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Research on Radar Jamming Evaluation Method Based on BP Neural Network

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Abstract. The radar interference effect evaluation method is a research hotspot in the field of radar countermeasures. In a complex battlefield environment, the assessment of interference effects by a single indicator usually does not reflect the actual state of the battlefield. Aiming at the complexity of radar interference evaluation on modern battlefields, this paper combines the effects of suppressive interference evaluation and deceptive interference, and uses neural network method to evaluate the composite interference effect. Firstly, the related knowledge of neural network and BP neural network is introduced. Then an interference effect evaluation model based on BP neural network is established. Finally, the simulation model is used for simulation analysis.

Introduction

With the emergence of various new technologies and new system radars, modern radar countermeasure technology has developed to a very high level. In order to suppress interference, modern radars often use a variety of anti-interference methods. Correspondingly, some new types of interference equipment and interference technologies have emerged, and their purpose is exactly the opposite of radar, which is to more effectively interfere with the radar. For the interfering party, it is mainly concerned with whether the interference is effective or effective for the radar; while the radar side is concerned about its ability to work under interference conditions or its ability to resist interference. In fact, the two can be unified into one problem, which is the interference evaluation problem.

At present, when introducing the evaluation indicators, the evaluation indicators of suppressed and deceptive interference are separately introduced. Because the two modes of action are different, the measurement methods of interference effects are also different. However, in the actual operational environment, both sides of the electronic confrontation will not use only a single interference mode. This results in both the components of the radar system that suppress interference and the components that deceive interference during an operation. Moreover, some suppression interferences can also exhibit certain characteristics of deceptive interference under certain conditions, such as smart suppression of interference. Therefore, in a complex battlefield environment, the assessment of the interference effect and the deceptive interference are usually not reflected in the actual battlefield conditions.

Aiming at the complexity of radar interference evaluation on modern battlefields, this paper combines the effects of suppressive interference evaluation and deceptive interference, and uses neural network method to evaluate the composite interference effect. The following will first introduce the relevant knowledge of neural network and BP neural network, and then establish a BP neural network based interference effect evaluation model, and finally use the simulation model for simulation analysis.

Analysis Method for the Server Process Network

Neurons and Neural Networks

The theoretical study of artificial neural networks began when the psychologist W. McCulloch and mathematician W. Pitts collaborated to propose mathematical models of neurons and neural networks in 1943, but it was not until nearly two decades. The basic idea of artificial neural networks is to simulate how the human brain processes data and how it perceives things. Similar to the human brain, a complete artificial neural network is a nonlinear system composed of a large number of neurons that are related to each other. The structure of each neuron is very simple, when a large number of neurons are connected together to form a nerve. The network can perform very complex functions. The artificial neural network has the characteristics of adaptability, non-linearity, strong fault tolerance, and distributed parallel processing capability, which makes it very important in pattern recognition, artificial intelligence, control engineering, optimization calculation and associative memory and signal processing. Wide application prospects[1,2].

The basic unit of artificial neural network is a neuron, which is a simplification and simulation of biological neurons. It can be regarded as a multi-input and single-output nonlinear threshold device[3]. Defining an input vector representing the neuron as $P=[p_1, p_2, \cdots, p_R]^T$; $W=[w_1, w_2, \cdots, w_R]$ indicating the strength of the connection of other neurons to the R of the neuron, that is, a weight vector; θ is a threshold of the neuron, if the weighted sum of the input vectors of the neurons $\sum_{i=1}^{R} w_i p_i$ is greater than the θ, It is activated, so the input weighted sum is also called the activation value; f represents the input/output relationship function of the neuron, that is, the transfer function. Because the larger the activation value, the more pulses the neuron excites, so the transfer function is usually a monotonic non-decreasing function. But it is also a finite value function because the number of pulses a neuron can emit is limited. The output of such a neuron can be expressed as:

$$a = f\left(\sum_{i=1}^{R} w_i p_i - \theta\right) \tag{1}$$

make $b=-\theta$,

$$a = f\left(\sum_{i=1}^{R} w_i p_i + b\right) \tag{2}$$

A typical neuron can be described in Fig. 1. It is necessary to propose that the weights and thresholds in the neurons can be adjusted, which is the basis for the neuron and the neural network to exhibit certain behavioral characteristics.

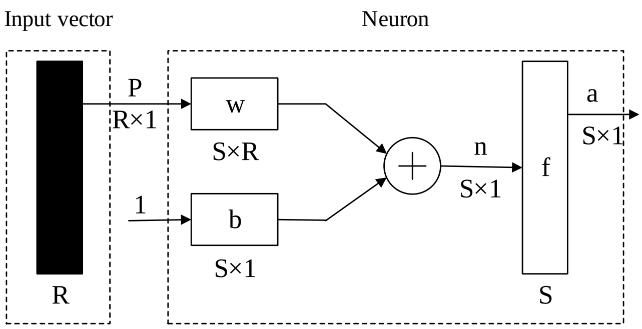

Figure 1. Model of single neuron

Only when hundreds of millions of biological neurons are connected into a biological neural network can the processing, memory, and learning of externally-perceived information be completed. Similarly, a single artificial neuron cannot complete the processing of the input signal. It must be connected to the network according to certain rules, and the weights and thresholds of each neuron in the network can be changed according to certain rules to realize the designed neural network. Artificial neural networks have a variety of connection forms and topologies, but in general there are two forms, hierarchical and interconnected neural networks. The hierarchical neural network can be divided into a simple feed forward network, a feedback feed forward network and an inner interconnection feed forward network. The BP neural network to be described below is a multi-layer feed forward neural network. The hierarchical neural network divides all neurons into several layers according to their functions. Generally, there are input layer, intermediate layer and output layer, and the layers are connected in sequence, as shown in Fig. 2. The middle layer can also be called a hidden layer. Depending on the processing function, the hidden layer can have multiple layers or no.

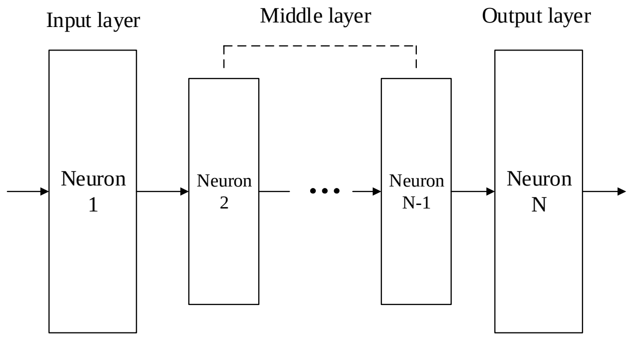

Figure 2. Structure of neural network

BP Neural Network

As mentioned earlier, the BP neural network is a multi-layer feed forward neural network. The layers are connected by a full interconnection, and there is no connection in the same layer. The most commonly used transfer function of BP neural networks is the Sigmoid function[4]:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Pure linear functions (Pure line) can also be used in some cases. If the BP network output layer uses the Sigmoid function, then the output of the entire network will be a continuous amount between $0 \sim 1$; if the output function used by the output layer is a pure line function, then the output of the entire network can take any value.

After the structure of the BP neural network is determined, it is necessary to train the BP neural network by using a certain number of learning samples through the error back propagation learning algorithm. The BP neural network is named after its Back Propagation learning algorithm. Given a learning sample (X,T), where the input sample is $X=[x_1,x_2,\cdots,x_3,\cdots]^T$, the expected output is $T=[t_1,t_2,\cdots,t_3,\cdots]^T$, the actual output of the network is $Y=[y_1,y_2,\cdots,y_3,\cdots]^T$, here x_k, t_k, y_k are both represent the vector. By adjusting the connection weights and thresholds of the network by learning the samples, the output of the network is approximated to the desired output. The adjustment algorithm is:

$$v(k+1) = v(k) - ag(k) \tag{4}$$

Where: $v(k)$ indicates the connection weight vector or threshold vector between the layers for the k time.

deceptive. When establishing the BP neural network-based interference effect index system, this paper does not specifically specify suppressed or deceptive interference, but tries to unify the evaluate of the two different modes of interference (suppressed and deceptive).

The interference evaluation indicators selected in this paper are: discovery time, distance tracking error, pitch tracking error, azimuth tracking error, stable tracking time, tracking time length, and radar resource consumption growth[5]. The evaluation model can be represented as Fig. 3.

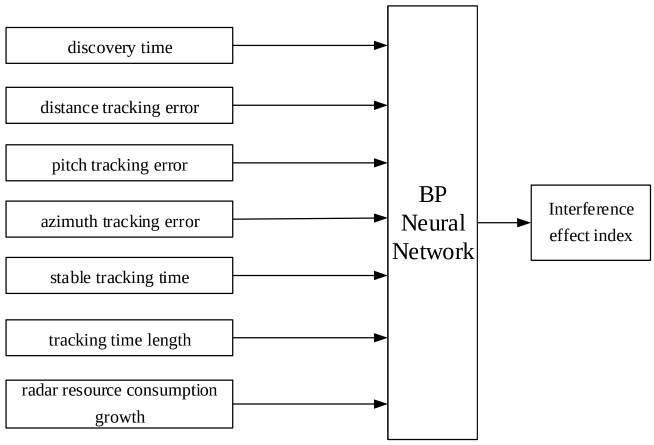

Figure 3. Interference effect evaluation model based on BP neural network

The interference effect evaluation indicators in the model all take relative values, so that the indicators are no longer limited to a certain simulation scenario. The results obtained under different simulation conditions are also comparable, which enhances the adaptability of the indicators. The above values range from 0 to 1. The smaller the value, the better the interference effect, 0 means the best interference, 1 means no interference or the interference is completely invalid. The output is the interference effect index, which ranges from 0 to 1. The interference effect index of 0 means that the interference effect is the best, and 1 means no interference or the interference is completely invalid.

Application Examples Training of BP Neural Network for Interference Effect Evaluation

According to the model established above, there are 7 interference effect evaluation index items, so the input variable dimension of the BP neural network is 7, and the output dimension of the neural network is 1, that is, the number of output layer nodes is 1. In this paper, a three-layer BP network structure is adopted. The number of neurons in each layer is 10, 5, and 1, respectively. The transfer functions between the layers are sigmoid functions. The network structure is shown in Fig. 4.

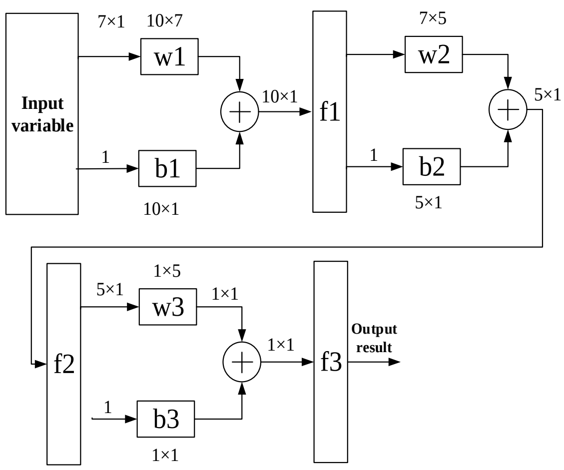

Figure 4. BP neural network for interference effect evaluation

After the BP neural network is established, the initial values of the weights and thresholds of each neuron are first assigned, that is, the initialization of the network is performed. There is a special function in the MATLAB neural network toolbox to perform this step. Then you need to train the network. The learning samples are mainly obtained through expert scoring and theoretical analysis of the data obtained. The learning samples used in this paper are shown in TABLE I.

Table 1. Learning samples of bp neural network

Number	Discovery time	Stable tracking time	Tracking time length	Distance tracking error	Pitch tracking error	Azimuth tracking error	Radar resource consumption growth	Interference effect index
1	0.9	0.9	1	1	1	1	1	0.992
2	1	1	1	0.9	0.9	0.9	0.8	0.956
3	0.9	0.9	0.95	0.8	0.8	0.8	1	0.907
4	1	1	0.8	0.8	0.9	0.9	0.9	0.852
5	0.8	0.8	0.9	0.8	0.8	0.8	0.5	0.821
6	0.9	0.9	0.9	0.5	0.5	0.5	1	0.813
7	0.8	0.8	0.9	0.8	0.8	0.8	0.85	0.704
8	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.681
9	0.5	0.5	0.9	0.6	0.6	0.6	0.8	0.608
10	0.5	05	0.6	0.5	0.5	0.5	0.7	0.553
11	0.2	0.2	0.3	0.4	0.4	0.4	0.7	0.523
12	0.1	0.2	0.4	0.6	0.6	0.6	0.3	0.455
13	0.9	0.9	0.4	0. 33	0. 33	0.33	0. 5	0.451
14	0.1	0.1	0.2	0.2	0.25	0.3	0.1	0.384

The training is performed using the steepest descent BP algorithm with variable learning rate. In fact, since the evaluation result in the learning sample is only accurate to 0.001, the error between the output of the network and the expected result is lower than 10^{-4} can meet the requirements of the accuracy of the network output. Therefore, when training the BP neural network, the training step is set to 5000 steps, and the set target error is 10^{-5} . After 5000 steps of training, the mean square error of the output and target output of the BP neural network is reduced to 1.00026×10^{-5} less than 1×10^{-4}, which can meet the requirements.

Evaluation and Analysis of Interference Effects on Simulation Results

After the neural network training is completed, it has the function of automatic evaluation. A set of interference effect evaluation indicators can be input into the neural network to obtain corresponding output results.

The simulation results can be obtained by inputting the data of TABLE II into the trained BP neural network. The NFM represents the noise FM interference, and the following figure represents the power of the jammer, and the unit is W. SJ indicates smart noise interference, and the following numbers indicate the interference pulse interval in us.

This result is the evaluation result obtained by BP neural network for interference effect evaluation, as shown in TABLE III.

According to the evaluation results, it can be seen that in the five sets of radar countermeasure simulation data, the best interference effect is the noise frequency modulation signal with power of 120w, and the worst is the noise frequency modulation signal with power of 80w. The interference effect of the smart noise interference signals of three different pulse intervals is between the two noise modulation interferences. Basically, it can be considered that the interference effect of smart noise interference with a power of 5W is similar to that of a noise FM signal with a power of 100W. As a kind of coherent interference, smart noise interference needs more information than ordinary noise interference. The evaluation results show that the interference effect is far better than the noise FM interference, and the near-distortion effect can be achieved at a small power. Therefore, the evaluation results are in line with expectations and are reasonable. Therefore, the BP neural network based interference effect evaluation model is effective.

Table 2. Simulation results

Number	Discovery time	Stable tracking time	Tracking time length	Distance tracking error	Pitch tracking error	Azimuth tracking error	Radar resource consumption growth
NFM 80	0.2763	0.7179	0.9882	0.9337	0.9412	0.8333	0.9991
NFM 120	0.0191	0.1160	0.7658	0.8687	0.9412	0.9524	0.9901
SJ 1	0.1123	0.4519	0.9626	0.9935	1.0000	0.8696	0.9872
SJ 0.5	0.1089	0.4438	0.9619	0.9316	1.0000	0.9091	0.9901
SJ 0.25	0.1000	0.4209	0.9578	0.9060	1.0000	0.8696	0.9976

Table 3. Interference effect valuation results by bp neural network

Interference pattern	NFM 80	NFM 120	SJ 1	SJ 0.5	SJ 0.25
Evaluation result	0.9889	0.9454	0.9734	0.9713	0.9661

Conclusion

The traditional radar interference effect evaluation research is often carried out from a relatively one-sided perspective. The existing evaluation index set is too large and loose, not intuitive and clear. And the BP neural network-based interference effect evaluation model has clear indicators and is easy to be calculated. Besides, it is concise and can reflect the characteristics of the final combat effect, and has a strong guiding significance for radar countermeasures.

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