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An Improved RBF Neural Network Method for Information Security Evaluation

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Abstract

It is well-known that information security means the protection of information, and ensuring the availability, confidentiality and integrity of information. The purpose of this paper is to present an improved RBF neural network method for information evaluation. Ant colony optimization is a multi-agent approach for difficult combinatorial optimization problems, which has been applied to various NP hard problems. Here, ant colony optimization algorithm is applied to optimize the parameters of RBF neural network. In this paper, we employ "unauthorized access", "unauthorized access to a system resource", "data leakage", "denial of service", "unauthorized modification data and software", "system crash" as the features of information security evaluation. It is indicated that the information security evaluation error of the improved RBF neural network is smaller than that of the RBF neural network. Thus, the improved RBF neural network is very suitable for information security evaluation.

Keywords: *improved RBF neural network, information security, evaluation method*

1. Introduction

It is well-known that information security means the protection of information, and ensuring the availability, confidentiality and integrity of information [1-5]. RBF neural network is a type of feed-forward network, which has three different layers. The input layer is used to collect the input information [6, 7]. The center layer includes radial basis functions, which is connected directly to all the elements in the output layer. The output of the neural network is a linear combination of the radial basis functions.RBF neural network can approximate continuous function mapping with the excellent accuracy. Ant colony optimization is a multi-agent approach for difficult combinatorial optimization problems, which has been applied to solve various NP hard problems [8-11]. Here, ant colony optimization algorithm is applied to optimize the parameters of RBF neural network.

The purpose of this paper is to present an improved RBF neural network method for information evaluation. The information intrusion types including "unauthorized access", "unauthorized access to a system resource", "data leakage", "denial of service", "unauthorized modification data and software", "system crash" have a great influence on information security. Thus, we employ "unauthorized access", "unauthorized access to a system resource", "data leakage", "denial of service", "unauthorized modification data and software", "system crash" as the features of information security evaluation. It is indicated that the information security evaluation error of the improved RBF neural network is smaller than that of the RBF neural network. Thus, the improved RBF neural network is very suitable for information security evaluation.

2. The Description of RBF Neural Network

RBF neural network is a type of feed-forward network, which has three different layers. The input layer is used to collect the input information. The center layer includes radial basis functions, which is called the hidden layer. It is connected directly to all the elements in the output layer, which can response decreases, or increases, monotonically with distance from a center point.

The output of the neural network is a linear combination of the radial basis functions.RBF neural network can approximate continuous function mapping with the excellent accuracy.

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The radial basis function of the hidden nodes is shown as follows:

$$G\left(\left\|x_j - c_i\right\|\right) = \exp\left[-\frac{\left\|x_j - c_i\right\|^2}{2\sigma^2}\right] \tag{1}$$

Where x_j is the input vector of the *j*th input node, c_i is the center of the *i*th RBF unit, and σ is the width of RBF unit.

The output of RBF neural network is formed by a linearly weighted sum of the number of radial basis functions in the hidden layer, which can be described as follows:

$$f_k(x) = \sum_{i=1}^{n} w_{ik} G\left(\left\|x_j - c_i\right\|\right) \tag{2}$$

Where w_{ik} is the weight from the *i*th hidden layer to the *k*th output layer.

3. Optimizing the Parameters of RBF Neural Network by Ant Colony Optimization

Ant colony optimization is a multi-agent approach for difficult combinatorial optimization problems, which has been applied to various NP hard problems. Here, ant colony optimization algorithm is applied to optimize the parameters of RBF neural network. The searching process of selecting the parameters of RBF neural network by ant colony optimization algorithm can be described as follows:

Step 1: Initially, a set of ants are initialized, the ants solution consists of ***n*** number of features each by using an initialization rule.

Step 2: Each of the ***r*** ants construct ***r*** different solutions, RBF neural network evaluates each subset by determining the error in prediction by using that subset of ***n*** features.

Step 3: A local updating rule is applied to the rest of the ants. Record the local best subset of feature.

Step 4: A global updating rule is applied to the solution set. Record the global best subset of feature.

4. Testing and Analysis for Information Security by Improved RBF Neural Network Method

The information intrusion types are mainly “unauthorized access”, “unauthorized access to a system resource”, “data leakage”, “denial of service”, “unauthorized modification data and software”, “system crash” ,which have a great influence on information security. Thus, we employ “unauthorized access”, “unauthorized access to a system resource”, “data leakage”, “denial of service”, “unauthorized modification data and software”, “system crash” as the features of information security evaluation, which are denoted as “1~6” respectively. The experimental data are shown in Table 1, among which the training data are shown in Table 2, and the testing data are shown in Table 3. The information security evaluation results of the experimental data are shown in Figure 1. In this experiment, the improved RBF neural network is applied to information security evaluation, the RBF neural network with six input nodes, six hidden nodes and one output node is used, and ant colony optimization algorithm is applied to optimize the parameters of RBF neural network.

The information security evaluation values of the improved RBF neural network are given in Figure 2, and the information security evaluation values of the RBF neural network are given in Figure 3. In order to show the superiority of the improved RBF neural network compared with the RBF neural network, the information security evaluation error of the improved RBF neural network and the RBF neural network is given. Figure 4 gives the information security evaluation error of the improved RBF neural network, and Figure 5 gives the information security evaluation error of the RBF neural network.

Table 1. The Experimental Data

	U_1	U_2	U_3	U_4	U_5	U_6	Evaluation values
1	0.4	0.3	0.4	0.6	0.5	0.3	0.38
2	0.3	0.5	0.8	0.4	0.2	0.5	0.45
3	0.5	0.6	0.2	0.8	0.7	0.5	0.62
4	0.4	0.3	0.4	0.2	0.3	0.4	0.38
5	0.3	0.2	0.3	0.2	0.2	0.4	0.26
6	0.4	0.3	0.4	0.6	0.5	0.4	0.47
7	0.7	0.6	0.8	0.7	0.8	0.6	0.75
8	0.3	0.2	0.3	0.2	0.4	0.2	0.24
9	0.5	0.4	0.5	0.6	0.4	0.4	0.48
10	0.5	0.5	0.6	0.8	0.4	0.5	0.56
11	0.6	0.7	0.8	0.5	0.7	0.7	0.72
12	0.3	0.2	0.4	0.5	0.3	0.2	0.35

Table 2. The Training Data

	U_1	U_2	U_3	U_4	U_5	U_6	Evaluation values
1	0.4	0.3	0.4	0.6	0.5	0.3	0.38
2	0.3	0.5	0.8	0.4	0.2	0.5	0.45
3	0.5	0.6	0.2	0.8	0.7	0.5	0.62
4	0.4	0.3	0.4	0.2	0.3	0.4	0.38
5	0.3	0.2	0.3	0.2	0.2	0.4	0.26
6	0.4	0.3	0.4	0.6	0.5	0.4	0.47
7	0.7	0.6	0.8	0.7	0.8	0.6	0.75
8	0.3	0.2	0.3	0.2	0.4	0.2	0.24

Table 3. The Testing Data

	U_1	U_2	U_3	U_4	U_5	U_6	Evaluation values
9	0.5	0.4	0.5	0.6	0.4	0.4	0.48
10	0.5	0.5	0.6	0.8	0.4	0.5	0.56
11	0.6	0.7	0.8	0.5	0.7	0.7	0.72
12	0.3	0.2	0.4	0.5	0.3	0.2	0.35

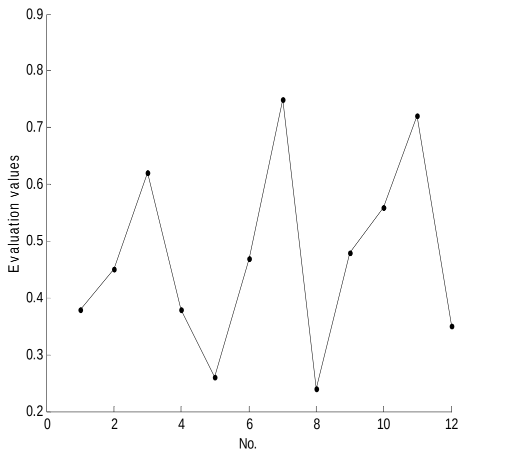

Figure 1. The Information Security Evaluation Results of the Experimental Data

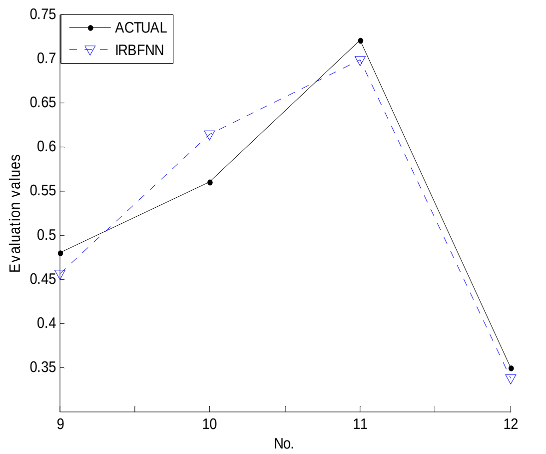

Figure 2. The Information Security Evaluation Values of the Improved RBF Neural Network

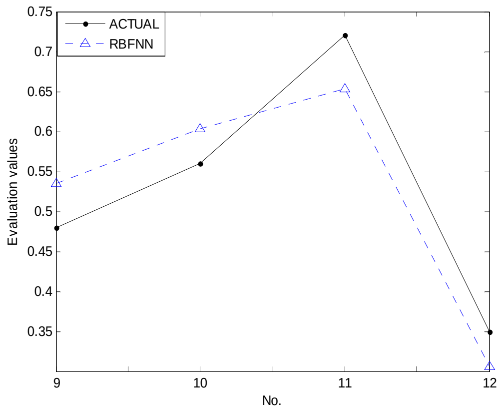

Figure 3. The Information Security Evaluation Values of the RBF Neural Network

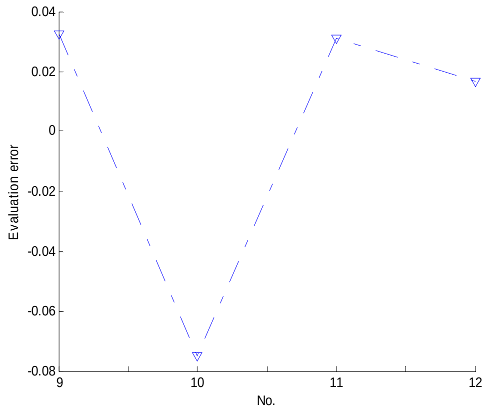

Figure 4. The Information Security Evaluation Error of the Improved RBF Neural Network

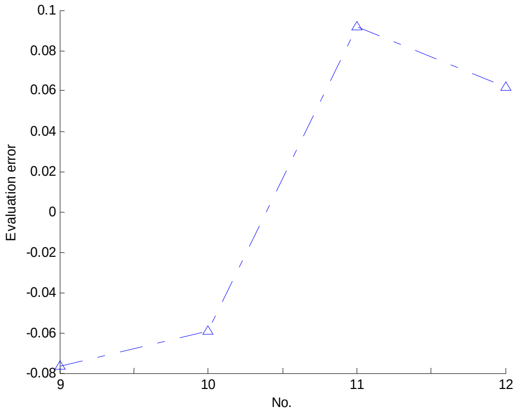

Figure 5. The Information Security Evaluation Error of the RBF Neural Network

It is indicated that the information security evaluation error of the improved RBF neural network is smaller than that of the RBF neural network. Thus, the improved RBF neural network is very suitable for information security evaluation.

5. Conclusion

This paper presents an improved RBF neural network method for information evaluation. RBF neural network can approximate continuous function mapping with the excellent accuracy. Ant colony optimization is a multi-agent approach for difficult combinatorial optimization problems, which has been applied to various NP hard problems. Here, ant colony optimization algorithm is applied to optimize the parameters of RBF neural network. The information intrusion types including “unauthorized access”, “unauthorized access to a system resource”, “data leakage”, “denial of service”, “unauthorized modification data and software”, “system crash” have a great influence on information security. Thus, we employ “unauthorized access”, “unauthorized access to a system resource”, “data leakage”, “denial of service”, “unauthorized modification data and software”, “system crash” as the features of information security evaluation. It is indicated that the information security evaluation error of the improved RBF neural network is smaller than that of the RBF neural network. Therefore, the improved RBF neural network is very suitable for information security evaluation.

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