Network Intrusion Prediction Model based on RBF Features Classification

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Abstract

According to the relationship between feature subset and parameters of RBF neural network, in order to improve the intrusion detection accuracy, it proposed an improved particle swarm optimization neural network of network intrusion detection model. Network feature subset and parameters of RBF neural network were regarded as a particle, through collaboration and information exchange between particles to find the optimal feature subset and parameters of RBF neural network, so as to establish the optimal network intrusion detection model, and using KDD Cup 99 data sets to carry out simulation experiment. The simulation results showed that, IPSO-RBF neural network reduced the feature dimensions, and the better parameters of RBF neural network was obtained then, which is a kind of network intrusion detection model with high detection accuracy and high speed.

Keywords: *Network intrusion; Particle swarm algorithm; Neural network; Feature selection*

1. Introduction

As the network user is increasing, network attack is becoming more and more frequent, it is very difficult for the passive, traditional firewall technology to meet the requirement of network security, while network intrusion detection system (IDS) is a kind of initiative precautionary technology, has become an important topic in the field of network security [1].

Network intrusion detection is the classification problem in pattern recognition, it mainly includes modules such as the feature selection and classifier selection and optimization, etc., the network data is very complex with characteristics of high dimension, and feature set contains some redundant features and useless features, these will increase the training time model and the computational complexity, and has adverse effects on the result of the intrusion detection [2]. Therefore, before the network intrusion detection modeling, it is often conduct feature selection algorithm to select feature subsets for detection results, and reduce feature dimensions, the current methods based on such as sequence search algorithms, principal component analysis, the genetic algorithm, particle swarm optimization algorithm and other feature selection methods [3-5]. In addition to feature subset, network intrusion detection results are also closely related to classifier and parameters, the current network intrusion detection model mainly include nonlinear classification algorithms as Bayesian network, neural network and support vector machine (SVM) [7-9]. Due to network intrusion detection is a system large sample classification problem, for such large sample classification problem, the training speed of support vector machine (SVM) is slow, which is not good for real-time and linear of network intrusion detection. Neural networks do not require a priori knowledge, but can make nonlinear, infinite approximation to system, especially the RBF neural network has some

advantages such as simple structure, fast learning, has been widely used in network intrusion detection [10]. In practical applications, the RBF neural network is closely related to the classification performance and its parameters, to obtain the optimal performance of network intrusion detection model, one needs to select the most adaptive RBF neural network parameters [11]. In current network intrusion detection model, feature selection and classifier parameters selection are separated, and independently implemented, so we have no idea about making feature selection first or RBF neural network parameter selection, and it is often identified by random, and thus difficult to get the optimal feature subset and RBF neural network parameters, to obtain the optimum effect of network intrusion detection, feature selection and parameters of RBF neural network should be done at the same time.

In order to improve the network intrusion detection accuracy, overcome the separate selection defect of traditional features and parameters of RBF neural network, it put forward the improved particle swarm optimization, IPSO to optimize the neural network intrusion detection model(IPSO RBF). Simulation experiments using KDD Cup 99 data sets, to verify the effectiveness and superiority of IPSO- RBF network intrusion detection model.

2. Feature Selection and RBF Neural Network Parameter Optimization

2.1. Feature Selection Optimization Problem

For network status feature set $F=\{f_1, f_2, \dots, f_n\}$, it adopts the binary vector to indicate feature selection as: $S=\{s_1, s_2, \dots, s_n\}$, $s_i \in \{0, 1\}$, $i=1, 2, \dots, n$, where n is the network feature dimension, 1 and 0 respectively represent the corresponding feature is selected or not.

The purpose of feature selection is to reduce feature dimension, and improve the network intrusion accuracy, so the network state feature optimization problem can be described as:

$$\begin{aligned} & \max_S G(S) \\ & s.t. \\ & \begin{cases} S = \{s_1, s_2, \dots, s_n\} \\ s_i \in \{0, 1\} \\ i = 1, 2, \dots, n \end{cases} \end{aligned} \quad (1)$$

2.2. RBF Neural Network Parameter Optimization Problem

RBF neural network is a kind of three-layer feed forward neural network, input layer connects network with outer environment, implicit layer makes mapping of signals between input and hiding layer, output layer outputs vector. The RBF neural network structure as shown in Figure 1, where R should be shown in C

Figure 1. RBF Neural Network Structure

Sets the input vector of the i th sample point as $X_i(i=1,2,\dots,n)$, the output vector of j th sample point as $Y_j(j=1,2,\dots,m)$, the j th radial basis function center vector as $C_j(j=1,2,\dots,n_c)$, then the network output for RBF neural network as

$$Y_{ij} = w_{i0} + \sum_k w_{ik} f(\|x_j - c_k\|) = \sum_{k=0}^{n_c} w_{ik} f(c_k - x_j) \quad (2)$$

In formula, w_{ij} is the weight between implicit layer and output node, w_{i0} is the threshold of the i th node, Y_{ij} is the output i th node, n_c is the number of implicit layer nodes, f is radial basis function, its definition as follows: formula (3) is wrong

$$R_i(x) = \exp\left(\frac{\|x - c_i\|}{2\sigma_i^2}\right) \quad i = 1, 2, \dots, m \quad (3)$$

Where, $\|x - c_i\|$ indicates the distance between x and c_i , c_i indicates the center value of implicit function, σ_i represents core width.

RBF neural network performance value w_{ij} , c_i and σ_i , the values are interrelated, to obtain the optimal RF neural network model, one needs to select the most appropriate w_{ij} , c_i , σ_i first, so RBF neural network parameter optimization model is:

$$M = \{w_{ij}, c_i, \sigma\} \quad (4)$$

Using the network intrusion detection accuracy (G) as objective function parameters optimization neural network, RBF neural network parameters of the optimization problem can be described as:

$$\begin{aligned} & \max_M G(M) \\ & s.t. \\ & \begin{cases} M = \{w_{ij}, c_i, \sigma_i\} \\ w_{ij} > 0 \\ c_i > 0 \\ \sigma_i > 0 \end{cases} \end{aligned} \quad (5)$$

2.3. Joint Optimization of Feature Selection and RBF Neural Network Parameter

For the optimization objectives of formula(1) and (5) are improving the detection accuracy of network intrusion detection, so in order to make the network intrusion detection results with better accuracy, excavating the relation between feature subset selection and RBF neural network parameters, the feature subset selection and parameters of RBF neural network optimization should be done at the same time.

The mathematical model of feature selection and parameters of RBF neural network joint optimization as:

$$\max_{S, M} G(S, M) \quad (6)$$

Where, G represents network intrusion detection accuracy; S represents feature subset; M represents RBF neural network parameters.

PSO algorithm is a kind of representative cluster intelligent algorithm simulated birds feeding behavior, through the information exchange between particles, mutual cooperation to find the optimal location, easy to implement and has strong parallelism and fast search capabilities, which is able to find the global optimal solution in a short time. Therefore, this study uses PSO algorithm to select feature subset and w_{ij} , c_i , σ_i parameter of RBF neural network, and make improvement on them, so as to improve the network intrusion detection accuracy.

3. Intrusion Detection Model of IPSO-RBF Neural Network

3.1. Improve Particle Swarm Optimization Algorithm (The Expression of Formula (7) is Error)

Set $X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,d}]$ and $V_i = [v_{i,1}, v_{i,2}, \dots, v_{i,d}]$ as the current position and velocity of particle i , respectively, $P_i = [p_{i,1}, p_{i,2}, \dots, p_{i,d}]$ and $p_g = [p_{g,1}, p_{g,2}, \dots, p_{g,d}]$ are the best positions of particle i and particle swarm experienced respectively, particle velocity and position updating formula as

$$v_{i,j}(t+1) = \omega v_{i,j}(t) + c_1 \times r_1 \times (p_{i,j} - v_{i,j}(t)) + c_2 \times r_2 \times (p_{g,j} - v_{i,j}(t)) \quad (7)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), j = 1, 2, \dots, d \quad (8)$$

Where, c_1 and c_2 are acceleration coefficient; K is the current iteration number; $R1$ and $R2$ are the random number within $[0, 1]$ scope; ω is inertia weight.

If a local optimum position is found on a particle, other particles then quickly aggregate to it, thus the particle swarm are easy to be local optimum, and appear prematurity phenomenon.

Chaos has sensitivity to initial conditions, with strong traverse ability, can use this property for particle swarm chaos disturbance, so as to improve the search ability of particle swarm optimization algorithm. A typical Logistic equation as shown in formula(9), it can be seen from formula (9), the random initial value z_0 can iterate a certain time sequence $z_1, z_2, z_3, \dots$

$$z_{i+1} = \mu z_i (1 - z_i), i \in (0, 1) \quad (9)$$

Where, μ is control parameter.

Based on the overall change of particle swarm fitness to judge whether the population appears premature state or not. The fitness variance of particle swarm (σ^2) can be defined as

$$\sigma^2 = \sum_{i=1}^N \left(\frac{f_i - f_{avg}}{f} \right)^2 \quad (10)$$

Where, N is particle swarm scale; f_{avg} is the average fitness of particle swarm; f is the normalized scaling factor; f_i is the fitness of the individual i .

3.2. Network Intrusion detection procedure of IPSO-RBF Neural Network

(1) Collect state information of network system, and transform it into the format can be identified by the RBF neural network.

(2) To generate initial particle swarm, particle bit string including network feature subset, RBF neural network parameters w_{ij} , c_i , σ_i , according to the initial particle fitness value to determine individual extremum value P_i and swarm extremum value P_g , and regard the adaptive optimal particle position as a global optimal solution.

(3) Decoding the bit string of the particle, and then according to the feature subset to process the training sample, input to the RBF neural network for training, parameters are w_{ij} , c_i , σ_i , and calculate the particle fitness value according to the results of the test. Fitness function $f(x)$ are defined as follows

$$f(x) = f(S, M) = \frac{p}{total} \times 100\% \quad (11)$$

Where, p indicates the detected intrusion number; $total$ indicates the total intrusion number, S indicates the selected feature subset, M indicates the selected RBF neural network parameters.

(4) If the particle fitness value $f(x_i)$ is better than that of its historical optimal value $f(p_{best,i})$, then the particle position to replace $f(p_{best,i})$. Similarly, if $f(x_i) > f(g_{best,i})$, then use the particle position instead of $f(g_{best,i})$.

(5) According to formula (7) and (8) to update the speed and position of the particle, and produce a new generation of particle swarm $x(t+1)$.

(6) Calculate the fitness variance (σ^2) of particle swarm, if the adjacent twice σ^2 difference are less than the threshold value of C, then indicates a premature phenomenon, and turn to step7; otherwise to Step8.

(7) to carry out chaos disturbance on optimal position of particle swarm vector $p_g = [p_{g,1}, p_{g,2}, \dots, p_{g,d}]$. Specific steps are as follows

① Let p_g mapping to definitional domain $[0,1]$ of formula (9) through the following equation.

$$z_i = \frac{p_{gi} - a_i}{b_i - a_i} \quad (12)$$

② $z_i^{(m)} (m=1,2,\dots)$. Through multiple iterations of Logistic equation $z_{i+1} = \mu z_i (1 - z_i)$, and obtained chaos sequence: $z_i^{(m)} (m=1,2,\dots)$.

③ The generated value by formula (14) inverse mapping back to the original solution space, and generate a chaotic variables feasible solution sequence accordingly :

$$p_g^{(m)} = (p_{g1}^{(m)}, p_{g2}^{(m)}, \dots, p_{gd}^{(m)})$$

$$p_{gi}^{(m)} = a_i + (b_i - a_i) z_i^{(m)} \quad (13)$$

④ Calculate the fitness value of feasible solution $p_g^{(m)} (m=1,2,\dots)$ after chaos processing, and the optimal value p^* of fitness value.

⑤ To replace the random selected particle position with p^* position vector.

(8) If the maximum number of iterations is reached, then return to the global optimal particle position, otherwise jump to step (3) for optimizing continuously.

(9) The optimal particle bit string will be decoded into network feature subset, RBF neural network parameters w_{ij} , c_i , σ_i .

(10) To established the optimal network intrusion detection model based on network feature subset and parameters of RBF neural network w_{ij} , c_i , σ_i .

4. Simulation Experiment

4.1. Data Sources

To test the performance of network intrusion detection model of IPSO - RBF neural network, it uses KDD Cup 99 data sets, and carries out simulation experiment on Matlab 2009 software. As the mass samples in KDD Cup 99 data sets, so it randomly selects a portion of data for the test, the data distribution are shown in table 1.

Table 1. Experiment Samples Distribution

Intrusion type	Training sample	Test sample
DoS	1200	300
Probe	2400	800
R2L	100	40
U2R	300	100

4.2. Comparison Model and Evaluation Index

In order to make the IPSO - RBF neural network detection results comparable, with neither no feature selection, and random selection of RBF neural network (RBF) parameters. Only using PSO for feature selection of RBF neural network (PSO - RBF1);no feature selection, only adopt parameters of RBF neural network (PSO - RBF2) optimized by PSO; using PSO for both feature selection and parameters of RBF neural network optimization, but the separated (PSO - RBF3) as comparison model. To evaluate the index collection and network intrusion detection accuracy.

4.3. Pre-Processing of the Data

In order to prevent the feature value over large or small to influence the speed of RBF neural network training, so it makes normalization processing on feature value and specified as

$$x'_i = \frac{x_i}{\max(x_i)} \quad (14)$$

Where, $\max(x_i)$ is the maximum of feature x_i , x_i 和 x'_i represents original and normalized features.

4.4. Results and Analysis

4.4.1. Comparison of Intrusion Detection Accuracy: Input all kinds of intrusion training samples into the RBF neural network for study, and make corresponding feature and parameter optimization, and establish the corresponding network intrusion detection model, and then do detection on test samples, the results of 10 times operation of each model on each data set, their average network intrusion detection accuracy (%) as shown in 2.

Figure 2. Accuracy Comparing Different Models of Intrusion Detection

The conclusions of the analysis of comparison results in Figure 2 are as follows:

(1) Relative to RBF neural network, the average detection accuracy of both feature selection and RBF neural network parameter optimization model are improved to some extent, this indicates that both feature subset selection and RBF neural network optimization can improve the network intrusion detection accuracy.

(2) The intrusion detection accuracy of IPSO -RBF neural network model is the highest, it shows that single feature subset selection or neural network parameters optimization, can optimize only one of its aspects, without considering the connection of both, while IPSO-RBF neural network make optimization on both feature selection and

RBF neural network parameters at the same time, thus can make good description of network state information, and detect network intrusion behavior accurately.

4.4.2. Detection Time Comparison: Network real time capability is very important to network intrusion detection, the use of tic and toc command to record average detection time (s) of test sample of each model, and test results are shown in table 2.

Table 2. Detection Time Comparison of Different Model

Intrusion type	RBF	PSO-RBF1	PSO-RBF2	PSO-RBF3	IPSO-RBF
Probe	16.25	12.22	11.06	9.80	6.17
DoS	11.87	9.23	8.88	6.06	5.20
U2R	4.42	2.79	2.58	1.92	1.46
R2L	2.79	2.03	1.28	1.13	1.06

It is known from table 2, among all the network intrusion detection models, the detection time of IPSO - RBF is the shortest, which indicates its detection speed is the fastest, this is mainly due to the IPSO - RBF made optimization on feature selection and parameters of RBF neural network at the same time, thus effectively reduced the feature dimension and RBF neural network input node number, and the computational complexity was also reduced, so the network intrusion detection was speed up accordingly.

5. Conclusion

After fully considering the relation between feature subset selection and parameters of RBF neural network, it proposed the network intrusion detection model of IPSO - RBF neural network. The simulation results showed that, compared with traditional network intrusion detection model, IPSO- RBF neural network reduced the feature dimension, and obtained the better parameters of RBF neural network, and thus improved the effect of the network intrusion detection.

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