Application of Nonlinear Classification Algorithm in Communication Interference Evaluation

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Abstract. Traditional methods of communication interference assessment belong third-party assessments that fail to meet the needs of real-time assessments. This paper proposes an interference level evaluation method under the nonlinear classification algorithm. Firstly, building data set with the eigenvalues that affect the interference effect, and then simulation verify by BP neural network and support vector machine. The simulation results verify the feasibility in communication interference assessment and providing the possibility for real-time evaluation.

Keywords: Interference level assessment · BP neural network · Support vector machine

1 Introduction

Modern warfare has changed from a single weapon war to an information warfare and electronic [8] warfare relying on communications, technology, and talent. Therefore, the demand for communication confrontation and anti-resistance is also increasing. Information warfare, as its name implies, is a war of communication information. It includes how to effectively interfere with enemy communications, how to grasp enemy communication information, and how to avoid interference in our communication [7]. In view of the above problems, the problem of evaluating the effects of communication interference has naturally become a more and more concerned issue in the military information warfare field.

The existing evaluation methods are usually very simple, and the advantage is that the accuracy of the evaluation is high but the adaptability of dynamic changes is not ideal [5]. However, the machine learning method used in the fields of electronic warfare and synthetic aperture radar [1] that, to some extent, avoiding unintentional interference from third parties, and can evaluate the interference effect in real time. There are three kinds of learning methods: semi-supervised [17], supervised and

S. Liu and G. Yang (Eds.): ADHIP 2018, LNICST 279, pp. 443–451, 2019.
https://doi.org/10.1007/978-3-030-19086-6_49

unsupervised for classification problems. In this paper, performing an interference level assessment under BP neural network and support vector machine respectively. By inputting the factors affecting the interference effect, the corresponding bit error rate level is obtained, so that the interference level can be grasped quickly and reliably. The verification process of this paper is shown in Fig. 1.

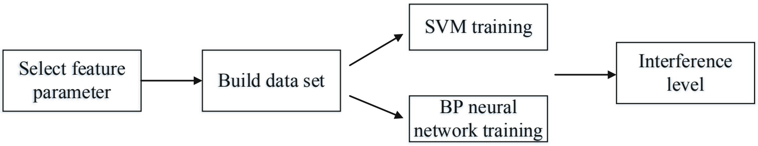

Fig. 1. Research process

2 Introduction to Nonlinear Classification Algorithm

2.1 BP Neural Network

BP neural network is one of the relatively mature neural networks. It has the advantages of strong generalization ability and strong fault tolerance [9]. Although it has local minimization and unstable results compared to other neural network algorithms [18], it is easy to obtain results because of its simple structure. Therefore, BP neural network is used to evaluate the interference level. The training process is as follows (Fig. 2).

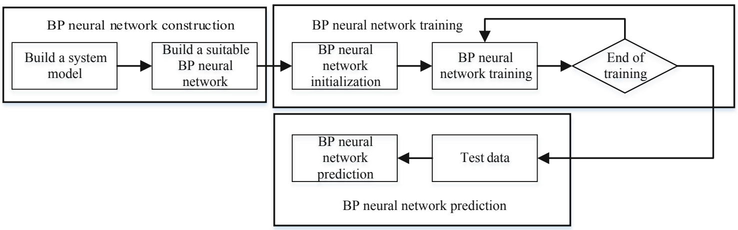

Fig. 2. BP neural network algorithm flow

2.2 Support Vector Machine

Support Vector Machine (SVM) is a technique for building an optimal binary classifier [10]. Later the technique was extended to regression and clustering problems. SVM is essentially a partial case based on the kernel approach. It uses a kernel function to map a feature vector into a high-dimensional space and establish an optimal linear discriminant function or optimal hyperplane suitable for training data in that space [11]. The following equation is used to divide the hyperplane:

$$f(\mathrm{x}) = \mathrm{w}^T x + b \tag{1}$$

3 Establish Interference Level Assessment Factors

Both interference and interfered parties have direct influence on the interference effect. The effective influencing factors include interference effect and anti-interception ability, interference transmitter power, communication signal frequency and interference signal frequency overlap, interference form, the technical performance of the receiver and many other factors [2]. Considering the signal characteristics of both communication parties and referring to the factors affecting the interference effect proposed in the literature [3, 12], without considering the adaptive spectrum common problem [19, 20], the following six parameters are considered as the eigenvalues of the input sample set.

Communication Signal Modulation Method. The digital signals obtained by differen-t modulation methods are used as the interfered parties of the communication system. The communication party signal is defined as a symbol F_1. The five digital modulated signals are sequentially taken as values of 1.0, 2.0, 3.0, 4.0, and 5.0.

Interference Power. The ratio of the interference signal power to the communication signal power is JSR. The symbol is defined as F_2.

Interference Signal Pattern. The Gaussian white noise is subjected to amplitude modulation, phase modulation, and frequency modulation to obtain interference of three different modulated signals. Set its symbol to F_3. Noise amplitude modulation interference 1.0, noise frequency modulation interference 2.0, noise phase modulation interference 3.0.

Interference Threat Time. When the interference signal interferes the communication signal, there is an effective interference time and an invalid interference time. The effective interference time is also defined as the effective threat time. The time range of the interference is $t_1 \sim t_2$, and the time to start the interference is t_g.

$$F_4 = \begin{cases} 0 & t_g < t_1 \\ 1 - \frac{t_g - t_1}{t_2 - t_1} & t_1 \le t_g \le t_2 \\ 0 & t_g > t_2 \end{cases} \tag{2}$$

Anti-Jamming Performance of the Interfered Signal. The more perfect the anti-interference ability of the interfered signal, the worse the interference effect is [13]. The ability of the interference signal to adapt to the change of the interfered signal is enhanced, and the interference effect is worse. Assuming that there are a total of ten anti-interference measures, the interference signals use N kinds of anti-interference measures [3]. Then define:

$$F_5 = 1 - N/10 \tag{3}$$

The smaller the value, the worse the interference effect and the better the antiinterference performance.

Bit Error Rate. The main intention of digital communication interference is to increase the error rate of the signal demodulated by the enemy receiver, the effectiveness of communication is impaired [14], and the reliability of communication is reduced. The bit error rate is often used as an indicator to measure the interference strength of a communication receiver. Therefore, the bit error rate level is taken as the final output parameter of the communication interference effect, and the interference level is divided according to the bit error rate as follows [4].

When $P_e \geq 0.2$ the interference level is three, which is set to 3.0;

When $0.05 \leq P_e < 0.2$ the interference level is two, which is set to 2.0;

When $P_e < 0.05$ the interference level is one, which is set to 1.0.

4 Simulation Results Analysis

4.1 Evaluation Model Parameter Settings

In view of the different influences of different parameters on the interference effect [16], the unknown parameters of the anti-interference performance and the interference threat time are specified, and the interference level is redivided as follows.

Anti-interference performance: $F_5 = 1 - N/10$, N is the number of anti-interference facilities, the larger N, the better the anti-interference performance.

$$\begin{array}{ll} P_{\mathrm{e}} \leq 0.05 & \text{Interference level is } 1 \\ 0.05 < P_e \leq 0.1 \begin{cases} N \geq 3 \\ N < 3 \end{cases} & \begin{array}{l} \text{Interference level is } 1 \\ \text{Interference level is } 2 \end{array} \\ 0.1 < P_e \leq 0.2 \begin{cases} N \geq 6 \\ N < 6 \end{cases} & \begin{array}{l} \text{Interference level is } 1 \\ \text{Interference level is } 2 \end{array} \\ 0.2 < P_e < 0.25 \begin{cases} N \geq 9 \\ N < 9 \end{cases} & \begin{array}{l} \text{Interference level is } 2 \\ \text{Interference level is } 3 \end{array} \\ P_{\mathrm{e}} \geq 0.25 & \text{Interference level is } 3 \end{array} \tag{4}$$

Interference threat time: Specify the time t_g to start interference. $t1 = 5s, t2 = 25s$

$$\begin{array}{ll} 21s < t_g < 25s, 0 < F < 0.2 & \text{Interference level is 1} \\ 9s < t_g < 21s, 0.2 < F < 0.8 & \text{Constant} \\ 5s < t_g < 9s, 0.8 < F < 1 & \begin{cases} \text{Interference level changed from 1 to 2} \\ \text{Interference level changed from 2 to 3} \end{cases} \end{array} \tag{5}$$

4.2 Communication Interference Assessment Based on BP Neural Network

Experiment one:

Set up a four-layer BP neural network, double hidden layer, in which the number of input layer nodes is 5, the number of output layer nodes is 1, and the number of hidden layer nodes is (5, 5) [15]. A data sample with a data volume of 2400 was created, with 100 test sets and 2300 training sets. Some of the prediction results are shown in the Table 1 below.

Table 1. BP neural network interference level prediction results

Evaluation parameter	Sample1	Sample2	Sample3	Sample4	Sample5	Sample6
F_1	3	1	2	1	3	2
F_2	4.6	16.56	−2.55	21.53	−1.29	−10.84
F_3	2	3	1	3	3	1
F_4	4	10	3	10	10	1
F_5	11.98	22.04	14.23	6.35	7.5	5.35
E_1	Expected value					
	3	1	1	3	3	2
E_2	Predictive value					
	3.005	0.9991	0.9976	2.9997	2.9983	1.9897

After several simulation experiments, the magnitude of the prediction error $10^{-2} \sim 10^{-3}$ fluctuates around. And the classification accuracy rate fluctuates between 93% and 98%, which verifies the feasibility of BP neural network for interference level prediction.

Experiment two:

In order to better analyze the prediction effect, the prediction results are categorized into 1–3 grades, and the recognition rate curves under 600, 1200, and 2400 different data sets are obtained.

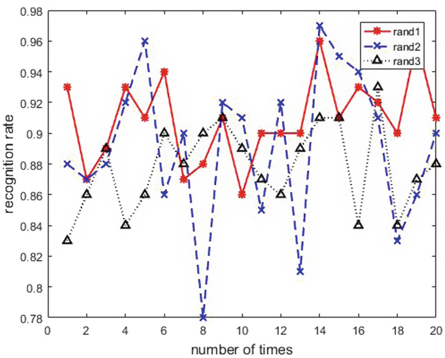

Fig. 3. Recognition rate curve sample set 600

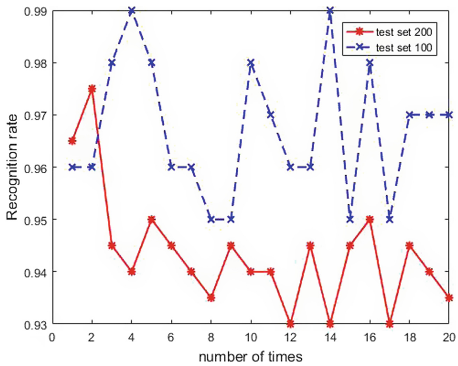

Fig. 4. Recognition rate curve sample set 2400

Figure 3 shows the recognition rate of rand1 is the most stable, and the rand2 recognition rate is the most volatile. when the data set is 600, the prediction result is unstable.

Figure 4 shows that the test set is 100, the recognition rate is almost higher than 200 except for the individual points. The smaller the proportion of the test set is, the higher the recognition rate is.

As can be seen from Fig. 5, the recognition rate fluctuates from 93% to 100%. Compared with the data set of 600, the recognition rate increases by about 10%, and the

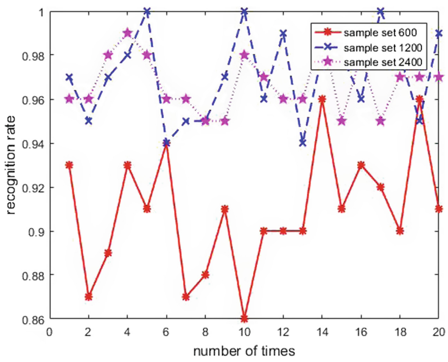

Fig. 5. Recognition rate curve test set 100

fluctuation is significantly reduced. With the increase of dataset, the accuracy gradually increases and tends to be stable.

4.3 Communication Interference Assessment Based on Support Vector Machine

Since svm is suitable for small sample classification problems, the data set used is 600, of which the test set is 100 and the training set is 500. The obtained partial interference level prediction results are as follows (Table 2).

Table 2. BP neural network interference level prediction results

Evaluation parameter	Sample1	Sample2	Sample3	Sample4	Sample5	Sample6
F_1	4	2	1	5	3	1
F_2	−13.2	11.2	8.06	−10.65	2.8	19.46
F_3	3	3	2	2	1	2
F_4	9	8	7	5	3	5
F_5	20.34	16.12	18.04	14.54	10.54	14.48
E_1	Expected value					
	1	3	1	2	3	2
E_2	Predictive value					
	1	3	1	2	3	2

The interference level evaluation results of support vector machine are ideal, and the correct rate is between 98% and 100% under small data, which verifies the feasibility of the method.

4.4 BP Neural Network and Support Vector Machine Algorithm Comparison

After 20 randomized trials, the average statistical results under 600 data sets:

Table 3. Comparison of support vector machine and BP neural network

	Predictive accuracy	Samples	Stability of results	Test set weight
Support Vector Machines	98.56%	Few	Stable	Larger
BP neural network	94.35%	Many	Unstable	Smaller

The simulation results show:

There are local optimal problems in BP neural networks, the training results are not stable, and large data sets are usually needed. Support vector machine generalization ability is better than BP neural network, the algorithm has global optimality and is suitable for small data sets. In short, support vector machine can better predict interference to smaller samples and have better High accuracy. SVM algorithm is difficult to implement for large-scale training samples, but BP neural network is suitable for large data sets. For the communication interference problem, according to the different processing problems, choose the support vector machine and BP neural network algorithm (Table 3).

5 Conclusion

In this paper, the experiment of communication interference level evaluation is carried out under two nonlinear classification algorithms. Firstly, the data set is constructed according to the characteristic parameters affecting the interference, and then the experiment is completed under the two algorithms. The results show that both of them can better evaluate the interference rate with high accuracy, which confirms the feasibility of the method. Compared with the BP neural network, the support vector machine avoids the disadvantages of local optimization and the evaluation results are stable and accurate under small data samples. Since the experimental conditions are too good and the actual interference is not considered, the correct rate is higher. How to experiment with real-time accepted signals and how to establish a complete interference system are the next research direction.

Acknowledgment. This work is supported by the National Natural Science Foundation of China (61771154) and the Fundamental Research Funds for the Central Universities (HEUCFG201830).

This paper is also funded by the International Exchange Program of Harbin Engineering University for Innovation-oriented Talents Cultivation.

Meantime, all the authors declare that there is no conflict of interests regarding the publication of this article.

We gratefully thank of very useful discussions of reviewers.

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