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An Optimized Indoor Localization Approach Based on RSSI with Pretreatment Filtering

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Abstract. *The major bottleneck in practical implementation of received signal strength indication (RSSI) based on indoor localization systems is that suffering from multi-path interference. Aiming to increase accuracy of localization, in this paper, we propose a new method by combining with filtering technology and optimization approach. In the pretreatment phase, we reduce the measurement error of RSSI by fitting curve technology. After initial positioning, the unconstrained optimization is applied to improve the accuracy of localization in the subsequent phase. The numerical simulation results suggest that our method is efficient in solving the localization problem of indoor environment with substantial obstacles.*
Keywords: RSSI; Indoor Localization; Fitting Curve; Unconstrained Optimization

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1. **Introduction.** Indoor localization methods based on wireless sensor networks (WSNs) have attracted much attention in recent years and have been extensively studied. These systems do not require investment in additional expensive device hardware. However, their operation is deficient in decreasing measurement errors of signals with making arrangement for the anchor nodes in WSNs [1-3].

Nowadays, some important methods toward improving the localization accuracy have been proposed in the indoor environment. In the paper [4], Z. Wu proposed an indoor localization method using online independent support vector machine (OISVM) classification method and under-sampling techniques which based on RSSI. This method decrease the time complexity both in the training and prediction process, but it is limited by the processing power and the memory for portable devices. Ismailova .etc. in paper [5] proposed a method that used the least squares for correcting the indoor localization distance and improved the accuracy of localization. It is benefit to locate a radiating source and decrease the error of localization, but it cannot be used widely. Banerjee proposed a method to avoid the redundancy of data in process of previous filtering methods while preserving the advantages of trilateral localization method [6]. However, this method is not practical because it requires specialized hardware which is not available to obtain conveniently. In the paper [7], to decrease the errors in RSSI observations which suffer from multipath interference in indoor dynamic environments, W. Xue proposed an algorithm to improve the result by selecting the average value of some most big RSSI observations.

In addition, in the paper[8], it is the first time to propose an adaptive indoor localization system called coupled RSSI and INS localization (CRIL), which can adapt to dynamic communication environments quickly and effectively. However, the calibration of the channel model in the method is complex, and it is time consuming. A. Maddumabandara.etc. in paper[9] proposed a technique to minimize the computational cost while conserving the robustness of steered response power-based phase transition algorithm. It is observed that the indoor localization performance can be greatly degraded by room reverberation.

Different from the reported literature, we put forward a new method named filtering technology and unconstrained optimization (FTUO). In the first, based on trilateral localization (TL) method, we reduce the measurement error and filter large noise by the fitting curve (FC) method different from the traditional K-means (KM) method. Secondly, the steepest descend (SD) method is used to optimize the location data. Finally, we conduct some numerical experiment to compare our method with others and analyze them in detail.

2. **Background and model.** Many applications in localization are based on WSNs. The WSNs localization system includes the anchor nodes and query node. The location of the anchor nodes are known and the query node is need to calculate. The localization process is realized by judging the distance between anchor nodes and query node based on the RSSI values. The scene graph of WSNs localization is shown as FIGURE 1.

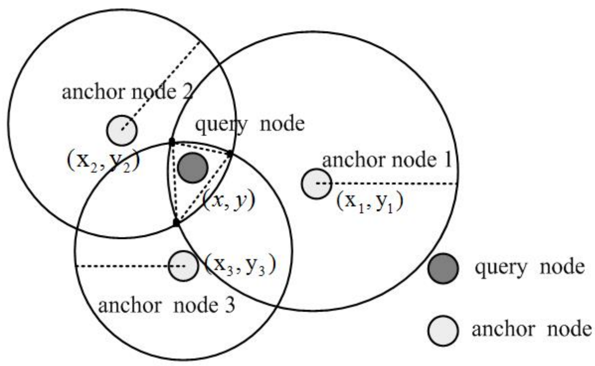

FIGURE 1. The scene graph of WSNs localization.

Before presenting our localization method, we first describe the classic framework of the localization system. The traditional model includes two phases, the pretreatment phase and localization phase. The following content will illustrate it in detail. The procedure of classic method is shown as FIGURE 2.

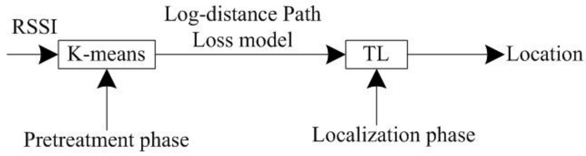

Figure 2. Procedure of classic method.

2.1. **Pretreatment phase.** In order to get more accurate location, the RSSI values should be filtered before localization. The main job of pretreatment phase is to filter outliers. In the paper[10], the K-means filtering method is proposed to improve the positioning accuracy and expand the area. K-means method is one of the most extensively applied in data mining which was proposed by Macqueen. The K-means clustering method divide n observations into k clusters in which each each observation belongs to the cluster with the nearest mean. The nearest distance is calculated by European distance minimum principle. These results show partition of the data space into various cells.

2.2. **Localization phase.** As to localization phase, there are different models such as curve-fitting model [11], polynomial model [12] and the Friis propagation model [13]. The Log-distance Path Loss (LDPL) model is given as

$$P(d) = P_t(d) - P_r(d) = P(d_0) - 10n\lg(\frac{d}{d_0}), \tag{1}$$

where $P(d)$ represents the path loss, $P_t(d)$ represents the transmission power level, $P_r(d)$ represents the received power level, $P(d_0)$ represents the received power at distance d_0 (typically 1m), n represents the environmental path-loss factor and d represents the distance between the anchor node and query node. The formula (1) can be rewritten as

$$RSSI = -(10n\lg d + A), \tag{2}$$

where A represents the received power at the distance is 1m from transmitted source and n represents attenuation factor. From formula (2), the distance between query node and anchor node can be obtained. After calculating the distance, the TL method is generally used to estimate the location. In the process of TL, the location of anchor nodes should be offered. In the paper [14], the Geo-n approach uses three circles to obtain overlap area but it only approximate the intersection points. Based on the Geo-n, TL method was used to solve the approximating problem. Assuming the anchor node coordinate is $(\mathrm{x}_i, \mathrm{y}_i)$, where $\mathrm{x}_i \in \mathbf{R}, \mathrm{y}_i \in \mathbf{R}$. The equations of trilateration can be written as

$$||(x - \mathrm{x}_i)^2 + (y - \mathrm{y}_i)^2|| = d_i, \quad i = 1, 2, 3, \tag{3}$$

where x, y represents coordinate of query node and d_i represents each distance between the anchor node and query node. When the three solutions of formula (2) is obtained, the solutions are defined as $(x_i, y_i), i = 1, 2, 3$, where x_i represents the x-coordinate of the circles intersection and y_i is the y-coordinate correspondingly. Then, the location coordinates can be calculated by

$$\bar{x} = \frac{1}{3}\sum_{i=1}^{3} x_i, \bar{y} = \frac{1}{3}\sum_{i=1}^{3} y_i. \tag{4}$$

3. **The proposed method.** Different from the traditional method, our method include three phases. In the first phase, FC filter the RSSI values of large fluctuation caused by multi-path interference. The second phase is localization phase, TL is a classic method and we still use it. The third phase is subsequent phase, we adopt to use SD method to acquire the optimal solution. The procedure of our method is shown in FIGURE 3.

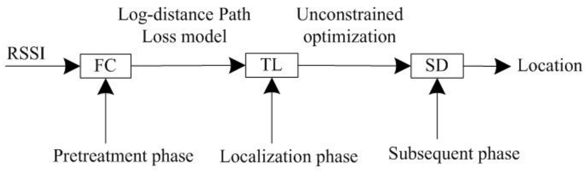

FIGURE 3. Procedure of our method.

3.1. **Pretreatment phase.** For there are lots of RSSI values in the query nodes, it needs a good filtering method to get rid of the outliers. In our research, we propose a novel filtering method in the pretreatment phase. The RSSI source involves a given matrix of m sensors specified by $\mathbf{RSSI} = \{\mathbf{RSSI_1}, \cdots, \mathbf{RSSI}_i, \cdots, \mathbf{RSSI}_m\}^T, i = 1, \cdots, m$. $\mathbf{RSSI}_i$ can be specified in detail by $\{rssi_{i,1}, \cdots, rssi_{i,j}, \cdots, rssi_{i,n}\}, j = 1, \cdots, n$. The formula of FC is given as

$$\overline{rssi_{i,j}} = \frac{1}{37}\left[-3(rssi_{i,j-2} + rssi_{i,j+2}) + 12(rssi_{i,j-1} + rssi_{i,j+1}) + 17rssi_{i,j}\right], \quad i = 1, \cdots, m, j = 3, \cdots, (n-2). \tag{5}$$

Calculating the value of $\left|\overline{rssi_{i,j}} - rssi_{i,j}\right|$, if it is less than the threshold value, we reserve it, otherwise, we delete it. Finally, we use arithmetic average method to calculate the final $RSSI_i$.

3.2. **Localization phase.** Trilateral localization is a classic method which only need to know three anchor nodes. Firstly, we draw three circles and obtain the overlap area of them. Then, we can estimate the location by triangle centroid. In this paper, we adopt this trilateral localization method in our proposed method.

3.3. **Subsequent phase.** It is worth noting that subsequent phase is an extra phase compare to the classic method. The steepest descent method, also known as gradient method, is a numerical method for solving the extremum of unconstrained multivariate function. It is one of the basis of the optimization method. Through the SD method, we can get more accurate result. Assuming the objective function is established as

$$\underset{x,y}{\text{minimize}}\ W(x,y) = \sum_{i=1}^{3} |\alpha_i| = \sum_{i=1}^{3} (x - \mathrm{x}_i)^2 + (y - \mathrm{y}_i)^2 - d_i^2, \tag{6}$$

where d_i represents the theory distance calculated by the LDPL and $\mathrm{x}_i, \mathrm{y}_i$ represent the x,y-coordinate respectively. The α_i denotes the distance error between actual distance and theory distance. Equation (6) can be rewritten as

$$\begin{aligned} &\underset{x,y}{\text{minimize}}\ M(x,y) = \sum_{i=1}^{3} \alpha_i^2 = \sum_{i=1}^{3} ((x-\mathrm{x}_i)^2 + (y-\mathrm{y}_i)^2 - d_i^2)^2, \\ &\text{subject.to:} \qquad \alpha_i = (x-\mathrm{x}_i)^2 + (y-\mathrm{y}_i)^2 - d_i^2 \quad . \end{aligned} \tag{7}$$

Let $u_i(x) = 0$, $i = 1, 2, 3$, the unconditional equality constraint can be written as

$$\begin{aligned} &\underset{x,y}{\text{minimize}}\, M(x,y) = \sum_{i=1}^{3} \alpha_i^2 = \sum_{i=1}^{3} ((x-\mathrm{x}_i)^2 + (y-\mathrm{y}_i)^2 - d_i^2)^2, \\ &\text{subject.to:} \qquad u_i(x) = (x-\mathrm{x}_i)^2 + (y-\mathrm{y}_i)^2 - \alpha_i - d_i^2 = 0 \ , \end{aligned} \tag{8}$$

where x, y can be obtained by the partial derivatives with objective function. In order to solve the equation (8), we solve the first order partial derivatives $\mathbf{g(x)}$ which can be written as $\left[\begin{array}{cc} \frac{\partial M}{\partial x} & \frac{\partial M}{\partial y} \end{array}\right]$.^{T} Because of the second order partial derivatives $\mathbf{G(x)}$ of objective function is required in the iterative formula, according to the equation(8), the $\mathbf{G(x)}$ can be describe as $\left[\begin{array}{cc} \frac{\partial^2 M}{\partial x^2} & \frac{\partial^2 M}{\partial x \partial y} \\ \frac{\partial^2 M}{\partial y \partial x} & \frac{\partial^2 M}{\partial y^2} \end{array}\right]$. Then, the iterative formula of the SD method is

$$x_{k+1} = x_k - \frac{g_k^T g_k}{g_k^T G g_k} g_k. \tag{9}$$

As $\frac{g_k^T g_k}{g_k^T G g_k}$ is constant and it can be defined as γ. Then, we can get: $x_{k+1} = x_k - \gamma * g_k$. If $|x_{k+1} - x_k| < \sigma$, σ is a threshold, then the iteration stopped and we get the optimal result x_k which is the solution of x. Similarly, y is calculated as same as x.

3.4. **Our algorithm.** Based on the LDPL model, we proposed an algorithm which combines FC method named as filtering technology and unconstrained optimization (FTUO). The algorithm of FTUO method are shown as TABLE 1.

TABLE 1. Algorithm of FTUO.

Algorithm of FTUO
Input: RSSI, coordinates $\mathbf{X}, \mathbf{Y}$ of anchor nodes, convergence tolerance ε;
Output: x_k, y_k of query node.
Step(1) Calculate formula (5) and obtain all $\overline{rssi_{i,j}}$ values. If $\overline{\lvert rssi_{i,j}} - rssi_{i,j}\rvert > \varepsilon$, remove $\overline{rssi_{i,j}}$; otherwise, reserve it;
Step(2) Calculate the remaining $\overline{rssi_{i,j}}$ values by using arithmetic averages and then obtain final $RSSI_i$;
Step(3) To get d from formula (3) and get $\bar{x}, \bar{y}$ from (4), (5), marked as x_0, y_0;
Step(4) Set x_0, y_0 as the initial value of formula (9) ;
Step(5) Iterate formula (9), until $\lvert x_{k+1} - x_k\rvert < \sigma$, stop iteration;

4. **Analysis of experimental results.** MATLAB R2010b is chosen as simulation platform. Simulation experiments are conducted in a zone of size 15*15m in 2D coordinate.

There are three anchor nodes (A,B,C) in our localization estimation. The locations of the anchor nodes A, B, C are close to the query point. Under the LDPL model, we set the pass-loss parameter n as 2 and suppose all these anchor nodes transmit at the different power levels(-48dB, -54dB, -60dB) with tolerance of ± 2dB. These elements are used to estimate location. Figure 4 show the specific distance error of all methods. The value indicated by K-means and trilateral localization(KMTL) method is the distance error which is calculated by TL method based on K-means(KM) method. The filtering technology and trilateral localization (FTTL) method use FC method. The value indicated by K-means and unconstrained optimization(KMUO) method calculate the distance error by SD method based on KM. The FTUO method use FC method. The distance error value indicated by K-means(KM) method is absent in TL method and it only use KM. The distance error value indicated by FT is excluded in using TL and only use FC method.

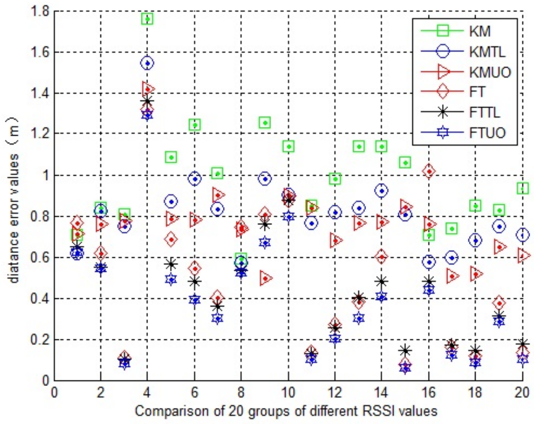

Figure 4. The distance error with different RSSI values.

As shown in FIGURE 4, in the same RSSI value, we can see distance error of FTUO is smaller than KM, FT, FTTL, KMTL and KMUO in most situation. At the RSSI value of 12, the distance error of FTUO is smaller than the KM nearly 0.8 m. The FTUO method is better than other methods apparently.

Furthermore, in FIGURE 5, we use cumulative distribution function (CDF) to show the distance error calculated by KM, KMTL, KMUO, FT, FTTL and FTUO.

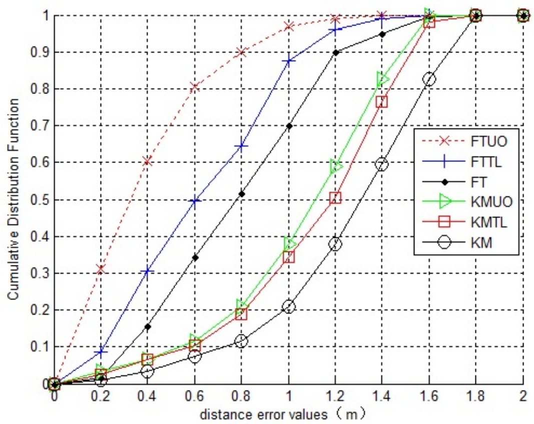

Figure 5. The CDF with distance error values increasing.

As shown in FIGURE 5, the error line of FTUO increases faster than others which represents the error of RSSI values. This means our method can get higher CDF than other methods in the same distance error. Moreover, we compare our approach to other approaches in detail as following. At the distance error of 1m, KM has the lowest CDF. KMUO and KMTL have similar performance and their CDF are both higher than KM almost 1.5. By filtering approach, FT and FTTL performance improve much and they are better than KMUO about 0.3 and 0.5. It is noteworthy that the FTUO we proposed get the highest CDF, and it's performance is better than the KM nearly 0.8 in CDF .

In order to show the error clearly, the resultant location errors(maximum, minimum and mean) of KM, KMTL, KMUO, FT, FTTL, FTUO method are given in TABLE 2.

TABLE 2. The distance error value in Max, Min and Mean.

Algorithm	Maximum(m)	Minimum(m)	Mean(m)
KM	1.8004	0.6004	1.2502
KMTL	1.7081	0.5642	1.0482
KMUO	1.6910	0.5048	1.0592
FT	1.6311	0.1243	0.6332
FTTL	1.4449	0.0920	0.4894
FTUO	1.3829	0.0516	0.3782

As seen from TABLE 2, the mean value of FTTL method is 0.4894 m and better than other traditional methods. However, by using our FTUO method, the mean value is 0.112 m lower than the value calculated by FTTL. At the same time, we can see the minimum error value reaches 0.0516 m which is far smaller than others. This table verify our method's effectiveness in another aspect.

5. Conclusion.

In this paper, we propose FTUO method to solve the localization problem of indoor environment with substantial obstacles. We use the FC to delete the large error of RSSI values and the SD to increase the accuracy of the location in our FTUO method. In the further work, the limiting amplitude wave filter method may replace fitting curve method to filter the RSSI values. In addition, for the variety of scenarios, the FTUO method cooperating with other new method could be needed to estimate accurate location.

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