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An Accurate Cooperative Localization Algorithm Based on RSS Model and Error Correction in Wireless Sensor Networks

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Abstract: Aiming at the problem that there is a big contradiction between accuracy and calculation and cost based on the RSSI positioning algorithm, an accurate and effective cooperative positioning algorithm is proposed in combination with error correction and refinement measures in each stage of positioning. At the ranging stage, the RSSI measurement value is converted to distance by wireless channel modeling and the dynamic acquisition of the power attenuation factor. Then, the ranging correction is carried out by using the known anchor node ranging error information. The Taylor series expansion least-square iterative refinement algorithm is implemented in the position optimization stage, and satisfactory positioning accuracy is obtained. The idea of cooperative positioning is introduced to upgrade the nodes that meet the requirements and are upgraded to anchor nodes and participate in the positioning of other nodes to improve the positioning coverage and positioning accuracy. The experimental results show that the localization effect of this algorithm is close to that of the Taylor series expansion algorithm based on coordinates but far higher than that of the basic least-squares localization algorithm. The positioning accuracy can be improved rapidly with the decrease in the distance measurement error.

Keywords: wireless sensor network (WSN); received signal strength (RSS); error correction; cooperative localization

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1. Introduction

A wireless sensor network (WSN) is an advanced information data processing platform, which relies on the sensor nodes to realize the data acquisition, processing, and wireless transmission in the monitoring area and can complete complex, large-scale monitoring and target tracking and other tasks [1–4]. The location information of sensor nodes is the first condition to realize the above tasks, so location research is one of the important fields in wireless sensor network applications [5,6]. As a part of the Internet of Vehicles technology, the node positioning technology provides more advanced functions and services for the vehicles. For example, through the communication between vehicles, vehicles can share status information, such as position and driving speed in real time, so as to judge the road traffic flow, realize collaborative driving between vehicles, and avoid collision. Vehicle manufacturers may offer optional schemes to vehicles that support Internet of Vehicles and node location technology as a higher level of options. Many scholars have carried out a lot of research on the key technologies of the Internet of Vehicles [7–9].

The location algorithm can be divided into range-based and range-free according to ranging or not ranging [10,11]. According to the topology information of sensor nodes such as network structure and connectivity, the range-free location algorithm estimates the absolute coordinate or relative coordinate of node position, which is coarse granularity location, and the error is often large. The range-based location algorithm obtains node-position information based on the distance or angle measurement between nodes that is generally more accurate. Generally, four ranging techniques belong to the category of range-based algorithms, such as Time of Arrival (TOA) [12,13], Time Difference of Arrival (TDOA) [14,15], Angle-of-Arrival (AOA) [16,17], and Received Signal Strength Indication (RSSI) [18–20], but TOA/TDOA and AOA need additional measuring equipment, and higher cost and communication overhead.

According to the numerical relationship between the power attenuation and propagation distance of the wireless signal, RSSI can realize low-cost ranging without adding measuring equipment based on wireless channel modeling. Because the RSSI ranging is greatly affected by wireless signal propagation, especially in the indoor environments, nonlinear modeling and parameter estimation must be carried out [21]. However, when more information is known, the measurement redundancy reduces the position error, and the satisfactory positioning effect can be obtained by combining multiple measurements and cyclic tracking [22].

2. Related Work

Wireless propagation modeling and parameter estimation are the basis of RSSI ranging. Since most localization algorithms based on RSSI tend to ignore the inherent uncertainty of network topology, and the location information of anchor nodes is usually assumed to be precisely known, for the problems caused by the above two cases, the solution has been given in [23]. The algorithm in [23] is based on the SPEAR localization framework and simultaneously estimates the location of the source node and the uncertain anchor node; using the Cramer–Rao information inequality, the source localization performance is improved from the basic lower limit of the SPEAR, thus providing a more reliable anchor node location estimation.

In [24], the authors first explained the principle of positioning using AOA, TDOA, and RSSI and then used the beacon nodes and arrival distance for sensor positioning. The simulation results showed that the system obtains a lower average estimation error when using RSSI localization. In [25], the authors analyzed and evaluated the RSSI-based ranging and adaptive techniques in outdoor WSN to improve the ranging quality. The authors highlighted the impact of the path loss index estimation error and temperature variation on RSSI-based ranging and proposed an RSSI-based adaptive ranging algorithm to improve the ranging quality under changing outdoor conditions. This algorithm includes link RSSI estimation, temperature compensation, PLE estimation, and inter-node distance estimation.

The disadvantage of the Bayesian estimation method is the existence of a large communication and computational overhead, and particle filtering (PF) technology often has problems of particle degradation and dilution [26], leading to the degradation of the WSN node-positioning performance, and it is even difficult to implement the positioning. The non-Bayes estimation method treats the position coordinates of unknown nodes as determined unknown parameters and then uses methods such as the least squares (LS) estimation [27] and maximum likelihood (ML) estimation [28] to obtain the localization solution.

In order to improve the positioning accuracy, many scholars have studied the cooperative positioning algorithm in recent years. Cooperative technology usually refers when nodes in the network that can realize communication pass messages or exchange information; implement distributional calculation, communicate, and storage operations; coordinate processing; and complete tasks such as event monitoring. Using cooperative ideas and technologies in WSN positioning is cooperative positioning. The information source of the positioning estimation data can not only come from the ranging between the unknown node and the anchor node, but also from the observation information between the anchor nodes and the ranging between the unknown nodes; therefore, the redundant data obtained can be used to optimize the positioning solution.

The algorithm in [29] studied the least squares (LS) cooperative positioning problem under arbitrary non-line-of-sight (NLOS) ranging deviation and proposed the network position error bound (PEB). Based on the Cramer–Rao lower limit (CRLB), quantified LS and distance square LS, by obtaining the positioning accuracy deviation of square distance weighted least squares (WLS), the authors proposed a simple LS distributed algorithm, which combined squared distance relaxation with Gaussian differential information to implement cooperative localization. The algorithm in [30] proposed a hybrid co-location scheme based on distance and angle measurement; that is, by modifying the linear least squares (LLS) hybrid scheme based on TOA-AOA and AOA-RSS, the authors proposed an optimized LLS estimate scheme. The simulation results showed that this algorithm is superior to the non-cooperative algorithm and iterative nonlinear least-squares algorithm based on the mixed signal.

On the basis of the RSS distance measurement, Katwe et al. [31] and Z. F. Wang et al. [19] proposed an estimation algorithm based on semi-definite planning and achieved a good positioning effect. Using RSS ranging technology, Zhou et al. [32] proposed a synchronous localization and tracking algorithm, made a detailed analysis of the error propagation of localization and tracking, and proved that the algorithm has a good estimation effect. In [32], by using TOA and RSS ranging, the authors accurately located targets under non-line-of-sight (NLOS) environments. In this algorithm, the author started from the general approximation of the maximum likelihood (ML) estimation problem, established the nonlinear weighted least squares (NLWLS) using the equilibrium parameters, and then used the semidefinite relaxation (SDR) technique to solve the NLWLS problem and verified that the proposed method significantly outperforms the existing methods. Although the above algorithms of model parameter estimation and location algorithm based on the RSS ranging improve the positioning accuracy and achieve the specific results, the communication cost and technical complexity of the algorithm are high, which is not easy to be implemented in large-scale low-power WSN positioning applications.

In this paper, aiming at the key stage of positioning estimation, we deeply study the idea of RSSI ranging and the requirements of the positioning system and then obtain the distance between nodes via wireless propagation modeling and using the close relationship between RSSI measured value and the distance between nodes. Finally, we use the relative distance error of the anchor node to correct the ranging, use the optimal anchor nodes to participate in the coordinate estimation, and implement the position coordinate optimization. The algorithm proposed in this paper has low computational complexity, small storage space, and communication overhead. Moreover, it can give full play to the advantages of cooperative positioning, upgrade the located nodes that meet the error requirements to anchor nodes to participate in the positioning of other unknown nodes, and effectively improve the positioning accuracy.

3. Distance Estimation Techniques

3.1. Calculating the Distance between Nodes

Depending on wireless communication function, the sensor nodes in the network can be measured with RSSI when data are received without additional equipment. Because of the influence of channel attenuation on RSSI ranging accuracy when radio signal propagates, considering factors such as multipath and obstacle occlusion in the environment, we use lognormal modeling in this paper. Assuming that the value of RSSI is $P_r(d)$, we have the following:

$$P_r(d) = P_t + G_a - P_l(d) \tag{1}$$

where P_t is the transmit power of node, G_a is the antenna gain of node, and $P_l(d)$ is the signal emission power loss after the propagation distance of d. Since

$$P_l(d) = P_l(d_0) + 10nlg\left(\frac{d}{d_0}\right) \tag{2}$$

we then have

$$P_r(d) = P_r(d_0) - 10nlg\left(\frac{d}{d_0}\right) + D_\sigma \tag{3}$$

where d_0 is the reference range, the general value is 1 m, $P_l(d_0)$ is the power loss through the transmission distance of d_0, n is the path damping factor, and $P_r(d_0)$ is power strength of the received signal at d_0 apart from the launch node. D_σ is the Gaussian random variable, the mean of which is zero.

The power loss $P_l(d_0)$ of the wireless signal after the transmission distance of d_0 is:

$$P_l(d_0) = -10lg\left[\frac{G_t G_r \lambda^2}{(4\pi)^2 {d_0}^2 L}\right] \tag{4}$$

where G_t is the transmit antenna gain of a node, G_r is the receiving antenna gain, the unit of G_t and G_r is dBi, L is the damping coefficient of wireless propagation, and λ is the signal wavelength (unit: m). Then, we get

$$P_r(d_0) = P_t + G_a - P_l(d_0) \tag{5}$$

Considering that the sensor nodes are deployed in the monitoring area randomly and uniformly, and the communication radius is the same, the communication range of the nodes can be roughly regarded as a circular region. By (3), if d_0 is 1 m, we can obtain

$$P_r(d) = P_r(1) - 10nlgd + D_\sigma \tag{6}$$

Assuming that more nodes are deployed within the communication range of the sensor nodes, according to the relationship between d and $P_r(d)$, we may consider the maximum value of the distance, d, corresponding to the minimum in the received signal strength, $P_r(d)$. Then, we have the following:

$$P_{rmin} = P_r(1) - 10nlgd_{max} + D_\sigma \tag{7}$$

and we have

$$n = \frac{P_r(1) - P_{rmin}}{10lgd_{max}} \tag{8}$$

where d_{max} approximates the communication radius, r.

Among the multiple RSSI values obtained by unknown nodes, the smallest RSSI values are marked as P_{rmin}, which corresponds to $d_{max} = r$, and then the value of d from unknown node to anchor node can be obtained. The search method of P_{rmin} is to put all the RSSI values received by the node to be located together with all the RSSI values received by its neighbor node, sort from large to small, and take the smallest RSSI value as P_{rmin}.

3.2. Measurement Distance Correction

Distance data between nodes are the basis of location calculation, and the ranging error can directly affect the positioning accuracy. The solution is to preprocess the distance value obtained by RSSI measurement and reduce the data errors. The usual preprocessing methods have algorithms such as multiple measurement loop correction and iterative refinement.

The steps of the cyclic correction algorithm are as follows: Firstly, the Euclidean distance between the anchor node and other anchor nodes in the communication range is calculated according to the coordinates of the anchor node, and then through wireless propagation modeling, the measurement distance is obtained by measuring the corresponding RSSI value. Finally, the difference between the measurement distance and the actual distance is the RSSI value measurement error. Therefore, to obtain the range value between the sensor node of an unknown location and its anchor node, we consider correcting this RSSI measurement error to overcome the unfavorable factors of the environment and improve the ranging accuracy.

Considering the two-dimensional conditions, an anchor node in a network is marked as N_0 (x_0, y_0), the other anchor node in its communication range is marked as N_j (x_j, y_j), j = 1, 2, . . ., M, where M is the number of neighbor anchor nodes of N_0. The actual distance from N_0 (x_0, y_0) to N_j (x_j, y_j) is marked as r_j, j = 1, 2, . . ., M. The distance obtained by RSSI measurement is marked as d_j, $j = 1, 2, \ldots, M$. Then, the relative error from RSSI ranging can be represented as follows:

$$\mu_j = \frac{r_j - d_j}{d_j} \tag{9}$$

The relative error correction coefficient of weighted ranging for the anchor node, N_j (x_j, y_j), is recorded as follows:

$$\mu_w = \sum\nolimits_{j=1}^{M} \frac{r_j - d_j}{d_j^2 \sum\nolimits_{j=1}^{M} \frac{1}{d_j}} \tag{10}$$

μ_w reflects the RSSI range error of the anchor node. The larger the distance between nodes, the larger the ranging error caused by RSSI measurement and the less the weight in the correction factor. The error correction distance based on the anchor node is represented as follows:

$$d_{uj}^c = d_{uj}\left(1 + \mu_j\right) \tag{11}$$

where d_{uj}^c is the correction distance between the anchor node, N_j, and the unknown position node; and d_{uj} is the measurement distance between the anchor node, N_j, and the unknown position node.

4. Distributed Collaborative Localization Algorithm

Distributed optimization collaborative localization usually includes two algorithm-implementation steps: node self-localization and information fusion collaboration. The process of information fusion collaborative positioning is based on the basis that observation information measurement between nodes has been implemented in each node in the network, and the unknown nodes that have realized the location receive the location information and observation information of the neighbor nodes, by fusion information and information interaction with the neighbor nodes, and then a certain collaborative location algorithm is implemented to obtain more accurate location information of the unknown nodes. The distributed optimization and collaborative localization process is shown in Figure 1.

According to the RSSI measurement distance from the unknown location node to its three neighbor anchor nodes, we use the triangulation method to calculate the position coordinates of the unknown node in the positioning process of the WSN node. Considering only from the spatial geometric position of the anchor node, the relevant research shows that there are two cases of positioning coordinate error. That is, the positioning coordinate error is the largest when the three anchor nodes are in the collinear state, while the positioning coordinate error is the smallest when the triangles surrounded by the three anchor nodes are equilateral triangles. Therefore, to improve the coordinate accuracy of unknown nodes, it is necessary to optimize the selection of anchor nodes.

Suppose there are m neighbor anchor nodes in a wireless network; then, the C_m^3 combinations of anchor nodes are formed. The optimization method of the anchor node is as follows. Firstly, choose any of the C_m^3 combinations of anchor nodes; calculate the radians of the three angles of the triangle formed by three anchor nodes; and then find the maximum and minimum values marked as, respectively, $\alpha_{max} = max\{\alpha_A, \alpha_B, \alpha_C\}$ and $\alpha_{min} = min\{\alpha_A, \alpha_B, \alpha_C\}$, finally, limiting angle so that the triangle formed by the anchor node is close to the regular triangle.

$$\alpha_{max} < \frac{\pi}{2}, \alpha_{min} > \frac{\pi}{6} \tag{12}$$

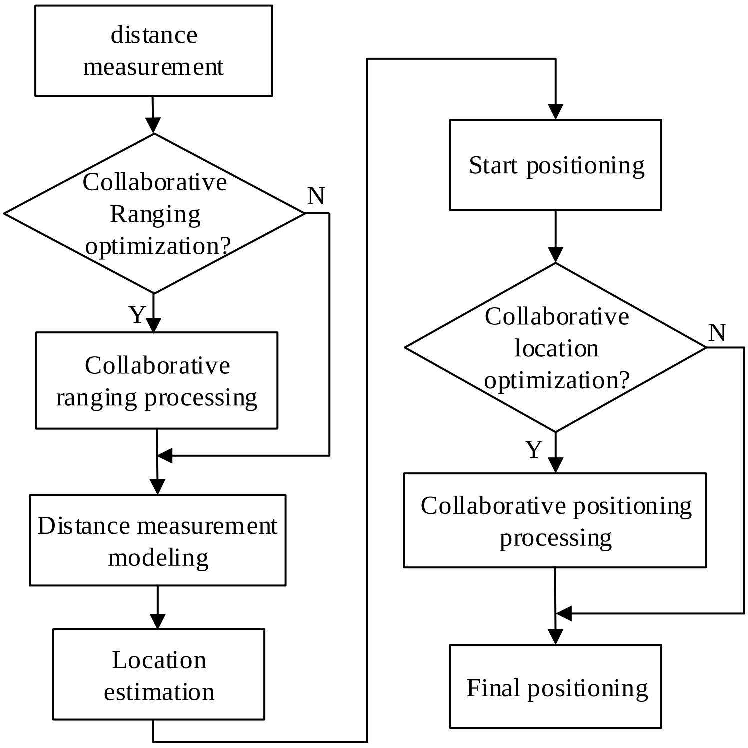

Figure 1. The flowchart of distributed optimization cooperative positioning.

4.1. Location Estimate

The RSSI ranging algorithm shows that, the larger the RSSI value is, the closer the distance between nodes is. Similarly, the closer the distance from an unknown node to anchor node is, the higher the credibility of the RSSI value is. So, the smaller the ranging error is, the better the accuracy of the location algorithm based on range is. To reflect the contribution of different RSSI ranges, we consider weighting different RSSI values, that is, using a weighted ranging localization algorithm to implement position estimation.

Considering that there is an unknown node marked as U in the network, three anchor nodes, marked as N_1, N_2, and N_3, respectively, suppose that the RSSI values of the node U to the three anchor nodes are marked as RSSI_1, RSSI_2, and RSSI_3, in turn. Supposing s_1, s_2, and s_3 are the measured distances from U to node N_1, N_2, and N_3 obtained from wireless propagation signal model, respectively, a_1, a_2, and a_3 are the weighted coefficients, $a_1 = 1/s_1$, $a_2 = 1/s_2$, and $a_3 = 1/s_3$, and let the coordinates of the unknown position monitoring node, U, is (x, y). Then, we have the following:

$$\begin{cases} x = \frac{a_1^k x_1 + a_2^k x_2 + a_3^k x_3}{a_1^k + a_2^k + a_3^k} \\ y = \frac{a_1^k y_1 + a_2^k y_2 + a_3^k y_3}{a_1^k + a_2^k + a_3^k} \end{cases} \tag{13}$$

where k is a weighted adjustment factor. During the implementation of the algorithm, the positioning parameters are adjusted experimentally for different application environments; changing the weighted factor, k, can adjust the positioning performance and improve the positioning accuracy. In addition, considering the angle information of the anchor node, the error can be further reduced. For each combination of the C_n^3 combinations of anchor nodes, its confidence level is $\mathrm{C}_{ABC}(i)$, and we have the following:

$$\mathrm{C}_{ABC}(i) = 1 - \frac{\alpha_{max} - \alpha_{min}}{\alpha_A + \alpha_B + \alpha_C} \tag{14}$$

where α_A, α_B, and α_C are the three angles of the triangle formed by three anchor nodes, and then

$$\begin{cases} \alpha_{max} = max\{\alpha_A, \alpha_B, \alpha_C\} \\ \alpha_{min} = min\{\alpha_A, \alpha_B, \alpha_C\} \end{cases} \tag{15}$$

If we consider the angle weighting of anchor nodes, the estimated coordinates $(\hat{x}, \hat{y})$ of the unknown node, U, are as follows:

$$\begin{cases} \hat{x} = \frac{C_{ABC}(i)x}{\sum C_{ABC}(i)} \\ \hat{y} = \frac{C_{ABC}(i)y}{\sum C_{ABC}(i)} \end{cases} \tag{16}$$

The correction coefficient, μ_w, can improve the accuracy of anchor node RSSI ranging, but it is powerless to interfere with the random error in the environment during the positioning process. Therefore, we consider making full use of the known position information of the anchor node to correct the positioning error further. Firstly, we calculate the actual distance between anchor nodes by using the known coordinate position information of anchor nodes, and then we estimate the coordinates of anchor nodes using a positioning algorithm. The difference between the estimated coordinate and the actual coordinate is the coordinate error of the anchor node. In the positioning process, it can effectively suppress all kinds of cumulative errors and improve the positioning accuracy using the coordinate error of the anchor node to correct the unknown coordinate estimation value.

Through RSSI ranging, the anchor node, $N_0(x_0, y_0)$, can estimate its position coordinate, $N_{c0}(x_{c0}, y_{c0})$, by the actual coordinate of its neighbor anchor node, $N_j(x_j, y_j)$. The difference between the actual coordinates and estimated coordinates of anchor nodes is the coordinate error, and the coordinate error of the anchor node is marked as $E(e_{x0}, e_{y0})$, where $e_{x0} = x_0 - x_{c0}$, and $e_{y0} = y_0 - y_{c0}$. Then, the normal form of the coordinate error of the jth anchor node is as follows:

$$\begin{cases} e_{xj} = x_j - x_{cj} \\ e_{yj} = y_i - y_{cj} \end{cases} \tag{17}$$

Thus, the weighted coordinate error for the positioning area is as follows:

$$\begin{cases} e_{wx} = \sum_{j=1}^{M} \frac{e_{xj}}{d_j^c \sum_{j=1}^{N} \frac{1}{d_j^c}} \\ e_{wy} = \sum_{j=1}^{M} \frac{e_{yi}}{d_j^c \sum_{j=1}^{N} \frac{1}{d_j^c}} \end{cases} \tag{18}$$

where M represents the number of anchor nodes participating in the network positioning error calculation, and d_j^c represents the correction distance of the jth anchor node.

The weighted coordinate errors, e_{wx} and e_{wy}, are the weighted values of the anchor node coordinate error and reflect the regional positioning ability of the algorithm. Therefore, after error correction, the coordinates of the node to be positioned are marked as (x, y):

$$\begin{cases} x = x_e + e_{wx} \\ y = y_e + e_{wy} \end{cases} \tag{19}$$

where (x_e, y_e) are the coordinate values of the node to be positioned estimated by the localization algorithm.

4.2. Location Optimization

The purpose of position optimization is to further reduce the error of estimating coordinates, take the previously determined coordinate value as the initial value, and use the Taylor series least-squares method to optimize the position. Based on the RSSI ranging modeling, it is as follows:

$$d_j = \sqrt{(x - x_j)^2 + (y - y_j)^2} \tag{20}$$

Suppose that the initial coordinates of the target are $A(x_0, y_0)$ and set function $f(x, y) = d_j$. At point $A(x_0, y_0)$, the Taylor series expansion of Equation (23) is carried out, and the second-order and above components are ignored, so we have the following:

$$f(x, y) = f(x_0, y_0) + f_x(x_0, y_0)\Delta x + f_y(x_0, y_0)\Delta y \tag{21}$$

It can also be written as follows:

$$\hat{d}_l = \hat{d}_{l0} + a_x \Delta x + a_y \Delta y \tag{22}$$

where

$$\begin{aligned} \hat{d}_l &= \sqrt{(x - x_j)^2 + (y - y_j)^2} \\ \hat{d}_{l0} &= \sqrt{(x_0 - x_j)^2 + (y_0 - y_j)^2} \\ a_x &= f_x(x_0, y_0) \\ a_y &= f_y(x_0, y_0) \end{aligned}$$

We consider the error, and Formula (22) can be abbreviated as follows:

$$b = H\Delta + v \tag{23}$$

where

$$\begin{aligned} b &= \left[\hat{d}_1 - \hat{d}_{10}, \quad \ldots, \quad \hat{d}_N - \hat{d}_{N0}\right]^T \\ H &= \begin{bmatrix} \frac{x_0 - x_1}{\hat{d}_{10}} & \frac{y_0 - y_1}{\hat{d}_{10}} \\ \vdots & \vdots \\ \frac{x_0 - x_N}{\hat{d}_{N0}} & \frac{y_0 - y_N}{\hat{d}_{N0}} \end{bmatrix} \\ \Delta &= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix}^T \end{aligned}$$

Using the weighted least-squares algorithm (WLS) for Formula (23), the estimates of Δ are as follows:

$$\Delta = H^{\dagger} b \tag{24}$$

where $H^{\dagger} = \left(H^T W H\right)^{-1} H^T W$ is a Moore–Penrose pseudo-inverse, and W is the covariance matrix of measurement error. Then, the updated position parameter vectors are as follows:

$$\theta(k+1) = \theta(k) + \varepsilon \tag{25}$$

4.3. Implementation of Collaborative Positioning

By introducing the idea of cooperative positioning, making full use of various measurement information between network nodes to implement data fusion, the energy consumed by a single node is reduced by cooperative signal and information processing between sensors. Thus, as much measurement information is obtained as possible, and, finally, we improve the positioning accuracy and robustness. For the unknown nodes that are accurately located, if they meet certain conditions, they are upgraded to anchor nodes to participate in the subsequent positioning calculation. The upgraded node, regarded as an anchor node, is called a pseudo-anchor node. In addition, we should consider the requirements of anchor node positioning; that is, compared with the anchor node, the pseudo-anchor node has a relatively stable positioning capability in an RSSI ranging environment. According to Formulas (6)–(8), we calculate the path loss factor between the anchor node and the pseudo-anchor node in the communication range and take the mean value for these path loss factors. The mean value should be equivalent to the mean of the path loss factor between the other anchor node and the nearest anchor node in the communication range. Therefore, in addition to accurate positioning, the upgrade node must satisfy the following conditions:

$$\left| \frac{1}{K} \sum_{k=1}^{K} n_{Uk} - \frac{1}{L} \sum_{l=1}^{L} n_{Al} \right| < n_{\Delta} \tag{26}$$

where n_{Uk} is the path loss factor between K anchor nodes and the upgrade node, U, in the communication range of the upgrade node, U; n_{Al} is the path loss factor between the nodes U and L and other anchor nodes within the nearest anchor node communication range from the node U; and n_{Δ} is the path loss factor threshold for node upgrading.

4.4. Algorithm Implementation

Based on the RSSI location, we list the proposed algorithm as follows:

(1) For the RSSI ranging model, according to Formulas (1)–(8), perform ranging.
(2) In the estimated ranging phase, according to Formulas (9)–(11), perform ranging correction.
(3) According to Formula (12), perform anchor selection optimization.
(4) In the ranging phase, according to Formulas (17)–(19), perform computing node coordinates.
(5) According to Formulas (20)–(25), perform position iterative optimization.
(6) The estimated location node of the satisfying Formula (26) is upgraded to an anchor node to participate in the subsequent node location calculation.

5. Simulation and Performance Evaluation

5.1. Simulation Model

We established a MATLAB 2020a simulation platform to verify and evaluate the positioning performance of this algorithm. The sensor nodes in the network are randomly distributed in a square region of 100 m × 100 m. The communication radius of the sensor nodes is 20 m, and other network parameters, such as the network size, the total number of nodes in the network, and the number of anchor nodes, are set according to the requirements of the experimental content. In order to effectively verify the performance of the algorithm, the same experimental content is realized after each reset of the network topology. Then, the average value of the results of 100 simulation experiments is used as the results.

We use root mean square error (*RMSE*) to evaluate the performance of the localization algorithm. The positioning error RSME can be expressed as follows:

$$RMSE = \sqrt{\frac{1}{M} \sum_{j=1}^{M} ||p_j - z_j||^2} \tag{27}$$

where M is the number of nodes to be positioned in the sensor network; $p_j = [\, p_{x_j} \; p_{y_j} \,]^T$ is the estimated position vector of the node j; and $z_j = [\, z_{x_j} \; z_{yj} \,]^T$ is the actual position vector of the node j. The smaller the value of *RMSE* is, the higher the accuracy of the positioning algorithm is. To compare the localization effect with other algorithms, we implement the least-squares localization algorithm using Taylor series expansion for the actual position and the common least-squares algorithm under the same experimental conditions.

In order to describe and study the relationship between the communication radius of sensor nodes, the number and density of reference nodes, and the accuracy of localization algorithms, the average positioning accuracy of network nodes was used in the localization experiment to comprehensively evaluate the algorithm performance. The average positioning accuracy of network nodes is denoted as E_a:

$$E_a = \frac{\sqrt{\sum_{j=1}^{M} ||p_j - z_j||^2}}{MR} \tag{28}$$

where R indicates the communication radius. From Equations (27) and (28), E_a reflects the positioning accuracy and also reflects the relation to the communication radius. The smaller the value of E_a is, the higher the positioning accuracy is.

The proposed algorithm in this paper is based on the RSSI model and error correction, which is called the proposed collaborative positioning algorithm (CLA) in order to compare the performance with other algorithms. The Taylor Series Expansion algorithm based on actual coordinates is simply called TSEA. In this section, we compare the proposed algorithm with the LS algorithm and TSEA algorithm. The LS algorithm is simple and intuitive, computationally efficient, and suitable for multiple scenarios, but it is sensitive to noise.

5.2. Relation between the Number of Anchor Nodes and the Positioning Accuracy

We set the total number of nodes in the network to 100; set the communication radius of nodes to 20 m; set the variance of ranging error σ^2 to 7; and set the number of anchor nodes to 5, 6, 7, 8, 9, 10, 11, and 12 in turn. The comparison of *RMSE* results obtained from the three algorithms is shown in Figure 2.

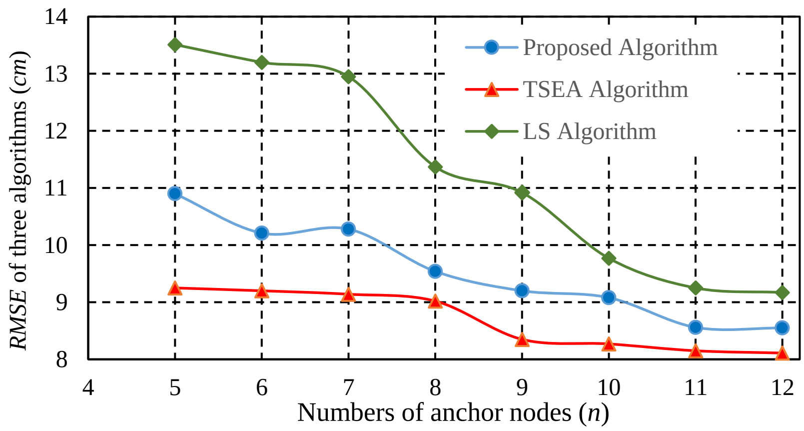

Figure 2. RMSE values of the three algorithms.

The smaller RMSE value indicates the higher localization accuracy. It can be seen from the changing trend of the above curves that the positioning accuracy of the three algorithms is increasing with the increase in the number of anchor nodes, which is because the increase in the number of anchor nodes increases the dimension of ranging observation value and more measurement redundancy information will improve positioning performance. It is shown in Figure 2 that the positioning precision of the proposed algorithm is close to that of TSEA algorithm and higher than that of LS algorithm at the same number of anchor nodes, and the positioning error decreases rapidly. It indicates that the proposed algorithm increases the number of valid anchor nodes after optimizing anchor nodes, and the positioning precision has been improved greatly.

5.3. Relation between Measurement Error and Algorithm Positioning Accuracy

The experiment environment is set up as follows: 100 nodes randomly are deployed in the network location area, including 20 anchor nodes; the communication radius of nodes is set to 20 m; and the variance of the ranging error, σ^2, increases from 3 to 10. The comparison of the *RMSE* results obtained from the three algorithms are shown in Figure 3.

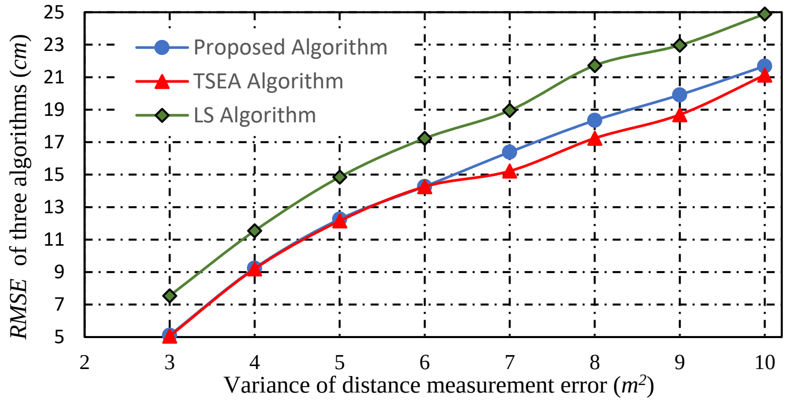

Figure 3. Influence of σ^2 on the RMSE.

From the changing trend of the above positioning error curve, with the increase in σ^2, the positioning error of the three algorithms increases. The curve shows that the ranging error has the greatest influence on LS algorithm; that is, with the increasing of σ^2, the positioning error increases faster. Though the positioning error of the proposed algorithm also increases with σ^2, it is always lower than LS algorithm, so it is not very sensitive to the distance measurement error. The reason is that the proposed algorithm takes RSSI distance error correction measures in the ranging stage and reduces the measurement error, so the positioning accuracy is improved.

5.4. Relation between Distance-Measuring Error and Positioning Precision

Then, we study the relation between the distance-measuring error and the positioning precision of the algorithm when the number of anchor nodes is different. The total number of nodes in the network is still 100. The communication radius of nodes is set to 20 m; the variance of ranging error, σ^2, increases from 3 to 10; and the number of anchor nodes is set to 6, 7, and 8, respectively. The results of *RMSE* obtained from the proposed algorithm are shown in Figure 4.

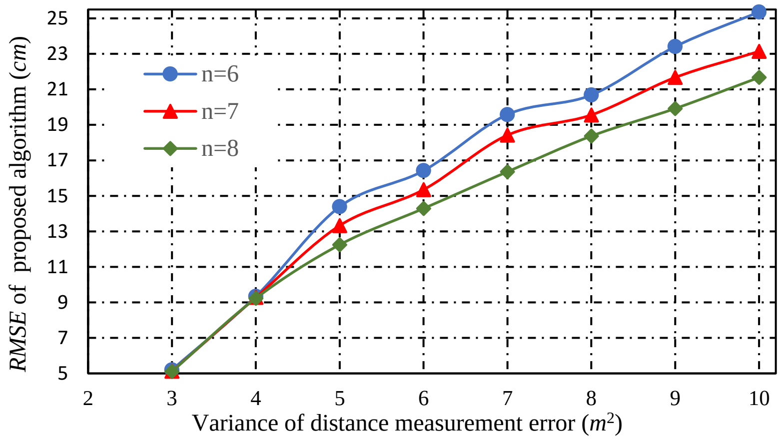

Figure 4. Influence of the number of anchor nodes on the RSME.

From the trend of three positioning error curves in Figure 4, we can see that, with the increase in the number of anchor nodes, the positioning error of the proposed algorithm decreases continuously, and the positioning effect is getting better. The reason is that the increase in the number of anchor nodes makes the information involved in positioning increase, and the result of the localization algorithm is closer to the actual value. As the variance of ranging error increases gradually in each curve, the positioning error of the proposed algorithm increases continuously. We can also see that the positioning error rises fastest when the number of anchor nodes is 6, and the positioning error rises slowly when the number of anchor nodes is 8. Therefore, the position information provided by anchor nodes is of great significance to improve the positioning accuracy; when conditions permit, increasing anchor nodes can improve positioning accuracy.

5.5. Relation between Node Communication Radius and Positioning Precision

Finally, we study the relationship between node communication radius and positioning accuracy. The total number of nodes in the network is still 100; the number of anchor nodes is 7; the variance of the ranging error is set to 6; and the node communication radius is set to 10 m, 15 m, 20 m, 25 m, 30 m, 35 m, and 40 m, respectively. The results of the RMSE of the three algorithms are shown in Figure 5.

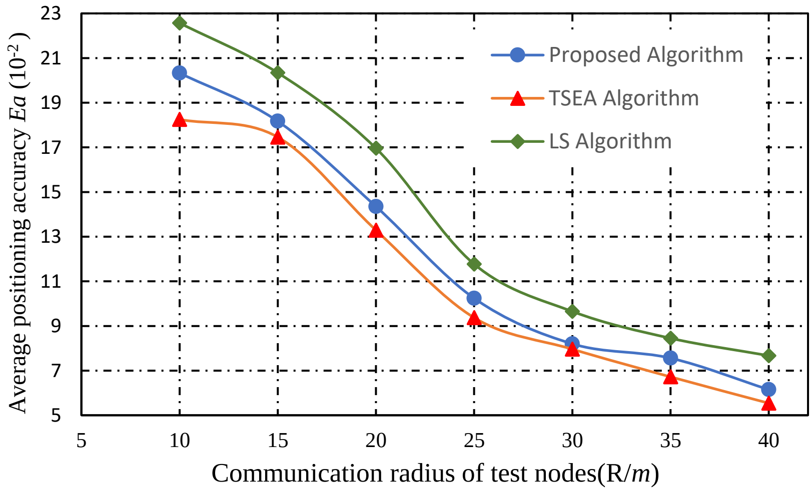

Figure 5. Influence of communication radius on positioning accuracy.

From Figure 5, we can see that, with the increase in the communication radius of the nodes, the positioning error of the three algorithms decreases, which is due to the increase in the communication radius; the increase in the anchor nodes involved in the positioning promotes the improvement of the positioning precision. However, the precision of the LS algorithm improved slowly, the proposed algorithm was close to the TSEA algorithm, and the positioning precision improved rapidly, and the proposed algorithm is always better than the LS algorithm at the same communication radius. The reason is that the RSSI distance error correction is carried out to the proposed algorithm, the ranging error is reduced, and the anchor node selection measure is implemented; hence, the positioning precision is higher than that of LS algorithm.

6. Conclusions

The algorithm proposed in this paper adopts a feasible scheme and gives full play to the advantages of RSS ranging technology based on the analysis of the characteristics of each stage of the positioning process. The proposed algorithm uses the error correction method to suppress the accumulated error in the distance measurement process, obtains the ranging value with high accuracy, and obtains a better positioning effect. Through the simulation platform, we verified the effectiveness of the proposed algorithm, and compared with the LS algorithm, the proposed algorithm has a better localization effect. The core of the algorithm is to introduce cooperative positioning, that is, upgrading the located nodes to anchor nodes and participating in other unknown positioning processes, which not only improves the location coverage but also has a better adaptability to the positioning environment.

Since the TSEA algorithm is a least-squares algorithm after the Taylor series expansion of the actual position, its localization accuracy must be optimal. The experimental results showed that the localization performance of the proposed algorithm is close to that of the

Taylor series expansion algorithm based on the actual coordinates and much higher than that of the basic LS localization algorithm when other conditions of the network remain unchanged. The essential reason for reducing the positioning error is that the optimal selection of anchor nodes is involved during the positioning process, and the node location is optimized by an iterative refinement positioning algorithm.

The next step will be to make the effective use of observation information to reduce the positioning calculation error, and the direct ranging between each node to participate in the cooperative positioning, so as to improve the positioning accuracy and robustness. The positioning algorithm in WSN is one of the important fields of wireless sensor network research. With the rapid development of the Internet of Things, the smart city, and industrial automation, higher requirements are put forward for the accuracy and reliability of the WSN positioning algorithm. The positioning algorithm in WSN is also a research field full of challenges and opportunities. In the future, we will further study the positioning algorithm from three aspects. Firstly, we will use advanced signal-processing technology, multi-source information fusion technology, and an optimization algorithm and other means to further study the high-precision positioning algorithm. Secondly, we will study the energy-saving positioning algorithm by optimizing the working mode of nodes, reducing the communication frequency, and adopting the measurement method of energy saving. Thirdly, we will study the distributed positioning algorithm to achieve efficient and accurate positioning through the collaboration and information sharing between nodes, the communication protocol between nodes, the data fusion strategy, and the optimization of positioning accuracy. In conclusion, in future research, we will need to continuously explore new technologies and methods to meet the needs of various application scenarios or solve some practical problems, such as hardware constraints, communication protocols, and scalability for large-scale networks, for example, LoRa, NB-IoT, etc.

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