RSSI-Fading-Based Localization Approach in BLE5.0 Indoor Environments

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Abstract. How to filter fluctuant RSSI signal has always been a difficult problem in an indoor localization system. This paper provides an efficient indoor localization algorithm in a BLE5.0 based scan-broadcast network by building RSSI path-loss model without a great deal of fingerprints. This method builds a RSSI-Distance fading model between one position node (PN) and one markup node (MN) by maximum likelihood estimation (MLE) based on Gauss distribution of RSSI data. Then the rough fading model about RSSI in data collecting intervals of 1 m will be get. In this paper we reduce the distance intervals in 0.1 m by fitting of path loss model and making discrete samples of confidence intervals to improve the accuracy of localization. Finally, the whole fading regularly will be fixed and the location errors of PN will be determined by centroid model (CM). The results show that sampling interval with high precision can benefit the accuracy performance in an indoor localization environment.

Keywords: RSSI · BLE5.0 · Maximum likelihood estimation (MLE) · Centroid model (CM) · Indoor localization

1 Introduction

With the development of wireless network, Internet of Things (IOT) has realized extensive service provisions and high quality of communication guarantees in our life [1]. In many application scenes, localization based services (LBS) [2] make the interaction between millions people. Two main scenes of the localization are open outdoor environment and indoor environment. Global Navigation Satellite System (GNSS) is the main implementation scheme in outdoor environments where scenes have low effect for transmission path. The density of outdoor

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This work was supported by Foundation Items: National Natural Science Foundation of China (61871237), Natural Science Foundation of China under Grant 61871446, National Science and Technology Major Project (2017ZX03001008), and Natural Science Foundation of the Higher Education Institutions of Jiangsu Province (16KJA510005).

M. Jia et al. (Eds.): WiSATS 2019, LNICST 281, pp. 131–144, 2019.
https://doi.org/10.1007/978-3-030-19156-6_13

objects is low, and in many scenes, determining an abbreviated distance is completely enough for LBS. The maximum precision of outdoor localization is 10 m [3]. However, GPS or other outdoor localization technologies have their limits in indoor environment [4]. Object blocking is complex in each specific scene where satellite signal will be weakened by roofs or walls and meter scale precise is no conformity for indoor environments. To solve the problem, scientists have promoted many coping strategies for indoor localization and their improved methods focus on two aspects: indoor communication technologies and localization algorithms.

Indoor communication technologies include widely used technology such as WLAN, Zigbee, Bluetooth (BLE), Zigbee and Radio Frequency Identification (RFID) [5]. Some special technologies for indoor localization are also born such as iBeacon (a technique for ios7 system mobile phone location by BLE) [6] and Ultra Wideband (UWB) [7]. They are all effective methods to make localization and there have no absolute superiorities or disadvantages among them, so they should be chosen according to the emphasis of the study.

In aspect to localization algorithms, according to the features from the localization network, can be divided into Angle of Arrival (AOA), Time difference of Arrival (TDOA), Time of arrival (TOA) and Received signal Strength (RSSI) [8]. No matter which methods be used, fluctuation of the collected features is difficult to clear up and even when we get the results of indoor localization, the amid coordination itself is still fluctuated. As a result, in a model of an indoor localization system needs consider the measures both in front filter and back filter [9]. In this paper, we just innovate the front filter algorithm and use RSSI as our features. Recent researches of revising RSSI will be displayed later.

1.1 Related Researches

Inventing a more advanced wireless technology or designing a more ingenious algorithm is the research direction in indoor localization. Advanced wireless technology such as UWB which mentioned above can transmit data from nanosecond to microsecond non sinusoidal pulse and many people think it as the mainstream technology of near field communication in the future. Ingenious algorithms such as neutral network which is hot spots of current research and is remarkable in many ways. The platform of our research is BLE5.0, and the algorithm purpose is to build a filter model of RSSI when the PN collects broadcast packets from MNs.

1.1.1 BLE5.0

BLE5.0: Why we choose BLE5.0 as our PN and MNs? The main consideration is its low power waste and the capacity of large deployment. BlE5.0 is a Bluetooth technology standard proposed by Bluetooth Technology Alliance in 2016.12. BLE5.0 can improve and optimize the speed of low-power devices and it has a wider coverage and 4 times faster speed for low-power devices. The upper limit of transmission speed is 24 Mbps, which is 2 times the previous version of

BLE4.2. The effective working distance can reach 300 m, which is 4 times that of the previous BLE4.2 version [10]. Although BLE5.0 has been optimized, the limitations of BLE5.0 is still exits. BlE5.0 only has penetration capacity within 10 m and the BLE5.0 chip can't collect precise time difference so that RSSI is almost the only feature to utilize [11]. BLE5.0 has the advantages of lower power consumption and transmission capacity. The localization of BLE5.0 is not particularly prominent, but in reality scenes, decimeter grade accuracy is enough for users and with the optimization of algorithm, location performance will become better and better.

1.1.2 RSSI in Indoor Localization

In most of the wireless system, RSSI is the value which without extra hardware for auxiliary measurement. Many researches of indoor localization use RSSI as their location parameters no matter which wireless technology they choose. The basic usage of RSSI in indoor localization is a three point centroid model [12]. This method detection RSSI in the PN surrounded by at least three MNs and through the junction point of RSSI, the PN will be located. Fingerprints based positioning strategy is another common strategy by collecting large amount of fingerprints and build a neural network based multi classification model to find the coordinate of PN [13]. Front filtering and back filtering are in [14] and [15], constantly changing RSSI sequence will be mapped to a particular distribution. In methods [16], Kalman filter, - filter and particle swarm are effective methods to reduce the jump of location results. Different indoor environments affect the performance of algorithm and a localization algorithm based on RSSI in specific indoor map can be found in [17]. Data filtering from a large number of MNs to find the most reliable RSSI is another thinking when the PN is in a dense MNs network [18]. RSSI maybe mutual interference when the network is concentrated and keeping the independence of RSSI is significant [19]. In this paper we examines the front filter algorithm to find the fading regularity between RSSI fading, and this regularity will realizes a convenient localization in non specific environments.

1.2 Mathematical Formulation: Centroid Model (CM)

One of the significant advantage in our method is that we discard the process of fingerprints collecting. Combining the RSSI-Distance model and centroid model will easily calculation the coordinate of PN. In weighted centroid model, we assume that the number of MN is 3 and the following function is formed:

$$f(x,y,t) = \begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = r_1(x_1, y_1, d_1, t) \\ (x_2 - x)^2 + (y_2 - y)^2 = r_2(x_2, y_2, d_2, t) \\ (x_3 - x)^2 + (y_3 - y)^2 = r_3(x_3, y_3, d_3, t) \end{cases} \tag{1}$$

where (x_1, y_1), (x_2, y_2), (x_3, y_3) are the coordinates of the nearest three MNs. $r(x, y, d, t)$ is the RSSI from MNs to PN at the linear distance d, t time. By calculating each d of MNs, PN coordinate (x, y) will be get. Because of RSSI fluctuation, (x, y) will jump in a certain range at different time. Within the time interval of T, if estimated by Gauss distribution, RSSI from MN_i can be defined as follows:

$$r_i(x_i, y_i, d_i, T) \sim \frac{1}{\sqrt{2\pi\sigma^2(d_i)}} e^{-\frac{(r-\mu(d_i))^2}{2\sigma^2(d_i)}} \tag{2}$$

where T is the time interval of RSSI samplings. d_i represents the distance from PN to MN_i and its constantly changing when the PN is moving. $\mu(d_i)$ and $\sigma(d_i)$ are parameters based on the distance from PN to ith MN and in a certain localization scene. In Fig. 1, we present CM model where radiation of RSSI is simplified from 3-D spherical radiation to a 2-D plane.

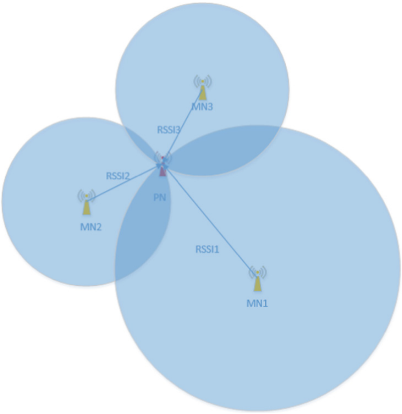


Fig. 1. Mathematical formulation: weighted centroid model based on RSSI

1.3 Problems: How to Make a Rapid Positioning

In a new indoor environment, the scenery is always specific. The method based on the fingerprints usually needs training data which are collected from the well divided train coordinates. With powerful classification ability of neural network, in a specific home, this method is effective. However, the process of collecting fingerprints is complex, in some exceptional case, such as military and fire rescue, localization of soldiers is hard to collect the fingerprints because of the limited time. We put forward a rapid measurement model which circumvent fingerprints collecting, and by build RSSI-Distance model, the accuracy of our method is reliable.

The remainder of this paper is organized as follow. Section 2 outlines the BLE5.0 scan-broadcast network and the preparation of features. The RSSI-Distance model based on MLE are discussed and we will know approximately trends of RSSI fading in interval of 1 m in Sect. 3, followed by a more precise evaluation model which makes fitting of path loss model and realizes discrete sampling of confidence interval in distance interval of 0.1 m. Experiments and results are in Sect. 4, followed by conclusion in Sect. 5. Measurements are carried out in Communications Technology Research Institute of Nanjing University of Posts and Telecommunications.

2 BLE5.0 Scan-Broadcasting Network

The scan-broadcast network includes the deployment of MNs and settings of transmission mechanism. MNs determine the localization of PN and when the PN moves out the area, the RSSI sequence will be eliminated that because RSSI will generate terrible amplitude twitter as the distance widening. Considering of the transmission capacity of BLE5.0, the maximum PN to MN distance should be within 10 m and if the number of PNs is enough, the density of PNs can be raised. In our research, transmission mechanism is based on the process of broadcasting and scanning. When the localization starts, MNs will in the state of fasting broadcast and the identification of the MNs is its MAC address. When the PN scans on the broadcast packets, it will analysis the MAC field of MNs and RSSI can be perceived. To make the MNs are unique in nearby BLE equipment, MAC addresses of PNs usually have its naming rules. The BLE5.0 scan-broadcasting network is shown in Fig. 2.

RSSI and MAC information will form the data sequence in (1) and (2). Usually a serial communication model (Lora or WIFI) assistants the PN to send the sequence to server where calculating the RSSI-Distance function. In addition, Mesh network by BLE5.0 [26] is another networking mode which realise the pressure of MN, however in our research, simplifying deployment process is our aim, so we will use a low complexity network. To say the least, BLE5.0 Mesh is nothing with the localization accuracy theoretically.

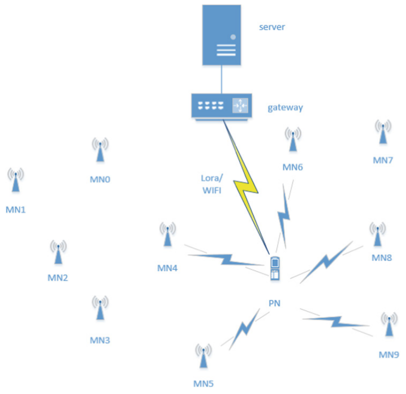


Fig. 2. The BLE5.0 scan-broadcasting network

2.1 Approximately RSSI Fading Model in Interval of 1 m

To make the current model can best reflect the real RSSI propagation, we need figure out μ and σ in (2) and make error analysis. We record RSSI sequence of MNs in a short time interval. The transmission speed of BLE5.0 is fast enough to divide the sequence into more groups where each group has independent and identical distribution. The RSSI sequence from MN_i in group j can be set as $\{R_{i-j-1}, R_{i-j-2}, \ldots, R_{i-j-N}\}$, where the N is the number of RSSI in each group. We set the number of groups is M. Each group separately calculate μ and σ in (2) by MLE. Finally, averaging the results of every group, the RSSI-Distance model of MN_i is formed. The formula as follows:

$$L\{\mu, \sigma^2\} = \prod_{n=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2(d_i)}} e^{-\frac{(R_{i-j-n}-\mu(d_i))^2}{2\sigma^2(d_i)}} \tag{3}$$

Using the MLE to get the value of $\mu(d_i)$ and $\sigma(d_i)$.

$$\begin{cases} \frac{\partial \log L(\mu(d_i),\sigma^2(d_i))}{\partial \mu} = \frac{1}{\sigma^2(d_i)} \sum\limits_{n=1}^{N} (R_{i-j-n} - \mu(d_i)) = 0 \\ \frac{\partial \log L(\mu(d_i),\sigma^2(d_i))}{\partial \sigma} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4(d_i)} \sum\limits_{n=1}^{N} (R_{i-j-n} - \mu(d_i)) = 0 \end{cases} \tag{4}$$

The result of μ and σ are as follows:

$$\mu(d_i) = \frac{1}{M}\frac{1}{N}\sum_{j=1}^{M}\sum_{n=1}^{N} R_{i-j-n} \tag{5}$$

$$\sigma^2(d_i) = \frac{1}{M}\frac{1}{N}\sum_{j=1}^{M}\sum_{n=1}^{N}(R_{i-j-n} - \overline{R_{i-j-n}})^2 \tag{6}$$

In the process of indoor localization, once we have get the distribution of $RSSI$ in (5) and (6), we need to build a standard which can prove the current distribution is the same with (5)–(6) or very close. Using hypothesis test is the common method to prove the consistency of distribution.

Assumption:

$$H_0 : \widehat{\mu_i} = \mu_i$$

$$H_1 : \widehat{\mu_i} \neq \mu_i$$

and test statistics:

$$T = \frac{\widehat{R_i(d_i)} - \mu(d_i)}{S(d_i)/\sqrt{MN}} \sim t(MN-1) \tag{7}$$

Reject region:

$$|T| \geq t_{\frac{\alpha}{2}(MN-1)}$$

where $\widehat{R_i(d_i)}$ is the $RSSI$ sample mean of MN_i and we keep the number of $RSSI$ received is MN which is same as that in (5), (6). $s(d_i)$ is sample variance of raw data. α is the significance level, usually $\alpha = 0.05$. Similarity, we also test $\sigma^2(d_i)$.
Assumption:

$$H_0 : \widehat{\mu_i} = \mu_i$$

$$H_1 : \widehat{\sigma_i} \neq \sigma_i$$

and test statistics:

$$F = \frac{max(S^2(d_i) - \widehat{S^2(d_i)})}{min(S^2(d_i) - \widehat{S^2(d_i)})} \sim F(M-1, M-1) \tag{8}$$

Reject region:

$$F \geq F_\alpha$$

where $\widehat{S^2(d_i)}$ is sample variance of current data. When all of the MNs are working together, the value of $RSSI$ which we choose is a normal value. For example, in time interval T, PN has scanned broadcast packets of MN_1, MN_2, MN_3. Other MNs maybe scanned yet, but we can easily calculate that $\mu(d_i)$ of them are too low and they will be excluded. The straight distances between three MNs shouldn't be too long or too short and according to our experiment, the range of the value is [1 m, 5 m]. In Fig. 3, we show RSSI-Distance model in distance difference of 1 m. Figure 4 is the verification environment of our experiments.

In Fig. 3, PN is collecting RSSI from MN_1. We set the PN moving in a specific route and equal distance cutting is carried out in this line. It is worth noting that MN_1, MN_2 and MN_3 build a right angle. The reason for this arrangement is that almost each house has a right angle of the roof, so when we use us indoor localization method in a new scene, we can realize rapid assembly of our system based on this structure without temporary test. In Fig. 4, means of RSSI-distance model indicates that when we uniform increase the distance between PN and MN_i, the attenuation of $RSSI$ will slow down and that is because the power of BLE5.0 is limited and the sensitivity of $RSSI$ detection can only work in a short range. Variances show the stability of the system and we find that variances are erratic. As a result, we will use means of $RSSI$ as our localization feature. The localization range of three MN_s should be limited less than $4 \times 4\,\mathrm{m}^2$.

Complements about confidence intervals of means are shown in Fig. 5 where we calculate in distance of 1 m, 2 m, 3 m and 4 m (5 m is excluded and we use opposite number to represent confidence intervals). The confidence interval in d_i is written as (PL_i, PH_i). Similarly as the conclusion in Fig. 4, in the distance of 4 m, the complement has a more board range in which we will have more difficulties in detecting whether a certain gauss distribution could be recognized as happened. We can imagine that with the distance increased, distribution between different length will be indistinct. As a conclusion, the range of localization must be limited in a area where statistical parameters have obvious discrepancy. The next work for us is to make evaluation model in which we will map gauss distribution into specific distance and we will try to narrow the intervals of distance.

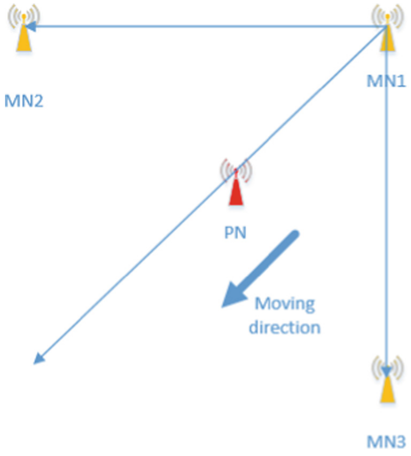


Fig. 3. RSSI collecting environment for RSSI-Distance model

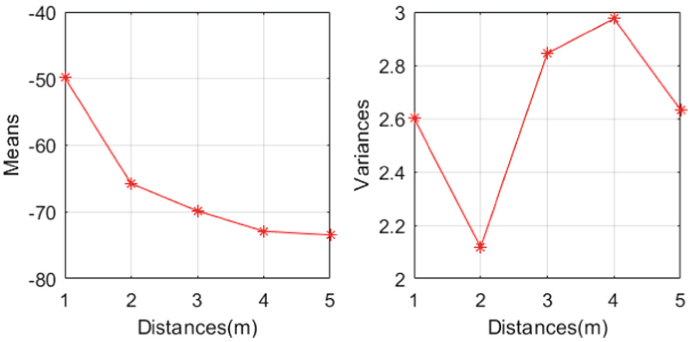


Fig. 4. Means and Variances of RSSI-Distance model

3 More Precise Evaluation Model in Interval of 0.1 m

Confidence intervals in Fig. 4 delimit appropriate mapping regularity when we know the current data distribution. In this paper, minimum unit of distance must be more precise and if we want to exclude interference caused by similar confidence intervals, the strategy of setting interval distance is the key. When we have a ideal partition strategy, the evaluation model will be more effectively to map $RSSI$ distribution to its adjacent straight distance.

3.1 Strategy of Making More Precise Interval

In real application, propagation model based on exponential decline is often used in $RSSI$ fading.

$$p_{d_i} = p_0 - 10\eta Log(d_i/d_0) + \varepsilon \tag{9}$$

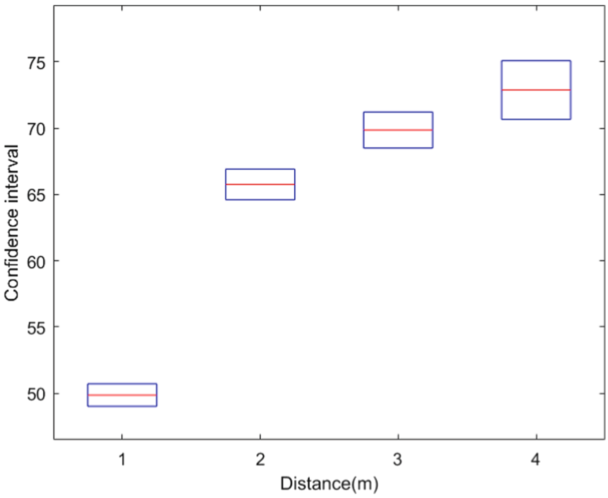


Fig. 5. Complements about confidence interval

where η is the path-loss exponent and ε represents the measurement error. Combined with Figs. 4 and 5, this logarithmic distribution is measured in real measurements. In this paper, we put forward two ways about mapping.

3.1.1 Fitting of Path Loss Model

Assuming that PN is in the process like in Fig. 3. According to interval T in one sampling and advanced partition distance, the RSSI-Distance sequence about PN and MN_i can be setted as

$$Q_i = \{R_{d_i1}, d_{i1}; R_{d_i2}, d_{i2}; \ldots; R_{d_iH}, d_{iH}\}$$

where R_{d_ih} is the aggregates of all groups of R_{i-j-n} where the distance is h which has been defined in part III. This two-dimension array will be fitted in the trend of function (9). We set function (10) is another form of expression about (9)

$$R_{d_ih} = R_0 + 10\eta log(d_{ih}) + \varepsilon \tag{10}$$

According to least square method fitting target is

$$\min \sum_{h=1}^{H} (R_{d_ih} - (R_0 + 10\eta log(d_{ih}) + \varepsilon))^2 \tag{11}$$

Once function of (11) is determined, distribution regularity of $RSSI$ from MN_i in limited transmission distance is fixed. The form of expression is a smooth logarithmic curve in which the input variables are $RSSI$ calculated in (5) and the reject region is nothing with this mapping process because the results of distance are continuous.

3.1.2 Confidence Interval in Precise Distance Interval

Unlike the continuous fitting of path loss model, discrete sampling about confidence interval set the distance measurement in particular distance intervals. For instance, in Fig. 5, the minimum interval is 1 m. In a ideal situation, if intervals could be set in a small enough value and the distance elongated can also be detected, the localization will be better performance. However, from the conclusion in Fig. 5, if the density of interval is concentrated, there will have the risk of failing to distinguish domain agents between different intervals. Conversely, extending interval distance will cause a low localization precision.

3.2 Calculating the Location of PN

CM talked above will be implemented in this section when we have researched the regulation of RSSI-Distance model both in continuous and discrete formal. In a localization system, regulation of $RSSI$ is not specific from different MNs, even the original power sets is the same which has shown in Fig. 4 and this characteristic is reflect in $r_1(x_1, y_1, d_1, t)$ in (1). As a result, combined with (1) and continues sampling algorithm or discrete sampling algorithm, the location of PN will be easily detected.

4 Results and Analysis

Figure 6 shows the experiment environment in our laboratory where the shaded areas are computer tables or other equipments. We set four MNs and they are

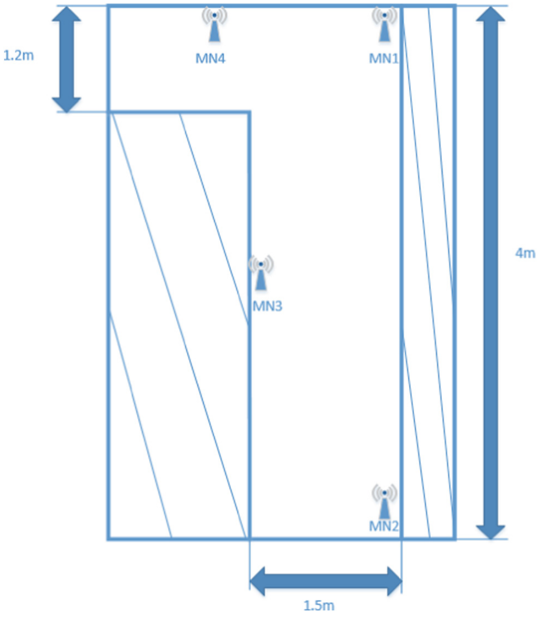
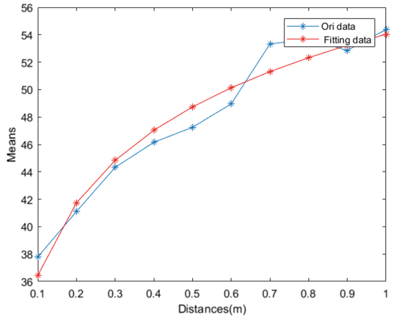


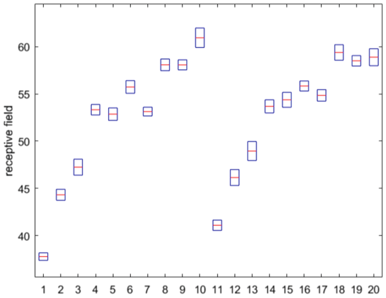
Fig. 6. Indoor location environment of experiment

fixed. We choose MN_i as the object node for RSSI-Distance research and the results are shown in Fig. 7(a) and (b).

We can compare Fig. 7(a) with Fig. 4 where the distance ranging is decreased from 4 m to 1 m and combined with two pictures, the regularity of *RSSI-Distance* model will be found. With the distance increased, the growth trend approach gentle, because the RSSI detection ability of BLE5.0 model is limited when the signal power is undersize. Another influence of distance increasing is shown in Fig. 7(b). The range of box shows the receive of means in a specific distance. We repeat doing two experiment in the same scenes. When the distance is 0.1 m, 0.2 m, 0.3 m, there are no overlap between boxes and with the distance increased, if we choose 0.1 m as the interval of discrete sampling, the phenomenon of overlapping in receive areas is serious.



(a) Means of RSSI in fitting of path loss model



(b) Confidence intervals in sampling interval of 0.1m (1-10 and 11-20 are results of the first and the second experiments in 1m)

Fig. 7. RSSI-Distance model interval of 0.1 m

The results of localization are shown in Table 1, we choose 10 coordinates as localization targets and errors are linear distances between calculation locations and 10 coordinates. The solution method is based on RSSI-Distance model and the CM algorithm which we have built above. In practice, solving the function of (1) is hard and in many situations the function is unsolvable, so we just give the minimum error distances, this value also can represent the accuracy of the BLE5.0 indoor localization system. Coordinates from MN_1 to MN_4 are follows: [0, 0], [0, 4], [1.5, 2], [1, 0].

Table 1. The comparison between accuracy in different sampling intervals

Coordinates (m)	[0.4, 0.4]	[0.8, 0.8]	[0.4, 1.4]	[0.4, 2.6]	[0, 2.6]
Errors (m) (interval of 0.1 m)	0.68	0.48	0.32	0.59	0.53
Errors (m) (interval of 1 m)	1.78	1.14	0.67	1.14	0.97
Coordinates (m)	[0.8, 2.8]	[0.8, 3.2]	[0.3, 3.2]	[0.4, 3.6]	[0.2, 3.8]
Errors (m) (interval of 0.1 m)	0.64	0.73	0.71	0.79	0.81
Errors (m) (interval of 1 m)	1.08	0.92	0.87	1.05	0.96

The results show that our method can limited the localization error in 1 m and using a more precise interval will improve the accuracy. In practice, the target point usually has its specific localization tasks, and in many scenes, the density of positioning task has exceed 1 m. So the result of our experience is reliable.

Concerning the results of our experiments, using *RSSI-Distance* model with the CM function is an efficient way in indoor localization. As shown in Fig. 7, we observe that if you just want to realize a function of close range perception, BLE5.0 is a dependable equipment which can distinguish the distance in 1 m. The only problem is that when the distance is increased, it's hard to make a precise measurement, so our recommendation is that trying to chose a more precise interval.

5 Conclusion

We investigate in this paper about the performance of *RSSI-Distance* model in a BLE5.0 indoor localization system. We show that building a reliable *RSSI-Distance* model can provide a low error localization accuracy without a mass of fingerprint collecting. The discrete sampling in short distance shows good performance and this regulation is suitable in a equipment perception system when the people approach the devices. Continue sampling is a feasible scheme when we need to know the specific coordinates in room, if the precise needed to be improved, tedious method of fingerprint collecting can only be used. Using the methods in this paper, user just need to associate the BLE5.0 module with its *RSSI-Distance* model, then the function of indoor localization will be realized. Of course, the next work for us is to consider of more complex features in the room and apply the indoor location in more scenes.

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