

A High-Precision Real-Time Distance Correction Three-Dimensional Localization Algorithm Based on RSSI for WSNs

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Abstract: In order to reduce the wireless localization error caused by RSSI, which is easily affected by environmental factors, a real-time distance correction three-dimensional localization algorithm is put forward. The algorithm configures reference nodes optimally and uses the Gaussian Model to filter values of RSSI received by nodes. Then distance data is corrected in real-time, the ill coefficient matrix correction and the maximum likelihood estimation are combined to determine unknown nodes preliminarily. After that, filtering and elimination technique are used to process location results, which effectively improve the localization accuracy. Experiment result proves that the algorithm has an excellent precision of 92.9 %, it also has characteristics of a shorter locating time, a lower hardware cost and energy consumption. So, the algorithm is of great stability and practicality. *Copyright © 2013 IFSA.*

Keywords: WSN, RSSI, Three-dimensional localization, Distance correction, Gaussian Model.

1. Introduction

Wireless Sensor Network (WSN), is a wireless network built by a set of sensor nodes in the form of ad-hoc network, it can perceive, collect and process perception object information of the geographical area covered by the network collaboratively, then issue the information to the host computer [1-3]. Localization algorithm can be divided into two categories in terms of the positioning technology: ranging-based localization algorithm and ranging-free localization algorithm. Ranging-based localization algorithm includes Received Signal Strength (RSSI),

Time of Arrival (TOA), Angle of Arrival (AOA), etc. Ranging-free localization algorithm, such as the centroid method, DV-Hop, APIT and MDS-MAP [4], etc., they do not need distance and angle information, and achieve node's locating based on the information such as network connectivity [5]. Ranging-free localization algorithm has some advantages, like the simple structure, and the node does not need additional hardware device, so it has a customer attention [6].

For WSN localization algorithm based on RSSI, there are a variety of ways to improve the localization precision: Weike Chen et al. [7] used the weighted centroid algorithm by determining weighted

parameters with the different influence between the reference node and the unknown node, to improve the localization precision; this algorithm has a good versatility, but it depends on path loss index largely in the signal propagation model. Y. Kwon et al. [8] adopted statistical filtering by averaging the measuring data, to eliminate static error caused by the accidental factors such as environmental interference; this method didn't work effectively because of node hardware failure or the ranging error caused by obstacles' blocking. Jiuqiang Xu et al. [9] introduced a dynamic EWMA window mechanism R-EWMA to process the interference, but still couldn't solve the problem of the huge communication overhead and the bad localization accuracy.

Based on the research of the existed variety of localization algorithm, the paper analyses the wireless signal propagation path loss model, energy and the quality of the data frame received by the node, then puts forward a high-precision real-time distance correction three-dimensional localization algorithm based on RSSI for WSNs, this algorithm has a small communication overhead, a low hardware cost, and can significantly improve the localization precision, so it has a great practical value.

2. The Ranging Principle and the Data Processing

By measuring the relationship between RSSI, and the distance, we can get the measuring distance with the received RSSI data, then realize the unknown node's locating.

2.1. The Ranging Principle Based on RSSI

The wireless signal propagation path loss has a great effect on localization accuracy of RSSI-based localization algorithm. Commonly used propagation path loss models are: the free-space propagation model, the logarithmic distance path loss model, log-normal distribution model, etc. This paper uses the simplified log-normal distribution model as following:

$$[PL(d_{RSSI})]_{dBm} = -[A_1 + B_1 \lg(d_{RSSI})], \quad (1)$$

where $PL(d_{RSSI})$ is the RSSI value received by the signal receiving node; A_1 is the RSSI value received by the signal receiving node when it's 1m far away from the signal transmitting node; B_1 is an empirical value, which should be measured in the actual specific environment. In this paper, we first filter the measuring RSSI values, then according to the Eq. (1) to get the relationship between the RSSI value and the distance with the filtered RSSI data.

2.2. The Gaussian Filtering of the Measuring data

Jianwu Zhang et al. [10] adopted the statistical mean value model, the random value model and Gaussian Model to correct the RSSI data, and found that data processing method with Gaussian Model has the best ranging accuracy: the accuracy is within 2 m in a small range of 20 m, which could meet the needs of most of the wireless sensor network node localization.

The principle of data processing with Gaussian Model is: eliminating events of small probability, and selecting RSSI values of high probability, then take the geometric mean of them. This approach reduces the interference effect to the overall measuring data, and improves the accuracy of the localization information.

The unknown node receives RSSI values from the same reference node in the fixed location, we record these receiving values to the array $Rssi_i[]$, then use Gaussian Model to process these RSSI values. The Gaussian distribution function is shown as the following [11]:

$$F(RSSI) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{RSSI} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \quad (2)$$

$$F(RSSI_{01}) = \alpha_1, i = 1, 2, \dots, n \quad (3)$$

$$1 - F(RSSI_{02}) = 1 - \alpha_2, j = 1, 2, \dots, n, \quad (4)$$

where μ is the mean of n nodes' RSSI values, and σ is the standard deviation of them, $RSSI_{01}$ and $RSSI_{02}$ are the lower limit and the upper limit after Gauss Model processing. When receiving RSSI value of the unknown node is in $[RSSI_{01}, RSSI_{02}]$, we think the value is a value of high probability and save it. α_1 and α_2 are undetermined parameters, having a certain influence on localization accuracy: if α_1 has a smaller value, and α_2 has a bigger value, after Gaussian Model processing, there's the amount of data but the accuracy is not high; On the other hand, if α_1 has a bigger value, and α_2 has a smaller value, after Gaussian Model processing, the data accuracy is higher but some information may be lost. In the paper, we set $\alpha_1 = 0.3$, $\alpha_2 = 0.7$ as the critical point. Algorithm selects the RSSI data from $Rssi_i[]$ in scope of $[RSSI_{01}, RSSI_{02}]$, then coexists them in $Rssi_gauss_i []$, finally takes the average of the data in $Rssi_gauss_i []$ as the ultimate RSSI value.

Gaussian Model can effectively solve the problem that RSSI is easily interfered by environmental factors in the actual test, and the poor stability, and it

does improve the localization accuracy of the unknown node.

3. Three-Dimensional Localization Principles

3.1. The Maximum Likelihood Estimation

Set n ($n \geq 4$) reference nodes in a three-dimensional space: $D_1(x_1, y_1, z_1)$, $D_2(x_2, y_2, z_2), \dots, D_n(x_n, y_n, z_n)$, the unknown node is $O(x, y, z)$, whose distance from reference nodes respectively are d_1, d_2, \dots, d_n , then according to the spatial distance formula between two points, we can get equations as following:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 + (z_1 - z)^2 = d_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 + (z_2 - z)^2 = d_2^2 \\ (x_3 - x)^2 + (y_3 - y)^2 + (z_3 - z)^2 = d_3^2 \\ \dots\dots \\ (x_n - x)^2 + (y_n - y)^2 + (z_n - z)^2 = d_n^2 \end{cases} \quad (5)$$

For the Eq. (5), from the first equation, former $n - 1$ equation minuses the last equation respectively and transport some items, then we can get the nonhomogeneous linear equations:

$$\begin{cases} 2(x_1 - x_n)x + 2(y_1 - y_n)y + 2(z_1 - z_n)z = (x_1^2 + y_1^2 + z_1^2) - (x_n^2 + y_n^2 + z_n^2) - (d_1^2 - d_n^2) \\ 2(x_2 - x_n)x + 2(y_2 - y_n)y + 2(z_2 - z_n)z = (x_2^2 + y_2^2 + z_2^2) - (x_n^2 + y_n^2 + z_n^2) - (d_2^2 - d_n^2) \\ \dots\dots \\ 2(x_{n-1} - x_n)x + 2(y_{n-1} - y_n)y + 2(z_{n-1} - z_n)z = (x_{n-1}^2 + y_{n-1}^2 + z_{n-1}^2) - (x_n^2 + y_n^2 + z_n^2) - (d_{n-1}^2 - d_n^2) \end{cases} \quad (6)$$

Set:

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) & 2(z_1 - z_n) \\ 2(x_2 - x_n) & 2(y_2 - y_n) & 2(z_2 - z_n) \\ \dots\dots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) & 2(z_{n-1} - z_n) \end{bmatrix}$$

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

$$b = \begin{bmatrix} (x_1^2 + y_1^2 + z_1^2) - (x_n^2 + y_n^2 + z_n^2) - (d_1^2 - d_n^2) \\ (x_2^2 + y_2^2 + z_2^2) - (x_n^2 + y_n^2 + z_n^2) - (d_2^2 - d_n^2) \\ \dots\dots \\ (x_{n-1}^2 + y_{n-1}^2 + z_{n-1}^2) - (x_n^2 + y_n^2 + z_n^2) - (d_{n-1}^2 - d_n^2) \end{bmatrix}$$

The nonhomogeneous linear equations of the Eq. (6) can be represented as:

$$AX = b$$

or

$$A^T AX = A^T b \quad (7)$$

Solving the Eq. (6), then we can get the coordinates $\hat{X}(x_0, y_0, z_0)$ of the unknown node O :

$$\hat{X} = (A^T A)^{-1} A^T b \quad (8)$$

If matrix $A^T A$ is a singular matrix, using its Moore-Penrose inverse to solve the Eq. (8), that is:

$$\hat{X} = (A^T A)^+ A^T b \quad (9)$$

3.2. The Ill Coefficient Matrix Correction

In order to prevent the occurrence of ill equations, we analyze the condition number of solving the Eq. (7):

$$k(A) = \|A\| \|A^{-1}\| \quad (10)$$

$k(A)$ reflects the relationship between the relative error of the solution of the Eq. (7) X and the relative error of the constant vector b . Condition number of a matrix is one important parameter to get the inverse matrix perturbation. Condition number gets larger, the relative errors of $(A + \Delta A)^{-1}$ and A^{-1} get bigger, where ΔA is the perturbation of the matrix A .

Commonly used condition number reflecting ill degree of the inverse matrix is the spectral condition number:

$$k(A)_2 = \|A^{-1}\|_2 \cdot \|A\|_2 = \sqrt{\frac{\lambda_{\max}(A^T A)}{\lambda_{\min}(A^T A)}} \quad (11)$$

When the matrix A is a real symmetric matrix:

$$k(A)_2 = \frac{|\lambda_1|}{|\lambda_n|}, \quad (12)$$

where $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$ are the eigenvalues of the matrix A .

Definition 1 Set the matrix $A \in R^{m \times n}$, if there exists the column orthogonal matrix $P_{m \times r}$, $Q_{n \times r}$ and the square $D_{r \times r} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_r)$, which makes $A = PDQ^T$ (where $r = r(A)$, $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0$ are non-zero singular values of the matrix A), then we define PDQ^T is the part singular value decomposition of the matrix A .

The part singular value decomposition of a matrix must exist. In fact, for a random arbitrary the matrix $A \in R^{m \times n}$, there exists the singular value decomposition as:

$$A = P \times \begin{pmatrix} \Sigma_{r \times r} & 0 \\ 0 & 0 \end{pmatrix} Q^T \quad (13)$$

where matrix P, Q are the orthogonal array of order m and order n , $\Sigma = \text{diag}(\lambda_1, \dots, \lambda_r)$, $\lambda_1, \lambda_2, \dots, \lambda_r$ are non-zero singular values of the matrix A . Decomposing matrix P, Q , which takes the former r columns as one block, and takes the rest of columns as one block, then we yield:

$$A = (P_1 : P_2) \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} (Q_1 : Q_2)^T = P_1 \times \Sigma \times Q_1^T \quad (14)$$

The Eq. (14) is the part singular value decomposition of the matrix A . Using the part singular value decomposition can do correction to the matrix, and makes its ill degree get improved.

Definition 2 Set all non-zero singular values of the matrix $A \in R^{m \times n}$ are $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0$, if there is a positive integer $1 \leq l \leq r$ making $\lambda_l \gg \lambda_{l+1}$, then define the matrix $P_1 \Lambda Q_1^T$ as correction or correction decomposition of the matrix A (where matrix $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_l)$, matrix P_1, Q_1 are the former one column of matrix P, Q in the singular value decomposition as the Eq. (13)). Mark $\tilde{A} = P_1 \Lambda Q_1^T$.

Theorem 1 Set the correction decomposition of the coefficient matrix $A \in R^{m \times n}$ of the Eq. (7)

as $P \Lambda Q^T$, then the solution after the coefficient matrix correction is:

$$\hat{X} = Q \Lambda^{-1} P^T b \quad (15)$$

Proof: As $\tilde{A} = P \Lambda Q^T$, we yield by the Eq. (9) that:

$$\begin{aligned} \hat{X} &= (\tilde{A}^T \tilde{A})^+ \tilde{A}^T b = [(P \Lambda Q^T)^T P \Lambda Q^T]^+ (P \Lambda Q^T)^T b \\ &= (Q \Lambda^2 Q^T)^+ Q \Lambda P^T b \\ &= Q \Lambda^{-2} Q^T Q \Lambda P^T b \\ &= Q \Lambda^{-1} P^T b \end{aligned}$$

So the Eq. (9) is rational.

4. The Optimal Configuration of Reference Nodes

For the maximum likelihood estimation, the configuration of reference nodes such as the location's setting and choosing and so on, which has great influence on precision and stability of localization. Deploy reference nodes optimally will improve the localization accuracy.

In order to improve the localization accuracy, we divide n ($n \geq 4$) reference nodes into different combination which has 4 location nodes in, and every combination will get a localization result, then do some processing on coordinates set, and get the final location coordinate.

For every combination of location nodes, Yan Zhou [12] et al. proved that in the three-dimensional space, when there were 3 location reference nodes $D_i(x_i, y_i, z_i)$ ($i=1, 2, 3$) and unknown node O in the same plane, wrote as the plane $D_i O$, and the angles $\angle D_i O D_j$ ($i, j=1, 2, 3$) between any two reference nodes with the unknown node O are 120° , and the line between the fourth reference node and the unknown node is perpendicular to the plane $D_i O$, then the localization error is the smallest, which is the optimal configuration.

According to the theory of inference [12], deploy optimally 4 reference nodes of every combination. By the Definition 1, we can know that the part singular value decomposition of a matrix must exist; therefore, coefficient matrix A formed by every location node combination in optimal configuration also has ill part. According to Definition 1, the part singular value decomposition of matrix A could correct the matrix and improve the ill degree.

At last, according to Theorem 1 we can get corrected location coordinate of every location node combination.

5. The Real-Time Distance Correction Algorithm

Because that RSSI is disturbed by environmental factors, even if the position of the unknown node is unchanged, the RSSI that received in different time by the coordinator is always changing, which leads to the large error in the RSSI-based ranging.

In order to correct distance in real-time, the paper add a distance correction node $D_0(x_0, y_0)$, whose function is same as the unknown node, the coordinator will receive RSSI between it and the other reference nodes; the difference between distance correction node and the unknown node is that distance correction node's position is fixed, so we can measure the real distance between it and reference nodes. The realization process of the algorithm can be described as following:

Shown as the Fig. 1, reference nodes are $D_1(x_1, y_1, z_1)$, $D_2(x_2, y_2, z_2)$, ..., $D_n(x_n, y_n, z_n)$, the unknown node is $O(x, y)$, and $D_0(x_0, y_0)$ is a distance correction node in n reference nodes, and the real distance between it and $D_1(x_1, y_1, z_1)$, $D_2(x_2, y_2, z_2)$, ..., $D_n(x_n, y_n, z_n)$ is d_1, d_2, \dots, d_n ; the RSSI measuring distance between unknown node $O(x, y)$ and reference nodes $D_1(x_1, y_1, z_1)$, $D_2(x_2, y_2, z_2)$, ..., $D_n(x_n, y_n, z_n)$ is d'_1, d'_2, \dots, d'_n .

When the environmental factors change, the RSSI between reference nodes $D_i(x_i, y_i, z_i)$ ($i=1, 2, n$) and the unknown node $O(x, y)$, distance correction node $D_0(x_0, y_0)$ will also change. As for the unknown node $O(x, y)$, distance correction node $D_0(x_0, y_0)$ are in the same magnetic field, the changing rule between them and the reference node is the same. According to this, we put forward a new algorithm of real-time distance correction:

Definition 3 The correction distance between the unknown node and the reference node i is:

$$d_i = d'_i [1 + (d'_{0i} - d_{0i}) / d'_{0i}] \quad (16)$$

where d'_{0i} is the RSSI measuring distance between the distance correction node and the reference node i , according to the Eq. (16) we can get the distance corrected with the RSSI measuring distance d'_i .

Adopting the real-time distance correction algorithm, when the RSSI measuring distance d'_i is

larger than the real distance, the RSSI received by the distance correction node $D_0(x_0, y_0)$ will reflect this rule: $(d'_{0i} - d_{0i}) / d'_{0i}$ is negative, then do decreasing correction to d'_i ; when the RSSI measuring distance d'_i is smaller than the real distance, $(d'_{0i} - d_{0i}) / d'_{0i}$ is positive, then do increasing correction to d'_i . In this way, the corrected distance d_i will get more approximate to the real distance.

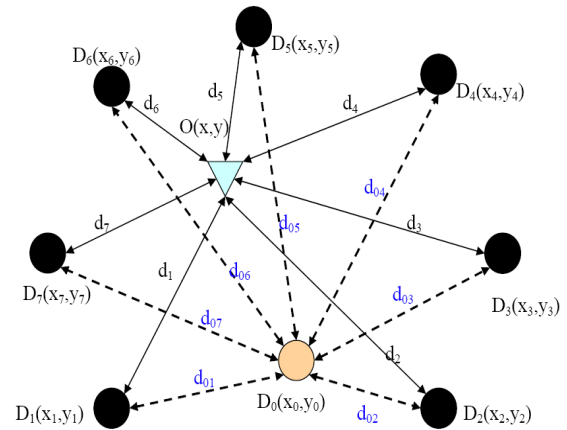


Fig. 1. Distance Correction.

6. Location Coordinate Data Processing

There are many location nodes combination in n reference nodes, and every combination can get a set of location coordinates, the paper optimizes the location coordinates of axis x , axis y , axis z successively as following:

- Elimination of abnormal values

Among these location results, some location coordinate values are far away from the range of the real coordinate, which leads bad precision. Therefore we must eliminate these abnormal values.

There are many ways to judge if one coordinate value is an abnormal value, such as Grubbs Test, Dixon's test, and Skewness-kurtosis test [13], etc; the paper adopts contracted elimination of abnormal value: eliminating values which are far away from the range that set before location as abnormal values.

- Data filtering

In order to get over random error, in accordance with statistical law, we can pre-process the coordinate data by the software algorithm after eliminating abnormal values, that is adopting data filtering to inhibit interference part of effective results, eliminating random error, and do some necessary data smooth processes, to make sure that data we get is as closer to the real data as possible [14-16].

Commonly used data filtering methods are limiter filter, median filter, and median average filter, the paper adopts median average filter: after eliminating abnormal values, then eliminates the maximum and minimum data, and take the average of the rest coordinate data as the final location coordinate.

7. The Realization of the Real-Time Distance Correction Three-Dimensional Localization Algorithm

By studying about traditional location algorithm, the paper puts forward a WSN real-time distance correction three-dimensional localization algorithm which would filter the RSSI based on Gaussian model. The main step is described as following:

Step1: place the unknown node, and deploy reference nodes optimally according to the inference [12];

Step2: according to Eq. (13), correct the ill coefficient matrix of the location node combination;

Step3: collect the data of RSSI and distance which are in the certain range of Step1, and process the data with the Gaussian Model, then fit these processed data with Eq. (1), and finally get the relationship between RSSI and distance;

Step4: according to the real-time distance correction algorithm, correct the RSSI measuring distance d_i' between the unknown node and reference nodes in real-time;

Step5: use the corrected maximum likelihood estimation to locate the unknown node, educe the set of location coordinates;

Step6: successively do the elimination of abnormal value, data filtering, and get the final location coordinate.

Step7: measure the real coordinate of the unknown node, and get the localization error.

In the experiment, choose the CC2530 chip as reference nodes and unknown nodes. Choose 8 reference nodes, and place one distance correction node. Adopt 4 location node combination, the configuration of location reference node combination is shown as Table 1.

Table1. Location reference node combination.

Reference node combination	Reference node label
Combination1	1, 2, 3, 6
Combination2	3, 4, 5, 8
Combination3	5, 6, 7, 2
Combination4	7, 8, 1, 4

In the algorithm test, set $a=0.9$, $b=0.1$. Select 50 positions as the coordinate of unknown node in locating area randomly, and deploy reference nodes optimally according to the inference [12], then adopt

the real-time distance correction three-dimensional localization algorithm to locate the unknown node, the result is shown as Table 2 and Fig. 2:

Table 2. The error of Self-adaptive distance correction location algorithm.

Min error (m)	Average error (m)	Max error (m)
0.3322	0.7138	1.3720

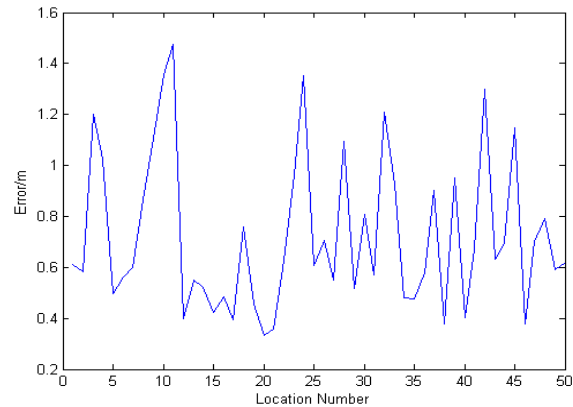


Fig. 2. Localization error of distance correction localization algorithm.

With Table 2 we can know, the real-time distance correction three-dimensional localization algorithm has a high precision, the average error is under 0.72 m, and the best localization precision can be up to 96.7 %, which is more precise than present three-dimensional localization algorithm.

Analyzing the Fig. 2 we can know that in the 50 times experiments, there are 38 times whose location error is under 1m, and it get stable around 0.7 m, the extreme difference of error is 1.04 m. These data proves that the algorithm that the paper puts forward has a good stability, and the error is stable around a little range, and won't occur the precision's mutation.

In conclusion, experiment result verifies the feasibility and superiority of the algorithm in this paper.

8. Conclusion

After studying the maximum likelihood estimation, the paper puts forward the WSN real-time distance correction three-dimensional localization algorithm. The algorithm filters the measuring data by Gaussian model and corrects the RSSI measuring distance between the unknown node and reference nodes, which achieves the aim of improving precision. The algorithm optimizes the configuration of reference nodes, and corrects the ill coefficient matrix of the location node combination, processes the data with data filter, etc, which reduce

localization error efficiently. Experimental simulation result shows that the algorithm effectively improves the localization accuracy of unknown nodes. Compared to the commonly used localization algorithm, this algorithm has higher localization accuracy. Within the scope of the localization area, the algorithm's average localization accuracy of unknown nodes could reach 91.8%. The algorithm can achieve location of nodes in a shorter time, and has a lower hardware cost, lower energy consumption. Therefore, the real-time distance correction localization algorithm based on RSSI proposed by the paper could locate nodes within a short range and have a great practicability.

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