TOF Indoor Location Algorithm based on RBF Neural Network

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Abstract: In the UWB positioning system, due to the existence of multipath effects, NLOS and other factors, a certain degree of measurement error will result. In particular, the NLOS error has become a key factor affecting the positioning accuracy. Large NLOS errors often lead to a sharp decline in the positioning performance of UWB Indoor Positioning System. In this paper, a large number of data with NLOS error is used as a sample, and it is trained by RBF artificial neural network algorithm. In this way, the influence of the NLOS error can be eliminated at the source, and the positioning accuracy of the TOF can be improved.

1 INTRODUCTION

In recent years, with the rapid update of wireless positioning technology, various mobile positioning-based applications such as target tracking, environmental monitoring, medical care, and space exploration have gradually revealed opportunities for development. In the existing wireless communication technology, the ultra-wideband (UWB) signal has the advantages of high transmission rate, low power consumption, and strong anti-interference (Segura et al., 2012), so that when it is applied to the wireless positioning system, In terms of positioning accuracy, there are advantages that other positioning technologies can't match, so it becomes a reliable choice for short-range wireless positioning (Wu et al., 2010).

In the UWB indoor positioning system, it can be generally divided into three levels, namely, a location sensing layer, a network transport layer, and a positioning application layer. The location-aware layer is composed of a UWB base station and a positioning tag, and is used to obtain tag validity information, and the network transport layer is responsible for transmitting the location-related information obtained by the location-aware layer to the background server by wire or wirelessly. The positioning application layer mainly includes a positioning engine and an application software. The positioning engine is used to calculate the position information of the positioning tag in real time, and the positioning application platform is used to implement human-computer interaction and provide various business function applications for the user.

At present, there are a variety of methods to obtain the location information of the mobile tag, that is, the location aware layer. The most widely used is based on Time Of Arrival (TOA) and Time Difference Of Arrival (TDOA). In general, the positioning accuracy of TOA should be slightly higher than TDOA, and the implementation cost is higher (Dashti et al., 2011). In this paper, the time of flight (TOF) is used for algorithm verification. The TOF is evolved from TOA. The TOA-based positioning method uses timestamps, while the TOF uses time periods to avoid between different devices. The strict requirements of clock synchronization. The two are only different in the way of obtaining the distance, that is, the former is one-way ranging, and the latter is two-way ranging, but the subsequent operation flow is consistent (Mazraani et al., 2017).

This paper proposes a TOF localization algorithm that uses the RBF neural network algorithm to eliminate NLOS errors. The algorithm is based on the TOF localization method, and the initial TOF measurement value is preprocessed by the RBF neural network algorithm, and then the initial positioning solution is calculated by the preprocessed value.The advantage of PSO in nonlinear optimization is to optimize the positioning

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result to obtain the final value. After comparison with the traditional positioning algorithm, the proposed algorithm can achieve better positioning performance in the NLOS environment.

2 TOF POSITIONING METHOD

Time of Flight (TOF) is a two-way ranging technology. It calculates the distance by measuring the time of flight of the UWB signal between the base station and the tag (Chantaweesomboon et al., 2016). The principle of ranging is shown in Figure 1.

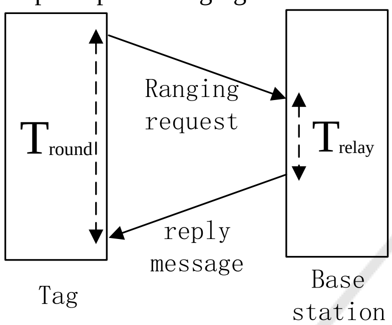


Figure 1: Schematic diagram of TOF distance measurement.

Mobile tag first transmits a ranging request to the positioning station, the base station receives a ranging request process, after a short time to process the return confirmation message to the mobile tag, were recorded UWB signal transmission and the received time stamp, thus calculated The flight time 'T_{round}' of the UWB signal and its' the processing time 'T_{relay}'. Then the distance between the tag and the base station can be expressed as:

$$d=\frac{(T_{round}-T_{relay})}{2}\times c \tag{1}$$

Where c is the speed of light, that is, the propagation speed of the UWB signal in the medium.

Taking two-dimensional positioning as an example, assume that the coordinates of base station A are (X_1, Y_1), and the coordinates of base station B are (X_2, Y_2), the coordinates of base station C are (X_3, Y_3), and the coordinates of the moving label are (x, y). The principle of positioning based on TOF is shown in Figure 2.

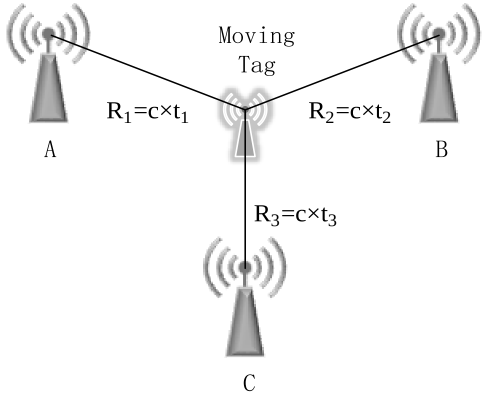


Figure 2: Principle of TOF positioning.

Where R_1 is the distance between the base station A and the mobile tag, R_2 is the distance between the base station B and the mobile tag, and R_3 is the distance between the base station B and the mobile tag, t_1, t_2, t_3 respectively indicate the propagation time of the UWB signal between each base station and the mobile tag. The following equations can be listed based on known information:

$$\begin{cases}((X_1-x)^2+(Y_1-y)^2)={R_1}^2\\((X_2-x)^2+(Y_2-y)^2)={R_2}^2\\((X_3-x)^2+(Y_3-y)^2)={R_3}^2\end{cases} \tag{2}$$

Solving the matrix of the above formula, you can get the position coordinates of the moving Tag:

$$\begin{bmatrix}x\\y\end{bmatrix}=\begin{bmatrix}2(X_1-X_3) & 2(Y_1-Y_3)\\2(X_2-X_3) & 2(Y_2-Y_3)\end{bmatrix}^{-1}\times\begin{bmatrix}{X_1}^2-{X_3}^2+{Y_1}^2-{Y_3}^2+{R_3}^2-{R_1}^2\\{X_1}^2-{X_3}^2+{Y_2}^2-{Y_3}^2+{R_3}^2-{R_2}^2\end{bmatrix} \tag{3}$$

The TOF-based positioning method is essentially the same as the TOA-based positioning method, and the TOF ranging does not depend on the time synchronization of the base station and the tag, so there is no error caused by the clock synchronization deviation, but the time of the TOF ranging method depends on Clock accuracy, clock skew can introduce errors. In order to reduce the ranging error caused by the clock offset, the measurement method of the forward and reverse directions is usually adopted, that is, the remote base station transmits the ranging information, the tag receives the ranging information and replies, and then the ranging information is initiated by the tag. The terminal base station replies and reduces the time offset between the two by obtaining the average flight time, thereby improving the ranging accuracy (Suwatthikul et al., 2017).

3 POSITIONING ALGORITHM

In the UWB positioning system, no matter what positioning method, the key reason for the final positioning accuracy is always due to the inability to obtain accurate UWB signal arrival time. For the TOF positioning method, although it does not directly use the timestamp for ranging, the influence of Non-Line of Sight (NLOS) still exists. Traditional positioning algorithms such as LS, WLS, and Chan are proposed under the condition that the system error must obey the Gaussian distribution, that is, the positioning effect is good in the Line of Sight (LOS) environment, and the effect is poor in the NLOS environment (Angelis et al., 2013; Tabaa et al., 2014). In this paper, the neural network algorithm is used to process the NLOS error, which is intended to eliminate the influence of NLOS error on the localization algorithm (Laoudias et al., 2010).

3.1 RBF Neural Network Algorithm

The Radial Basis Function (RBF) network is a typical forward neural network with approximation function of nonlinear continuous rational function (Seshagiri et al., 2000). The NLOS error can be corrected by using the TOF measurement values of multiple positioning base stations, so that the measured value of the TOF is close to the measured value in the LOS environment, and the positioning accuracy in the NLOS environment is improved.

The RBF neural network model consists of input layer, hidden layer and output layer. The clustering method, gradient training method and orthogonal least squares training method are often used to adjust the network error. As shown in Figure 3, the input layer consists of five TOF measurements provided by five positioning base stations. The input vector is $x=[x_1\ x_2\ x_3\ x_4\ x_5]$, the activation function (base function) in the implicit node selects the Gaussian function. The output layer is the corrected TDOA value, and the output vector $y=[y_1\ y_2\ y_3\ y_4\ y_5]$.

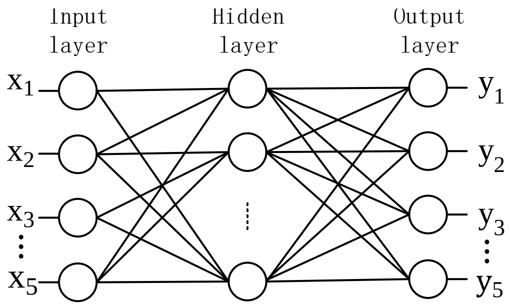


Figure 3: RBF model for correcting TOF measurements

In this paper, the gradient training method is used to inversely adjust the network error. There are three parameters to be learned in the RBF network, namely the data center, variance and output unit weight of each RBF. By the chain partial differential rule, the amount of adjustment for each data center, variance, and weight can be obtained as follows:

$$\Delta_{c_i}=\eta_1 \frac{\omega_i}{\sigma_j^2}\sum_{j=1}^{N} e_i G(x_j)(x_j-c_i) \quad (4)$$

$$\Delta\sigma_i=\eta_2 \frac{\omega_i}{\sigma_j^2}\sum_{j=1}^{N} e_i G(x_j)\left\|x_j-c_i\right\|^2 \quad (5)$$

$$\Delta\omega_i=\eta_3 \sum_{j=1}^{N} e_i G(x_j) \quad (6)$$

Where G represents a Gaussian function; i, j are subscripts of the number of hidden layer nodes and the number of samples, respectively; c, σ, ω represent the network data center, width, and weight, respectively, η_1, η_2, η_3 respectively represent the respective learning rates; e represents the residual between the network output value and the sample value; the gradient RBF network hidden layer neurons are composed of the activation function and the distance function The closer the sample is to the data center, the more likely it is to be activated. The more it deviates from the training samples in the data center, the less the network responds to it. The algorithm flow chart is shown below.

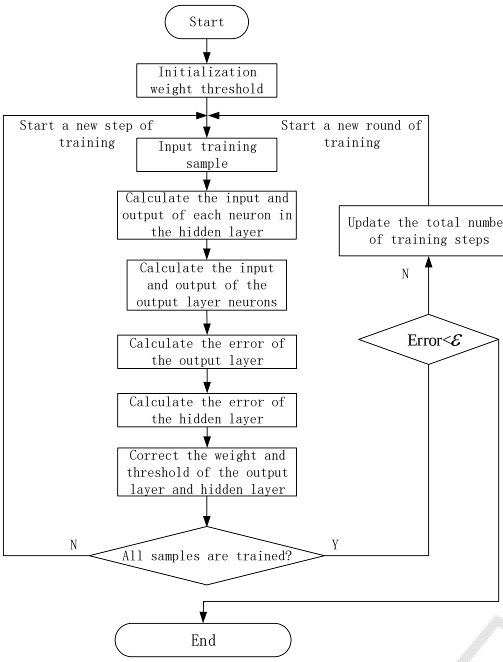


Figure 4: RBF algorithm flowchart.

After the NLO error is processed by the RBF neural network algorithm, the measured value of the TOF is already more reliable. The positioning accuracy can be improved by using the traditional positioning algorithm, but in order to remove the influence of NLOS more, the particle can be used. The group optimization algorithm finally corrects the initial solution of the positioning (Rivas et al., 2004).

3.2 Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) algorithm is an intelligent optimization algorithm based on population iteration. By initializing a group of random particles, each particle is moved by a certain distance in each dimension to find the optimal solution (Gao et al., 2009). The program design flow chart is shown in Figure 5. The specific implementation steps are as follows:

Step 1: Initialize the particle swarm size, velocity, and position, as well as other parameters such as inertia factor, acceleration constant, maximum number of iterations, and minimum allowable error for algorithm abort.

Step 2: Evaluate the initial fitness value of each particle.

Step 3: Takes the initial value as the local optimal value of each particle, and takes the position corresponding to each fitness value as the location of the local optimal value of each particle.

Step 4: Adapt the optimum initial value as the current value of the global optimum, and the best fitness value corresponding to the position as a position where the global optimum.

Step 5: Update the velocity and position of the current individual particles within the limits.

Step 6: Find the global optimal fitness value in the current population, and take the position corresponding to the global optimal value as the location of the local optimal value of each particle.

Step 7: Repeat 4~6 until the set minimum error is met or the maximum number of iterations is reached.

Step 8: Output the global optimal solution as the final solution for positioning.

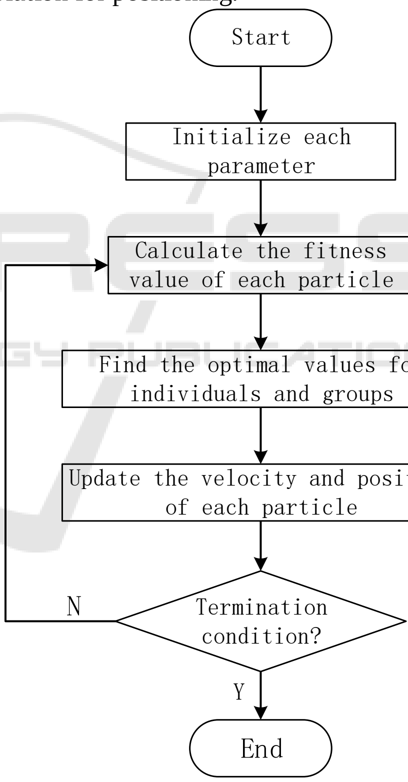


Figure 5: PSO program flow chart.

In the UWB positioning system, the TOF error can be used as the fitness function f, as shown in the following equation:

$$f = \frac{1}{n}\sum_{i=2}^{n}\left|\hat{R}_{i,1} - R_{i,1}\right| \quad (7)$$

Where n represents the number of positioning base stations, i represents the i-th base station, $R_{i,1}$ represents the TOF value, and $\widehat{R}_{i,1}$ represents the TOF value derived from the PSO. In order to find the optimal solution, f needs to be minimized.

The current fitness value of each particle is compared with the fitness value p_i^d of the optimal position reached before, and if it is better, it is the current best position. Compare it to the fitness value of the best position passed globally. If it is better, it will be the best Current global optimal position.

The velocity and position of each particle is updated by Equations 3-5 and 3-6 in each iteration.

$$v_i^d = \omega v_i^d + c_1 r_1 \left(p_i^d - x_i^d\right) + c_2 r_2 \left(p_g^d - x_g^d\right) \tag{8}$$

$$x_i^d = x_i^d + \alpha v_i^d \tag{9}$$

In the formula, $i=1, 2, \cdots, m$, represents the i-th particle, m is the total number of particles; $d=1, 2, \cdots, D$, represents the d-th dimension, D is The largest dimension, in a two-dimensional positioning system, D takes 2; c_1 and c_2 represent learning factors, which are non-negative constants; r_1 and r_2 are random numbers that vary within the range [0, 1]; α is a constraint factor that is used to control the weight of the velocity.

The termination condition of the iteration is set to the maximum number of iterations or the minimum tolerance of the objective function (Cai et al., 2018; Okamoto et al., 2015).

3.3 Evaluation Standard

To evaluate the positioning accuracy of the algorithm, the mean square error (MSE), the root mean square error (RMSE), and the Cramer's lower limit are generally used as evaluation criteria, and the most commonly used ones are MSE and RMSE (Landolsi et al., 2016).

The MSE characterizes the expected value of the square of the difference between the parameter estimation value and the parameter true value, and can evaluate the degree of change of the data. The smaller the value of the MSE, the better the accuracy of the prediction model describing the experimental data.

Assuming that the real position coordinate of the moving tag is (x, y), the positioning algorithm estimates the position coordinate as $(\hat{x}, \hat{y})$. Then the MSE mathematical expression is:

$$\mathrm{MSE} = E\left[(\hat{x}-x)^2 + (\hat{y}-y)^2\right] \tag{10}$$

RMSE is the arithmetic square root of the mean square error, and its mathematical expression is as follows:

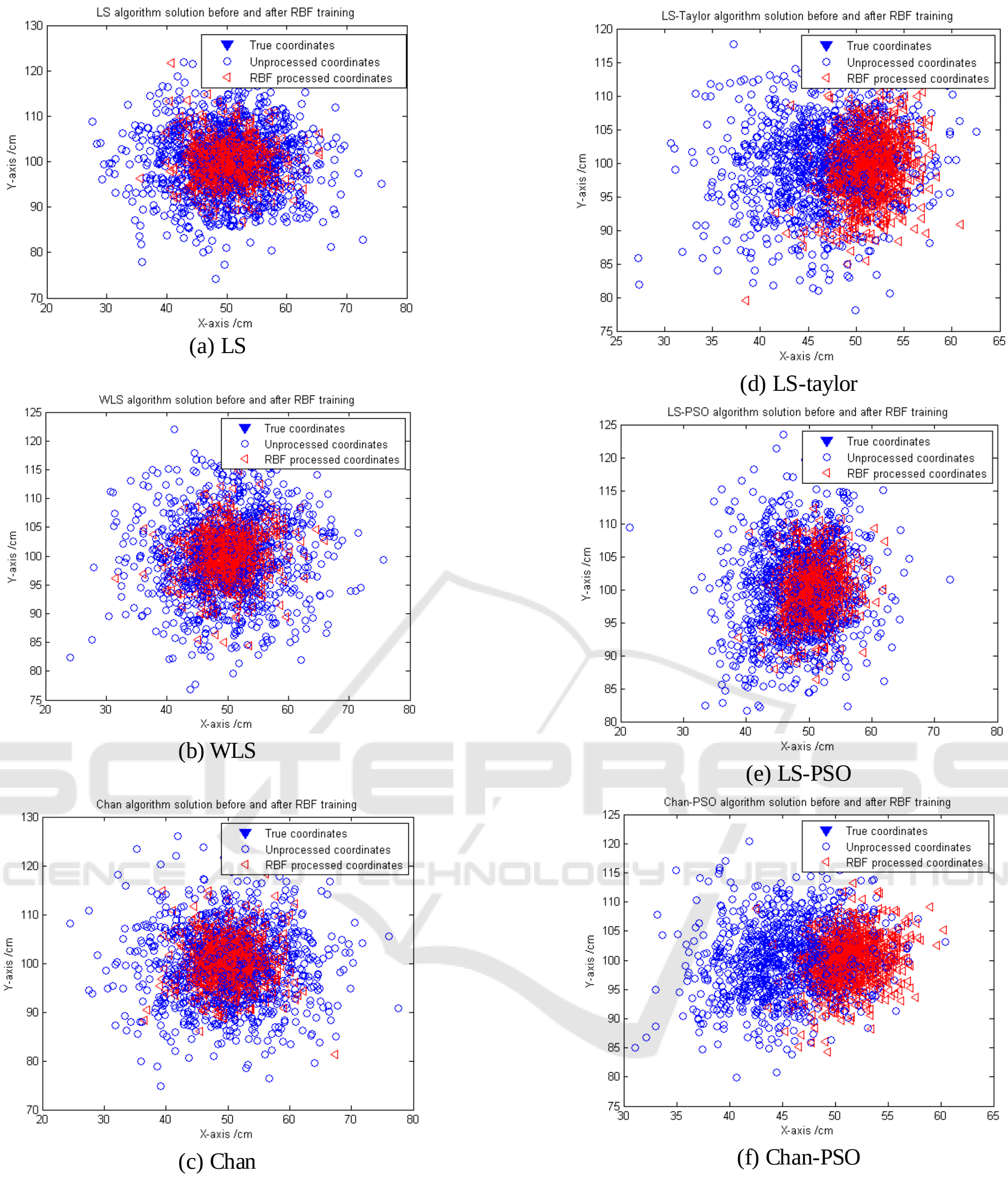
$$\mathrm{RMSE} = \sqrt{E\left[(\hat{x}-x)^2 + (\hat{y}-y)^2\right]} \tag{11}$$

This paper uses RMSE as the criterion for judging data measurement error.

4 ALGORITHM ANALYSIS

Assuming that the real position coordinates of the moving tag are (50, 100), the NLOS error is uniformly distributed, and the TOF measurement error obeys the Gaussian distribution. After RBF training, the NLOS error of TOF can be reduced to some extent. The results of various algorithms such as LS, WLS, Chan, and Taylor are solved 1000 times before and after RBF training, as shown in Figure 6. Compared with before RBF training, the positioning effect of the above algorithm after RBF training is significantly improved.

As can be seen from Figure 7, traditional positioning algorithm cannot get the optimal solution in the NLOS environment, and the overall positioning effect is not good. The LS-Taylor, LS-PSO, and especially the Chan-PSO algorithm perform well in the NLOS environment. When the measurement error (ie, the standard deviation of the measurement distance) is small, the positioning accuracy is relatively stable, and when the measurement error is high, the positioning accuracy decreases as the measurement error becomes larger. However, the positioning algorithm based on Taylor series expansion has some slight improvement in positioning accuracy, but because its positioning accuracy is closely related to the number of required iterations, the time complexity of the algorithm is improved, compared with WLS and Chan algorithms. Real-time positioning applications perform poorly. Overall, LS-PSO is the best overall performance algorithm.



(a) LS

(b) WLS

(c) Chan

(d) LS-taylor

(e) LS-PSO

(f) Chan-PSO

Figure 6: Effect of each algorithm before and after RBF processing.

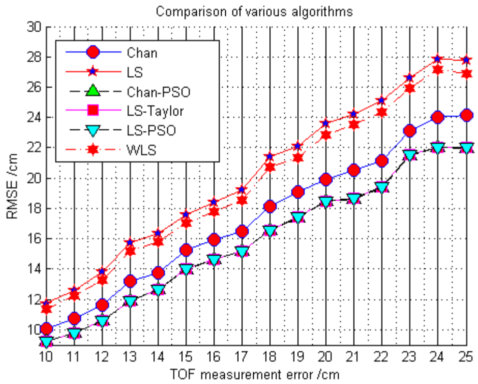


Figure 7: Comparison of algorithm errors.

5 CONCLUSION

This paper describes in detail the TOF positioning method in the ultra-wideband positioning system. And for the reality that the UWB positioning system in the NLOS environment cannot meet the actual positioning service demand due to large errors, relying on the advantages of RBF neural network algorithm in data modeling and prediction, the RBF neural network algorithm is used to preprocess the TOF measurement with large error. Then relying on the outstanding performance of the particle swarm optimization algorithm in the direction of nonlinear optimization, a well-implemented fusion localization algorithm is designed. It is verified that the algorithm has better positioning effect than the traditional WLS, Chan, Taylor series expansion algorithms.

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