

Research on Impulse Radio Ultra - wideband Positioning Method Based on Combined BP Neural Network and SVM

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Bo. Song*, Army Logistics University of PLA, China, 545641621@qq.com
Shenglin. Li, Army Logistics University of PLA, China, 1936423516@qq.com
Qinghui. Ren, Army Logistics University of PLA, China, renqinghui007@163.com
Chen. Chen, Army Logistics University of PLA, China, 433432@qq.com

ABSTRACT

Intelligent tour guide is a comprehensive service based on tourist's location, which is closely related to Geographic Information System (GIS), mobile positioning technology and Location-Based Service (LBS). But the intelligent tour guide field urgently needs the integrated positioning and navigation technology inside and outside the room. IR-UWB technology is suitable for positioning, tracking, navigation and communication in complex indoor environment, and is considered as the most potential indoor positioning technology to realize seamless connection between indoor and outdoor with outdoor positioning technologies such as GPS. However, one of the main problems facing IR-UWB positioning is Non-Line-Of-Sight (NLOS) error. Based on the advantages of BP neural network and support vector machine, this paper proposes a multi-model fusion algorithm to mitigate the NLOS propagation error of the time difference of arrival (TDOA) and the angle of arrival (AOA) of IR-UWB signal, and then uses TDOA/AOA hybrid positioning that mitigates the NLOS error. Simulation results show that the combined algorithm has stronger NLOS resistance and higher positioning accuracy than the single machine learning algorithm in mitigation NLOS errors.

Keywords: Intelligent tour guide, Non-Line-Of-Sight error, TDOA / AOA, hybrid positioning, multi-model fusion.

*Corresponding author

INTRODUCTION

With the development of wireless communication technology, the demand for wireless positioning has increased day by day, and it has been widely used and can better meet the requirements of outdoor positioning. With the rapid development of China's tourism market and the continuous progress of tourism informatization construction, the emphasis on informatization, quantitative digital tourism and digital scenic spots has gradually shifted to intelligent tourism and intelligent scenic spots that emphasize humanized and intelligent services. However, the traditional outdoor positioning technology represented by GPS and cellular mobile positioning system is difficult to satisfy the tourist guide service with both outdoor scenic spots and indoor exhibition areas and exhibits, so the indoor and outdoor integrated positioning and navigation technology and its application in the field of intelligent tour guide need to be studied urgently (Yu, 2013). Impulse Radio Ultra-Wideband (IR-UWB) is a non-carrier communication technology and GHz bandwidth, with better penetration and anti-multipath characteristics, which can effectively reduce the transmit signal power and system complexity while providing centimeter-level positioning accuracy. It is an ideal indoor positioning technology (Hazas & Hopper, 2006).

The biggest factor affecting indoor positioning is the larger masking error caused by the NLOS propagation of the signal, which will lead to the distance measurement being positively biased and its distribution has a large gap with Gaussian distribution. Most of the traditional positioning algorithms are designed based on Gaussian or approximate Gaussian measurement error model, so the performance will decrease obviously in indoor environment. According to the current research situation, IR-UWB indoor precise positioning algorithms can be divided into five categories: based on signal direction of arrival (TOA) (Xu, Jiang & Sha, 2009), based on signal time difference of arrival (TDOA) (Gardner & Chen, 1992), based on angle of arrival (AOA) (Juan, Miguel & Angela, 2011), based on received signal strength indication (RSSI), and hybrid positioning algorithm. Literature (Yang, Huang & Zhu, 2007) discusses the TDOA / AOA hybrid positioning method, and proves that the hybrid positioning algorithm has higher positioning accuracy than TDOA and AOA single positioning algorithm in NLOS environment. Literature (Dong, Cui & Zhang, 2010) proposes to use the nonlinear approximation capability of BP neural network to mitigate the ranging error caused by NLOS propagation and improve the positioning accuracy. Literature (Wymeersch, Marano & Gifford, 2012) uses the waveform characteristics of the received signal and adopts SVM method to mitigate NLOS errors and improve positioning accuracy. But also ensure the stability of the positioning error. Therefore, this paper proposes a multi-model fusion localization algorithm based on BP neural network and support vector machine. Compared with the single machine learning algorithm, our method improves the localization accuracy and reliability.

TDOA / AOA HYBRID LOCATION BASED ON BP AND SVM

Measurement Error Models of TDOA and AOA

Let τ_i be the TOA measurement of electromagnetic wave between tag and base station BS_i . Since multipath and NLOS phenomena of IR-UWB signals in indoor propagation are the two main causes of TOA ranging error, τ_i can be expressed as:

$$\tau_i = \tau_i^0 + \tau_{ei} \quad i = 1, 2, 3, \dots, M \quad (1)$$

Where τ_i^0 is the ranging error caused by multipath propagation, τ_{ei} is the extra time delay caused by NLOS propagation, and M is the number of base stations participating in positioning. Further, there is TDOA measurement error:

$$\tau_{i,l} = \tau_i - \tau_l = (\tau_i^0 - \tau_l^0) + (\tau_{ei} - \tau_{el}) = \tau_{i,l}^0 + \tau_{ei,l} \quad i=2,3,\dots,M \quad (2)$$

Where $\tau_{i,l}$ is the TDOA measurement in indoor NLOS environment, $\tau_{i,l}^0$ is the TDOA measurement in LOS environment, and $\tau_{ei,l}$ is the NLOS error caused by NLOS environment. At present, there is no relevant research on statistical modeling.

Let α_i be the AOA measurement value between the tag and BS_i . Due to the system measurement error and the additional angle error caused by NLOS phenomenon, can be expressed as:

$$\alpha_i = \alpha_i^0 + \alpha n_i + \alpha_{ei} \quad i = 1, 2, \dots, M \quad (3)$$

In the formula, α_i^0 is AOA measurement value in line-of-sight environment, αn_i is system measurement error, and α_{ei} is additional angle error caused in NLOS environment, which is the main error of AOA measurement value. Since wall-to-wall propagation is closely related to specific environmental parameters, there is little statistical modeling research on it at present.

Error Mitigation Model Of TDOA/AOA Based On BP

At least four base stations are needed to obtain the three-dimensional position information of the target in the NLOS environment. Increasing the number of base stations can correspondingly improve the positioning accuracy, but the cost will also increase. The BP neural network model for mitigating TDOA and AOA measurements of four base stations consists of an input layer, an implicit layer and an output layer, as shown in figure 1.

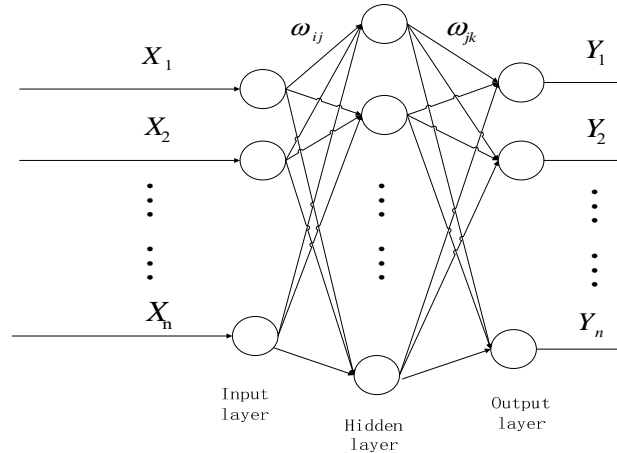


Figure 1: Topology diagram of BP neural network

The process of TDOA non-line-of-sight error mitigation based on BP neural network is as follows:

a) The input layer consists of three TDOA measurements and four AOA measurements provided by four base stations participating in the positioning. Input vector:

$$X = [TDOA_{21}, TDOA_{31}, TDOA_{41}, AOA_1, AOA_2, AOA_3, AOA_4] \quad (4)$$

b) The number of neurons in the hidden layer is usually obtained by the following formula:

$$m = \sqrt{n + l} + \lambda \quad (5)$$

Where n is the number of nodes in the input layer, l is the number of nodes in the output layer, all of which are 7 in this paper, and λ is a constant between 1 and 10. According to the calculation results of the formula and complexity analysis, the number of hidden layer nodes in this paper is 12.

c) The output layer consists of 7 neurons, and the output vector is the mitigated TDOA and AOA, and the formula is as follows:

$$Z = [RTDOA_{21}, RTDOA_{31}, RTDOA_{41}, RAOA_1, RAOA_2, RAOA_3, RAOA_4] \quad (6)$$

In the learning process of BP neural network, there are two learning stages:

- (1) Calculating the output of each hidden layer and input layer from front to back;
- (2) Error back propagation is used to correct the weights of each hidden layer and input layer from back to front.

This paper sets the input vector $X = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]$ and the weight matrix from the input layer to the hidden layer $\omega = [\omega_1, \omega_2, \dots, \omega_{12}]$. Where ω_j is the weight vector corresponding to the j th neuron in the hidden layer. The output vector of the hidden layer is $Y = [y_1, y_2, \dots, y_{12}]$. The weight matrix from the hidden layer to the output layer is $v = [v_1, v_2, \dots, v_7]$, Where v_t is the weight vector corresponding to the first neuron in the output layer. The output layer vector is $Z = (z_1, z_2, z_3, z_4, z_5, z_6, z_7)$ and the expected output vector is $d = (d_1, d_2, d_3)$. The standard BP neural network excitation function adopts unipolar sigmoid function:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (7)$$

Its value can be arbitrary, and its output value is between - 1 and + 1, continuously derivable, and

$$f'(x) = f(x)[1 - f(x)] \quad (8)$$

The transfer function uses the Purelin function: $g(x) = x$. The error function is

$$E = \frac{1}{2}(d - Z)^2 = \frac{1}{2} \sum_{t=1}^7 (d_t - z_t)^2 \quad (9)$$

The error gradient descent method is used to correct the weights, and the process is as follows:

$$\begin{cases} \Delta \omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} & i = 1, 2, \dots, 7 \quad j = 1, 2, \dots, 12 \\ \Delta v_{jt} = -\eta \frac{\partial E}{\partial v_{jt}} & j = 1, 2, \dots, 12 \quad t = 1, 2, \dots, 7 \end{cases} \quad (10)$$

Where η is a scaling factor between 0 and 1, for the output layer, It can write as

$$\Delta v_{jt} = -\eta \frac{\partial E}{\partial v_{jt}} = -\eta \frac{\partial E}{\partial z_t} \cdot \frac{\partial z_t}{\partial net_t} \cdot \frac{\partial net_t}{\partial v_{jt}} \quad (11)$$

Where

$$\frac{\partial E}{\partial z_t} = -(d_t - z_t), \quad \frac{\partial z_t}{\partial net_t} = g'(net_t) = 1, \quad \frac{\partial net_t}{\partial v_{jt}} = \sum_{j=1}^{12} y_j \quad (12)$$

Similarly, for the hidden layer we can get

$$\Delta \omega_{ji} = -\eta \frac{\partial E}{\partial \omega_{ji}} = -\eta \frac{\partial E}{\partial y_j} \cdot \frac{\partial y_j}{\partial net_j} \cdot \frac{\partial net_j}{\partial \omega_{ji}} \quad (13)$$

Where

$$\frac{\partial E}{\partial y_j} = -\sum_{t=1}^7 (d_t - z_t) g'(net_t) \sum_{j=1}^{12} v_{jt}, \quad \frac{\partial y_j}{\partial net_j} = f'(net_j), \quad \frac{\partial net_j}{\partial \omega_{ji}} = \sum_{i=1}^7 x_i \quad (14)$$

So, We can finally get

$$\begin{cases} \Delta v_{jt} = -\eta \frac{\partial E}{\partial v_{jt}} = \eta (d_t - z_t) \cdot g'(net_t) \cdot \sum_{j=1}^{12} y_j \\ \Delta \omega_{ji} = -\eta \frac{\partial E}{\partial \omega_{ji}} = \eta \left[\sum_{t=1}^7 (d_t - z_t) g'(net_t) \sum_{j=1}^{12} v_{jt} \right] \cdot y_j \cdot (1 - y_j) \cdot \sum_{i=1}^7 x_i \end{cases} \quad (15)$$

The above is the adjustment process of weights in the two learning stages of BP neural network using gradient descent method, and the adjustment process of thresholds can be obtained in the same way.

TDOA/ AOA Hybrid Location Model Based On SVM

SVM method is a new machine learning method proposed by VA Pnik et al. according to statistical learning theory in the early 1990s. Based on the principle of structural risk minimization, the actual risk of the learning machine is minimized by properly selecting the subset of functions and the discriminant function in the subset, ensuring that the small error classifier obtained through limited training samples still has a small test error for the independent test set.

Its outstanding advantages are as follows: (1) based on the principle of structural risk minimization in statistical learning theory and VC dimension theory, it has good generalization ability, which is, small errors obtained from limited training samples can ensure that independent test sets still keep small errors. (2) The solution of support vector machine corresponds to a convex optimization problem, so the local optimal solution must be a global optimal solution. (3) The successful application of the kernel function transforms the nonlinear problem into a linear problem. (4) Maximizing the classification interval makes the support vector machine algorithm more robust. The structure diagram is shown in figure 2.

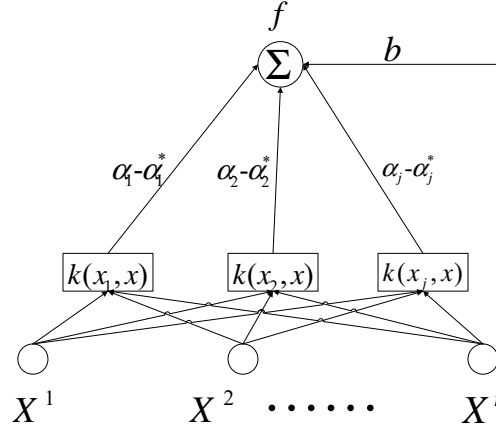


Figure 2: Basic structure diagram of support vector machine model

In this paper, multi-input multi-output SVM is used to mitigate TDOA and AOA NLOS errors measured by the system. The input vector is still three TDOA values and four AOA values measured by four base stations, $Y = [TDOA_{21}, TDOA_{31}, TDOA_{41}, AOA_1, AOA_2, AOA_3, AOA_4]$.

The output vectors are TDOA and AOA values that mitigate NLOS errors, $Z = [RTDOA_{21}, RTDOA_{31}, RTDOA_{41}, RAOA_1, RAOA_2, RAOA_3, RAOA_4]$. Before establishing the multi-input multi-output SVM regression model, we first construct l sets of samples of the support vector machine: $S = (Y^1, Z^1), (Y^2, Z^2), \dots, (Y^l, Z^l), Y \in R^m, Z \in R^m$, where m represents the number of inputs and outputs.

The multi-output linear regression function is in the form of $Z_i = f_i(Y) = v_i Y + b_i$, and It satisfies the constraint conditions:

$$\begin{cases} Z_i^j - v_i^T Y^j - b_i \leq \xi_i^j + \varepsilon_i \\ v_i^T Y^j + b_i - Z_i^j \leq \xi_i^j + \varepsilon_i \end{cases} \quad i=1,2,m; j=1,2,\dots,l \quad (16)$$

The relaxation factor $\xi_i^j, \xi_i^{j*} \geq 0$ is introduced in consideration of the allowable fitting error, and the objective function is solved to obtain the minimum value.

$$\min \Phi(v_i, \xi_i^j, \xi_i^{j*}) = \frac{1}{2} \sum_{i=1}^m \|v_i\|^2 + C \sum_{i=1}^m \sum_{j=1}^l (\xi_i^j + \xi_i^{j*}) \quad (17)$$

where A is C constant greater than 0. This is an optimization problem under inequality constraints. The solution to this problem is the same as that of single output support vector machine regression. Introduce Lagrange function:

$$\begin{aligned} L(v_i, b_i, \alpha_i^j, \alpha_i^{j*}) = & \frac{1}{2} \sum_{i=1}^m \|v_i\|^2 + C \sum_{i=1}^m \sum_{j=1}^l (\xi_i^j + \xi_i^{j*}) - \sum_{i=1}^m \sum_{j=1}^l \alpha_i^j (\varepsilon_i + \xi_i^j + Z_i^j - v_i^T Y^j - b_i) - \\ & \sum_{i=1}^m \sum_{j=1}^l \alpha_i^{j*} (\varepsilon_i + \xi_i^{j*} - Z_i^j + v_i^T Y^j + b_i) - \sum_{i=1}^m \sum_{j=1}^l (\eta_i^j \xi_i^j + \eta_i^{j*} \xi_i^{j*}) \end{aligned} \quad (18)$$

Where $\alpha_i^j, \alpha_i^{j*} \geq 0$ is a Lagrange multiplier and the extreme value of function L should satisfy the following conditions:

$$\begin{cases} \frac{\partial L}{\partial v_i} = 0 \rightarrow v_i = \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j*}) Y^j \\ \frac{\partial L}{\partial b_i} = 0 \rightarrow \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j*}) = 0 \\ \frac{\partial L}{\partial \xi_i^j} = C - \alpha_i^j - \eta_i^j = 0 \\ \frac{\partial L}{\partial \xi_i^{j*}} = C - \alpha_i^{j*} - \eta_i^{j*} = 0 \end{cases} \quad (19)$$

The conversion to Lagrange dual problem is:

$$\begin{aligned} \max_{\alpha_i^j, \alpha_i^{j*}} L(\alpha_i^j, \alpha_i^{j*}) = & -\frac{1}{2} \sum_{i=1}^m \sum_{j,k=1}^l (\alpha_i^j - \alpha_i^{j*})(\alpha_i^k - \alpha_i^{k*})(Y^j \cdot Y^k) + \sum_{i=1}^m \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j*}) Z_i^j - \sum_{i=1}^m \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j*}) \varepsilon_i \\ \text{st} \quad & \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j*}) = 0, 0 \leq \alpha_i^j, \alpha_i^{j*} \leq C, j=1,2,\dots,l \end{aligned} \quad (20)$$

The expression of multiple output linear regression function can be obtained after finding the optimal solution $\alpha_i^j, \alpha_i^{j^*}$. The function is $Z_i = f_i(Y) = v_i Y + b_i$. Where $v_i = \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) Y^j$.

According to Karush—Kuhn—Tucker (KKT) conditions, the following conditions are satisfied at the optimal solution:

$$\begin{cases} \alpha_i^{j^*} (\varepsilon_i + \xi_i^{j^*} - Z_i^j + v_i^T Y^j + b_i) = 0 \\ \alpha_i^j (\varepsilon_i + \xi_i^j + Z_i^j - v_i^T Y^j - b_i) = 0 \\ i = 1, 2, \dots, m; j = 1, 2, \dots, l \end{cases} \quad (21)$$

$$\begin{cases} \eta_i^j \xi_i^j = 0 \\ \eta_i^{j^*} \xi_i^{j^*} \\ i = 1, 2, \dots, m; j = 1, 2, \dots, l \end{cases} \quad (22)$$

The threshold variable b can be obtained:

$$\begin{cases} b_i = Z_i^j - \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) Y^j - \varepsilon_i, \alpha_i^j \in (0, C) \\ b_i = Z_i^j - \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) Y^j + \varepsilon_i, \alpha_i^{j^*} \in (0, C) \end{cases} \quad (23)$$

The threshold variable can be obtained by using the obtained optimal weight vector and any one of the support vectors.

The multi-output nonlinear regression function obtained by using kernel function $K(Y^j, Y^k) = \psi^T(Y^j) \psi^T(Y^k)$ is expressed as:

$$Z_i = f_i(Y) = \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) K(Y^j, Y) + b_i \quad (24)$$

The threshold variable b can also be found.

$$\begin{cases} b_i = Z_i^j - \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) K(Y^j, Y) - \varepsilon_i, \alpha_i^j \in (0, C) \\ b_i = Z_i^j - \sum_{j=1}^l (\alpha_i^j - \alpha_i^{j^*}) K(Y^j, Y) + \varepsilon_i, \alpha_i^{j^*} \in (0, C) \end{cases} \quad (25)$$

The detailed derivation of multivariate support vector machine model can be found in reference (Wang, Jin & Cao, 2007).

TDOA / AOA LOCATION ALGORITHM BASED ON BP AND SVM FUSION

When BP neural network regression and multivariable SVM regression mitigate NLOS errors of TDOA and AOA in different scenario and time ranges, the accuracy of the two algorithms is different. Therefore, according to the characteristics that the location of tourists will change with time indoors, the mitigation results of the two methods are weighted and fused. In this way, not only can the positioning accuracy be improved, but also the stability of the positioning error can be guaranteed. Therefore, this paper proposes a multi-model fusion location algorithm based on BP and SVM, thus giving full play to the respective advantages of the two methods.

The Steps Of Multi-Model Fusion Algorithm

The multi-model fusion algorithm is a method to mitigate NLOS errors based on the method of data fusion. This algorithm has two main steps in the application process:

- (1) Basic method mitigation: TDOA and AOA data collected by four base stations at time $T+1$ are used as input of BP neural network and SVM. Then the correction values of the TDOA and AOA are obtained respectively.
- (2) Fusion correction results: For the current time $T+1$, the correction results of the two methods are weighted according to the minimum square sum of error of l groups of data before time $T+1$ by the basic method, and the new correction values obtained is the result of multi-model fusion correction. The calculation formula is as follows:

$$\hat{Z}_{T+1} = \omega_{BP} \hat{Z}_{T+1}^{BP} + \omega_{SVM} \hat{Z}_{T+1}^{SVM} \quad (26)$$

In the formula, $\omega_{BP}, \omega_{SVM}$ respectively correspond to the weights corresponding to BP neural network and SVM error correction values. The flow chart of multi-model fusion positioning algorithm is shown in figure 3.

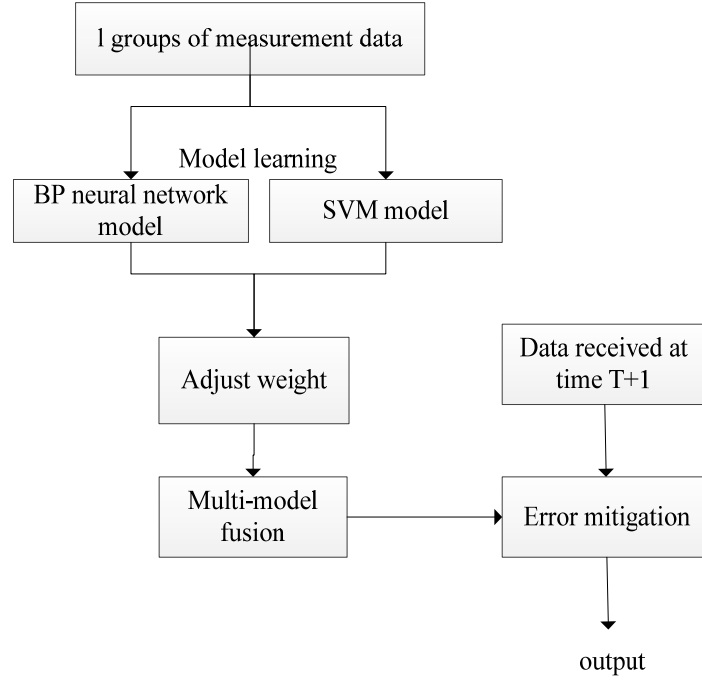


Figure 3: Flow chart of multi-model fusion positioning algorithm

Weight Determination Of Multi - Model Fusion

Fusion model is a model constructed by combining two or more single models according to a certain weight. Because individual models often have their own shortcomings, the error correction values are not all good when they are used in different scenario, so various information of a single model can be combined by using multi-model fusion, so that problems can be comprehensively handled, and the obtained results are higher in correction accuracy and more stable in error than those of a single model.

The linear fusion model selected in this paper takes the minimum square sum of error as the objective function. Define the minimum error sum of squares function as:

$$\min f = \min \sum_{T=1}^I \left[Z^T - \omega_{BP} \hat{Z}_{BP}^T - \omega_{SVM} \hat{Z}_{SVM}^T \right]^2$$

$$s.t. \begin{cases} \omega_{BP} + \omega_{SVM} = 1 \\ \omega_{BP} \geq 0, \omega_{SVM} \geq 0 \end{cases} \quad (27)$$

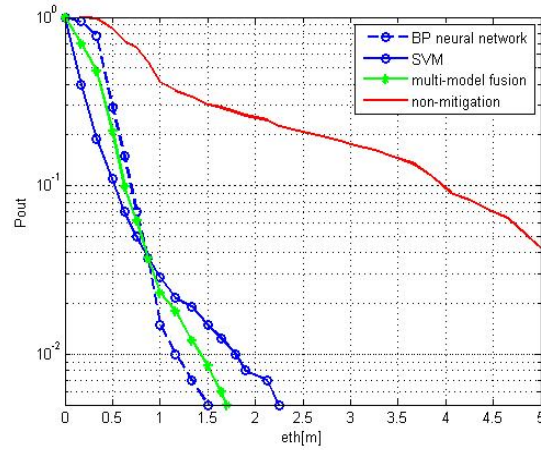
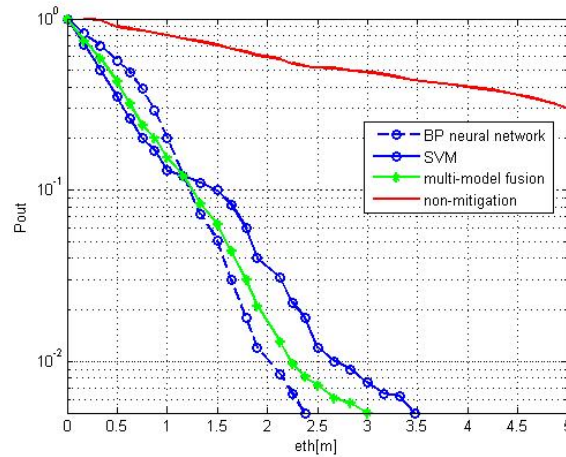
The solution of the above problem belongs to the extreme optimization problem. Lingo can be used to solve the problem. After the weight is calculated, the error correction value of the fusion algorithm can be obtained.

TDOA / AOA Hybrid Location Based On Multi-Model Fusion Algorithm

In order to verify the effectiveness of the proposed multi-model fusion location algorithm, we designed a comparative experiment on the platform of MATLAB 2013 based on the received signal waveform data set. The data set used in the experiment is 1024 measurements (including 512 NLOS measurements and 512 LOS measurements) and their actual values from the MIT measurement competition. We will evaluate the localization performance for a fixed number of anchors $N_b = 4$ and a varying probability of NLOS condition $0 \leq P_{NLOS} \leq 1$. In order to ensure the reliability of the experimental results, we used 10-fold cross validation. In the simulation experiment, we use the calculation result of the following formula as the evaluation index of the algorithm proposed in this paper.

$$P_{out} = \text{Prob} \left\{ \|P - \hat{P}\|_2 > e_{th} \right\} \quad (28)$$

Where P_{out} represents the probability that the 2 norm of the deviation between the actual position and the estimated position is greater than e_{th} . The simulation result is shown in figure 4 and figure 5.

Figure 4: Position Error Probability of Three Algorithms with $P_{NLOS}=0.25$ Figure 5: Position Error Probability of Three Algorithms with $P_{NLOS}=0.5$

CONCLUSION

This paper proposes a multi-model fusion positioning algorithm based on the combination of BP neural network and SVM algorithm, which is mainly used to realize the integrated positioning and navigation inside and outside intelligent tourism. Due to BP neural network and SVM algorithm have different accuracy for error mitigation in different scenarios in different time periods, a multi-model fusion method is proposed to improve positioning accuracy and ensure error stability. Simulation result shows that this method can effectively solve the problem of NLOS error in IR-UWB indoor positioning, and the algorithm has good performance, can adapt to various scenarios, and has a certain application prospect.

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