strength in the server as a vector. When the users walk into the positioning area, the users can get positioning coordinates. The mobile devices send the RSSI to the database in the server and the server calculates the distance between the RSSI which the mobile devices collect and the data in the database. The method positions indoor accurately, but the workload of setting up fingerprint database is too big. It should be done manually, which needs to spend a lot of time to set up fingerprint database. Once the coordinates of Bluetooth ibeacons are changed, the database should be set up renewedly. Li [27] improves Omar Cruz algorithm. He proposes to uses the Bluetooth transmission model and analyzes the linear small squares and nonlinear least square method and total least squares method and the weighted least squares. Finally he chooses the linear least square method to estimate the location of the target object. According to the test results the position precision can satisfy the requirements in the indoor environment. But the experiment environment is simple, and there is no specific Bluetooth transmission formula of model.

This paper trains the Bluetooth transmission model and collects the RSSI and the distance parameter. At last, This paper gets a suitable Bluetooth model in the experiment. At the same time this method combines the least square method and quadrilateral localization method to realize the indoor positioning. And this method considers the signal drift, shock and other issues. In the experiment, the Kalman filter is adopted to smooth Bluetooth signal to reduce the RSSI signal drift and shock problem. The experimental result shows that the method has good localization accuracy and do not need to spend a lot of time to set up fingerprint database.

2 Methods

2.1 The Process of Localization Algorithm

Figure 1 shows the whole indoor positioning process. The whole positioning system consists of three parts, (1) real-time acquisition Bluetooth signal system (2) the Bluetooth signal propagation model (3) real-time position output.

Data acquisition system mainly collects Bluetooth beacon signal strength in the indoor environment and then measures the distance between the cell phones and Bluetooth beacon. In the process of the training parameters, we should process the RSSI data. Firstly we get rid of the obvious error of RSSI values and then collect multiple sets of (RSSI, d). In the end, we get the parameters in the formula. In order to verify the accuracy of the

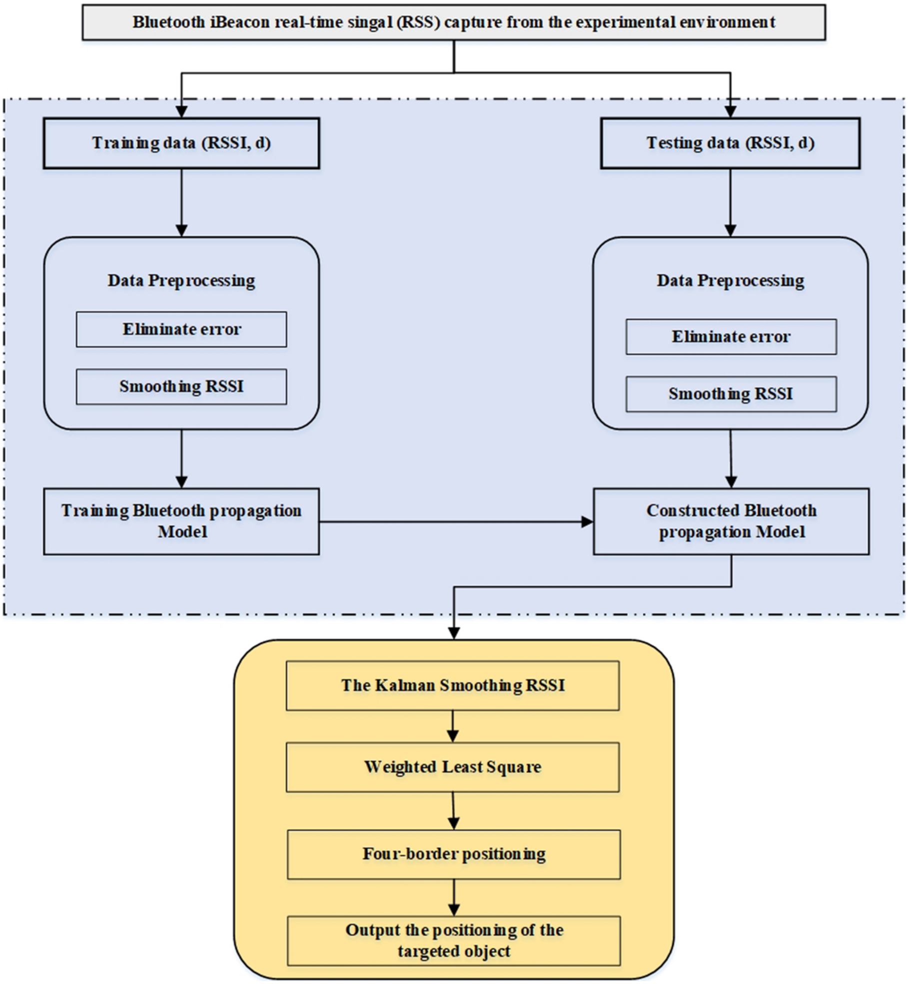

Fig. 1 The experiment schematic diagram

Bluetooth transmission model, the test data is divided two sets. One is test data, the other is training data. Finally, we get the Bluetooth signal propagation model.

2.2 Deriving a RSSI Model

The precision of indoor positioning is one of the urgent problem. Classical regression algorithm, neural network, case -based reasoning, k-Nearest Neighbor and fingerprinting algorithm can all improve the positioning precision, but in the mobile terminal which using could make the positioning speed slow and poor real-time performance. Therefore, this paper proposes a method based on traditional wireless signal propagation model. But traditional propagation model has some difference with Bluetooth signal propagation model, we need to train environment parameter and the standard RSSI value in the 1 m. The wireless signal transmission follows the logarithmic behavior [28, 29]. The formula as shown in (1)

$$\begin{aligned} R = P_R &= P_T + G_T + G_R + 20\log(\lambda) - 20\log(4\pi) - 10n\log(d) \\ &= -(10n\log(d) + (20\log(4\pi) - P_T - G_T - G_R - 20\log(\lambda))) \\ &= -(10n\lg(d) + a) \end{aligned} \tag{1}$$

where R is the RSSI, P_R is the power level of the receiver, which is equal to R, P_T is the power level of the transmitter, G_T is the antenna gains of the transmitter, G_R is the antenna gains of the receiver, λ is the wavelength of Bluetooth signal, n is the attenuation factor and denotes influence of walls and other obstacles, d is the propagation distance from sender to receiver, a is the parameter which is related to P_T, G_T, G_R and λ.

Thus propagation distance can be represented by RSSI as following equation.

$$n_i = \left(\frac{RSSI - a}{10\mathrm{lgd}_i}\right) \tag{2}$$

RSSI is the received power of reference node, d is the distance between the two reference nodes and it is known. We can get environmental factors between the two reference nodes i, j. For every positioning area we can get some pairs of environmental factors. Because fluctuations in the RSSI measurements exist, so the final result of environmental factors is not the same. Suppose in t time n stay in the same value. N of the nearest reference node, we get N environmental factors, taking mathematical expectation we have:

$$\hat{n} = E\left(\frac{RSSI_i - a}{10\mathrm{lgd}_{ij}}\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{RSSI_i - a}{10\mathrm{lgd}_{ij}} \tag{3}$$

$i = \{1\ldots N\}$ is the set of all reference nodes, the *RSSI*, *a* is updating as time *t* as period. In order to reduce the error of environmental factors generated by measured data, take the expectation of measurement result of *n* time. Take period T, let updating time $n = T/t$, so the estimated environmental factors are:

$$\hat{n} = E\left(\frac{RSSI_i - a}{10\mathrm{lgd}_{ij}}\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{E * RSSI_i - a}{10\mathrm{lgd}_{ij}} \tag{4}$$

The $E(RSSI) = 1/n\sum RSSI$, when the mobile enter the positioning unit, the reference nodes transmit the value A and n to the mobile as the environmental factor. In this work, we gathering different distances and RSSI value among the four reference nodes in the testing area. Using (4) we finally get a = 62.5, n = 2.65 to represent our special testing area, so (1) can be transformed into (5):

$$RSSI = -(10 * 2.65 \lg d + 62.5) \tag{5}$$

2.3 Smoothing RSSI

Using the formula (5), it is easy to use a mobile device to get RSSI and calculate the distance between the user and access points. But, as mentioned before, the RSSI is not stable and it is prone to be refracted have diffraction and be blocked by wall and other obstacles. As shown in Fig. 2, the phone can gather the A, B, C, D Bluetooth beacons RSSI. But the RSSI is not primitive, it has been refracted has diffraction and is blocked by wall and other obstacles. So, we should use algorithms to deal with it and then we can estimate the location of the users accurately. This paper makes filtering algorithm process the RSSI. This paper uses average filtering and median filtering and gaussian filtering and kalmia filtering to process the RSSI. In some extent, in can solve the problem of RSSI signal drift. But by contrast, the Kalman is the most effective to solve the problem.

The basic idea of Kalman filtering is: using the minimum mean square error as the best estimate of time, using the state space model of signal and noise, use a moment before estimation and the current observations to update the estimation of the state variables and then getting the estimation (Fig. 3).

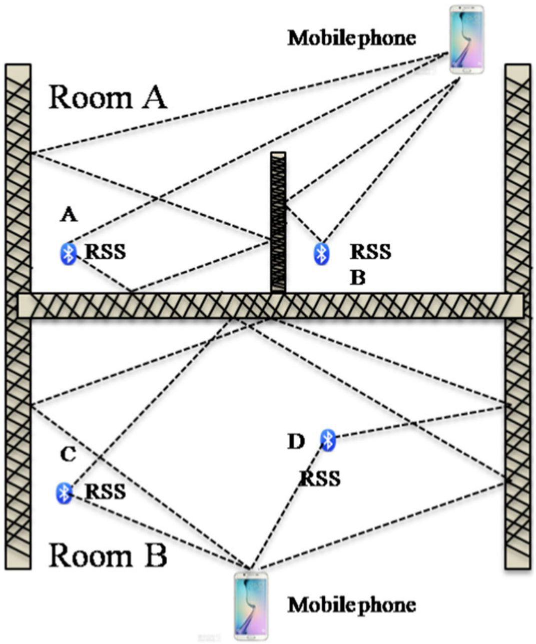

Fig. 2 The signal block and refraction of RSS

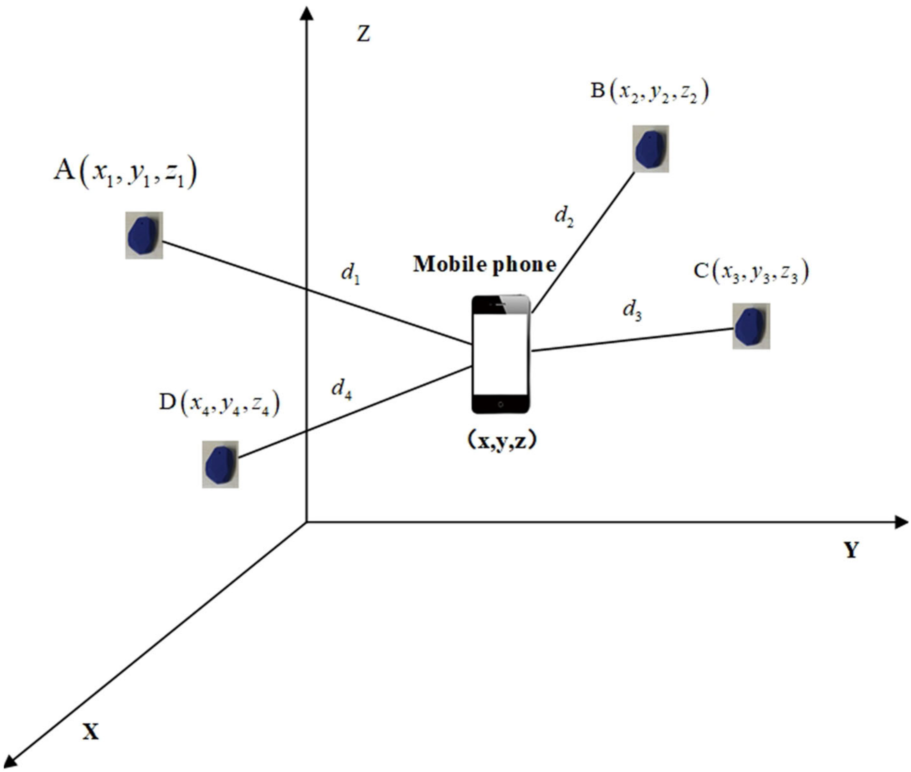

Fig. 3 Four-border positioning concept

The state equation:

$$x_k = \varphi_{k,k-1} * x_{k-1} + w_{k-1} \tag{6}$$

The observation equation:

$$y_k = x_k + v_k \tag{7}$$

Combined with the state Eq. (6) and observation Eq. (7), we can get Eq. (9):

$$\hat{x} = E[x_0] = \bar{x}_0 \tag{8}$$

$$p_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right] = p_{x_0} \tag{9}$$

2.4 Weighted Least Square

Weighted least square Least square algorithm supposes that all the elements of error vector have the same variance, and all the elements are uncorrelated. This is not true for real situation. So a weight should be added to each element of error vector. Weighted least square algorithm provides the right solution, and it can be depicted as following.

$$\mathrm{var}(e) = w$$

$$W = CC^T$$

$$C = diag(\sqrt{w_1}, \sqrt{w_2} \ldots \sqrt{w_m})$$

$$C^{-1}Ax = C^{-1}b$$

$$x_{WLS} = (A^T W^{-1} A)^{-1} A^T W^{-1} b \tag{10}$$

Weighted least square algorithm minimizes the following square error.

$$Q(x) = e^T W^{-1} e \tag{11}$$

2.5 Four-Border Positioning

Let (x, y, z) be the unknown 3D coordinate of target Bluetooth device. Let $(x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), (x_4, y_4, z_4)$ be the known 3D coordinate of the reference Bluetooth devices, whose signal can be received by target Bluetooth device. Let d1, d2, d3 and d4 be the known distances between target Bluetooth device and the four reference Bluetooth devices. Four-border (FB) positioning method can be described as following.

$$\begin{aligned}
(x - x_1)^2 + (y - y_1)^2 + (z - z_1) &= d_1^2 \\
(x - x_2)^2 + (y - y_2)^2 + (z - z_2) &= d_2^2 \\
(x - x_3)^2 + (y - y_3)^2 + (z - z_3) &= d_3^2 \\
(x - x_4)^2 + (y - y_4)^2 + (z - z_4) &= d_4^2
\end{aligned} \tag{12}$$

3 Experiments

3.1 Environment and the Design of the Positioning System

This paper uses Huawei honor 6 as the experimental mobile phone and the Bluetooth ibeacons are produced by the Estimote. The indoor area covers an area of 140 square meters. 17 Bluetooth ibeacons are deployed in the Experimental environment, as shown in Fig. 4. After testing, each positioning area can collect the Bluetooth signal.

There are mainly three parts in the whole positioning system: Bluetooth ibeacon network, mobile devices and the server, as shown in Fig. 5. The server is used to record Bluetooth signal strength and stores the coordinates of Bluetooth beacon in the laboratory. As long as the mobile phone collects Bluetooth beacon signal strength, the server can calculate the distance between the users and ibeacons by the database in the server.

3.2 The Result of RSSI Model

We use mobile phones to collect 17 Bluetooth beacons RSSI in the experimental environment by every 10 ms. We spend 10 min collecting the RSSI and 60000 RSSI data is collected. The data is divided into two groups, one is experimental data, the other is test

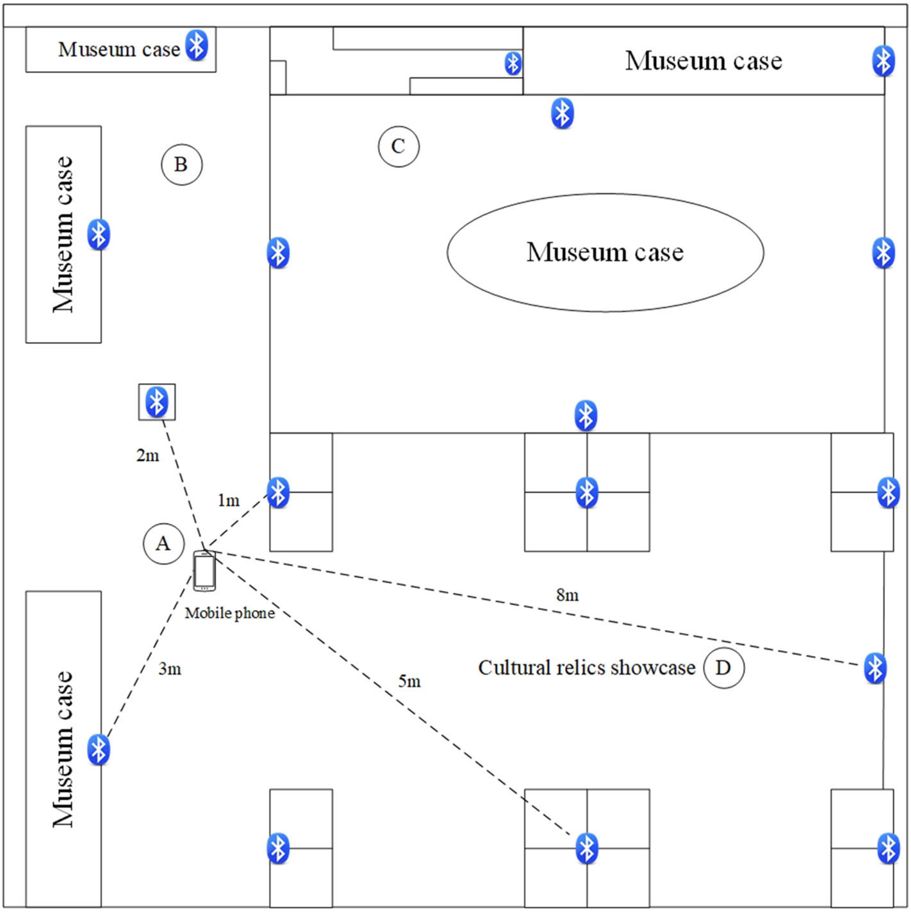

Fig. 4 The detailed map of the capital museum

data. First, We work with RSSI data and remove some trip points as well as the obvious error points. And then we average the RSSI. This can reduce error partly which causes by the RSSI drift. It is concluded that the Bluetooth transmission model is more accurate. Finally, we get the parameter a and n, which is respectively 62.5 and 2.65. We can get generation formula (5). The result is shown in Fig. 6. In order to verify the accuracy of the formula, we input the test data and find it can match well with the formula (5). In the Fig. 6, the blue curve is obtained by the experimental data and the red points is obtained by the test data.

3.3 The Result of Smoothing RSSI

Using RSSI to calculate the distance, we, to filter the RSSI for signal drift, oscillation and other issues. We chose the mean filtering and Kalman filtering to process the RSSI. Kalman filtering can weaken the deviation caused by noise superposition. After dealing with the Kalman filtering, the stability of the RSSI is better than before. In the Experiment, we collect the RSSI data in 8 m. As shown in Fig. 7, the black spots is the initial data. The

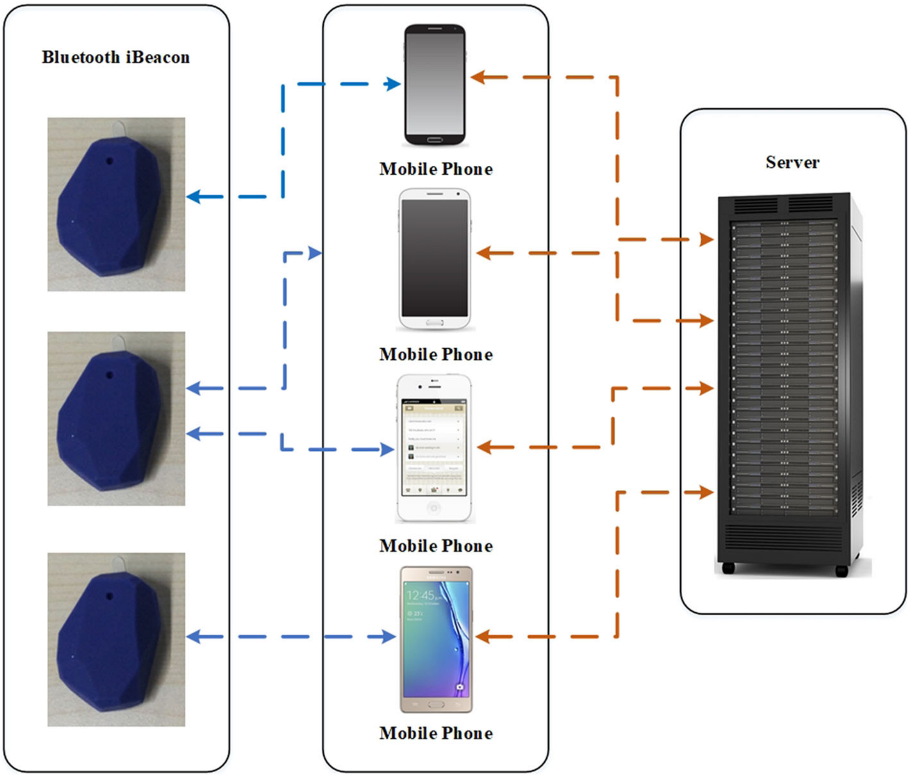

Fig. 5 Bluetooth iBeacon indoor positioning system

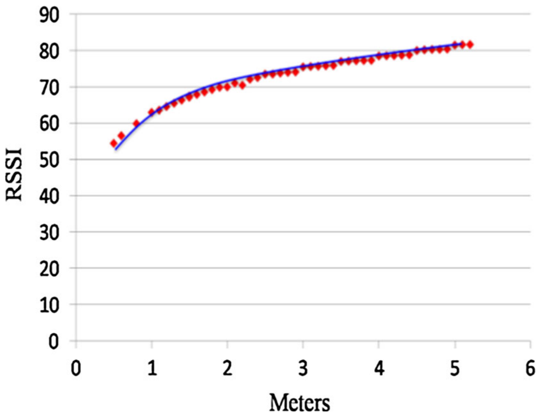

Fig. 6 Bluetooth signal propagation model

distance is not accurate by the formula 5, so we choose the filtering to smooth the RSSI. Through comparison, we can see that the Kalman filtering and mean filtering can reduce and weaken the RSSI signal drift and shock to a certain extent, but the effect of the Kalman filter is much better than average filtering, as shown in Fig. 7. The black spots is the initial data and the wathet spots is handled by average filter and the red spots is handled by Kalman filter.

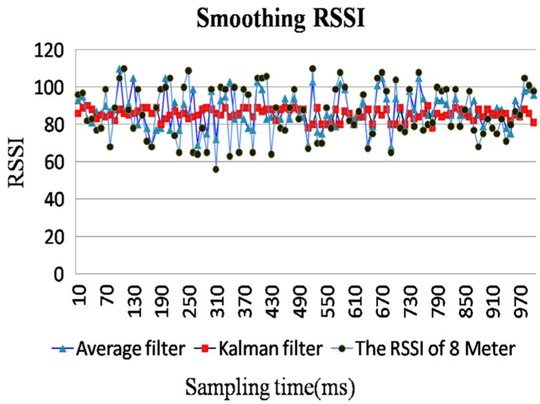

Fig. 7 Contrast after pretreatment before processing

In order to test the effect of Kalman filtering further, we collect the RSSI data in 1, 4.5, 5 and 6.5 m, in every position, we spend 5 min collecting the RSSI data and then select each position of 450 data. Finally, we use Kalman filtering to process the data. After processing, we find that the Kalman filter can solve the problem of signal drift and shock to some degree which can improve the accuracy of positioning. The result of Kalman filtering is shown in Fig. 8.

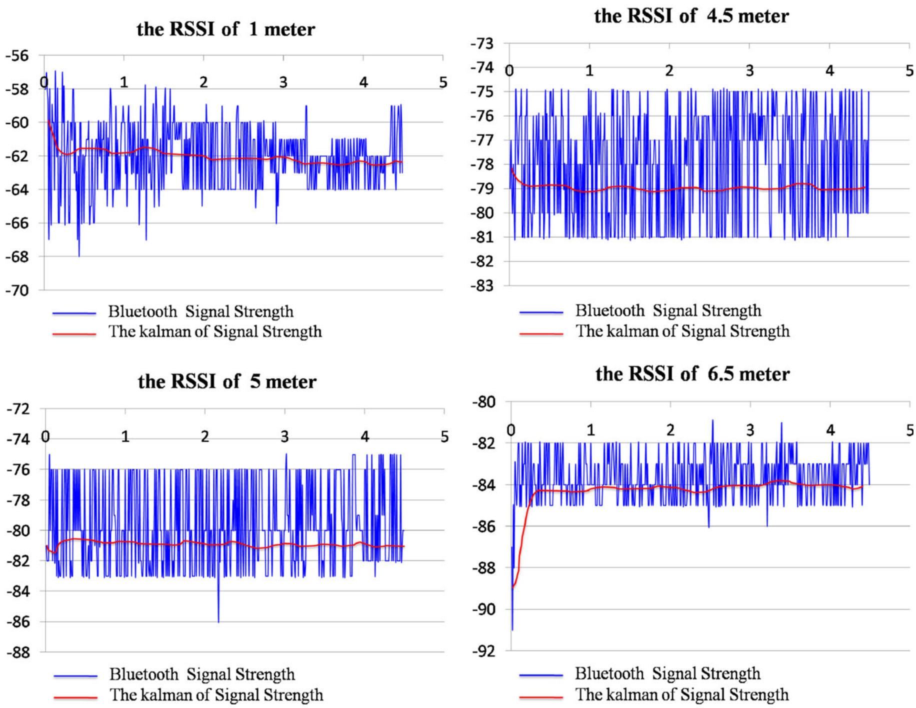

Fig. 8 The RSSI after Kalman filter

3.4 Experimental Results and Analysis

In the experiment, we choose eight positioning area in the indoor location, which is respectively (100,100,100), (200,400,150), (350,250,100), (467,375, 60), (565,405,120), (600,600,200), (745,565,160), (890,350,110), and then we get the position of the target object. Compared with the method of fingerprint algorithm, centroid algorithm, least square method, our method is relatively accurate. The result is shown in Fig. 9. Then we calculate the distance between the real points and experimental points and find that our method is superior to other algorithms, as shown in Fig. 10. Compared with the fingerprint algorithm, the accuracy of our method is close to it.

In Fig. 9, the red tag is the real coordinates, the blue tag is obtained by our algorithm coordinates, the pink tag is obtained by the fingerprint method, the black box tag is obtained by least square method, the green tag is obtained by the trilateration localization algorithm, the black sexangle is obtained by the centroid algorithm. From the Fig. 9, our method is close to the real position coordinates and the positioning accuracy is significantly higher than trilateration localization algorithm, centroid algorithm and least square method. Compared with fingerprint algorithm, the accuracy of our method is very close to the fingerprint algorithm.

In addition, by calculating the distance between the real points and the test points, we can compare the positioning accuracy more intuitively. We totally test eight sets data, the coordinates of which are (100,100,100), (200,400,150), (350,250,100), (467,375, 60), (565,405,120), (600,600,200), (745,565,160), (890,350,110). According to the experimental results, the distance of the first positioning point and the real positioning point are: 0.25, 0.29, 1.45, 2.65, 3.55 m by our method, the method of fingerprint algorithm, the least square method, trilateration localization algorithm and centroid algorithm. The distance of the second positioning point and the real positioning point are: 0.29, 0.5, 1.88, 3.88, 5.86 m. The third are: 0.34, 0.39, 1.55, 2.88, 4.56 m. The fourth are: 1.04, 1.03, 2.78, 4.85, 6.63 m and the fifth are: 0.99, 1.09, 2.25, 3.66, 4.56 m. The sixth are: 0.3, 0.4, 1.59, 2,

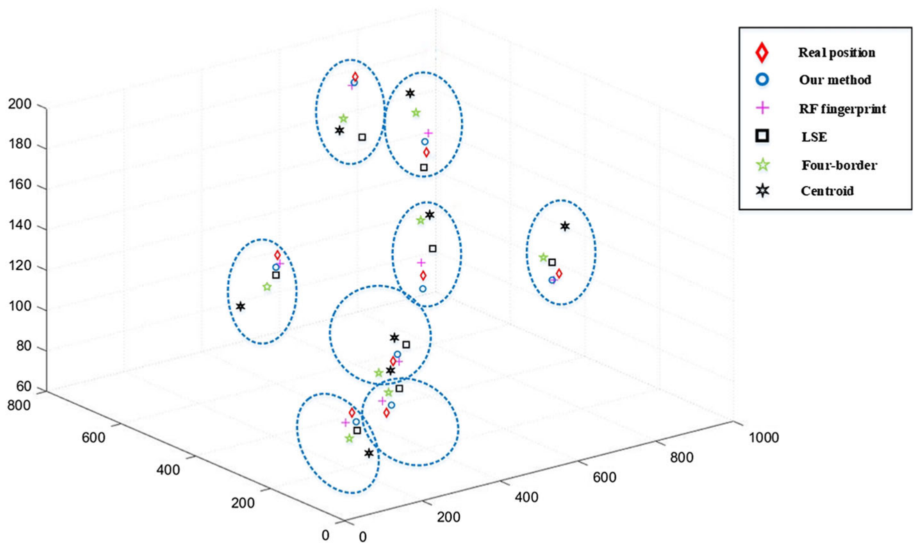

Fig. 9 The estimation of testing points positioning and real position

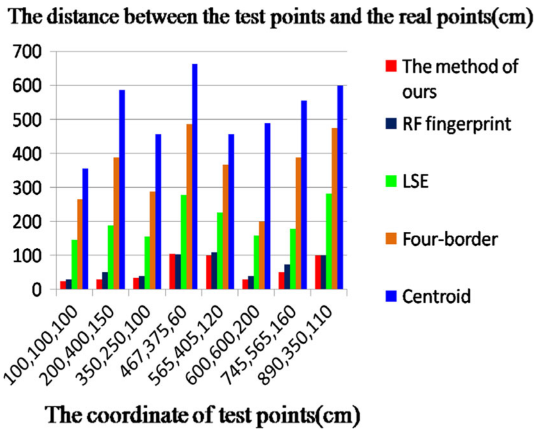

Fig. 10 The distance between the test points and real points

4.89 m. The seventh are 0.5, 0.74, 1.78, 3.88, 5.56 m and the eighth are 0.99, 1, 2.81, 4.74, 5.99 m. The distance between real positioning points and testing points by our method is obviously smaller than the least squares method, trilateration localization algorithm and centroid algorithm. Compared with the fingerprint algorithm, the accuracy is very close, as shown in Fig. 10.

This paper puts forward a concrete Bluetooth transmission model based on the RSSI. We collect RSSI and remove some obvious false RSSI and combine the distance to get the parameter of a and n. Finally, we get a proper Bluetooth propagation model. Then we collect another RSSI to match the Bluetooth transmission model, It find that the test data and the Bluetooth transmission model match well. So the Bluetooth transmission model in this experimental environment is relatively accurate. In the indoor environment, the Bluetooth signal easily affects by obstacles, the human body, which make the Bluetooth signal refraction and diffraction. Refraction and diffraction could lead to the Bluetooth signal volatility and drift. Mean filtering, average filtering, gaussian filtering and Kalman filtering can solve the problem. These algorithms have their own characteristics to solve the problem. Such as mean filter, the method is simple and easy to implement, but the precision is not high and the effect is not good. The effect of gaussian filtering is much better than the mean filter, but it is complicated and takes up more memory space. Kalman filter can weaken the deviation caused by noise superposition to some degree, after dealing with the Kalman filter the stability of RSSI is better than before. At last, by contrast, it find that the effect of Kalman filter is best which is shown in Fig. 7. Then combined with the weighted least squares method and four-border positioning, the positioning accurate is increased in the experiment.

4 Conclusions and Future Work

In this paper, we proposed a positioning method based on the RSSI. We have trained a Bluetooth signal propagation model. Firstly, we use mobile phones to collect RSSI data and remove some wrong points. Then according to the formula 4, we get the parameters of n and a and finally get the formula 5 to train a proper Bluetooth transmission model. It is concluded that the Bluetooth transmission model is respectively accurate in the experimental environment. To get the accurate positioning area, first, we should ensure the RSSI accurate. In order to solve the problem of RSSI signal drift and superposition, we use the Kalman filter to suppress the RSSI oscillation and drift. Kalman filtering can weaken the deviation caused by noise superposition. After filtering, the stability of RSSI is better than before. In this experiment, 17 Bluetooth beacons are deployed and we use weighted least squares to improve the positioning accuracy. Finally, we combine with four-border positioning method to get the coordinates of target objects. Compared with the method of fingerprint algorithm, we don't need much more fingerprint data and save a lot of resources. We also can realize rapid positioning and accurate positioning The positioning accuracy meet the requirements of the indoor positioning.

The experimental results show that the positioning accuracy meet the requirements of the indoor positioning. However, the fourth positioning point and the fifth positioning point are far from the real positioning point. The error is bigger than other points. Although the accuracy meets the requirements, but compared with other positioning point, it is not precision. The reason is that the fourth positioning point and the fifth positioning point are near the obstacles. Filtering just weaken the RSSI drift to some extent. The next step, we will study the RSSI signal drift as well as the superposition problem tomake the RSSI signal is more stable and the positioning accuracy is more precision.

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