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Radar track prediction method based on BP neural network

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Abstract: Taking into account the complex electromagnetic environment in which the radar target is located, it is difficult for the traditional track prediction method to adapt for the high complexity, randomness, and uncertainty of the manoeuvring target track. This study proposes a radar track prediction method based on backpropagation (BP) neural network. According to the historical track of the radar target, this method uses BP neural network to model its movement law and obtain the target's predicted track. Finally, the track prediction experiment was conducted with measured data and compared with the Kalman filter track. The results show that the proposed method has higher track prediction accuracy and can be used for radar track prediction.

1 Introduction

As the electromagnetic environment becomes more and more complex, the radar will suffer from various uncertainties when acquiring the coordinate position of the target. It is difficult for the radar data processing system to obtain timely and accurate data calculation results in a short time. This not only poses great challenges and difficulties for the real-time detection of the target location but also imposes higher requirements on the real-time and accuracy of the radar data processing system [1]. The radar track prediction technology can track the real-time location of the target in time, which solves these problems easily, and has important engineering background and practical application significance.

In recent years, radar target track prediction has been a hot research issue. At present, most of the estimation methods based on Kalman filter are used. The most commonly used prediction methods include Kalman filter, $\alpha - \beta$ filter, and interactive multi-model filter. In literature [2], a moving target's track prediction method based on Kalman filter was proposed, by establishing a state equation and an observation equation, an optimal prediction result in the sense of minimum mean square error (mse) was given. In literature works [3, 4], a noise-adaptive Kalman tracking algorithm was proposed. The noise covariance matrix $\boldsymbol{Q}$ and the measurement noise covariance matrix $\boldsymbol{R}$ in the estimation process were adaptively processed to achieve higher filter accuracy. The literature works [5–7] predict the track based on $\alpha - \beta - \gamma$ filter, particle filter, and interactive multiple models, respectively. The above studies are based on the establishment of kinematics equations, using traditional Kalman filter and particle filter to achieve the target track prediction. However, due to the interference and influence of environmental factors, the motion of the target has complexity and uncertainty [8]. From an engineering point of view, it is not only difficult to establish a kinematics equation in real time, but also has a high requirement for data. The track prediction method is more suitable for research under ideal conditions.

This paper proposes a radar track prediction method based on backpropagation (BP) neural network for the problem of track prediction in hotspots. The method uses BP neural network to train and learn the historical track of radar target and establishes the track prediction model, thus avoiding the complex mathematical modelling process of traditional Kalman filter algorithm and making the model more in line with the actual situation of the target. Through the experimental research on the measured data of the air traffic control (ATC) radar, the reliability of the method is verified. Finally, this paper gives two conclusions.

2 BP neural network

Neural network is a complex network formed by interconnecting a large number of simple neurons. It has a high degree of non-linearity and can perform complex logic operations and the realisation of non-linear relationships. BP neural network is one of the most widely used and successful neural network at present. It includes the input layer, hidden layer, and output layer. The network structure is shown in Fig. 1.

The BP neural network is divided into the positive propagation process of information and the BP process of errors [9, 10]. Take a three-layer BP neural network as an example. Let the input be $\boldsymbol{x}$ and the input layer has m neurons; the hidden layer output is $\boldsymbol{a}$, the hidden layer has n neurons, and the activation function is f_1; the output layer's output is z, the expected output is $\boldsymbol{t}$, and there is one neuron in output layer and the activation function is f_2 [11].

If ω_{ij}^1 is the weight between the input layer and the hidden layer, and b_i^1 is the bias value of the neuron in the hidden layer, let

$$a_i = f_1\left(\sum_{j=1}^{m} \omega_{ij}^1 x_j + b_i^1\right) \quad (i = 1, 2, \ldots, s) \tag{1}$$

be the output of the ith neuron in the hidden layer.

If ω_{ki}^2 is the weight between the hidden layer and the output layer, and b_k^2 is the bias value of the neuron in the output layer, let

$$z_k = f_2\left(\sum_{i=1}^{s} \omega_{ki}^2 a_i + b_k^2\right) \quad (k = 1, 2, \ldots, n) \tag{2}$$

be the output of the kth neuron in the output layer.

The error function is defined as

$$E = \frac{1}{2}\sum_{k=1}^{n} (t_k - z_k)^2 \tag{3}$$

The network propagates backward and constantly adjusts the weights ω to minimise errors E. The weights between the input layer and the hidden layer, and the weights between the hidden layer and the output layer are adjusted to

$$\omega_{ij}^1 = \omega_{ij}^1 - \eta \cdot \frac{\partial E(\omega, b)}{\partial \omega_{ij}^1} \tag{4}$$

$$\omega_{ki}^2 = \omega_{ki}^2 - \eta \cdot \frac{\partial E(\omega, b)}{\partial \omega_{ki}^2} \tag{5}$$

Among them, η is the learning rate of the BP neural network.

3 Methodology

Due to the complexity of the environment, it is difficult for the kinematic model to adapt to the diversity and uncertainty of the target movement. The BP neural network can realise any non-linear mapping from the m-dimensional input to the n-dimensional output, and the BP neural network can be used to better fit the non-linear curve according to the target historical track data, thus improving the track prediction performance. The radar track prediction method proposed in this paper mainly has three research steps.

Step 1. Data preprocessing

(i) Wild value elimination

There will be some obvious abnormal values in the radar track data. In order to reduce the calculation amount and improve the prediction accuracy of the track, it is necessary to eliminate the wild value first.

ii) Data normalisation

Normalisation of data has been widely used in data preprocessing. Before network training, radar target's distance information is normalised, and the input and output of neural network are limited to [−1,1] through transformation processing, in order to reduce the influence of maximum and minimum values in the data during the prediction of neural network, and improve the computation speed of the neural network at the same time [12]. Let

$$p_{\text{norm}} = 2 \times \frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \tag{6}$$

be the normalised formula. Where, P and p_{norm} represent the values before and after normalisation, $p_{\max}$ and $p_{\min}$ represent the maximum and minimum values.

iii) Dividing data sets

The track data set contains several tracks, 70% of tracks are randomly selected as training sets and the remaining 30% are used as test sets.

Step 2. Building a BP neural network model

First, the network is initialised, including the initialisation of weights and thresholds, the number of neural network and neurons in each layer and the types of transfer functions, model training algorithms, number of iterations, and training objectives are defined for each layer [13]. The mathematical model of the BP neural network is as follows:

(i) Use the first six historical track points to predict the seventh track point, the X, Y-axis coordinate position of target point at time intervals $t, t-1, t-2, t-3, t-4, t-5$ are treated as the BP neural network's input, the X, Y-axis coordinate position of target point at time $t+1$ is treated as the BP neural network's output.

(ii) In the training process, the excessive number of neurons in the hidden layer increases the complexity and training time of the network, the number of neurons is too small to achieve the expected prediction effect. The number of common hidden neurons is set to about three times that of the input layer. In this paper, the number of input layer nodes is 12, so the number of hidden layer nodes is 36.

(iii) In BP neural network, the transfer functions of the hidden layer and the output layer are tansig and logsig, respectively. The learning rate of the network is 0.01, the maximum number of iterations is 1000, and the goal error is 10^{-6}.

(iv) Levenberg–Marquardt (L-M) learning rule is used to train BP neural network. L-M algorithm is a combination of steepest descent and Newton's method to reduce network training time [14]. The training function uses the trainlm function and uses the mse to evaluate the network.

Step 3. Track prediction

Using the test set track in Step 1 to test the predictive performance of the BP neural network model, the predicted value of the track is obtained and compared with the real track.

The overall research structure of the radar track prediction method proposed in this paper is shown in Fig. 2.

4 Experiments and analysis

A total of 73 tracks were selected for the experiment, all of which were derived from actual measurement data of the ATC radar. The data contained radar multi-target position information at different times and the sampling period of the ATC radar is $T = 10\,\text{s}$. In total, 51 of the tracks were randomly selected as training set data, and the remaining 22 tracks were selected as test set data. Suppose there are n track points in a track, $(x_i, y_i)_{i=1,\dots,n}$ represents the position coordinates of the ith track point, samples $\{(x_1, y_1), (x_2, y_2), \dots, (x_6, y_6)\}, \{(x_2, y_2), (x_3, y_3), \dots, (x_7, y_7)\}, \dots,$ $\{(x_{n-6}, y_{n-6}), (x_{n-5}, y_{n-5}), \dots, (x_{n-1}, y_{n-1})\}$ are taken as the input of the BP neural network, and samples $\{(x_7, y_7)\}, \{(x_8, y_8)\}, \dots, \{(x_n, y_n)\}$ are taken as the output of the BP neural network. The experiment was conducted under the matlab2017b and win10 operating system. The BP neural network was used to train and learn the historical track, and the predicted

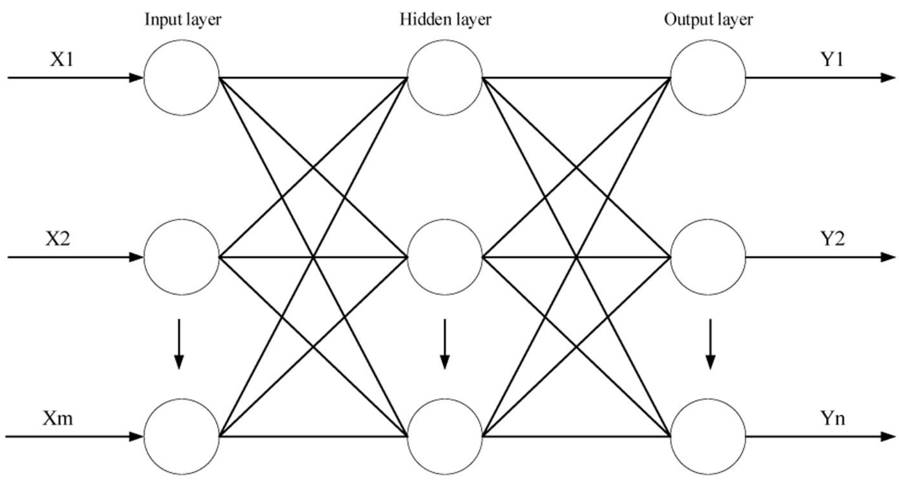

Fig. 1 *BP neural network structure*

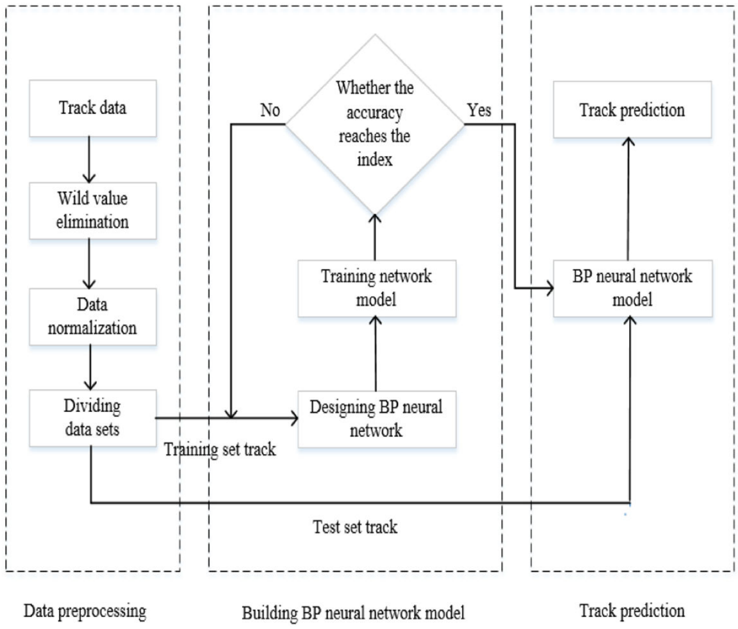

Fig. 2 *Block diagram of radar track prediction based on BP neural network*

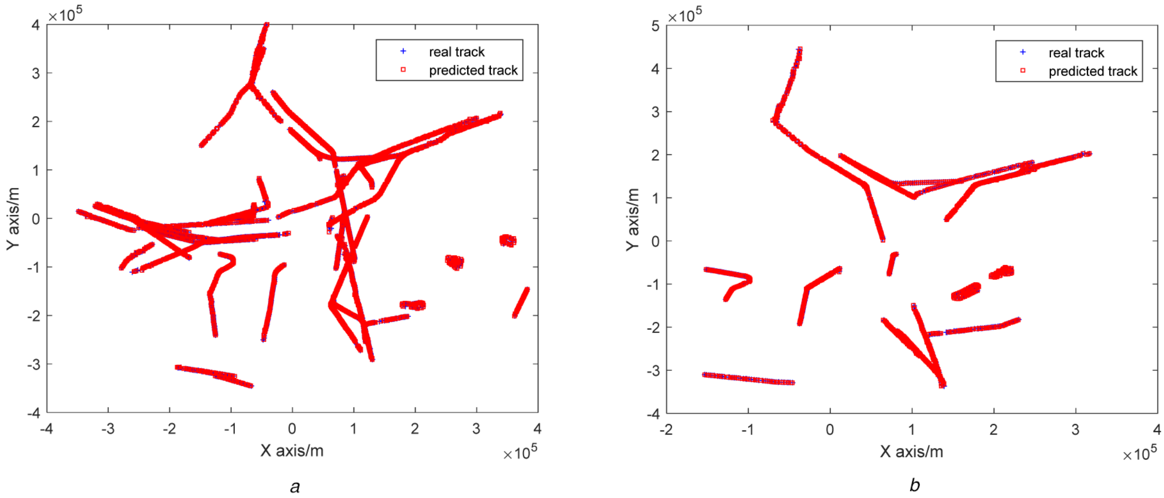

Fig. 3 *Real track and predicted track map*
(a) Track training result, ***(b)*** Track test result

track was compared with the Kalman filter track that uses the constant velocity (CV) model.

4.1 Track prediction experiment based on BP neural network

First, we need to train the BP neural network with a part of the training data, and then use another part of the test data to test the performance of the BP neural network. In this experiment, 51 tracks were selected as training data, the remaining 22 tracks were used as test data. The results are shown in Figs. 3*a* and *b*.

Fig. 3*a* shows the training result of the track. The blue trajectory with plus sign represents the actual track of the target, and the red trajectory with square sign represents the predicted track of the BP neural network. Fig. 3*b* shows the test result of the track. The blue trajectory with plus sign and red trajectory with square sign represent the real track and the predicted track of the target, respectively. From the above two graphs, it can be seen that the track predicted by the BP neural network fits the real track of the target very well, and the trajectories basically overlap. This experiment verifies the excellent radar track prediction performance of BP neural network.

Fig. 4 shows the training performance of the BP neural network. The horizontal axis shows the number of training iterations and the vertical axis shows the root mse. When the training iteration reaches the 12th, the root mse remains basically the same, and the BP neural network reaches convergence. The root mse at this time is about 5.4841×10^{-6}.

4.2 Comparison and analysis

Traditional track prediction methods mainly use the Kalman filter algorithm. However, in the complex and changeable electromagnetic environment, the inaccuracy in the establishment of the radar target motion model will result in low accuracy of track prediction. In order to verify the superiority of the track prediction method proposed in this paper, this experiment compared the difference of BP neural network and Kalman filter in track prediction.

Through the analysis of the 22 test set tracks, the target was considered to be moving at a uniform speed. Therefore, Kalman's motion model adopted the CV model. The sampling period is $T = 10\,\text{s}$ and status transition matrix is

$$\boldsymbol{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

measurement matrix is

$$\boldsymbol{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}.$$

The Kalman filter trajectory is shown in Fig. 5.

The blue track with plus sign in Fig. 5 represents the target's real track and the red track with square sign represents Kalman filter trajectory that uses the CV model. Comparing Fig. 5 with Fig. 3*b*, it is obvious that the predicted track of the BP neural network is closer to the target's real track than the Kalman filter trajectory. Each predicted track of the BP neural network is in good agreement with the actual track, but there are clearly deviated tracks in the Kalman filter track, this has a lot to do with the difficulty of establishing the mathematical model. However, the BP neural network avoids inaccuracies caused by artificially establishing a motion model, and thus the predicted track is more accurate.

In order to compare the difference in track prediction performance between BP neural network and Kalman filter, the deviations between the predicted and real tracks of the two methods in X and Y directions were derived, as shown in Fig. 6.

The 22 test tracks contain a total of 1229 track points. Figs. 6*a* and *b* represent deviations in the X and Y-axis directions, respectively. The red curve shows the error of BP neural network in predicting the track. The blue dotted line represents the error of Kalman filter trajectory. According to Figs. 6*a* and *b*, it is clear that the BP neural network's track prediction error is less than the Kalman filter's error. The track prediction error of the BP neural network is basically maintained between -1000and1000 m in the X and Y directions, and there is no large fluctuation. The Kalman filter's error remains mostly between -2000 and 2000 m, but the fluctuation is large, and the error of some points even exceeds 4000, 6000 m.

Let

$$\text{mse} = \sqrt{\frac{\sum_{t=1}^{N} (Z_{\text{pred}}(t) - Z_{\text{real}}(t))^2}{N}} \tag{7}$$

be the mse function. $Z_{\text{pred}}(t)$ and $Z_{\text{real}}(t)$ represent the predicted values and true values of the different track point, respectively. N represents the total number of track points.

Table 1 shows the mse values of the track predicted by the two methods in X and Y directions.

According to Table 1, it can be seen that the error of the Kalman filter track is large, which is mainly caused by the inaccuracy of the establishment of kinematic equation. In the case of serious environmental disturbances and no fixed rules of the target track, the track prediction performance of the BP neural network is superior to the traditional Kalman filter algorithm.

Table 2 shows a comparison of the time used by the BP neural network and the Kalman filter on track prediction. The Kalman filter took 2.619 s and the BP neural network spent 2.974 s, but this 2.974 s included the time spent in track training. In other words, the BP neural network can improve track prediction performance without consuming more time.

5 Conclusion

Due to the complexity of the environment, it is difficult for the traditional Kalman filter algorithm to adapt to the diversity and uncertainty of the target motion, and hence it is difficult to improve the track prediction performance. In order to solve this problem, this paper proposes a radar track prediction method based on BP neural network. According to the historical track data, the BP neural network is used to train and learn the motion law of the target, and the predicted track is obtained and compared with the Kalman filter trajectory. Through the experiment we can get the following two conclusions:

(1) The radar track prediction method based on BP neural network is more accurate than the traditional Kalman filter algorithm. In the X and Y directions, the track prediction error of BP neural network is lower than the Kalman filter's error, and the time consumed by the two methods is almost the same.

(2) In the case of traditional track prediction method, kinematic models are created, which are computationally complex and difficult to implement. The proposed method avoids the inaccuracy brought by artificially building mathematical models, effectively predicts the track, has strong robustness and timeliness, and provides technical reference for radar target tracking and other practical engineering problems.

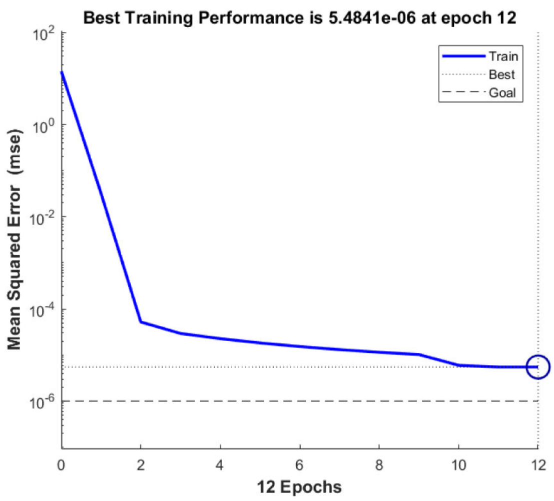

Fig. 4 *Training performance*

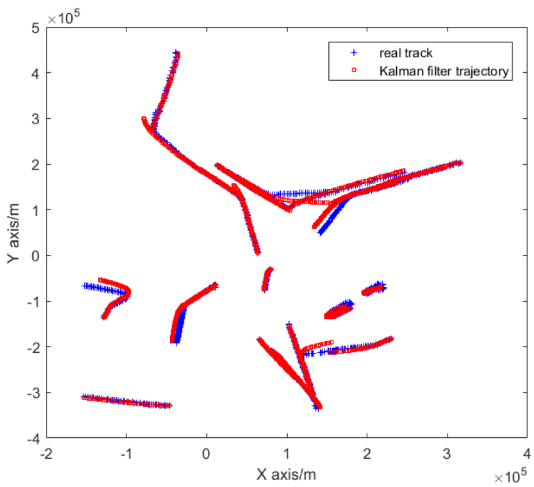

Fig. 5 *Kalman filter trajectory*

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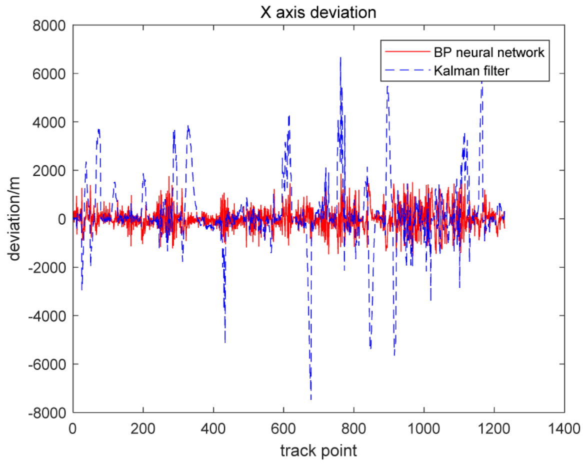
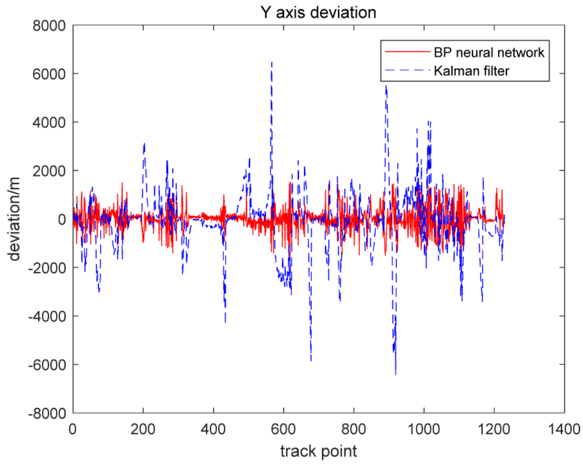


a



b

Fig. 6 *Deviation of BP neural network and Kalman filter*
(a) *X*-axis deviation, ***(b)*** *Y*-axis deviation

6 Acknowledgments

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Table 1 Mean square error

	BP neural network	Kalman filter
X–axis, m	637.7	1466.3
Y-axis, m	649.5	1285.6

Table 2 Comparison of time

	BP neural network	Kalman filter
time, s	2.974	2.619

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