A Localization Method based on Bluetooth Network using Received Signal Strength

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***Abstract* — With the development of micro-electronics, wireless communication and sensor technologies, wireless sensor network (WSN) attracted considerable attention. The node localization problem is a major challenge in wireless sensor network. Bluetooth network owns wide range of application, so Bluetooth network based localization method using received signal strength (RSS) has been widely used in indoor localization scene. However, the RSS measurements are vulnerable for the environmental disturbance. Therefore, in order to estimate the parameters in propagation model of RSS, the EM (Expectation Maximization) method is firstly used in this paper. And then the improved Tabu search based localization method is proposed to estimate the position of unknown node. Finally, the simulation results are performed to evaluate the performance of the propose method.**

Keywords - Wireless sensor network; Bluetooth network; localization; received signal strength; expectation maximization

I. INTRODUCTION

The wireless sensor network (WSN) consists of hundreds of low-cost and low-power nodes. WSN has the advantages of multi-hop communication and self-healing network, so it has been used in many scenes such as patient surveillance and indoor disaster relief. The indoor localization problem is hot research topic in WSN. The position information is critical for the application of the WSN. There are many technologies have been used for network based localization, such as computer vision [1], WiFi [2], ZigBee [3], RFID [4], UWB [5], Bluetooth [6] and ultrasonic [7]. The computer vision technology needs high requirement for hardware. WiFi and ultrasonic technologies have the characteristics of high power consumption. UWB, ZigBee and RFID technologies are not widely used in consumer device. The Bluetooth owns the advantage of low-power and good versatility. Therefore, we employ the Bluetooth node as physical measurements device.

There are four measurement modes for WSN based localization methods: time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) and received signal strength (RSS). The TOA method needs high clock synchronization in the sensor node and it need higher hardware cost. The TDOA and AOA methods require extra hardware such as ultrasonic, infrared equipment or array antenna. The RSS method does not need extra hardware and owns character of low-power and low-cost, so it is suitable for the application of WSN. In this paper, we consider the localization of the unknown node using the RSS value for Bluetooth network.

Two main contributions of this paper are listed as follows:

- The proposed method could estimate the parameters in propagation model using the EM method.
- The improved Tabu search method is proposed to estimate the position of the unknown node.

The reminder of this paper is organized as follows: in section II, we describe the related works about the RSS based localization methods for wireless sensor network. The some basic notations and measurement model are presented in section III. In section IV, the proposed Bluetooth network based localization method is presented. The simulation results are presented in section V. Section VI concludes this paper.

II. RELATED WORKS

The RSS technology has received The RSS based localization methods can be classified into two categories: range-based and map-based localization methods. The range-based methods convert the RSS value into the distance. And position of unknown node is estimated using the distance and the position of beacon node. A game theoretical algorithm [8] is proposed to optimize resource in a wireless sensor network. This algorithm could minimize the transmit power of nodes and maintain the adjustable localization accuracy using the GDOP. To overcome the local optima problem in non-convex objective function, a new non-convex estimator [9] is proposed to estimate the position of unknown node using RSS measurements. A novel localization scheme [10] based on curve fitting and location search is proposed. The curve fitting technique is used to construct a fitted RSS-distance function for each transmitter in each subarea. Then two location search algorithm is used to find a location within the selected subarea. The weighted multi-lateration techniques [11] are used to obtain the robustness with respect to the inaccuracies measurement.

The map-based localization method consists of two steps: the off-line measurement and online localization. In the off-line step, the RSS value in the selected reference positions and record them in the data set. In the online step, the reference position which is closet to the on-line RSS value is selected as the estimated position. A hybridism of particle swarm optimization and kriging [12] is used in fingerprinting localization method. A dynamic fingerprinting combination algorithm [13] is proposed to improve the localization accuracy by dynamically weighting the spatial correlation form multiple fingerprinting systems. The likelihood-

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calculation mechanism [14] is proposed for the particle filter. This algorithm is interpreted as a soft version of base station strict approach applied in the static case. An efficient localization system that uses a new empirical propagation model [15] is proposed. The novel model is called regional propagation model which is based on the cluster based propagation model theory. The range-based localization methods own higher localization accuracy, but the computational complexity is also higher. The map-based methods are easily affected by environmental factors.

III. Problem Statement

A. Basic Notations

There are three types of sensor nodes in network based localization system: beacon node, unknown node and base station. The beacon node is pre-deployed in the network initialization phase and its position is known. The unknown node receives the signals transmitted from beacon nodes and converts the signals to distance. The base station estimates the position of unknown node using the estimated distance. All of the three types of nodes are equipped with the Bluetooth devices. The Bluetooth module which employs the CC2540 chip, shown in Figure 1, is used in our experiments. This module could measure the RSS value without any extra hardware. In this paper, we consider a network which consists of N beacon nodes and one unknown node in a two-dimensional space. The position of *i-th* beacon node is $\boldsymbol{X_i}=[x_i,y_i]$. The position of unknown node is $\boldsymbol{U}=[u_x,u_y]$. The true distance between the *ith* beacon node and mobile node as

$$d_i = \left\| \mathbf{X}_i - \mathbf{U} \right\| \tag{1}$$

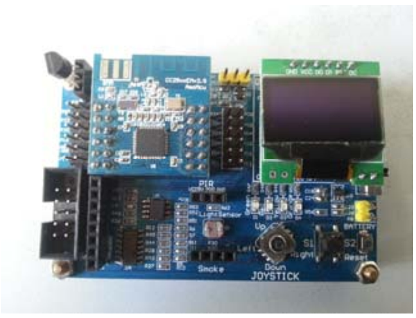

Figure 1. Bluetooth module

B. Measurement Model

Many measurement models have been proposed for RSS measurement. We employ the log-normal shadowing model [16-17] in this paper. We assume that the beacon node owns variable transmitting power. The RSS of *i-th* node can be expressed as:

$$P_{ik} = P_{0,k} - 10\beta_i \log_{10}(d_i/d_0) + S_i \tag{2}$$

where $P_{0,k}$ is the path loss at d_0 meter for *k-th* transmitting power. We set d_0=1 in this paper, β_i is the path loss exponent for *i-th* node. S_i is the shadowing effect. It is modeled as μ_i mean white Gaussian with variance σ_i^2 in LOS condition (*i.e.* $S_i \sim N\left(\mu_i, \sigma_i^2\right)$).

The traditional methods convert the RSS P_i into distance as follows

$$d_i = 10^{\left(\frac{P_0 - P_i + S_i}{10 \cdot n}\right)} \tag{3}$$

The relationship between the mean RSS value and distance is shown in Figure 2. We can see that the monotonicity of propagation model is not obvious since the large parameter perturbation. Therefore, the estimated distance in Eq.(3) owns large error.

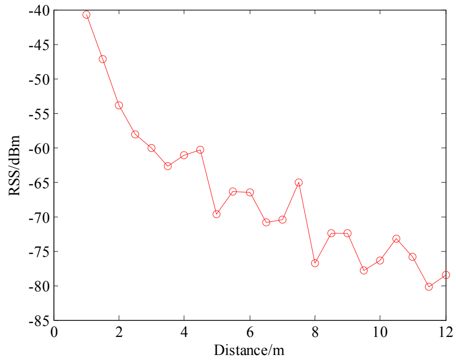

Figure 2. The relationship between distance and RSS

IV. Proposed Method

In this paper, the localization method consists of two steps: parameters estimation step and the localization step. In parameters estimation step, the beacon node communicates with each other. We firstly estimate the parameter β. And then the EM (Expectation Maximization) algorithm is employed to estimate the parameters of noise using the measurements from beacon nodes pair. In localization step, the estimated distance can be obtained using the Eq.(3). And then the improved Tabu search method is used to estimate the position of unknown node.

A. Estimate β

We assume that *j-th* beacon node transmits the signal and the *i-th* beacon node receives it. The received signal strength is P_{ij}. And the beacon node owns variable transmitting power.

According to Eq.(2), the estimated path loss exponent β_i for *i-th* beacon node as

$$\hat{\beta}_i = \frac{\sum_{k=0}^{K}\left(P_{0,k} - P_{ik}\right)}{10 \cdot \sum_{k=0}^{K} \log_{10} d_{ij}} \tag{4}$$

where, d_{ij} is the distance between *i-th* beacon node and *j-th* beacon node, the beacon node owns K transmitting power.

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$P_{0,k}$ is the path loss for *k-th* transmitting power in *j-th* beacon node.

B. Estimate the parameters of noise

The Eq.(2) can be rewritten as

$$S_i = \underbrace{P_0 - P_{ik} - 10\beta_i \log_{10}(d_i/d_0)}_{y_{ik}} \tag{5}$$

The probability density function of y_{ik} denotes as

$$f(y_{ik}) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(y_{ik}-\mu_i)^2}{2\sigma_i^2}\right) \tag{6}$$

The likelihood function is

$$\begin{aligned} L(\mathbf{y},\mu_i,\sigma_i^2) &= \prod_{k=1}^{K} f(y_{ik},\mu_i,\sigma_i^2) \\ &= (2\pi\sigma_i^2)^{-K} \exp\left(-\frac{1}{2\sigma_i^2}\sum_{k=1}^{K}(y_{ik}-\mu_i)^2\right) \end{aligned} \tag{7}$$

The log-likelihood function as

$$\ln L(\mathbf{y},\mu_i,\sigma_i^2) = -\frac{K}{2}\ln(2\pi) - K\ln(\sigma_i) - \frac{1}{2\sigma_i^2}\sum_{k=1}^{K}(y_{ik}-\mu_i)^2 \tag{8}$$

where, $\mathbf{y}=[y_1,y_2,\ldots,y_K]$.

Then the estimation of the unknown parameters which maximize the likelihood of the Eq.(8) is investigated. Since the Eq.(8) is a nonlinear equation, direct maximization cannot be obtained. In this paper, we employ the EM (Expectation Maximization) algorithm to solve it. The EM algorithm consists of two steps: E-step which creates a function for expectation of the log-likelihood function using the current estimate for the parameters, and M-step which compute parameter maximizing the expected log-likelihood function found on the E-step. The unknown parameters denote as $\boldsymbol{\theta} = [\mu_i,\sigma_i^2]$.

In E-step, we compute the expected value of the log-likelihood function with respect to the conditional distribution of $\mathbf{y}$ under current estimate of the parameter $\boldsymbol{\theta}^t$:

$$\begin{aligned} Q(\boldsymbol{\theta}|\boldsymbol{\theta}^t) &= E\left[\ln L(\mathbf{y},\boldsymbol{\theta})\middle|\mathbf{y},\boldsymbol{\theta}^t\right] \\ &= -\frac{K}{2}\ln(2\pi) - K\ln(\sigma_i) - \frac{1}{2\sigma_i^2}\sum_{k=1}^{K} E\left[(y_{ik}-\mu_i^t)^2\middle|\mathbf{y},\boldsymbol{\theta}^t\right] \end{aligned} \tag{9}$$

We assume the measurements are not missing. In Eq.(9), we get that

$$E\left[(y_{ik}-\mu_i)^2\middle|\mathbf{y},\boldsymbol{\theta}^t\right] = \sum_{k=1}^{K}(y_{ik}-\mu_i^t)^2 \tag{10}$$

Therefore, Eq.(9) can be written as

$$Q(\boldsymbol{\theta}|\boldsymbol{\theta}^t) = -\frac{K}{2}\ln(2\pi) - K\ln(\sigma_i) - \frac{1}{2\sigma_i^2}\sum_{k=1}^{K}(y_{ik}-\mu_i^t)^2 \tag{11}$$

In M-step, we find the parameter that maximizes the quantity:

$$Q(\boldsymbol{\theta}^{t+1}|\boldsymbol{\theta}^t) = \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}|\boldsymbol{\theta}^t) \tag{12}$$

In order to finding a maximum likelihood solution, it requires taking the derivatives of Eq.(12) with respect to all the unknown parameters.

$$\begin{cases} \dfrac{\partial Q(\boldsymbol{\theta}^{t+1}|\boldsymbol{\theta}^t)}{\partial \mu_i} = 0 \\ \dfrac{\partial Q(\boldsymbol{\theta}^{t+1}|\boldsymbol{\theta}^t)}{\partial \sigma_i} = 0 \end{cases} \tag{13}$$

According to Eq.(13), the estimated parameters as

$$\mu_i^t = \frac{1}{K}\sum_{k=1}^{K} y_{ik} \tag{14}$$

$$(\sigma_i^t)^2 = \frac{1}{K}\left[\sum_{k=1}^{K} y_{ik}^2 - K\cdot(\mu_i^t)^2\right] \tag{15}$$

The estimation parameters processing is

(1) Initialize the parameters θ to some random values.

(2) Compute the path loss exponent according to Eq.(4).

(3) Compute the mean of the noise according to Eq.(14).

(4)Compute the variance of the noise according to Eq.(15).

(5) Iterate step 2-4 until $\left\|\boldsymbol{\theta}^{t+1} - \boldsymbol{\theta}^t\right\| < \varepsilon$.

C. Localization Method

The estimated parameters of the noise is $\left[\hat{\beta}_i,\hat{\mu}_i,\hat{\sigma}_i^2\right]$ according to section IV(A) and IV(B). The maximum likelihood function can be obtained as

$$\left[\hat{u}_x,\hat{u}_y\right] = \arg\max H(u_x,u_y) \tag{16}$$

where,

$$H(u_x,u_y) = (2\pi\hat{\sigma}_i^2)^{-N-K} \exp\left(-\frac{1}{2\hat{\sigma}_i^2}\sum_{i=1}^{N}\sum_{k=1}^{K}\left(P_{0,k} - P_{ik} - 10\hat{\beta}_i\log_{10}(d_i/d_0) - \hat{\mu}_i\right)^2\right)$$

The estimated position of unknown node is to maximum the Eq.(16). In this paper, we employ the improved Tabu search method [18-19] to estimate the position of unknown node. The Tabu search method uses a neighborhood search procedure to iteratively move from one potential solution to an improved solution, until the stopping criterion has been satisfied.

The definition of the notations as follows: ***V*** is the set of feasible solutions, $v^k = [u_x,u_y]$ is the current solution in *k-th* iteration, v_b is the best solution reached, v_{gb} is the best solution among of trial solutions, $H(v)$ is the objective function Eq.(16) of solution v, $N(v)$ is the set neighborhood of v, *TL* is the Tabu list, *AC* is the aspiration criterion.

The improved generation the neighborhood criterion as follows:

$$v^k = v^{k-1} + b_1\left(v^{k-1} - v_b\right) + b_2\left(v^{k-1} - v_{gb}\right) \quad (17)$$

where, b_1 and b_2 two uniform random numbers in [0,1].

The steps of the Tabu search based localization method as follows

Step 1: Initialize the *TL*, *AC*, iteration counter k=0, initial solution v and v_b=v.

Step 2: Generate the set of solution neighborhood of v, and compute v_{gb} is the best trial solution.

Step 3: If $H(v_{gb})>H(v_b)$, goto step 4, else set the best solution $v_b=v_{gb}$ and goto step4.

Step 4: Perform the tabu test. If v_{gb} is not in the *TL*, then accept it as a current solution, set $v=v_{gb}$, and update the *TL* and *AC* and goto step 6, else goto step 5.

Step 5: Perform the *AC* test. If satisfied then override the Tabu state, set $v=v_{gb}$, update the *AC*.

Step 6: Perform the termination test. If the stopping criterion is satisfied then stop, else $k=k+1$ and goto Step 2. The estimated position of the unknown node is v_{gb}.

V. Simulation Results

In this section, the performance of the proposed method is evaluated. The localization scenario is considered as: N beacon nodes are deployed in 10m×10m square space. The beacon nodes communicate with each other to determine the parameters in propagation model using the proposed methods in section IV(A) and IV(B). The parameters of the propagation model are shown in Table 1. We compare the proposed method with maximum likelihood (ML) method. The simulation results are obtained by 500 Monte Carlo runs. The average localization error is used to evaluate the localization accuracy and it is defined as

$$AVE = \frac{1}{MC}\sum_{i=1}^{MC}\sqrt{\left\|\hat{U}_i - U_i\right\|^2} \quad (18)$$

where, U_i is the true position of unknown node for *i-th* trial. $\hat{U}_i$ is the estimated position of the unknown node.

TABLE I. The Default Parameters

Parameters	Symbol	Default Values
The number of beacon nodes	N	6
The standard deviation of S	σ_i	4
The mean of S	μ_i	0.1
The path loss exponent	β_i	3
The number of transmitting power	K	4

Fig.3 show the estimation error of σ_i under different value of K. It can be observed that the larger number of transmitting power, the less estimation error of σ_i. And the proposed method could estimate the parameters accurately.

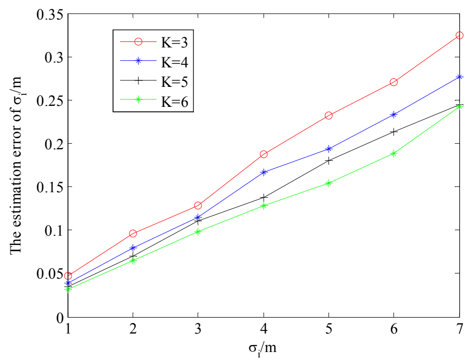

Figure 3. The estimation error of σ_i under different value of K

Fig.4 shows the relationship between the standard deviation σ_i of S and the average localization error. When the value of σ_i is low, the localization error of the two methods is close to each other. However, when the value of σ_i is high, the localization error of the ML method increases rapidly and the proposed method increases slowly. On the whole, when compared with the ML method, the proposed method is robust to the measurement noise.

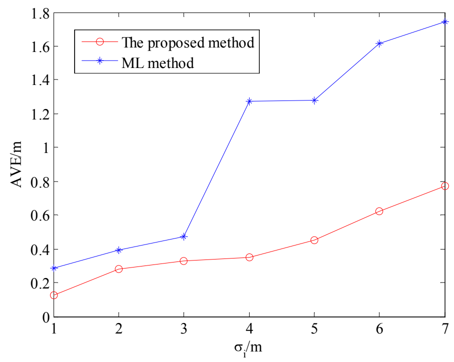

Figure 4. The relationship between the standard deviation of S and AVE

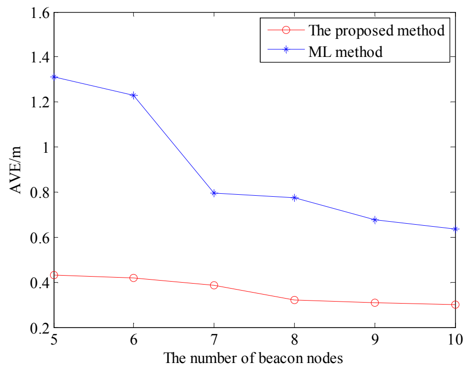

Figure 5. The relationship between the number of beacon nodes and AVE

Fig.5 shows the impact of the number of beacon nodes on the average localization error. It can be observed that the number of beacon nodes has moderate effect on the proposed method. The localization error of the proposed method improves 60.07% when compared with the ML method.

Figure 6 shows the evaluation for the convergence rate for the improved Tabu search method. Obviously, the convergence of improved algorithm occurs when the number of iteration is 21. The proposed method could find the optimal result with less iteration.

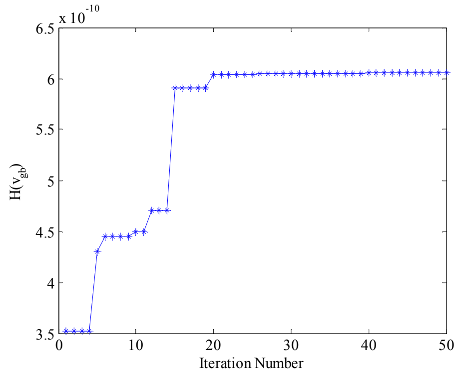

Figure 6. The convergence of the Tabu search

VI. CONCLUSIONS

In this paper, we investigate the localization problem for Bluetooth network using the RSS measurement. The radio propagation model is firstly introduced. And then the estimation of path loss exponent is proposed. Further, the parameters of measurement noise are investigated using the EM algorithm. Finally, Tabu search based localization method is proposed to estimate the position of unknown node. The simulation results show that the proposed method could estimate the parameters in propagation model and the position of unknown node accurately.

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