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Air Quality Monitoring Network Localization Algorithm Based on RSSI Ranging

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Abstract. To keep abreast of the situation of environmental air quality, improve the quality of life, based on the actual needs of the air quality safety monitoring, a location method of the air quality monitoring network is proposed based on ranging correction and recursive LS estimation. This method mainly includes the RSSI ranging, the measurement distance correction, the monitoring node localization and so on. The system can realize the automatic monitoring and localization of environmental air quality. Compared with the conventional LS location algorithm, the mean value E_i of positioning error is 0.2433 and 0.2910, and the average running time is 0.2475s and 0.2946s respectively, which shows that the proposed localization algorithm has higher accuracy and lower computational complexity**.**

Introduction

WSN(wireless sensor network)is composed of a large number of low power consumption small sensor nodes, is able to sense other nodes and communication with other nodes through the nodes deployed in the area of environmental monitoring [1, 2]. The air quality monitoring system can provide the information of the air quality in real time, predict the trend of the air quality change, and easy to analyze and formulate effective measures for the prevention and control of pollution by quantifying the degree of air pollution [3] [4] [5]. In positioning, the positioning algorithm is used to calculate or estimate the position of unknown position [6]. The RSSI ranging method is low in power consumption and cost, but used alone, the relative error is high, often through the use of multiple measurements and loop location refinement to reduce the positioning error.

In the modeling of references [7] [8], the dynamic model parameters are obtained, which can not only reduce the distance error based on RSSI, but also improve the positioning accuracy. The references [9] is aimed at analyzing and finding out the difference of the path loss factor of different wireless signal link, and then proposes a new RSSI location algorithm based on grid partition.

In this paper, the relative distance error coefficient of the actual coordinate information provided by the anchor node is corrected, and based on the smaller error distance, the recursive least square algorithm is used to estimate the coordinates of the unknown monitoring nodes. For the isotropic WSN, this algorithm uses the Taylor series expansion method to make the nonlinear observation equation linearized, which not only reduces the computational complexity of the position, but also improves the location accuracy by taking into account the prior information of the existing network.

Estimation of Distance between Nodes

RSSI Ranging Model. In the public space of using air quality monitoring system, due to intensive personnel and facilities in the building, and the existence of flow and uneven distribution, with the multipath, diffraction, obstacle and other factors of monitoring environment, the wireless signal transmission tends to be anisotropic, therefore, it is reasonable to consider the log normal distribution model for wireless communication. The expressions is as follows:

$$P_r(d) = P_t - P_L(d_0) - 10nlg\left(\frac{d}{d_0}\right) + N_\sigma \quad (1)$$

Where d_0 (unit: m) is the reference distance of signal propagation, d is the measuring distance between nodes, $P_r(d)$ (unit: dBm) is the received signal strength when the distance is d, n is the path loss factor related to the monitoring environment, P_t is the wireless signal emission intensity, The measurement noise N_σ is the Gaussian random variables which mean is 0 and the standard deviation is σ_N^2, P_L (d_0) is a RF power loss after a distance of d_0.

Considering the communication range of node z_i in the network, the measurement distance is d from the neighbor node z_j to z_i, then the wireless signal receiving intensity $P_r(d_0)$ of z_i can be expressed as:

$$P_r(d_0) = P_t - P_L(d_0) \quad (2)$$

From the Eq. 1, we can get:

$$P_r(d) = P_r(d_0) - 10nlg\left(\frac{d}{d_0}\right) + N_\sigma \qquad (d > d_0) \quad (3)$$

Where, $P_r(d_0)$ is the wireless signal receiving intensity corresponding to reference distance d_0.

RSSI Ranging Preliminary Estimate. RSSI location algorithm is based on ranging, the precision of distance estimation has a direct impact on the positioning accuracy. From the Eq. 1, we can get:

$$P_r(d) = PN - 10nlgd \quad (4)$$

Where

$$PN = P_r(d_0) - N_\sigma \quad (5)$$

Then

$$10nlgd = PN - P_r(d) \quad (6)$$

If enough other monitoring nodes are uniformly randomly deployed in the communication range of a monitoring node, according to the inverse relationship between $P_r(d)$ and measuring distance d, we think that the maximum distance is d_{max} corresponding to the minimum received signal strength P_{min} of the monitoring node. Therefore, there is:

$$10nlgd_{max} = PN - P_{min} \quad (7)$$

From the Eq. 8, we can get:

$$n = \frac{PN - P_{min}}{10lgd_{max}} \quad (8)$$

Then the Eq. 9 is solved for n and substituted in Eq. 7, the estimated distance is calculated:

$$d = d_{max}^{\frac{PN-P_r(d)}{PN-P_{min}}} \approx r^{\frac{PN-P_r(d)}{PN-P_{min}}} \quad (9)$$

Thus, the measuring distance between any monitoring node z_i and its neighbor nodes can be calculated. In the values of $P_r(d)$ obtained from the unknown nodes, the minimum value of $P_r(d)$ is P_{min}, corresponding to $d_{max} = r$, that is the communication radius, and thus the value of d from the unknown node to the anchor node can be obtained.

Ranging Correction Based on RSSI. Let the actual distance from the anchor node $A_i(x_i,\ y_i)$ to other anchor nodes in the network is $r_{ik}, k = 1,\ 2,\ \cdots,\ n,\ k \neq i$. The measured distance from the anchor node A_i to other anchor nodes is d_{ik}. Then the average relative error between the actual distance and the measured distance from the anchor node A_i is:

$$\mu_i = \frac{1}{n-1}\sum_{k=1,\ k\neq i}^{n} \frac{r_{ik}-d_{ik}}{d_{ik}} \quad (10)$$

Then the error coefficient of distance measurement based on RSSI of the anchor node A_i is obtained. According to the relative error coefficient of anchor nodes, the measurement range d is carried out for ranging correction based on the Eq.11.

$$d_{ui}^c = d_{ui}(1 + \mu_i) \quad (11)$$

where, d_{ui} is the measuring distance between the monitoring node and anchor node A_i, d_{ui}^c is the correction distance between the monitoring node and anchor node A_i, μ_i is the relative error coefficient of anchor node A_i.

Positioning Algorithm of Target Monitoring Node

Assume that in the network, N anchor nodes are denoted as $A_i(x_i,\ y_i)$, $i = 1,\ 2,\ \cdots,\ N$, their measurement distance to the blind node $B(x_1, y_1)$, unknown location is d_i, $i = 1,\ 2,\ \cdots,\ N$, then the measurement equations are expressed as:

$$\widehat{d_i} = d_i + v_i,\ i = 1,\ 2,\ \cdots,\ N \tag{12}$$

Where, v_i is the measurement error, $d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2}$. Square operations are performed on both sides. After arranging, the above equation can be abbreviated as

$$h = G\theta + v \tag{13}$$

Where,

$$G = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ \vdots & \vdots & \vdots \\ -2x_N & -2y_N & 1 \end{bmatrix}$$

$$h = \left[\hat{d}_1^2 - (x_1^2 + y_1^2),\quad \dots,\quad \hat{d}_N^2 - (x_N^2 + y_N^2)\right]^T$$

$$v = \left[2\hat{d}_1 v_1 - {v_1}^2,\quad \dots,\quad 2\hat{d}_N v_N - {v_N}^2\right]^T$$

$$\theta = [x \quad y \quad R]^T$$

$$R = x^2 + y^2$$

Then the solution of LS algorithm is adopted:

$$\hat{\theta}_{ls} = (G^T G)^{-1} G^T h \tag{14}$$

The solution of WLS algorithm is adopted:

$$\hat{\theta}_{wls} = (G^T W G)^{-1} G^T W h \tag{15}$$

Where, $W = cov^{-1}(v)$ is the weighted matrix.

In order to achieve the purpose of real-time, using the recursive algorithm is a better solution. The observed model represented by the eq. 13 is rewritten as follows:

$$H = G\theta + v \tag{16}$$

The solution of LS algorithm is

$$\hat{\theta}_{ls} = (G^T G)^{-1} G^T H \tag{17}$$

Set $\hat{\theta}_k$ is the estimated value of the least squares algorithm obtained by using the first k observation data, then

$$\hat{\theta}_k = (G_k^T G_k)^{-1} G_k^T H_k \tag{18}$$

Let

$$Q_k = (G_k^T G_k)^{-1} \tag{19}$$

Because

$$H_k = [H_{k-1} \quad h_k]^T, G_k = [G_{k-1} \quad g_k]^T$$

Thus

$$Q_k = [Q_{k-1}^{-1} + g_k^T g_k]^{-1} \tag{20}$$

By using the matrix inversion lemma, we have

$$Q_k = Q_{k-1}[I - g_k^T (I + g_k Q_{k-1} g_k^T)^{-1} g_k Q_{k-1}] \tag{21}$$

Then by Eq. 19, yields

$$\hat{\theta}_k = Q_k [G_{k-1}^T g_k^T][H_{k-1}^T h_k^T]^T \tag{22}$$

The eq. 23 can be simplified:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + Q_k g_k^T \left[h_k - g_k \hat{\theta}_{k-1}\right] \tag{23}$$

The eq. 23 is the expression of the recursive least square algorithm.

Experimental Simulation and Verification

Simulation Model and Test Data. Gauss-semi-Markov mobility model more realistically reflect the movement of the monitoring node. The rate and direction of the *n*th moment of the moving node are respectively expressed as follows:

$$v_i = \xi v_{i-1} + (1 - \xi)\bar{v} + \sqrt{1 - \xi^2}\tilde{v}_{i-1} \tag{24}$$

$$\phi_i = \xi\phi_{i-1} + (1-\xi)\bar{\phi} + \sqrt{1-\xi^2}\tilde{\phi}_{i-1} \quad (25)$$

Where ξ is the memory coefficient related to the motion, ranging from 0 to 1. $\bar{v}$ and $\bar{\phi}$ respectively represent the mean velocity and direction of motion. The $\tilde{v}_{i-1}$ is a Gauss random variable, which mean is 0, the standard deviation is σ_v. The $\tilde{\phi}_{i-1}$ is a Gauss random variable, which mean is 0, the standard deviation is σ_ϕ. So, at the moment of i, the expression of node coordinate is as follows:

$$x_i = x_{i-1} + v_{i-1} \times cos(\phi_{i-1}) \quad (26)$$

$$y_i = y_{i-1} + v_{i-1} \times sin(\phi_{i-1}) \quad (27)$$

In the fixed experimental area (about 100m*100m), 15 anchor nodes are arranged along the upper and lower boundary, and the model parameters are set: ξ=0.6, $\bar{v}$=1m/s, $\bar{\phi} = \pi/2$. The starting position of the monitoring node is set to (40 m, 40 m), and a positioning is finished every 5s, so there are 15 times in total for the algorithm performance testing. The moving track of the mobile monitoring node is shown in Fig. 1.

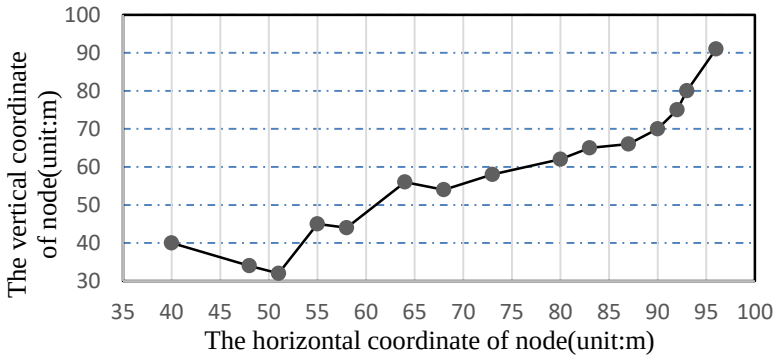

Fig. 1 The moving track of the mobile monitoring node

Simulation Experiment and Analysis

The location error of the nodes in the network is defined as:

$$E_i = \frac{||p_i - z_i||}{R} \quad (28)$$

Where R is the communication radius. $p_i = [p_{xi} \quad p_{yi}]^T$ is the final estimate position of node i, and $z_i = [z_{xi} \quad z_{yi}]^T$ is the true position of node i. The average location error E_a of the nodes in the network is defined as:

$$E_a = \frac{\sqrt{\sum_{i=1}^{N} ||p_i - z_i||^2}}{NR} \quad (29)$$

Where $i = 1,2,\ldots,N$, N is the number of unknown nodes in the network. The smaller the average positioning error E_a, the higher the positioning accuracy.

Using the proposed algorithm in this paper, we analyzed the test data of the 15 groups. The measurement noise is $N_\sigma(0,5)$, 100 nodes are randomly distributed in the region of $100m \times 100m$, The node's communication radius is $40m$ and the reference node number is 20. In order to reduce the random error, the results are the mean of the 100 times simulation results under the same parameters. The positioning error of the test data is shown in Fig. 2.

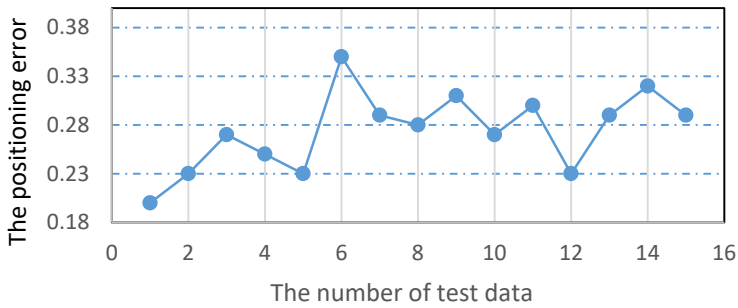

Fig.2 The positioning error of the test data

After the analysis of the Fig. 2, we can see that the maximum error is 0.35 and the minimum value is 0.20. Because the 10 reference nodes are spaced along the upper and lower boundaries, so the location error of the edge of the experimental area is large and the overall positioning effect is good. If we deploy some reference nodes to the edge of the test area, we can further improve the positioning effect.

Selecting the different noise variance to position the test data, the reference node value is 20 and the number of nodes is 100. The positioning results are shown in Fig. 3.

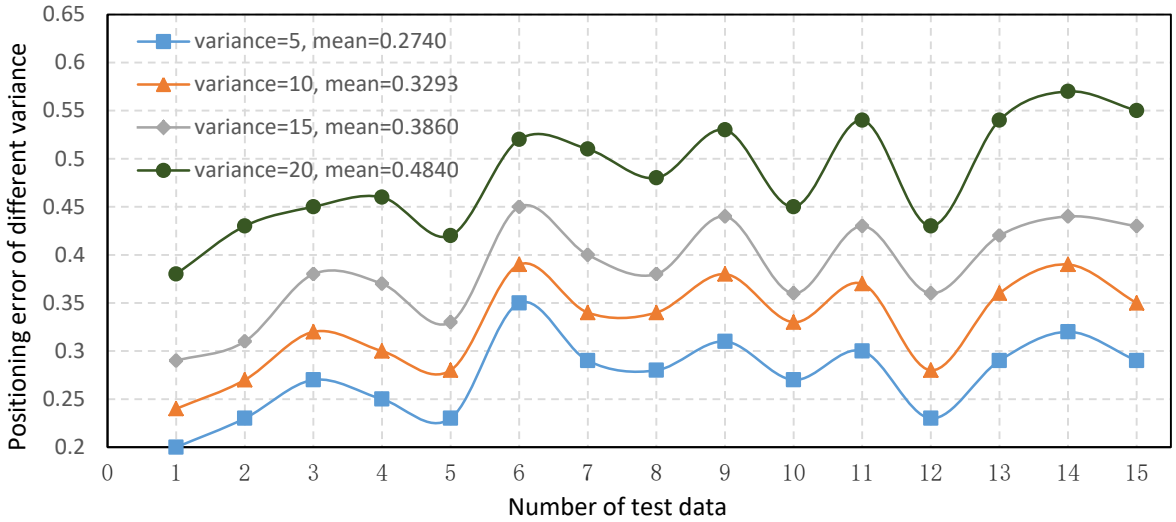

Fig.3 Effect of measurement noise on positioning error

From the Fig.3, we can see that the positioning error E_i of the test data is increasing with the increase of the variance σ_N^2 of the random variables, but the positioning error of the edge of the test area is not obvious. The mean value of the positioning error is 0.2740.3293,0.3860 and 0.4840 respectively in four cases, which shows that the proposed algorithm is not sensitive to ranging error, that is, this algorithm has good environment adaptability.

Summary

This paper presents a recursive least square algorithm based on RSSI distance measurement and relative error correction relative distance error correction coefficient, which is used to monitor the air quality. The relative distance error coefficient is chosen to make the distance correction, and the position estimation section uses the recursive least square algorithm to estimate the coordinates of the unknown monitoring nodes in this algorithm. The simulation results is that the average location error of the this algorithms is 0.2433, and the average running time of the positioning process is 0.2372s, whereas the average location error and the average running time are 0.2910 and 0.3063s respectively for the LS localization algorithm, which show that the proposed algorithm in this paper has good performance in both the accuracy and the computational complexity compared with the LS localization algorithm.

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