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# Trajectory Prediction Based on TDOA Principle Using MPGA-BP Algorithm in Multilateration (MLAT) System

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ABSTRACT

The Multilateration (MLAT) system, as an advanced scene monitoring method, uses the existing surveillance equipment in the airport to form a monitoring system. It has high positioning precision, fast refresh frequency, small equipment volume, convenient installation and maintenance, low maintenance cost and less influence on the weather. It has been fully utilized in some large and medium sized airports in China. In the MLAT system, the time difference between the signal (TDOA) to the ground station is used as the basis for calculating the position of the target, which is beneficial to reduce the influence of the time measurement error and improve the positioning accuracy. In this paper, the GA-BP algorithm is used to track the dynamic trajectory of the target in the MLAT system, and the algorithm is improved. The value of weight and threshold generated by the BP neural network is divided into multiple populations called MPGA-BP, and the new initial population is formed by selecting the individuals with larger fitness value. This not only accelerates the convergence speed of the algorithm, but also reduces the number of iterations. At the same time, the momentum factor is used to train the BP network, so that the network has a certain anti shock ability. The simulation results show the effectiveness of the improved algorithm.



## 1. Introduction

With the rapid development of civil aviation, aviation dominated transportation and related industries occupy a larger proportion in China's economic field. In order to meet the increasing demand for traffic and improve the transportation efficiency of domestic aviation, the construction scale of the airport is increasing, the distribution of airline is more and more dense, the number of annual landing gear is more and more, and the planning and construction of the airport runway is becoming more and more complex. The rapid development of civil aviation has also exposed many problems, which are mainly embodied in: (1) the number of general airports is less, the infrastructure is relatively simple, and the pressure of safe operation is great. (2) the visual surveillance is mainly based on personnel and the monitoring accuracy is low. (3) the coverage of surveillance is small, and it is impossible to guard against the occurrence of unexpected events around the airport. At present, the existing monitoring methods mainly rely on one or two radar monitoring, with small coverage, low monitoring precision, heavy rain and snow weather and terrain, its construction cost and maintenance cost are relatively high. This monitoring method not only increases the labor burden of the staff of the airport, but also increases the burdens of the workers at the same time, and the probability of the occurrence of an event.

MLAT (Multilateration) technology uses the existing airport scene monitoring equipment to build multiple ground receiving units into an information transmission network and identify, locate and track the target through a certain measurement technology (time measurement, frequency measurement, angle measurement, etc.). The MLAT system can monitor the aircraft and vehicles carrying A/C/S mode and ADS-B mode transponder, and provide a new positioning system for the ANSP: air navigation service providers and expand the space surveillance area. In the past few decades, only the traditional two radar SSR has been used to consider the requirements of airspace. Therefore, the air traffic management department has always made compromises on monitoring coverage. It is necessary to increase the "gap filling" device or to restrict the aircraft to perform flight tasks within the unmonitored range. These restrictions are removed by the application.

In the MLAT system, clock synchronization and site selection are two important technologies, and also an effective method to improve the positioning accuracy of MLAT system. The clock synchronization technology mainly includes centralized clock synchronization, distributed clock synchronization, GNSS clock

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synchronization, reference transponder synchronization, atomic clock synchronization and so on.

Centralized clock synchronization is to send the signals received by each remote receiving station back to the center processing station, and the central processing station is unified to mark the information of each receiving station. This clock synchronization method easily causes the time delay too large and the time of the signal arrives at the remote receiving station is large, but the device is easy to install, The structure is simple. In order to reduce the time error caused by information transmission, the TDOA principle (time difference of arrival) is used to solve the target location.

The distributed clock synchronization is to mark the information received by each remote receiving station, and measure the time of arrival of the signal, that is, the TOA data, and then transmit the information to the center processing station, and the target location is calculated by the center processing station.

GNSS clock synchronization technology is used by the GNSS satellite to give time to each receiving station, mark the time of signal arrival, and then transfer it to the center processing station to calculate.

The synchronization of the reference transponder means that the remote receiving station receives the clock signal from the reference transponder, and the time difference between the time signal and the time signal, and the clock synchronization is realized by the difference of the calculation time difference.

The clock synchronization is the time synchronization of the central processing station by the high precision atomic clock, and then the clock calibration of the remote receiving station through the data network, so as to achieve the clock synchronization.

For the first four clock synchronization techniques, it is necessary to pay attention to the time offset and time compensation between the remote station and the center processing station, so as to reduce the positioning error caused by the clock synchronization. For atomic clock synchronization technology, it would be beneficial for us to pay attention to external temperature interference, electromagnetic interference and other factors.

## 2. Multilateration technology theory

### *2.1 Fundamental theory for MLAT system*

The distributed clock synchronization is used based on TDOA theory in this paper, TDOA (the difference location of arrival time is called "hyperbolic positioning", mainly based on the time difference of radio waves containing the target state information to multiple ground stations.

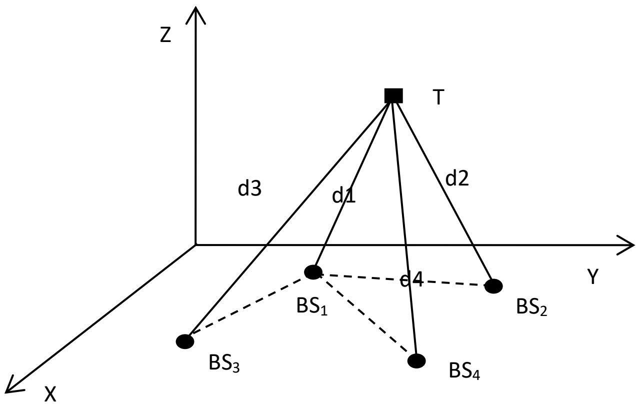


**Fig.1** The four base stations for MLAT system

It is similar to the TOA positioning principle, all of which are located by measuring time. The difference is that the measurement of TDOA positioning is different. The time difference of the base station is made up of the distance difference equation group to solve the target position. Therefore, the TDOA principle is not necessary to keep the high clock synchronization between the ground station and the target. In the TDOA positioning algorithm, four ground stations, that is, the time difference of three groups of time, can be used to realize the three-dimensional space positioning, the principle is like Figure 1.

According to the hyperbolic positioning principle, two ground base stations can form a group of time differences, that is, a hyperbola is formed, when the location is invalid. When there are three ground base stations, the intersection of the two hyperbola is the target position, and this is only in the two-dimensional plane. A ground base station is added and the three hyperbola intersects only. It can realize the three-dimensional space positioning, that is to say, at least four base stations can realize the accurate location of the three-dimensional space target, the theory as Figure.2

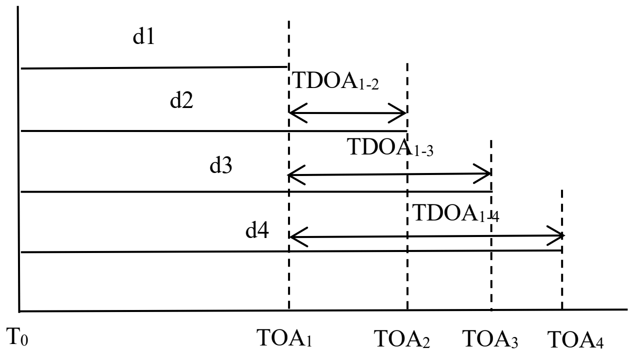


**Fig.2** The theory for TDOA principle

### *2.2 Mathematical model for MLAT system*

The location of TOA (Time of Arrival) is mainly based on the time when the radio wave arriving at the base station containing the target state information is located. First, the time to reach the base station is measured. Due to the different location of the base station, there are some differences in the receiving time. The propagation speed of radio waves is fixed, so different distance equations are formed by different receiving time. The location of the target can be determined according to the distance to the different receiving stations. TOA positioning is simple, positioning accuracy is low, and response time is slow.

The mathematical model is as follows:

$$\begin{cases} \sqrt{(x-x_1)^2+(y-y_1)^2+(z-z_1)^2}=ct_1 \\ \sqrt{(x-x_2)^2+(y-y_2)^2+(z-z_2)^2}=ct_2 \\ \sqrt{(x-x_3)^2+(y-y_3)^2+(z-z_3)^2}=ct_3 \end{cases} \tag{1}$$

where $c$ is the velocity of light. $t_1, t_2, t_3$ represent the time of the electromagnetic waves containing the state information emitted by the target $T\ (x, y, z)$ to the ground stations BS1 $(x_1, y_1, z_1)$, BS2 $(x_2, y_2, z_2)$ and BS3 $(x_3, y_3, z_3)$, respectively.

The main factors affecting the positioning accuracy of TOA mainly include two aspects: one is the time measurement error. Because the electromagnetic wave propagating at the speed of light, the small time measurement error will lead to the larger distance estimation error. Therefore, the accuracy of the estimated target location is low. The two is clock synchronization. If there is no accurate clock synchronization between the ground station and the target, there will be some error in the transmission time. And because of the propagation of light speed, it will lead to large positioning errors in solving the target location process. Usually, when using TOA principle, precise time detection device is required.

TDOA (the difference location of arrival time is called "hyperbolic positioning", mainly based on the time difference of radio waves containing the target state information to multiple ground stations. It is similar to the toa positioning principle, all of which are located by measuring time. The difference is that the measurement of TDOA positioning is different. The time difference of the base station is used to solve the target position of the distance difference equation group. Therefore, the TDOA principle is not necessary to keep the high clock synchronization between the ground station and the target.

The mathematical model is as follows:

$$\begin{cases} R_1^2 = (x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 \\ R_i^2 = (x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2 \\ R_{i,1} = R_i - R_1 = c\tau_{i,1} \\ (i = 2,3,4) \end{cases} \tag{2}$$

where $R_i$ indicates the distance between the aircraft and the $ith$ station, $R_{i,1}$ represents the distance difference between the aircraft arriving at the main station and the secondary station. $\tau_{i,1}$ he time difference between the signal sent by the aircraft and the $ith$ station.

In TDOA positioning, the receiving antenna only needs to be a monitoring antenna, with simple structure, good environmental compatibility and strong anti-interference capability. In the process of signal propagation, bandwidth determines the accuracy of time measurement. The wider the bandwidth, the higher the accuracy. Therefore, TDOA positioning is suitable for wideband low power spectrum signal.

## 3. The theory of BP neural network

According to the neural network structure and learning algorithm is usually divided into single-layer or multi-layer feedforward neural networks and stochastic neural networks, feedback neural network and competitive neural network. The structure of neural network including input layer, one or more hidden layers and the output layer, each layer between the neurons connected with inter layer neurons are independent of each other, between the layers of randomly generated weights and thresholds, and choose different transfer function to get different output. Therefore, according to the characteristics of TDOA measurement data, it is very important to choose the right type of neural network.

The principle of TDOA using time difference of target location, target equation is not linear equation, and the positioning accuracy of measurement error increases with time gradually decreased, when the target is far from the ground station, using the principle of TDOA single positioning and its effect is not ideal, at the same time, using the TDOA principle for trajectory tracking prediction It needs to deal with a large number of measured data. Therefore, it requires the use of autonomous learning ability and strong adaptability to the structure of neural network training sample data, makes the network tracking and prediction according to the experience of the previous data, in order to reduce the effects of measurement errors on the positioning accuracy of the time. The BP neural network because of its special signal transmission process (work, positive signal propagation error signal back propagation) and structure of the network, not only can realize the parallel processing of data, but also can reduce the time error influence on the positioning accuracy.

BP neural network is a forward neural network with independent learning ability and multiple hidden layers, but it is necessary to determine the input and output network of samples.

It is assumed that there is a three layer BP neural network with the number of neurons in the input layer, the hidden layer and the output layer respectively are $M$ $I$ $J$, the connection weight between the input layer and the hidden layer is $\omega_{mi}$, and the connection weight between the hidden layer and the output layer is $\omega_{ij}$, $\theta_i, \theta_j$ represent the threshold of the hidden layer and the output layer, $u, v$ represent the input and output of each layer. $E(n), E_j(n)$ represent the total system error and the signal error of the $ith$ output neurons of the $n$ iteration.

### *3.1 Forward propagation of work signal*

In the BP neural network, the working signal starts from the input layer and reaches the output layer through the hidden layer. Finally, the total error of the system is obtained. Taking the three level BP neural network as an example, we first calculate the output of the input layer. The output of each input layer neuron is equal to the input signal of the network. The input of the hidden layer neurons is equal to the weighted sum of the previous input neurons. Therefore, the input of the hidden layer neurons is:

$$u_I^i(n) = \sum_{m=1}^{M} \omega_{mi}(n) x_m(n) + \theta_i(n) \tag{3}$$

The output of the neurons in the hidden layer is:

$$v_I^i(n) = f\left( \sum_{m=1}^{M} \omega_{ij}(n) x_m(n) + \theta_i(n) \right) \tag{4}$$

The input of the output layer neurons is equal to the weighted sum of the hidden layer output of the previous layer:

$$u_J^j(n) = \sum_{i=1}^{I} \omega_{ij}(n) v_I^i(n) + \theta_j(n) \tag{5}$$

The output of the output layer neurons is:

$$\begin{aligned} v_J^j(n) &= g\left(u_J^j(n)\right) \\ &= g\left( \sum_{i=1}^{I} \omega_{ij} f\left( \sum_{m=1}^{M} \omega_{ij} x_m(n) + \theta_i(n) \right) + \theta_j(n) \right) \end{aligned} \tag{6}$$

The signal error of the $ith$ output neuron is as follows:

$$E_j(n) = v_J^{j'}(n) - v_J^j(n) \tag{7}$$

$v_J^{j'}(n)$ represents the expected output of the j output neuron.

The total error is:

$$E(n) = \frac{1}{2} \sum_{j=1}^{J} E_j^2(n) \tag{8}$$

*3.2 Back propagation of error signal*

For the correction of weights, the weights and thresholds between the output layer and the hidden layer are adjusted first along the direction of error reduction:

$$\Delta\omega_{ij}(n) = -\eta \frac{\partial E(n)}{\partial \omega_{ij}(n)} \tag{9}$$

$$\Delta\theta_j(n) = -\eta \frac{\partial E(n)}{\partial \theta_j(n)} \tag{10}$$

Among them, $\eta$ indicates the learning rate, on the top of the arrangement, we can get:

$$\frac{\partial E(n)}{\partial \omega_{ij}(n)} = \frac{\partial E(n)}{\partial v_J^j(n)} \times \frac{\partial v_J^j(n)}{\partial u_J^j(n)} \times \frac{\partial u_J^j(n)}{\partial \omega_{ij}(n)} \tag{11}$$

$$\frac{\partial E(n)}{\partial \theta_j(n)} = \frac{\partial E(n)}{\partial v_J^j(n)} \times \frac{\partial v_J^j(n)}{\partial u_J^j(n)} \times \frac{\partial u_J^j(n)}{\partial \theta_j(n)} \tag{12}$$

According to the previous definition:

$$\frac{\partial E(n)}{\partial v_J^j(n)} = -\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right) \tag{13}$$

$$\frac{\partial v_J^j(n)}{\partial u_J^j(n)} = g'\left(u_J^j(n)\right) \tag{14}$$

$$\frac{\partial u_J^j(n)}{\partial \omega_{ij}(n)} = v_I^i(n) \tag{15}$$

$$\frac{\partial u_J^j(n)}{\partial \theta_j(n)} = 1 \tag{16}$$

Replace the upper form:

$$\Delta\omega_{ij}(n) = \eta\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right)g'\left(u_J^j(n)\right)v_I^i(n) \tag{17}$$

$$\Delta\theta_j(n) = \eta\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right)g'\left(u_J^j(n)\right) \tag{18}$$

Therefore, the adjusted weights and thresholds can be written as follows:

$$\omega_{ij}(n+1) = \omega_{ij}(n) + \Delta\omega_{ij}(n) \tag{19}$$

$$\theta_j(n+1) = \theta_j(n) + \Delta\theta_j(n) \tag{20}$$

Then the weights and thresholds between the hidden layer and the input layer are adjusted:

$$\Delta\omega_{mi}(n) = -\eta \frac{\partial E(n)}{\partial \omega_{mi}(n)} \tag{21}$$

$$\Delta\theta_i(n) = -\eta \frac{\partial E(n)}{\partial \theta_i(n)} \tag{22}$$

Collation can be obtained:

$$\frac{\partial E(n)}{\partial \omega_{mi}(n)} = \frac{\partial E(n)}{\partial v_I^i(n)} \cdot \frac{\partial v_I^i(n)}{\partial u_I^i(n)} \cdot \frac{\partial u_I^i(n)}{\partial \omega_{mi}(n)} \tag{23}$$

$$\frac{\partial E(n)}{\partial \theta_i(n)} = \frac{\partial E(n)}{\partial v_I^i(n)} \cdot \frac{\partial v_I^i(n)}{\partial u_I^i(n)} \cdot \frac{\partial u_I^i(n)}{\partial \theta_i(n)} \tag{24}$$

By definition:

$$\frac{\partial E(n)}{\partial v_I^i(n)} = -\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right) \cdot g'\left(u_J^j(n)\right) \cdot \omega_{ij} \tag{25}$$

$$\frac{\partial v_I^i(n)}{\partial u_I^i(n)} = f'\left(u_I^i(n)\right) \tag{26}$$

$$\frac{\partial u_I^i(n)}{\partial \omega_{mi}(n)} = x_m(n) \tag{27}$$

$$\frac{\partial u_I^i(n)}{\partial \theta_i(n)} = 1 \tag{28}$$

The substitution can be obtained:

$$\begin{aligned}\Delta\omega_{mi} &= \eta\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right) \cdot g'\left(u_J^j(n)\right) \cdot \omega_{ij} \\ &\cdot f'\left(u_I^i(n)\right) \cdot x_m(n)\end{aligned} \tag{29}$$

$$\begin{aligned}\Delta\theta_i &= \eta\sum_{j=1}^{J}\left(v_J^{j'}(n) - v_J^j(n)\right) \cdot g'\left(u_J^j(n)\right) \\ &\cdot \omega_{ij} \cdot f'\left(u_I^i(n)\right)\end{aligned} \tag{30}$$

Therefore, the weights and thresholds of the adjusted hidden layer can be written as follows:

$$\omega_{mi}(n+1) = \omega_{mi}(n) + \Delta\omega_{mi}(n) \tag{31}$$

$$\theta_i(n+1) = \theta_i(n) + \Delta\theta_i(n) \tag{32}$$

After the above steps, the weights and thresholds of the BP neural network are updated. In this process, it is important that the update process be derived from the backward direction (the negative direction of the gradient) from the backward direction.

## 4. The process of MPGA-GA algorithm

The traditional BP neural network algorithm is easy to get into the local optimum, that is, it often falls into the local minimum. At the same time, the algorithm is more dependent on the initial weight. If the initial weight is far from the optimal weight value, it will greatly increase its training time, and it is difficult to achieve the desired effect.

Genetic algorithm optimizes the weights and thresholds of BP network, not only can choose the best initial value among many weights and thresholds, but also accelerates its training speed. This paper improves on the traditional GA-BP algorithm and uses a multiple population genetic algorithm (MPGA) to train the BP network. By determining the structure of the genetic algorithm and BP neural network, the weights and thresholds determined randomly in the BP neural network are divided into multiple groups. Several populations of genetic algorithm are formed by coding and their fitness values are calculated. Screening of larger individual fitness value from each group to form a new initial population, make selections, crossovers, and mutations then check whether the population has genetic degeneration, eliminate the inferior individual and supplement the other individual. For the BP neural network part, the momentum BP method is used to train the network. The optimization of network weights and thresholds through MPGA-BP algorithm avoids the defect that the most qualified and adaptive individuals in the traditional GA-BP algorithm are not selected. It solves the problem of gradual deterioration of individual diversity and improves the convergence speed of BP neural network in the data prediction process.

The MPGA algorithm adopted in this paper is very different from the Parallel Genetic Algorithm. The parallel genetic algorithm divides the population into multiple subpopulations. Each subpopulation runs the genetic algorithm in parallel and independently. After selection, crossover, and mutation operations, the populations exchange certain individuals to maintain the diversity of the population and prevent premature convergence. Therefore, the key to the parallel genetic algorithm is how to exchange individuals and exchange which individuals are the key to their structure and selection. The conditions are more complicated. The main purpose of the MPGA-BP algorithm in this paper is to optimize the weights and thresholds of the BP neural network by genetic algorithm. The aim is to find a group of better weight thresholds near the optimal threshold value as the initial weight threshold of the network, and then speed up the convergence speed of the neural network, and get the network structure that meets the requirements. Therefore, the MPGA algorithm involved in this paper only filter out individuals with large fitness values from multiple genetic algorithms to form a new population. On the basis of maintaining the diversity of the population, the parallel selection crossover mutation operation of the genetic algorithm is reduced. At the same time, it also satisfies the goal of optimizing the BP network weight threshold, which makes the genetic algorithm converge faster and also reduces the number of BP network training.

## 5. Simulation for MPGA-BP based on TDOA theory

With each group of five time differences as the input of the MPGA-BP neural network, the target tracking range m is selected $3000\times3000$ m and the target function is trained and predicted with the interval of 0.003m, and one million sets of training data are produced. The setting end condition is to satisfy the training error to reach the 0.0001m, the maximum number of training is 5000 times, the output is the final system error, the output is the final system error. The station coordinates are $BS_1$ (320, 280, 0), $BS_2$ (590, 1400, 0.1), $BS_3$(1050, 290, 0.1), $BS_4$(1100, 100, 0.1), $BS_5$(1520, 1380, 0.2), $BS_6$(1300, 2120, 0.1). The training process of BP, GA-BP, MPGA-BP are shown as follows:

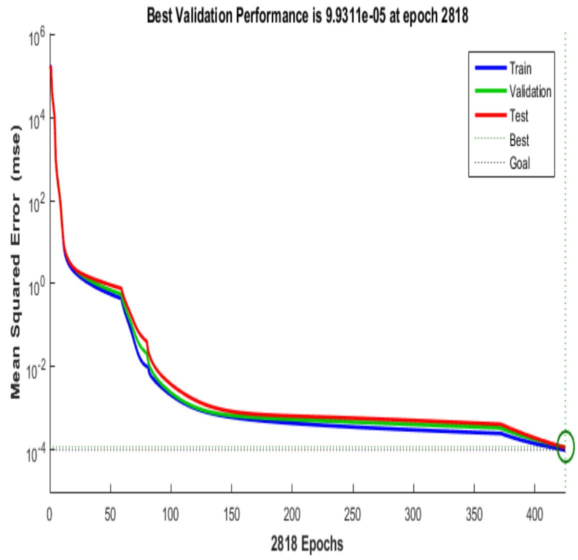


**Fig.3** BP algorithm for TDOA theory

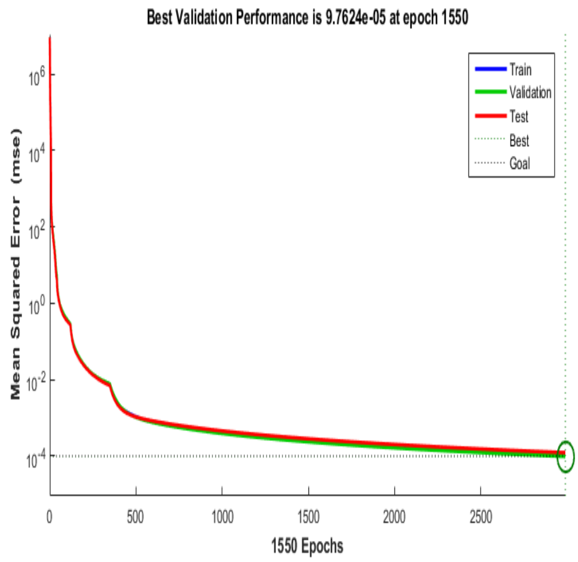


**Fig.4** GA-BP algorithm for TDOA theory

The algorithm flow is as follows:

Step S1: Determine the structure of MPGA algorithm and BP neural network;

Step S2: Network training starts, weights and thresholds are randomly determined;

Step S3: Encode the weights and thresholds, set the genetic algorithm parameters, calculate the fitness value, and group the weights and thresholds to form N populations;

Step S4: Filter out the individuals with larger fitness in each group to form a new initial population;

Step S5: Perform selection, crossover and mutation operations and calculate new fitness values;

Step S6: Determine whether genetic degeneration has occurred.

If so, eliminate individuals M below the average fitness value, and randomly add M individuals from N populations, and then go to step S5 until no genetic degradation occurs.

Step S7: Judging whether the end condition is met, that is, whether it reaches the set number of iterations of the genetic algorithm, if it is satisfied, it outputs the individual with the greatest degree of fitness in all iterative processes. If not, goes to step S5;

Step S8: The GA algorithm decodes to obtain better weights and thresholds.

Step S9: Momentum BP method training network;

Step S10: Calculate the error and update the weight threshold;

Step S11: Judging whether the end condition is satisfied, that is, whether the training error is within the set range. If it is satisfied, the training result and the weight threshold are output. If not, go to step S9;

Step S12: The simulation ends.

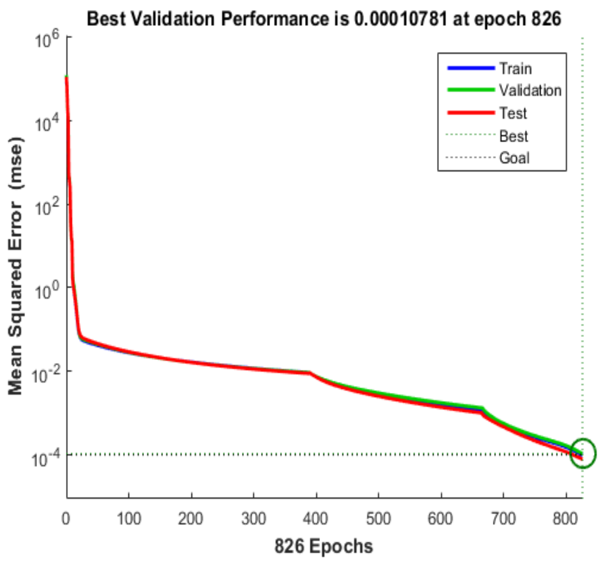


**Fig.5** MPGA-BP algorithm for TDOA theory

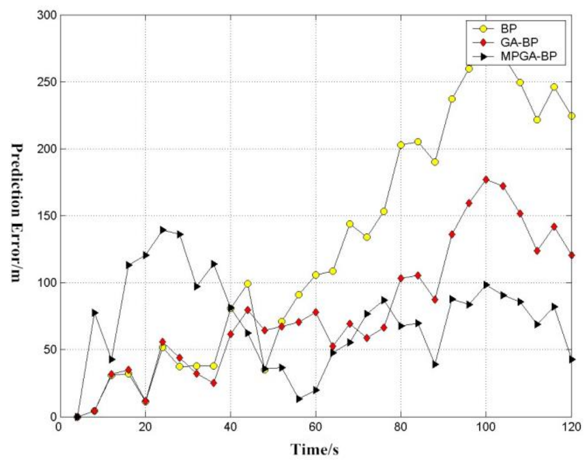


**Fig.6** There algorithm's prediction error for TDOA theory

## 6. Conclusion

It can be seen that the MPGA-BP algorithm effectively reduces the training times of BP network, and speeds up the convergence speed of BP neural network. The accuracy of the trajectory prediction in the early stage of MPGA-BP algorithm is lower than that of the GA-BP and BP algorithms, but with the increase of time, the precision of the prediction is getting increasingly higher. The reason is that the weight threshold is divided into multiple populations in the early stage of the MPGA-BP algorithm, and the diversity of the population is reduced to a certain extent, so it may lead to the convergence of the BP network to the local minimum. With the increase of the distance between the target location and the ground receiver, the prediction error of the three algorithms is increasing gradually, which leads to the gradual decrease of the positioning accuracy. However, because the MPGA-BP algorithm introduces momentum factor, the network has a certain anti concussion ability. Therefore, the variation of prediction error is smaller than that of the GA-BP algorithm and the BP algorithm. The effectiveness and feasibility of the MPGA-BP algorithm is illustrated by the above simulation results and specific experimental data.

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***Yin Jin*** is a worker of the Datang International Power Generation Co, is responsible for the centralized operation and routine maintenance of the power plant. The research direction includes the intelligent control of linear and nonlinear systems, and is good at the research of multi-point positioning technology, and in-depth study of centralized power supply and power transmission for power plants.