RSSI Based Bluetooth Low Energy Indoor Positioning

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***Abstract*—The presentation of Bluetooth Low Energy (BLE; e.g., Bluetooth 4.0) makes Bluetooth based indoor positioning have extremely broad application prospects. In this paper, we propose a received signal strength indication (RSSI) based Bluetooth positioning method. There are two phases in the procedure of our positioning: offline training and online locating. In the phase of offline training, we use piecewise fitting based on the lognormal distribution model to train the propagation model of RSSI for every BLE reference nodes, respectively, in order to reduce the influence of the positioning accuracy because of different locations of BLE reference nodes. Here we design a Gaussian filter to pre-process the receiving signals in different sampling points. In the phase of online locating, we use weighted sliding window to reduce fluctuations of the real-time signals. In addition, we propose a distance weighted filter based on triangle trilateral relations theorem, which can reduce the influence of positioning accuracy due to abnormal RSSI and improve the location accuracy effectively. Besides, in order to reduce the errors of targets coordinates caused by ordinary least squares method, we propose a collaborative localization algorithm based on Taylor series expansion. Another important feature of our method is the active learning ability of BLE reference nodes. Every reference node adjusts its pre-trained model according to the received signals from detecting nodes actively and periodically, which improve the accuracy of positioning greatly. Experiments show that the probability of locating error less than 1.5 meter is higher than 80% using our positioning method.**

Keywords*—*Bluetooth Low Energy; Active Learning; Gaussian Filter; Triangle Trilateral Relations Theorem; Taylor series expansion;

I. INTRODUCTION

Indoor positioning is realized by establishing a tracking network constituted by wireless sensors and perceiving users' states in real time. The current commonly used wireless sensor positioning technology includes Infrared positioning, typical system implementation like Active Badge in [1]; Ultrasonic positioning, typical system implementation like Active Bat in [2]; Wi-Fi positioning, typical system implementation like RADAR in [3] and Horus in [4]; RFID positioning, typical system implementation like LAND MARC in [5]; and signal propagation model based ZigBee in [6] positioning technology. However, position accuracy of infrared positioning is relative low, which can only achieve room-level location. Although ultrasonic positioning can realize cm-level position accuracy, it needs costly equipment with special hardware. Both of these two technologies are difficult to realize large-scale deployment and promotion. What is even worse is that they cannot realize wide-range positioning due to poor penetration of the wireless signals. The implementation of RFID positioning is based on the idea of reference point, namely the accuracy of positioning depends on the density of nodes deployed. Due to the short range and high latency defects of 802.15.4 wireless technology, ZigBee positioning has certain limits on positioning in real-time when using RSSI. In fact, Wi-Fi positioning is one of the hot points in Location Based Services (LBS) thanks to its widely deployed infrastructures and general equipment. However, realizing high accuracy of Wi-Fi positioning requires constructing huge fingerprint database. In addition, it is difficult to eliminate the differences between APs.

Bluetooth indoor positioning is one of the hotspots in LBS since Bluetooth 1.0 published in 1999. At present, more than 80% of mobile devices support Bluetooth, including nearly 100% of smart phones and PDAs. Besides, it is easy to establish an economic Bluetooth wireless sensor networks due to its low cost and low power consumption. BLE adopted by Bluetooth Special Interest Group in 2010 has many improvements compared with the traditional standard. The most prominent feature is its low energy consumption. Very low operation and standby power can make a button battery works continuously for several years, which makes using Bluetooth to realize the indoor positioning has broad application prospect. Another advantage is the longer range than originals. It can be as long as 100 meters by adjusting the transmit power, which makes it possible to realize wide range indoor positioning by using Bluetooth 4.0. In addition, Bluetooth 4.0 is fully compatible with previous standards and retains the adaptive frequency hopping mechanism, which makes the Bluetooth positioning more feasible and reliable than other positioning technologies.

This paper focuses on BLE indoor positioning. BLE provides several major kinds of parameters related with location estimation such as received signal strength indicator (RSSI) and link quality indicators (LQI). We concern with RSSI only in this paper. RSSI based positioning methods commonly used can be divided into range-based methods and range-free methods and we will study the former in this paper. Therefore, the algorithm developed in this paper is to find the relation between RSSI and range, which would be used in real-time location. Lots of work has been done on this direction. [7], [8], [9] focus on optimizing correlation model between RSSI and distance, while [10] is interested in establishing the relational database for RSSI and distance.

In this paper, we divided our positioning method into four stages. The first stage is offline training for BLE reference nodes, namely the establishment of accurate RSSI propagation model. The second stage is the smoothing process of real-time RSSI and process of abnormal RSSI detection. The third stage is the real-time positioning process, which we proposed a cooperative localization method. The fourth stage is active learning process for BLE reference nodes, namely the adjustment of RSSI propagation model. It should be noted that the last stage is performed periodically and not synchronized with the real-time positioning.

Therefore, we put forward some improvements to enhance the positioning performance in our method in this paper. First of all, using the mode of unified sampling but training alone for every BLE reference node in training process, which can reduce differences between reference nodes due to different locations without increasing the workload. Secondly, taking advantage of the combination of Gauss filter and piecewise function in training process in order to fitting the RSSI's propagation characteristics in real environment at the most extent; The third, we propose a distance weighted filter based on triangle trilateral relations theorem to eliminate the abnormal RSSI in real time, instead of just using weighted sliding window. The fourth, we propose a collaborative localization algorithm based on Taylor series expansion to optimize the result of multilateral positioning. Last but not least, an active learning method for reference nodes is proposed to adjust the RSSI propagation model periodically, which can improve the robustness of positioning method in practical use. Our positioning method is illustrated by the following image.

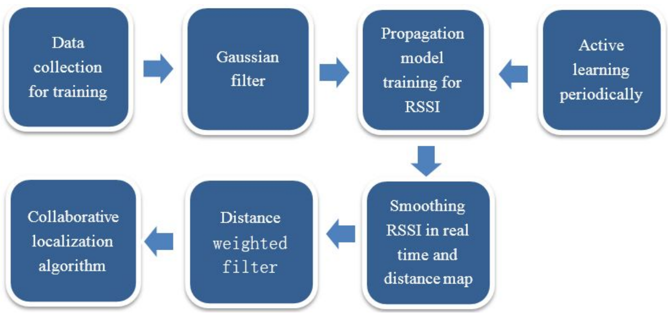

Figure 1. Flow diagram of BLE positioning method

The most contribution of our paper is that we provide an accurate transmission model for BLE, as well as a complete position method with good performance using abnormal detection and active learning.

The paper is organized as follows: Section II describes the offline training for RSSI propagation model of BLE reference nodes; Smoothing process of real-time RSSI and abnormal RSSI detection will be described in section III. Section IV describes the cooperative localization method. Active learning method is shown in Section V and, finally, conclusions are discussed in Section VI.

II. OFFLINE TRAINING OF RSSI PROPAGATION MODEL

A. *Basis of Attenuation model of RSSI of BLE*

Numerous theoretical derivation and empirical formula show that there is a definite relationship between the RSSI and range. In fact, there are repeatability and interchangeability in measurement of RSSI and moderate changes of RSSI have rules to follow. In this paper, we analyze the relationship between BLE RSSI and transmission distance based on the commonly used logarithmic attenuation model in [11] that is shown in (1).

$$[P_r(d)]_{dBm} = [P_r(d_0)]_{dBm} - 10nlg\left(\frac{d}{d_0}\right) + X \qquad (1)$$

$P_r(d)$ represents the received signal strength of receiving end when it is d away from transmitting end; $P_r(d_0)$ represents the received signal power when the it is the reference distance away from transmitting end and d_0 is the reference distance; n is attenuation factor for RSSI; X is normally distributed variable whose average is 0. It can be seen from above, RSSI decreases as distance increase and each RSSI mapping for a distance value. However, we would use a simplified formula below based on (1), which we set the reference distance is 1 meter.

$$P = A - 10n\lg d \qquad (2)$$

Here, we use P represents the received signal strength of receiving end when it is d away from transmitting end; A presents the received signal power when the it is 1m away from transmitting end and n represent the attenuation factor.

B. *Unified sampling but training alone*

We design and develop four CC2540 development boards integrated with BLE function as the BLE reference nodes in positioning in our research. Although the structures and features of these nodes are of the same kind, their propagation model of RSSI has certain differences because of different location. In order to eliminate the heterogeneities between reference nodes, we develop the RSSI sampler on smart phones, which is able to sample uniformly for different reference nodes at a time. Training method takes the MAC address marked in the training data of reference node as an identifier to isolate it and performs training for these nodes respectively. The result is shown in figure 2.

The results show that unified sampling but training alone can reduce the differences between reference nodes in real environment, which could improve the accuracy of positioning in real time without increasing the workload.

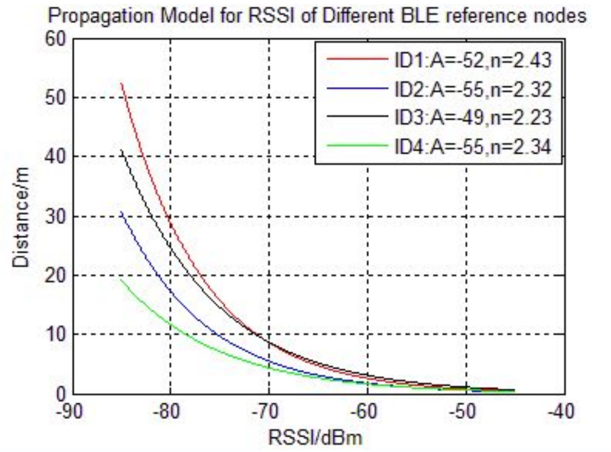

Figure 2. Propagation Models of different reference nodes

C. Gaussian filter for training data

The value of RSSI will fluctuate because of the randomness of RF signals when you collect the training data. Consequently, there is no one-to-one correspondence relationship exists between RSSI and distance any more, which makes it hard for sample data used directly. Therefore, the premise of improving accuracy of positioning is to reduce the randomness of training data.

The method commonly used is averaging the data obtained from multiple sampling and taking the result as the valid value. It can be seen as shown in formula (3):

$$RSSI = \frac{1}{m}\sum_{i=1}^{m} RSSI_i \tag{3}$$

However, using the averaging method does not reflect the actual features of RSSI in real environment. What's the worse, the effects of reducing the randomness would be remarkable only when large amount of data is collected, especially there is a big random perturbation exists in data, which increase the workload greatly.

Another method is to take the RSSI and distance of known pairs of nodes as reference when you calculate the distance between targets and known nodes, namely, using the existing information to adjust the real-time RSSI. However, it is not always effective because of differences that exist in structures and real environment of different nodes. Besides, there is no exact proportional relationship between RSSI and distance.

Lots of research has been done on RSSI propagation and they attempt to explain the fluctuations of RSSI. Reference [12] uses the Markov model to perform joint state estimation of no-line-of-sight propagation and line-of-sight propagation, which aims at judging whether the RSSI suffers reflection and diffraction effect. However, the method is of complicated calculating and multipath effect is difficult to quantify. Therefore, practicality of this method is not high.

It is known to all that the limit distribution of the sum of independent random variables is normal distribution. In fact, a large number of experiments show that the randomness of RSSI is relative dependent and the distribution of RSSI at a certain point can be thought as a Gaussian distribution. To be cautious, we perform extensive statistical analysis on BLE RSSI and the result is shown in figure 3.

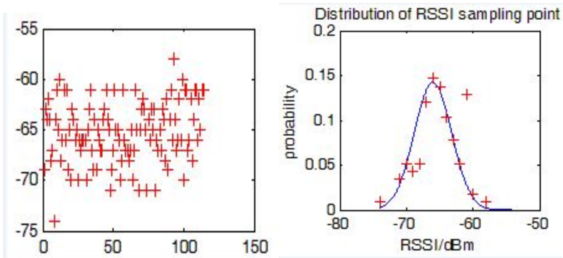

Figure 3. Distribution of BLE RSSI at a certain point

As can be seen above, Gaussian distribution can reflect the randomness of RSSI in real environment better. Therefore, we will use Gaussian filter to filter out the values of RSSI of small probability to solve the problem that propagation of BLE RSSI are susceptible to interference, as well as to eliminate those short disturbance of small probability. Algorithm process as shown below:

1. Using an array to store the training data for every sampling point.
2. Calculating the mean and variance of every Gaussian filter with the formulas below.

$$\mu = \frac{1}{m}\sum_{i=1}^{m} RSSI_i \tag{4}$$

$$\sigma^2 = \frac{1}{(m-1)}\sum_{i}^{m}(RSSI_i - \mu)^2 \tag{5}$$

$$f(RSSI) = \frac{1}{\sigma\sqrt{(2*\Pi)}} e^{-(\frac{(RSSI-\mu)^2}{2*\sigma^2})} \tag{6}$$

3. Determining the effective range of RSSI according to μ and σ^2 the critical value choose to be 0.6 according to analysis of large amount of trainging data. Fomula is shown as below.

$$0.6 < \int_{MIN\_RSSI}^{MAX\_RSSI} f(RSSI)\,dRSSI < 1 \tag{7}$$

4. Averaging the values which are in the effective range and taking the results as the input of the training model.

D. Piecewise fitting based on least-square in model training

1) Least Squares(LS) based training

Least Square method aims at finding the best match function by minimizing the sum of squared residuals. Its basic principle is as follows. For a data set { (x_i, y_i) }, making sure that the sum of squared difference between target function $f(x)$ and the real value of y_i to the minimum. However, it is used as follow in our research.

1. Setting the number of sampling points m and calculating the actual distance d between the reference nodes and sampling points according to coordinates of reference nodes and sampling points.
2. Collecting training data at each sampling point and performing Gaussian filtering described above. Consequently, each reference node can get m pairs of mapping between $RSSI$ and d $(RSSI, d)$.
3. Making following changes according to (2):

$$\beta_0 = A, \beta_1 = n, X = 10lg(d), Y = P$$

$$Y = \beta_0 - \beta_1 X$$

$$Q = \sum_i^m (Y_i - \beta_0 - \beta_1 X_i)^2$$

So we can get β_0 and β_1 by minimizing the average loss function Q. For extremum problems, making the partial derivative to 0, which can be seen as follows.

$$\beta_0 = \frac{n\sum X_i^2 \sum Y_i - \sum X_i \sum X_i Y_i}{n\sum X_i^2 - (\sum X_i)^2} \tag{8}$$

$$\beta_1 = \frac{n\sum X_i Y_i - \sum X_i \sum Y_i}{n\sum X_i^2 - (\sum X_i)^2} \tag{9}$$

In this way, we can get the attenuation factors and reference RSSI for each BLE reference node.

2) *Piecewise fitting*

It is known to all that the attenuation speed of BLE RSSI will become faster as the transmission range exceeds a certain distance. Consequently, the fitting degree of the model will decline gradually. The tiny deviation of RSSI can lead to a large error on distance calculating at this point. Therefore, in order to improve the accuracy and robustness of distance calculating as well as the error due to randomness of RSSI, we design the piecewise fitting method for propagation model of BLE RSSI, which is shown as follows.

1. Performing model training based on LS described above for every reference node respectively according to its ID. Drawing the initial curve of propagation model of every reference node.
2. Setting the reasonable segmental threshold for the model, namely the value of RSSI at the critical point on the curve. For example, if the transmission range of BLE reference node is 20 meters, we can set threshold to the corresponding RSSI value of 10 meters.
3. Dividing the training data that has been preprocessed into two parts according to the threshold for each reference node: the data of one part is larger than or equal to the threshold and the other is smaller than threshold. Performing the same training process for each part of training data and every BLE reference node can obtain two propagation models of RSSI.

Now that we finish the model training process of BLE RSSI and its ranging performance can be seen in figure 4 when the transmission range is 10 meters and 20 meters.

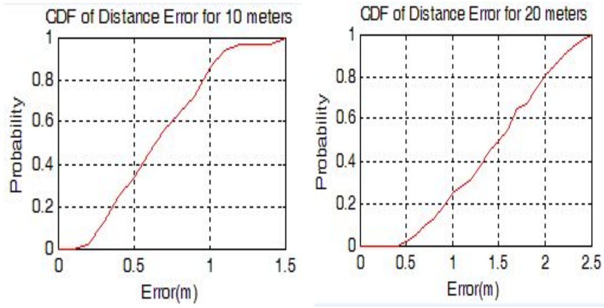

Figure 4. The cumulative probability distribution(CDF) of training model that uses piecewise fitting based on LS

III. Smoothing process of real-time RSSI and process of abnormal RSSI detection

A. *Weighted sliding windows*

It can be seen from figure 3 that though the value of BLE RSSI are subject to Gaussian distribution, its randomness can lead to variation as large as 12dbm. This is why we must smooth the real-time received RSSI in high accuracy positioning. Here, we use the method of weighted sliding windows to reduce the stochastic volatility of RSSI in real time.

Weighted sliding windows based processing has the following advantages: 1) by controlling the value of each weights in the sliding windows, it can not only reduce large fluctuation of RSSI by using history information, but also reflect the current RSSI better; 2) weighted sliding windows is simple to implement and its size is easy to control. In this way, we neither need a certain amount of accumulated data which cannot be meet in real-time for moving target, nor need to consider the history information too much that lead to decrease of real-time performance.

We have done a lot of attempt in our research on people's walking speed and corresponding size and weights of sliding windows in positioning according to [13]. For example, when people walking at a speed of 1.2m/s and the broadcast cycle of reference nodes are 500ms, we find that the size of sliding windows to 4 and the weights set as [0.1, 0.2, 0.2, 0.5] perform best in positioning at time N, which is shown as follows:

$$RSSI_N = 0.5 * RSSI_N + 0.2 * RSSI_{N-1} + 0.2 * RSSI_{N-2} + 0.1 * RSSI_{N-3} \tag{10}$$

The result after using weighted sliding windows for real-time RSSI from start to 10 seconds later is shown in figure 5.

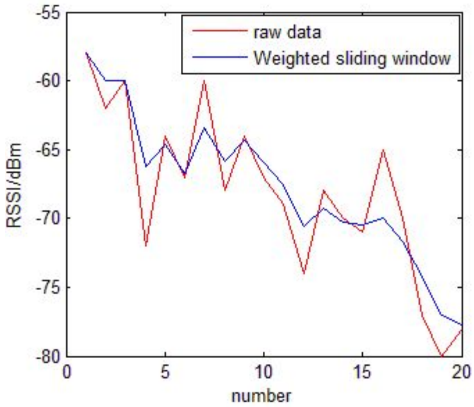

Figure 5 Weighted sliding windows for real-time

B. A distance weighted filter based on triangle trilateral relations theorem for abnormal RSSI detection

Although weighted sliding windows is used to reduce the randomness of real-time BLE RSSI, it cannot eliminate the variation of RSSI, especially the environment changing with the moving target. In order to reduce error position result due to abnormal RSSI, we propose a distance weighted filter based on triangle trilateral relations theorem. The filter can filter out the distance value that deviates from the real value. That is to say, the wrong distance value caused by abnormal RSSI cannot be taken into consideration in online positioning.

Now，taking the scenario that has four BLE reference nodes for example to illustarte our method. The scenario can be seen in figure 6.

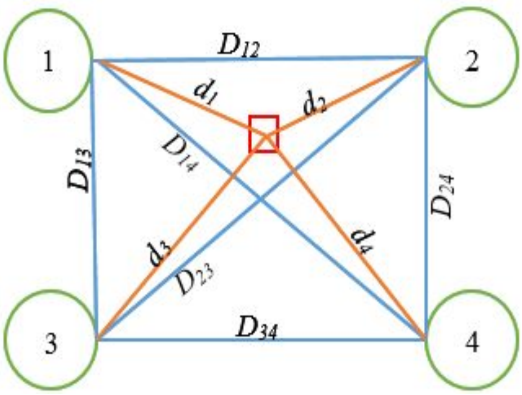

Figure 6. Test scenario of 4 BEL positioning.

In figure 6, four circulars represent the four BLE reference nodes. The rectangle in the middle represents the target node. Capical letter D represents the distance between reference nodes while little “d” represents the distance between target node and reference ndoe. Full algorithm is shown as follows.

(1) Calculating the distance set between reference nodes: $D=\{D_{12},D_{13},D_{14},D_{23},D_{24},D_{34}\}$ and the distance set between reference nodes and target node: $d=\{d_1,d_2,d_3,d_4\}$ according to propagation model of RSSI.

(2) For each element in the set in d, finding its sum set $SUM_i=\left\{sum_{ij}=d_i+d_j, j\neq i\right\}$ and absolute difference set $SUB_i=\{sub_{ij}=\left|d_i-d_j\right|, \mathrm{j}\neq i\}$ with rest of the collection elements. In addition, the weight set of each d_i in d is initialized as follows: $W=\{w_1=0,w_2=0,w_3=0,w_4=0\}$.

(3) For each element in sum_{ij} and correspondent element in sub_{ij}, comparing them with element D_{ij} in D. Once the triangle theorem of trilateral relations cannot be met, w_i plus one.

(4) Picking out the largest value w_i in W, and the correspondent d_i is filtered out.

Following is the pseudo-code for the algorithm.

Algorithm 1: Weighted Distance Filter

Input:

Distance set between reference nodes:

$D=\{D_{12},D_{13},D_{14},D_{23},D_{24},D_{34}\}$

Distance set between reference nodes and target node: $d=\{d_1,d2,d3,d4\}$

Weight set of each d_i:

$W=\{w_1=0,w_2=0,w_3=0,w_4=0\}$

Output:

The d_i with the largest weight would be filtered out.

1 Calculate data set $SUM_i=\left\{sum_{ij}=d_i+d_j, j\neq i\right\}$

2 Calculate data set $SUB_i=\{sub_{ij}=\left|d_i-d_j\right|, \mathrm{j}\neq i\}$

*3 **For each** d_i in d*

a) **if** $sum_{ij}<d_i \parallel sub_{ij}>d_i$

b) $w_i=w_i+1$

c) **else**

d) continue

4 Find w_i of the maximum value in data set W.

5 Filter out the corresponding d_i

End

The positioning result can be seen in figure 7.

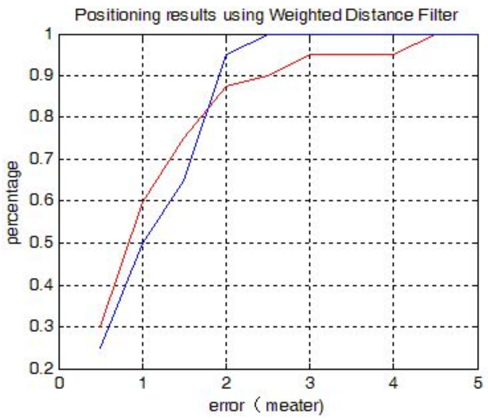

Figure 7. The cumulative probability distribution(CDF) of positioning results using weighted distance filter

Results shows that though weighted distance filter cannot improve the positioning accuracy much, it can reduce the times of error position effectively. Consequently, our algorithm makes positioning more robust and more practical.

IV. TAYLOR SERIES EXPANSION BASED COLLABORATIVE POSITIONING

Now we can get the target node location according to the processed pairs of distances d between target node and BLE reference nodes. Assuming coordinates of target node is (x, y) and coordinates of reference nodes are $\{(x_i, y_i)\}$, then the following equations can be obtained:

$$(x-x_1)^2+(y-y_1)^2=d_1^{\,2}$$
$$(x-x_1)^2+(y-y_1)^2=d2^2$$
$$\vdots$$
$$(x-x_n)^2+(y-y_n)^2=d_n^{\,2}$$

(11)

From over-determinant equations above we known that the greater the number of reference nodes is, the higher the accuracy of the positioning results are. Although the many methods are proposed in [14] such as Newton-iterative method, we use the linear method in this paper.

A. Linear method for over-determinant equations

First of all, an equation is established as follow:

$$(x-\bar{x})^2+\left(y-\bar{y}\right)=\bar{d}^2 \tag{12}$$

$$x=\frac{1}{n}\sum_{i=1}^{n}x_i,\ y=\frac{1}{n}\sum_{i=1}^{n}y_i,\ \bar{x}^2=\frac{1}{n}\sum_{i=1}^{n}x_i^{\,2}$$
$$\bar{y}^2=\frac{1}{n}\sum_{i=1}^{n}y_i^{\,2},\ \bar{d}^2=\frac{1}{n}\sum_{i}^{n}d_i^{\,2}$$

(13)

Using first n-1 equations in (10) to minus the (11), and then we can get the following equations:

$$2(x_i-\bar{x})+2(y_i-\bar{y})=\bar{d}^2-d_i^{\,2}+x_i^{\,2}-\bar{x}^2+y_i^{\,2}-\bar{y}^2,$$
$$i\in[1,n-1]$$

(14)

For linear equations in (13), we do the following transformation:

$$A=2\left[(x_i-\bar{x}),(y_i-\bar{y})\right]$$

$$\mathrm{B}=\left[d^2-d_i^{\,2}+x_i^{\,2}-x^2+y_i^{\,2}-y^2\right]$$

$$\mathrm{X}=\begin{bmatrix}x\\ y\end{bmatrix}$$

From above we can know that AX=B. Then we can get the formula $X=(A^TA)^{-1}A^TB$ according to LS. Therefore, we can get the target node's initial position (x_0, y_0) by solve the linear matrix.

B. Positioning optimization based on Taylor series expansion

It is known to us that LS based positioning ensures that the sum of mean-squared error is minimized only. However, it cannot be sure whether each value estimated is optimal, which lead to a positioning result of low accuracy. To this end, we use the Taylor series expansion to optimize the location of target node.

The initial value of the position results should be relative accurate for Taylor series expansion, or it may not convergence to certain values. Therefore, we take the initial position obtained by solving linear matrix as the input of Taylor series expansion. We use the first order Taylor series expansion in order to reduce computational complexity, which can be seen in (15):

$$d_i\left(X\right)=d_i\left(X+dX\right)d_i\left(X_0\right)+f_x^{(i)}dx+f_y^{(i)}dy \tag{15}$$

Consequently, we can get the following equations:

$$\frac{x_0-x_1}{d_1(X_0)}d_x+\frac{y_0-y_1}{d_1(X_0)}d_y=d_1-d_1(X_0)$$
$$\frac{x_0-x_2}{d_1(X_0)}d_x+\frac{y_0-y_2}{d_1(X_0)}d_y=d_2-d_2(X_0)$$
$$\vdots$$
$$\frac{x_0-x_n}{d_1(X_0)}d_x+\frac{y_0-y_n}{d_1(X_0)}d_y=d_n-d_n(X_0)$$

(16)

Using the same method described in *A* to calculating (dx, dy) until $\sqrt{(d_x^2 + d_y^2)} < \delta$. The value of δ is set to 0.5 in our research and the step size is set to dX/2.

Now the final positioning results of target nodes we have get are $(x_0 + dx, y_0 + dy)$. The position results before and after using the Taylor series expansion can be seen in Figure 8.

The results show that using Taylor series expansion can reduce the probability of large position error effectively compare with using Linear method only.

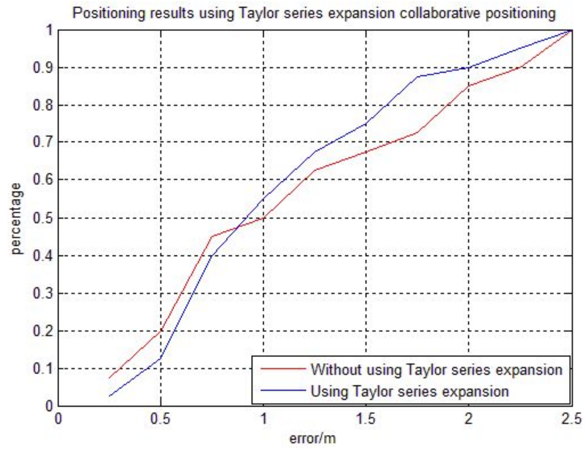

Figure 8. The cumulative probability distribution(CDF) of positioning results using Taylor series expansion collaborative positioning

V. ACTIVE LEARNING FOR PROPAGATION MODEL ADJUSTMENT

It is impossible that the attenuation factors of BLE reference nodes keep unchanged effected by time and space factors such as antenna gain. Therefore, using the constant training model cannot satisfy the requirement of high accuracy positioning. Here, we propose an active learning method in this paper which can be used in adjusting the propagation models of reference nodes.

The active learning method is based on the idea of detecting node. In our research, we have place a modified BLE node called detecting node within the range of BLE reference nodes in a certain location. The detecting node can receive the RSSI and send its data set to the server. The server will adjust the propagation model of each reference nodes according to the data set and the positional relationship between detecting node and reference nodes. The adjustment method for each reference node is shown below.

$$n_{new} = \frac{A - P}{\lg(D)} \quad (16)$$

$$n_{real} = w_1 * n + w_2 * n_{new} \quad (17)$$

D represents the distance between reference nodes and detecting node; *P* is the value of RSSI received by detecting node from reference nodes, which has been filtered and averaged during update period. w_1 and w_2 are calculated according to statistical analysis in real environment and $w_1 + w_2 = 1$; n_{real} is the final value of attenuation factors used in positioning. Formula (17) shows that the actual attenuation factors being used is adjusted based on the original training model while takes current time and space factors into consideration.

In order to reduce the environmental effects on received RSSI, the detecting node should be placed in the location that is difficult to be blocked. In our research, we compare the positioning results before and after using active learning in 6pm, the time that 10 hours after the positioning system started running.

From figure 9 we know that using active learning can reduce the positioning errors compared with before.

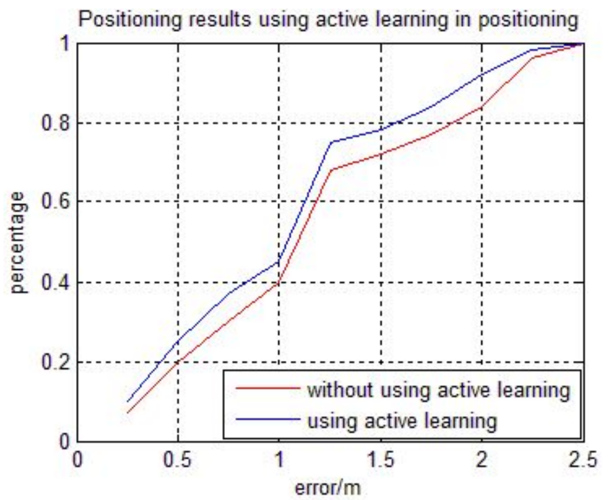

Figure 9. The cumulative probability distribution(CDF) of positioning results using active learning

VI. CONCLUSIONS

Very low power consumption and easy to deploy make the BLE based indoor positioning become one of the current research hotspots. In this paper, we propose the complete positioning method and a series of optimization to improve positioning accuracy, including Gaussian filter and LS based piecewise fitting for offline training, weighted sliding windows and weighted distance filter for real-time RSSI processing, Taylor series expansion based cooperative localization. Besides, an active learning method is proposed to adjust the training models periodically. Experiment results show that our positioning method has much more robustness in actual localization with satisfying locating results.

ACKNOWLEDGMENT

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