A Modified RSSI-Based Indoor Localization Method in Wireless Sensor Network

Zhe Chen
School of Information and Communication Engineering
Dalian University of Technology
Dalian 116024, China
zhechen@dlut.edu.cn

Wenting Han
School of Information and Communication Engineering
Dalian University of Technology
Dalian 116024, China
my900728@mail.dlut.edu.cn

Yuchao Jiang
School of Information and Communication Engineering
Dalian University of Technology
Dalian 116024, China
Jiang.yuchao0@gmail.com

Fuliang Yin
School of Information and Communication Engineering
Dalian University of Technology
Dalian 116024, China
flyin@dlut.edu.cn

Abstract—Node location is one of the basic problems in wireless sensor networks (WSN). We investigate the wireless localization methods based on providing received signal strength index (RSSI) measurements between a mobile node and several access nodes in a WSN. In order to estimate the distance between two nodes, a propagation model is used to transform RSSI into the corresponding distance that the mobile node is away from the access points according to the RSSI signals. Next, the mobile node coordinate can be obtained by any location algorithm such as weighted B-box considered as the better method compared with the trilateraion method. To achieve a better location result, Gaussian filtering, piecewise fitting, and total least square estimation are introduced to improve precision of estimated model parameters, and iterative algorithm is adopted to further reduce positioning errors. Several simulation results reveal that the MSE of the proposed method is cut off at lease 2/3 while comparing to the B-box algorithm.

Keywords- location; RSSI; B-box; Iteration

I. INTRODUCTION

Positioning technology, such as the famous Global Positioning Systems (GPS), is widely used in many outdoor applications, such as environment monitoring, military surveillance, search-and-rescue operations, etc. [1-3]. The GPS technology locates a terminal basing on the signals transmitted from different satellites. Especially, knowing the location of person, equipment, and materials is important information for various production activities such as safety management, material management, and production planning in indoor environments. Unfortunately, not all positioning technologies such as the GPS technology can serve indoor environment due to improper precision, speed, reliable and so on. Recently, Wireless sensor network (WSN) developed in recent years is suitable enough and can meet the indoor positioning requirements. A WSN usually position a terminal by detecting the signal strength of nodes from sensors whose locations are already known. Unlike the GPS which provides global positioning, the sensing area of a WSN is limited in its coverage. There are many different positioning approaches in a WSN. The existing indoor location algorithms can be summarized into two categories, i.e. range-based and range-free [4, 5]. Comparing to the poor positioning accuracy of latter one, the range-based localization method can provide higher precision because it exploits measurements of physical quantities related to signals traveling between a mobile node and access points (APs). Radio signal measurements include received signal strength index (RSSI), angle of arrival (AOA), time of arrival (TOA), and time difference of arrival (TDOA) [6-8]. In these measurements, time-based methods have crucial problems in indoor environments. First, it is difficult to find a line-of-sight (LOS) path between a radio signal emitter and its receiver. Next, the multi-path effect also affects the arrival time of radio signal, which leads to reducing the accuracy of the estimated location. Moreover, time measuring schemes have some specific requirements for network, e.g. the network has to be precisely synchronized, which may require specialized and expensive hardware integrated into the existing equipment. Therefore, strength-based methods are more attractive for indoor wireless location than time-based ones (e.g. AOA, TOA and TDOA) [9].

The strength-based localization methods also have two types, fingerprint-based [10, 11] and signal propagation model-based [12]. The main drawback of fingerprint method is the extensive and accurate measurements, during the off-line phase, required to create the database. The construction of the database is not automatic but human-based. The construction is a time-consuming operation and also is a practical barrier to its wider adoption.

A method to improve the quality of localization exploiting a number of RSSI measurements averaged in a time window to counteract interference and fading has been proposed in [13]. The E. Elnahrawy in [14] suggest that algorithms estimating distances between two wireless devices based on their reciprocal RSSI are unable to capture the myriad of effects on signal propagation in an indoor environment. The Barsocchi in [6] uses a virtual calibration method of the propagation model that does not require human intervention. A preliminary report of location estimation combining an inertial navigation algorithm and wireless modules is shown in [15]. The real-time environmental parameters based on the RSSI are used to reduce the environmental impact in [16]. In this paper, Gaussian filtering, piecewise fitting, and total least square estimation is introduced to improve precision of estimated model parameters. Different localization algorithms such as the Trilateration, the Min-Max and Maximum-Likelihood algorithms are compared in [2] and [17]. The simple Min-Max algorithm has better performance than other algorithms. In this paper, a new iterative algorithm combining with weighting bounding box (B-box, also named as Min-Max) is used to further reduce positioning errors. The rest of the paper is organized as follows. Section II introduces our indoor positioning approaches with RSSI. Section III presents some experiments to evaluate the proposed positioning approach. In section IV, some conclusions will be drawn.

II. LOCALIZATION ALGORITHM

The indoor localization algorithm in this paper can be divided into three modules. They are the module of fitting the model parameters of propagation, the distance estimation module and the localization module. The module of fitting the model parameters of propagation serves the module of distance estimation and localization. The RSSI data and the corresponding distance from the AP to the terminal are captured to acquire the model parameters of the Log-normal shadow model. In the module of the distance estimation, the distance corresponding to the real time RSSI is calculated according to the model parameters. Last, the coordinates of the mobile node are obtained in localization module. Next, they will be discussed in details.

A. Log-normal Shadow Model of Propagation

The indoor propagation of electromagnetic wave has several characters: (a) Free space propagation path loss; (b) Attenuated by the objects on the propagation path, such as walls, windows and floors of a building; (c) Scattered and interfered by itself [12]. In other words, the propagation path loss severely impacts on the precision of RSSI-based localization, therefore it is very important that choosing the proper propagation model. The model widely used in WSN is the log-normal shadow model (LNSM) [12].

$$PL(d) = PL(d_0) + 10n\log_{10}(\frac{d}{d_0}) + X_\sigma \tag{1}$$

Where, d is the distance between an anchor node and target node. d_0 is a reference distance, usually set d_0=1 meter. $PL(d_0)$ is a known reference pass loss (expressed in dBm) at d_0. $PL(d)$ is the received signal power loss(also expressed in dBm). n is the path loss exponent and depends on the specific propagation environment. X_σ is the Gaussian random variable with zero-mean and σ^2-variance.

Considering the received signal intensity and the logarithm of corresponding distance are linear relation. Equation (1) can be simplified to the log-normal shadow model as follows.

$$RSSI(d) = a + b\log_{10}(d) \tag{2}$$

Notice that the RSSI data collected from APs usually have an intense fluctuation due to unpredictable attenuation and reflection of radio signal. The fluctuation will be larger along with increasing distance. Taking this fact into account, Several approaches, including Gaussian filtering, piecewise fitting and total least square (TLS), are introduced to estimate model parameters accurately. The kernel steps of the approaches are as follows.

1) Acquisition of training data

In positioning region, M RSSI data are acquired from each distances d_i, i=1, 2, …, N. In order to guarantee model parameters accurately, these distances must be chosen carefully, generally selected uniformly from the distance close to the reference node to the maximum measurement distance away from the reference node.

2) Gaussian filtering

Calculate the mean and variance of the RSSI at the distance di, i=1, 2, …, N.

$$\mu_i = \sum_{j=1}^{M} RSS_{i,j} \tag{3}$$

$$\sigma_i^2 = \sum_{j=1}^{M} (RSS_{i,j} - \mu_i)^2 \tag{4}$$

Choose these RSSI data falling in the confidence interval [μ_i-3σ_i, μ_i+3σ_i], and re-calculate $\mu_{new,i}$ the mean of the RSSI at each distance with the filtered out sample values. $\mu_{new,i}$ can be regarded as the true RSSI corresponding to d_i.

3) Piecewise fitting based on TLS algorithm

The RSSI data are affected by the different noise degree at different distances. Typically, there is a threshold d_c ,d_c can be set as the α times of the longest distance d_{max}, $0 < \alpha < 1$. When $d \le d_c$, corresponding RSSI data have little fluctuation; when $d > d_c$, RSSI data fluctuate seriously. To reduce the influence of *RSSI-d* curve fluctuation, a piecewise TLS curve fitting method is employed. A *RSSI-d* curve is divided into two segments. At each segment, the log-normal ranging model is used to fit the curve between RSSI value and its distance.

$$RSSI\,(d) = a_1 + b_1\log_{10}(d),\ \text{when } d \le d_c \tag{5}$$

$$RSSI\,(d) = a_2 + b_2\log_{10}(d),\ \text{when } d > d_c \tag{6}$$

Then the TLS estimation algorithm is used to calculate the corresponding coefficients i.e. a_i and b_i, i=0, 1.

Assume that m_0 is the number of the RSSI data corresponding to the distance less than the d_c by the Gaussian filtering, while m_1 is the number of the RSSI data corresponding to the distance greater than the d_c by Gaussian filtering. From (5) and (6),we have

$$\begin{bmatrix} 1 & \log_{10}(d_1) \\ \vdots & \vdots \\ 1 & \log_{10}(d_{m_i}) \end{bmatrix} \begin{bmatrix} a_i \\ b_i \end{bmatrix} = \begin{bmatrix} RSS(d_i) \\ \vdots \\ RSS(d_{m_i}) \end{bmatrix} \quad i = 0, 1 \tag{7}$$

Then assemble the augmented matrix B_i.

$$B_i = \begin{bmatrix} -RSS(d_1) & 1 & \log_{10}(d_1) \\ \vdots & \vdots & \vdots \\ -RSS(d_{m_i}) & 1 & \log_{10}(d_{m_i}) \end{bmatrix} \quad i = 0, 1 \tag{8}$$

Apply singular value decomposition(SVD) on B_i.

$$B_i = U_i \sum V_i^T \quad i\text{=0, 1} \tag{9}$$

where U_i and V_i is the left and right singular matrix of B_i. The unique solution is given by the right singular vector corresponding to the smallest singular value(size of V is 3 ×3), i.e.

$$\begin{bmatrix} a_i \\ b_i \end{bmatrix} = \frac{1}{v_i(1,3)} \begin{bmatrix} v_i(2,3) \\ v_i(3,3) \end{bmatrix} \quad i\text{=0, 1} \tag{10}$$

B. Distance estimation

According to the estimated LNSM parameters, the distance is figured out corresponding to the acquisition RSSI data in real-time location. The appropriate model parameters are selected according to the value of the RSSI.

When $RSSI\,(d) > RSSI\,(d_c)$, a_1 and b_1 are used

$$d = 10^{\frac{RSS - a_1}{b_1}} \tag{11}$$

When $RSSI\,(d) \le RSSI\,(d_c)$, a_2 and b_2 are used

$$d = 10^{\frac{RSS - a_2}{b_2}} \tag{12}$$

Unlike average RSSI data firstly in other algorithms [6], we calculate the distance first with (11) or (12), and then average the distances.

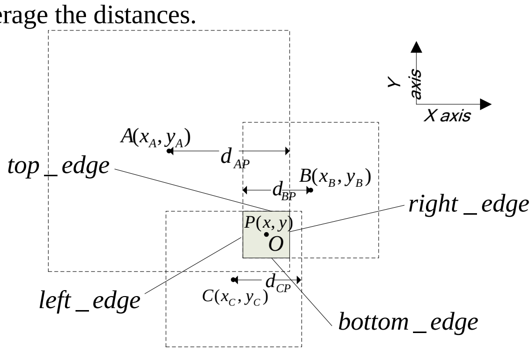

Figure 1. B-box algorithm.

C. Location Algorithm

1) B-box algorithm

B-box algorithm, as a typical localization algorithm, is widely applied due to its low computational complexity and high precision [18]. For instance, there are three access points, i.e. A(x_A, y_A), B(x_B, y_B), C(x_C, y_C) shown in Fig.1; the mobile node is $P(x, y)$; the estimated distances between P and A, B, C are d_{AP}, d_{BP}, d_{CP} respectively. The specific procedure of the B-box algorithm is as below.

As shown in Fig.1, set A, B and C as the centers, d_{AP}, d_{BP} and d_{CP} as half of each border length. Draw three rectangles.

Then obtain the location of the area's up, down, left and right border, as following formula shows.

$$\begin{cases} right\_edge = \min(x_A + d_{AP}, x_B + d_{BP}, x_C + d_{CP}) \\ left\_edge = \max(x_A - d_{AP}, x_B - d_{BP}, x_C - d_{CP}) \\ top\_edge = \min(y_A + d_{AP}, y_B + d_{BP}, y_C + d_{CP}) \\ bottom\_edge = \max(y_A - d_{AP}, y_B - d_{BP}, y_C - d_{CP}) \end{cases} \tag{13}$$

where min( ) and max( ) are the finding minimum or maximum functions respectively.

Calculate the centroid of the overlap O as the location of the mobile node P.

$$\begin{cases} x = (right\_edge + left\_edge)/2 \\ y = (top\_edge + bottom\_edge)/2 \end{cases} \tag{14}$$

It is easy to generalize the result to the case that multi-APs existing. Obviously, if there are N_{ap} APs, the overlapped square is

$$\begin{cases} x_r = \min(x_i + d_i) \\ x_l = \max(x_i - d_i) \\ y_t = \min(y_i + d_i) \\ y_b = \max(y_i - d_i) \end{cases} \quad i\text{=1, 2, …, } N_{ap} \tag{15}$$

where d_i is the distance between the mobile node and any anchor node(x_i, y_i), i=1, 2, …, N_{ap}. Then the mobile node $P(x, y)$ position is

$$\begin{cases} x = (x_l + x_r)/2 \\ y = (y_t + y_b)/2 \end{cases} \quad i\text{=1, 2, …, } N_{ap} \tag{16}$$

2) Weighting B-box

Applying a proper weighting factor into B-box algorithm can further reduce the error area and increase the positioning accuracy. Based on (15), during the calculation of the coordinates of $P(x, y)$, a weighting factor l_i on the basis of the B-box algorithm.

$$\begin{cases} x = (x_l \cdot l_1 + x_r \cdot l_2)/(l_1 + l_2) \\ y = (y_t \cdot l_3 + y_b \cdot l_4)/(l_3 + l_4) \end{cases} \tag{17}$$

where l_1 is the distance which corresponds to the i node that make x_i+d_i maximum; l_2 is the distance which corresponds to the i node that make x_i-d_i maximum; l_3 is the distance which corresponds to the i node that make y_i+d_i maximum; l_4 is the distance which corresponds to the i node that make y_i-d_i maximum.

3) Iterative Algorithm

It is well known that trilateration is a fundamental positioning algorithm [3]. However, approving solution can not be obtained due to intense fluctuation of RSSI data in a WSN. An iterative trilateration algorithm based on normalized least mean square (NLMS) principle and combining with weighting B-box is herein proposed as follows.

The location result ($x(0)$, $y(0)$) by the weighting B-box based on (14) or (15) is set as the initial value of the iterative algorithm.

Perform the equations from (18) to (20) periodically.

$$e_{n+1} = r^2_{n\,\mathrm{mod}\,\mathrm{N_{ap}}} - [x(n) - x_{n\,\mathrm{mod}\,\mathrm{N_{ap}}}]^2 - [y(n) - y_{n\,\mathrm{mod}\,\mathrm{N_{ap}}}]^2 \tag{18}$$

$$\begin{aligned} x(n+1) &= x(n) + \\ &2\cdot\mu\cdot e_{n+1}\cdot[x(n) - x_{n\,\mathrm{mod}\,\mathrm{N_{ap}}}]/[(x(n) - x_{n\,\mathrm{mod}\,\mathrm{N_{ap}}}]^2 + [y(n) - y_{n\,\mathrm{mod}\,\mathrm{N_{ap}}})^2] \end{aligned} \tag{19}$$

$$\begin{aligned} y(n+1) &= y(n) + \\ &2\cdot\mu\cdot e_{n+1}\cdot[y(n) - x_{n\,\mathrm{mod}\,\mathrm{N_{ap}}}]/[(y(n) - x_{n\,\mathrm{mod}\,\mathrm{N_{ap}}})^2 + (y(n) - y_{n\,\mathrm{mod}\,\mathrm{N_{ap}}})^2] \end{aligned} \tag{20}$$

where ( ) mod ( ) is the remainder function, μ is the step size. r_i, i = 0, 1, …, (N_{ap}-1) represents the distance from the mobile node to the *i-th* AP. (x_i , y_i), i = 0, 1, …, (N_{ap}-1) represents the coordinates of the APs. e_n represents the error at the n-th iteration. ($x(n)$, $y(n)$) represents the result at the n-th iteration. if e less than a defined limit or the iteration time reaches a certain number, then the iteration operation is terminated, and output ($x(n)$, $y(n)$) of this moment as the final result. If not, repeat the operations according to (18)-(20).

III. SIMULATION AND RESULT DISCUSSION

To evaluate a positioning algorithm, the positioning mean square error (PMSE) is used. The PMSE of *NUM* sampling points' position results is:

$$PMSE = \sqrt{\frac{\sum_{i=1}^{NUM}[(x_i - x'_i)^2 + (y_i - y'_i)^2]}{NUM}} \tag{21}$$

where (x_i, y_i)denote the location results of the i sampling point and(x'_i, y'_i)are the real location coordinate of it.

A. Simulation data

To verify the effectiveness of the proposed method, simulative location experiments are carried out. A Texas Instruments' CC2530 WSN ZigBee chip is referenced. It has a location engine system with a free protocol stack. Its operating frequency is f = 2.4GHz in the ISM band and equivalent wavelength is $\lambda = 3\times10^8/2.4\times10^9 = 0.125$ m. Its transmit power is P_t = 4.5 dBm, i.e. 2.51 mW. Assume d is the distance away from transmission antenna, P_r is the received power, G_r and G_t are the directivity of the receiving and transmitting antenna respectively, According to [12], the received power $P_r(d)$ is

$$P_r(d) = \frac{P_t}{4\pi d^2} G_r G_t (\frac{\lambda^2}{4\pi}) \tag{22}$$

then $P_r(1)$ is

$$P_r(1) = G_r\, G_t\, 2.51\, 0.125^2/(4\pi)^2 = G_r\, G_t\, 2.48\times10^{-4} \text{ mw} \tag{23}$$

Based on $P_r(1)$, the received power $P_r(d)$ can be calculated as

$$P_r(d) = P_r(1)/d^2 \tag{24}$$

In a real environment, the received power will be fluctuation caused by noise. To describe the fact, an additional white Gaussian noise $X_\sigma \sim N(0, \sigma^2)$ is added into the received power. Let $P(d)$ denote the received power mixed with noise, then

$$P(d) = P_r(d) + X_\sigma \tag{25}$$

Lastly, use (26) to calculate the simulation RSSI data corresponding to the distance d

$$RSSI(d) = 10 \log_{10}[P(d)] \tag{26}$$

As shown in Fig. 2, we choose a location area of 10m×10m as the experimental area, four APs are placed at each corner, their coordinates are (0, 0)m, (0, 10)m, (10, 0)m and (10, 10)m. The mobile node may appear at (10i, 10j)m, i, j=0, 1, …, 10. In order not to coincide with the position of the APs in the location area, the mobile nodes at the four corners are moved inside of the square (0.1, 0.1)m. Therefore, we can obtain 121 sampling points.

RSSI data corresponding to four APs can be received to generate the log-normal shadow model of propagation. Another group of data will be used in real-time location. In our simulations, set α = 0.6, the limit of e is set as 10^{-3} in (18), the upper limit of iteration time is set as 100, and $\mu = 10^{-7}$.

B. Performance analysis

In [2], it is found that the simple B-box algorithm has better performance than other algorithms. The LS algorithm is used to obtain the propagation model parameters, the distance will be obtained corresponding to an average RSSI data according to the model parameters. Finally, the B-box algorithm is for calculating location result. The PMSE of the proposed method and the one in [2] were compared in Fig. 3, when the SNR is from 20dB to 60dB. The PMSE value came from the average over 80 times Monte Carlo simulations.

In the environment of the smaller noise such as when the SNR more than 25, the proposed algorithm has a significant effect of improving the positioning accuracy, as shown in Fig. 3, the PMSE of the proposed method is cut off at lease 2/3 while comparing to the B-box algorithm.

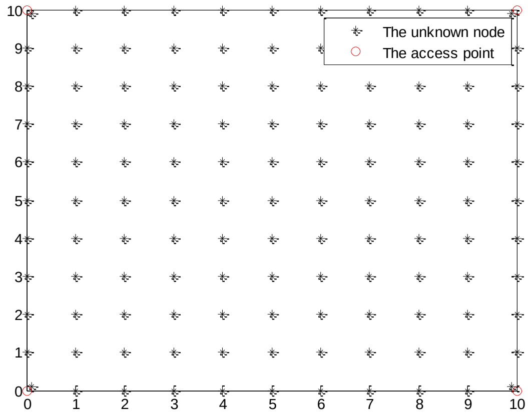

Figure 2. The node location map.

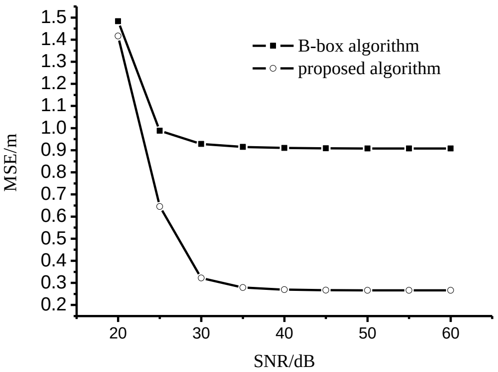

Figure 3. The node location map.

IV. CONCLUSION

In this paper, a modified RSSI-based localization method is proposed. The Spatial Gaussian filtering, piecewise curve fitting and total least square estimation are introduced to obtain a more accurate indoor propagation model. The Gaussian filtering and the piecewise fitting can weak the interface of noise; the model parameters can be more accurate by the TLS instead of the LS. And then, the distance corresponding to the acquisition RSSI data at real-time location will be obtained according to the appropriate model parameters and the average processing of the distances will be taken to improve the localization effect. Based on the initial position result with the weighting B-box, the iteration algorithm is used to further optimize the location result. The experimental results show that the modified algorithm can greatly reduce the ranging error comparing with the common B-box algorithm.

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