A Direct Location Algorithm Based on Gauss Newton Iteration

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Abstract. Introduction: With the rise of logistics, navigation, takeout and other industries, location information plays a more and more important role in daily life. It is different from military positioning, which takes high positioning accuracy as the main principle. Due to the need to consider its popularity, civil positioning generally focuses on the principle of economy, and strives to reduce the hardware requirements of the positioning system as much as possible under the condition of reasonable and relaxed positioning accuracy.

Objective: This paper aims to use the received signal strength to locate the emitter signal, and improve the positioning accuracy of the algorithm through continuous iteration and correction, so as to ensure the positioning accuracy on the premise that the positioning method based on RSS does not need additional hardware equipment.

Methods: The algorithm in this paper locates the emitter based on the received signal strength, uses the median weighted filter to collect the emitter power and preliminarily screen out the gross error, then uses the genetic algorithm to select the initial point of the iteration, and uses the improved weighted least squares algorithm based on Gauss Newton iteration to estimate the parameters. Finally, an error correction module is added to further ensure the positioning accuracy.

Keywords: Received signal strength · Median weighted filtering · Direct location algorithm

1 Introduction

Thanks to the vigorous development of deep learning, image processing, computer vision and other technologies, the machine is equipped with eyes that can see the world. Modern life is gradually developing in the direction of intelligence and automation. In people's daily life, many applications, such as automatic driving, automatic storage, machine meal delivery and other services [10], need to obtain the location information of the target. It can be seen that the popularization of positioning information is of key significance for building an interconnected society.

In military affairs, the location of radiation source is an important characteristic information of electromagnetic radiation source, and has a relatively stable state [17]. It is

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not only closely related to battlefield situation, mission planning and combat operations, but also an important basis for distinguishing different radiation sources [16, 17]. The location of radiation source is an important work that needs to be processed and used in all kinds of electronic warfare [5]. The distributed communication jamming network based on multiple beacon nodes can obtain the position or distance information of multiple enemy emitter nodes, provide useful state information for target intention recognition, and improve the state perception level of emitter targets.

Document [7] proposes an improved indoor positioning system method based on WiFi triangle. The improved model is based on the test results using Intel Galileo (Gen2) board as the access point. By improving the measurement of received signal strength, the problem of signal blocking caused by obstacles in the building is solved. Document [18] proposes a new uncertainty analysis method of RSSI based distance estimation (uam-rde) to study the uncertainty propagation in RSSI based distance estimation.

In order to improve the positioning accuracy of emitter target positioning based on received signal strength (RSS), this paper first innovates in data preprocessing, abandons the traditional average filter and selects the median weighted filter to reduce the gross error more effectively. Then, the target position is preliminarily estimated by genetic algorithm, and then the modified Gauss Newton iterative algorithm is used for secondary positioning, and the final convergent iterative result is taken as the target position. At the same time, the error correction module is added to iterate the convergence result twice to further improve the positioning accuracy. Simulation results show that the algorithm can save cost and ensure positioning accuracy at the same time.

2 Normal Shadow Fading Model

Commonly used RSSI propagation models include free space propagation model, ground reflection (two ray) model, log distance path loss model and log normal shading model. In practical applications, the situation is much more complex, especially in densely distributed wireless sensor networks. Reflection, multipath propagation, non line of sight, antenna gain and other problems will produce significantly different propagation losses at the same distance. Therefore, the log distance path loss model and log normal shadow model are two path loss estimation models suitable for sensor networks, they all describe the characteristics of the logarithm of path loss. The former is a deterministic model and describes the average characteristics of signal strength, while the latter describes different random shadow effects with the same distance on the propagation path. Lognormal shadow model is often used in the design and analysis of wireless communication system, so as to calculate and simulate the received power at any position. In this paper, the lognormal shadow model is used as the simulation model to verify the reliability of the algorithm. The calculation formula is as follows:

$$PL(d)[dB] = \overline{PL}(d) + X_\sigma = \overline{PL}(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{1}$$

where: d is the distance between the receiving end and the transmitting end; d_0 Is the reference distance, generally 1 m; $\overline{PL(d)}$ is the received signal power of the receiving end; $\overline{PL(d_0)}$ is the received signal power corresponding to the reference distance point

d_0; X_σ is a Gaussian random variable with a mean value of 0, which reflects the change of received signal power when the distance is fixed; n is the path loss index, which is a value related to the environment

Through the analysis of lognormal shadow model, it can be seen that there is random error in using this method to estimate the distance. In addition, due to the influence of multipath and reflection of wireless channel, there are still errors between the established model and the signal propagation model of actual environment. Therefore, it is not enough to simply use Eq. (1) for ranging. RSSI values shall be measured many times under the same conditions, and these RSSI values shall be screened to discard the RSSI values with large error and leave the RSSI values with small error, so as to improve the ranging accuracy.

3 Methodology

3.1 Data Preprocessing

Based on the strong anti error ability of the median, aiming at the positioning problem in the actual typical environment, this paper first communicates between the two nodes for a period of time, obtains a certain amount of data, finds the median of the signal strength in the signal sequence, then calculates the weight of each signal strength in the signal sequence according to the median, and finally multiplies each signal by the corresponding weight, Then sum the signal value between the two nodes and output it. The distance estimation method based on median weighting proposed in this paper mainly includes four steps: data sampling, obtaining the median of signal sequence, calculating weight and estimating distance, as shown below:

Sampling Measurement
Firstly, the information sent by the unknown node is received at the same location, and the RSSI propagation loss of the signal is calculated automatically. In order to obtain the distribution characteristics between nodes, it is necessary to sample multiple times in a certain time period to obtain RSSI sequence $\{RSSI_1, RSSI_2, RSSI_3, ..., RSSI_n\}$.

Get the Median of Signal Sequence
Take the median of the obtained signal sequence. The median represents the value in the middle when a group of data is arranged in the order of size. Calculate the median of RSSI sequence:

$$Med_{RSSI} = \begin{cases} RSSI_{(n+1)/2}, N \textit{ is an odd number} \\ \frac{1}{2}\left(RSSI_{\frac{n+1}{2}} + RSSI_{\frac{n}{2}+1}\right), N \textit{ is an even number} \end{cases} \tag{2}$$

Calculate Weight
On the basis of obtaining the median of the signal sequence above, first calculate the variance between each signal value in each RSSI signal sequence and the median of the sequence. The variance is calculated as follows:

$$\mathbf{Var}_i = (RSSI_i - Med_{RSSI})^2 \tag{3}$$

Secondly, in order to avoid that there is a RSSI signal in the sequence whose value is the same as the median of the sequence, resulting in zero variance, the non normalized weighting coefficient can be calculated according to the following formula:

$$\mathrm{R}_i = 1/(1 + \mathbf{Var}_i) \tag{4}$$

Then, sum and normalize the weighting coefficients obtained by the above formula. The formula is as follows:

$$\mathrm{w}_i = \mathrm{R}_i/(\sum_{i=1}^{n} \mathrm{R}_i) \tag{5}$$

The larger the difference between the RSSI value and the median in the sequence, the smaller the corresponding weighting coefficient. When the RSSI value and are equal, the weighting coefficient is the largest, and the corresponding RSSI value is given the maximum weight at this time. Because the difference between the RSSI value and the median in the sequence is directly used to determine the weight, when the RSSI signal value containing gross error in the sequence is too close to the median value of the sequence, it is possible to give these RSSI signals too large weight, resulting in the decline of algorithm performance. Therefore, we set a threshold. If the variance is greater than the threshold T, the weight is determined by the variance; If the variance is less than the threshold, it is determined by the threshold. Then the weight of each RSSI signal in each sequence can be calculated according to the following formula:

$$\mathbf{w}_i = \frac{1}{\sum_{i=1}^{n} \frac{1}{1+\max\{T, (RSSI_i - Med_{RSSI})^2\}}} \tag{6}$$

where, T is the mean value of the variance between each signal value and median in the RSSI signal sequence, which is called the threshold, which can be expressed by the following formula:

$$\mathbf{T} = \frac{\sum_{i=1}^{n} (RSSI_i - \mathrm{Med}_{RSSI})^2}{n} \tag{7}$$

Among them, $RSSI_i$ is the ith $RSSI$ signal value in the region. It can be seen that the greater the difference between $RSSI_i$ and Med_{RSSI}, the smaller the corresponding weighting coefficient w_i, and T changes with the $RSSI_i$ and sum variance Med_{RSSI}.

Estimated Distance

Use the method in step 3 to obtain the corresponding weight of each signal value in the signal sequence, multiply and sum each signal value in the signal sequence with the corresponding weighting coefficient, that is $\mathrm{RSSI} = \sum_{i=1}^{n} w_i \times RSSI_i$, output it as the RSSI signal value between node pairs, and calculate the distance from the signal point to the unknown location node using the RSSI ranging formula.

The advantages of using this processing method are as follows: (1) when calculating the weight based on the median, a very small weight is given to the RSSI value containing the gross error signal, the value with error can be ignored during accumulation, some abnormal points are filtered, and the gross error data is not simply deleted; (2) Accumulation is similar to the use of mean model, which can filter out some random noise; (3) The algorithm is suitable for different complex environments, which increases the applicability of the algorithm.

3.2 Gauss Newton Iterative Algorithm

Advantages of Gauss Newton Iterative Algorithm over Maximum Likelihood Estimation Algorithm

Target position estimation is to determine the approximate position of the target node by using the measured distance, angle and other data and other information. The common methods of position calculation are trilateral method and triangular method. If there is noise in the measurement data, the maximum likelihood method or its improved method can be used to estimate the unknown node coordinates. It only needs the ranging information and does not need the prior information of the position [20].

Maximum likelihood estimation is a statistical method, which takes the maximum probability of the occurrence of the observed value as the quasi measurement. It is considered that the wireless sensor network $\{X_1, X_2, ..., X_n\}$ composed of N nodes $X_i (i = 1, 2, ..., n)$ is deployed in the $d (d = 2, 3)$ dimensional monitoring area. The IDs of the nodes are 1, 2,…, N, the real coordinates of the nodes X_i are (x_i, y_i), and the distances from them to the unknown node D are d_i respectively, assuming that the coordinates of D are $X = (x, y)$. Then there is a coordinate distance relationship equation between the beacon node and the unknown node, that is

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 = d_1^2 \\ (x - x_2)^2 + (y - y_2)^2 = d_2^2 \\ \vdots \\ (x - x_n)^2 + (y - y_n)^2 = d_n^2 \end{cases} \tag{8}$$

Among them, if the first to Nth-1 equations are subtracted from the nth equation respectively, the following can be obtained:

$$\begin{cases} 2(x_n - x_1)x + 2(y_n - y_1)y = d_1^2 - d_n^2 + y_n^2 + x_n^2 - y_1^2 - x_1^2 \\ 2(x_n - x_2)x + 2(y_n - y_2)y = d_2^2 - d_n^2 + y_n^2 + x_n^2 - y_2^2 - x_2^2 \\ \vdots \\ 2(x_n - x_n)x + 2(y_n - y_n)y = d_{n-1}^2 - d_n^2 + y_n^2 + x_n^2 - y_{n-1}^2 - x_{n-1}^2 \end{cases} \tag{9}$$

Order

$$\mathbf{A} = 2 \times \begin{bmatrix} (x_1 - x_n) & (y_1 - y_n) \\ (x_2 - x_n) & (y_2 - y_n) \\ \vdots & \vdots \\ (x_{n-1} - x_n) & (y_{n-1} - y_n) \end{bmatrix} \tag{10}$$

$$\mathbf{b} = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 + d_n^2 - d_2^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix} \tag{11}$$

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \tag{12}$$

The above equations can be transformed into the form of $AX = b$. Although the noise reduction processing is carried out in the ranging process, there is always a certain error in the distance measurement in the actual environment, so the equation can be expressed as:

$$AX = b + \xi \tag{13}$$

In order to obtain the optimal solution of unknown node position, the sum of squares of errors is used as the judgment standard, so there is a loss equation $S(\boldsymbol{x})$:

$$\begin{aligned} S(\mathbf{x}) &= \|\xi\|^2 = \|\mathbf{Ax} - \mathbf{b}\|^2 \\ &= (\mathbf{Ax} - \mathbf{b})^T(\mathbf{Ax} - \mathbf{b}) = \mathbf{x}^T\mathbf{A}^T\mathbf{Ax} - 2\mathbf{b}^T\mathbf{Ax} + \mathbf{b}^T\mathbf{b} \end{aligned} \tag{14}$$

In order to obtain the optimal solution, the partial derivative of the loss equation is obtained and set equal to 0, and the following is obtained:

$$\partial\|\xi\|^2/\partial\mathbf{x} = -2\mathbf{A}^T\mathbf{b} + 2\mathbf{A}^T\mathbf{Ax} = 0 \tag{15}$$

Calculation shows that

$$\mathbf{A}^T\mathbf{b} = \mathbf{A}^T\mathbf{Ax} \tag{16}$$

If the beacon point is not on a straight line, when the square array $\mathbf{A}^T\mathbf{A}$ is reversible, the estimated coordinates of the unknown node can be obtained from Eq. (16):

$$\hat{\mathbf{x}} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{b} \tag{17}$$

Therefore, it is the whole principle of using the maximum likelihood estimation method to solve the coordinates of unknown points. From the above analysis process, it can be seen that there is a disadvantage of using the maximum likelihood estimation method, that is, in the calculation process, this method uses equation subtraction to eliminate the quadratic term for linearization. This simple coordinate subtraction will have a certain loss of known coordinate information. At the same time, it is considered that the farther away from the unknown node, the greater the ranging error of the beacon node.

The Steps of Gauss Newton Iterative Method

In this project, the weighted least square estimation method based on Gauss Newton iteration is used to estimate the position of unknown targets. Its basic principle is as follows:

Order $f(x, y) = \sqrt{(x - x_i)^2 - (y - y_i)^2}$, The first-order Taylor expansion of the $f(x, y)$ formula at point (x_0, y_0) is obtained:

$$
\begin{aligned}
f(x, y) = f(x_0 + h, y_0 + k) &= \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2} \\
&+ \frac{(x_0 - x_i)}{\sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}} h + \frac{(y_0 - y_i)}{\sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^2}} k
\end{aligned} \tag{18}
$$

Apply Eq. (18) to equation group (8) to obtain:

$$
\begin{cases}
\frac{(x_0 - x_1)}{\sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2}} h + \frac{(y_0 - y_1)}{\sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2}} k = d_1 - \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} \\
\frac{(x_0 - x_2)}{\sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2}} h + \frac{(y_0 - y_2)}{\sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2}} k = d_2 - \sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2} \\
\vdots \\
\frac{(x_0 - x_n)}{\sqrt{(x_0 - x_n)^2 + (y_0 - y_n)^2}} h + \frac{(y_0 - y_n)}{\sqrt{(x_0 - x_n)^2 + (y_0 - y_n)^2}} k = d_n - \sqrt{(x_0 - x_n)^2 + (y_0 - y_n)^2}
\end{cases} \tag{19}
$$

Then the Gauss Newton iterative method is used to approximate the solution of Eq. (19). The main steps are as follows:

Step one: Initialize (x_0, y_0) and select the midpoint of each beacon node;
Step two: For Eq. (19), the least square method is used to solve h and k;
Step three: Judge whether the h and k solved in step two meet the inequality $\sqrt{h^2 + k^2} < \varepsilon_{th}$. If it is true, stop the calculation; Otherwise, increase the step size of (x_0, y_0), update Eq. (19), continue the cycle from step two until the threshold ε_{th} condition is meet, and stop the calculation;
Step four: The output (x_0, y_0) is the approximate solution of the target coordinate (x, y) to be estimated.

Considering that the distance error between nodes varies with the distance between nodes, if different weighting values are given to each node according to the distance accuracy of each node, that is, in the least squares estimation based on Gauss Newton iterative method mentioned above, different weighting coefficients are added to the decomposed Eq. (19), so as to obtain the weighted least squares method based on Gauss Newton iterative method, The positioning accuracy can be improved.

3.3 Direct Location Algorithm

Principle of Direct Positioning Algorithm

When using RSSI for two-step positioning, first collect the power and convert the distance between each node through the power, that is, there is a functional relationship between the distance and power:

$$\mathrm{P} = \mathrm{F(D)} \tag{20}$$

Finally, the position parameters are solved through geometric relationship and coordinate system, and the calculated position parameter is set as X, that is, there is also a functional relationship between parameter position and distance:

$$\mathrm{X} = \mathrm{G(D)} \tag{21}$$

The main idea of direct positioning is to convert the formula into

$$\mathrm{X} = \mathrm{G}\left(\mathrm{F}^{-1}(\mathrm{P})\right) \tag{22}$$

That is, the steps of calculating and storing distance parameters are omitted, and the radiation source is located directly through the data collected by the node.

The Steps of Direct Positioning Method

According to the shadow fading model. Since the reference distance d_0 is usually taken as one meter. It can be obtained by transforming the above formula (1):

$$\mathrm{d} = 10^{\left(\frac{pld - pl(d_0) - x}{10n}\right)} \tag{23}$$

According to Taylor expansion:

$$\boldsymbol{a^x = e^{x \ln a} = 1 + \frac{x \ln a}{1!} + \frac{(x \ln a)^2}{2!} + \frac{(x \ln a)^3}{3!} + \cdots} \tag{24}$$

Combining the two formulas can be obtained:

$$\mathrm{d} = 10^{\left(\frac{pl(d) - pl(d_0) - x}{10n}\right)} = 1 + \frac{\left(\frac{pl(d) - pl(d_0) - x}{10n}\right) ln10}{1!} + \frac{\left(\left(\frac{pl(d) - pl(d_0) - x}{10n}\right) ln10\right)^2}{2!} + \frac{\left(\left(\frac{pl(d) - pl(d_0) - x}{10n}\right) ln10\right)^3}{3!} \tag{25}$$

Obviously, d can be expressed as:

$$\mathrm{d} = \mathbf{A} * \mathbf{P} \tag{26}$$

where a vector and P vector are respectively:

$$\mathbf{A} = \left[1, \frac{\frac{\ln 10}{10\mathrm{n}}}{1!}, \frac{\left(\frac{\ln 10}{10\mathrm{n}}\right)^2}{2!}, \frac{\left(\frac{\ln 10}{10\mathrm{n}}\right)^3}{3!} \ldots\right] \tag{27}$$

$$\mathbf{P} = \left[1, (pl(d) - pl(d_0) - x), (pl(d) - pl(d_0) - x)^2, (pl(d) - pl(d_0) - x)^3, \ldots\right]^{\boldsymbol{T}} \tag{28}$$

where a vector is a coefficient vector, which is determined by A. since a = 10 is a constant value, it is a constant coefficient vector. P is the power vector, which is determined by the power collected by each node in real time. Therefore, D = F^{-1}(P) can be obtained on the basis of retaining the high-order item information.

Combined with Eq. (19) above, We can get the matrix expression:

$$[\mathrm{E}] * [\mathrm{h, k}]^T + [e] = [A] * [P] \tag{29}$$

The specific expressions of each matrix are:

$$[\mathrm{E}] = [\begin{matrix} \frac{x_0-x_1}{\sqrt{(x_0-x_1)^2+(y_0-y_1)^2}} & \frac{y_0-y_1}{\sqrt{(x_0-x_1)^2+(y_0-y_1)^2}} \\ \frac{x_0-x_2}{\sqrt{(x_0-x_2)^2+(y_0-y_2)^2}} & \frac{y_0-y_2}{\sqrt{(x_0-x_2)^2+(y_0-y_2)^2}} \\ \cdots & \cdots \end{matrix}] \tag{30}$$

$$[\mathrm{e}] = [\begin{matrix} \sqrt{(x_0 - x_1)^2 + (y_0 - y_1)^2} \\ \sqrt{(x_0 - x_2)^2 + (y_0 - y_2)^2} \\ \cdots \end{matrix}] \tag{31}$$

$$[\mathrm{A}] = [\begin{matrix} \mathbf{A} \\ \mathbf{A} \\ \cdots \end{matrix}] \tag{31}$$

$$[\mathrm{P}] = [\begin{matrix} \mathbf{P}_1 \\ \mathbf{P}_2 \\ \cdots \end{matrix}] \tag{32}$$

[E], [e], [P] are called the characteristic matrix of the anchor node group, where E and e are determined by the position parameters of the iteration initial point and the anchor node itself, and P is determined by the power collected by the anchor node group.

We can obtain the following matrix expression from multiple groups of anchor node groups:

$$\begin{gathered} [\mathrm{E}_1] * [\mathrm{h, k}]^T + [e_1] = [A] * [P_1] \\ [\mathrm{E}_2] * [\mathrm{h, k}]^T + [e_2] = [A] * [P_2] \\ \cdots \\ [\mathrm{E}_n] * [\mathrm{h, k}]^T + [e_n] = [A] * [P_n] \end{gathered} \tag{33}$$

Multiple sets of $[\mathrm{h, k}]^T$ values are obtained through the simultaneous constant coefficient matrix $[A]$, so as to realize the direct positioning based on Gauss Newton iteration and improve the positioning accuracy.

3.4 Error Correction

Based on the improved Gauss Newton iterative algorithm, it still needs to calculate the Hessian matrix and select the initial value strictly. If this matrix is ill conditioned, it may lead to iterative failure or output local optimal solution. Therefore, this paper adopts the operation of multiple positioning of the same radiation source after receiving the radiation source power through the node and preprocessing the data. In multiple iterations of the same radiation source, the initial point is selected from the optimal population of the point provided by GA genetic algorithm to ensure that each initial point is different. Because the Heisenberg matrix is ill conditioned only at a specific initial value, it can converge to the global optimal solution for most initial points under the joint action of the improved Gauss Newton iterative algorithm and the direct location algorithm. For very few cases, although a certain initial point can cause the Heisenberg matrix to become an ill conditioned matrix, which will lead to the failure of the iteration and output the local optimal solution, that is, the iteration will bring a large mean square error. However, due to multiple positioning of the same radiation source, a series of positioning results at the same point will be stored. The median weighted output of a series of positioning results can greatly reduce the mean square error caused by matrix ill condition in a certain iteration (Figs. 1 and 2).

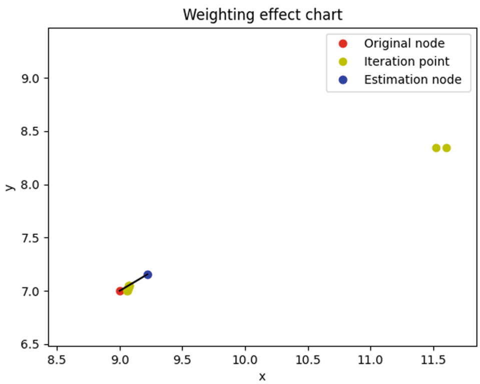

Fig. 1. The figure on the left shows 11 times of positioning for (7, 9), of which the results of two iterations obviously deviate from the expected results. It is found from the final positioning results (blue dots) that the results of these two deviations can be corrected (Color figure online)

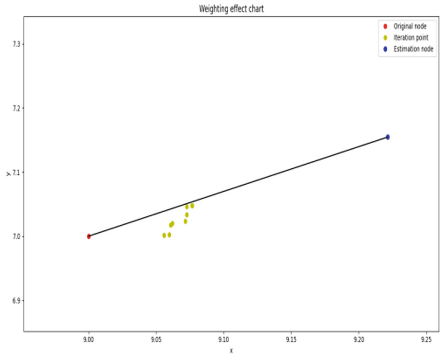

Fig. 2. The upper right figure is the enlarged figure of the left figure near (7, 9). It can be found that most iterative results belong to the normal error range

4 Experimental Results and Conclusions

As can be seen from the above figure, the traditional maximum likelihood estimation method uses equation subtraction to eliminate the quadratic term for linearization in the calculation process. This simple coordinate subtraction will have a certain loss of known coordinate information. Therefore, the mean square error of ML algorithm in most variance scenarios is greater than that of the other two algorithms (Figs. 3 and 4).

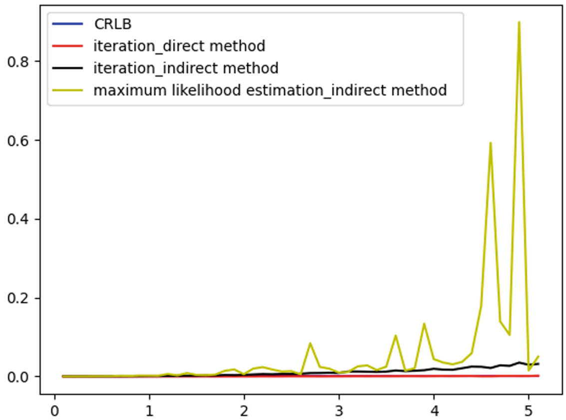

Fig. 3. The above figure is the comparison diagram of positioning mean square error of three kinds of algorithms under different variances. Where x-axis is variance and y-axis is mean square error.

It can be seen from the above figure that under the same other conditions, compared with the two-step positioning algorithm, the direct positioning algorithm can significantly reduce the mean square error of positioning parameter estimation under the high variance power signal (i.e. the power signal is greatly affected by shadow fading at this time) (Fig. 5).

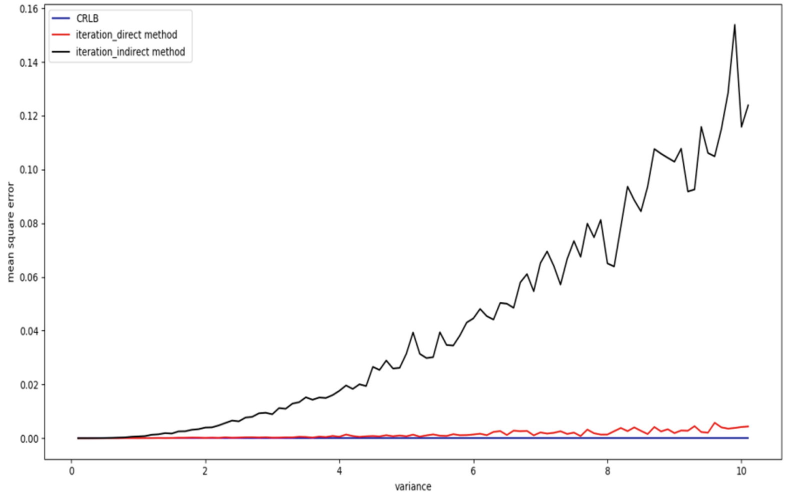

Fig. 4. The above figure shows the comparison of the mean square error of direct positioning algorithm and two-step positioning algorithm under different variance conditions. Where x-axis is variance and y-axis is mean square error.

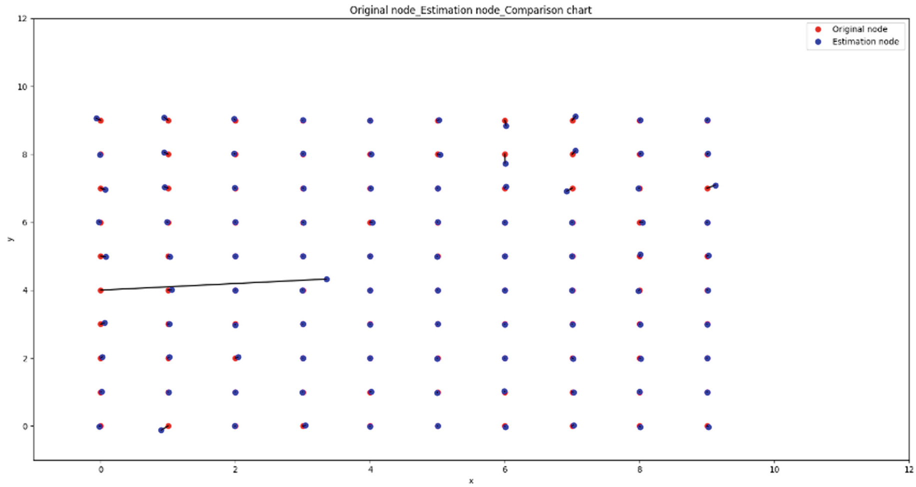

Fig. 5. In the figure above, the red point is the actual point and the blue point is the positioning result output by the algorithm. The higher the coincidence degree of the two points, the better the positioning effect of the point (Color figure online)

This paper explores the emitter location algorithm based on the received signal strength. On the premise of retaining the low cost of RSSI based location algorithm, the location accuracy is improved by integrating the advantages of various algorithms.

The experimental results show that compared with the traditional two-step location algorithm, the direct location algorithm is closer to the lower bound of CRLB under the condition of large noise interference, can better reduce the mean square error of location, and has strong anti-interference ability.

Gauss Newton iterative algorithm can effectively solve the disadvantage that the maximum likelihood estimation algorithm uses equation subtraction to eliminate the quadratic term to linearize in the calculation process, resulting in a certain loss of known coordinate information. Ensure positioning accuracy.

Carry out multiple power acquisition for the same radiation source and preprocess the collected dataThe paragraph starting with "This work is supported by..." has been treated as "Acknowledgment". Kindly check and confirm. After that, the target is located for many times, and the median weighting processing of the positioning results can greatly reduce the impact of the local optimal solution on the positioning results. To some extent, solve the problem that Gauss Newton iterative algorithm will fail due to singular matrix.

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