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ROBUST IDENTIFICATION ALGORITHM OF NETWORK COMMUNICATION SIGNALS VIA MACHINE LEARNING MODEL

PEIFENG SUN *AND GUANG HU †

Abstract. The efficiency of communication processing and control depends heavily on the recognition of network signals, however irregularities and mistakes frequently arise during the application process. In this work, we leverage machine learning models to automatically identify computer network communication signals, leveraging recent advancements in artificial intelligence technology. In the simulation, we employed a support vector machine (SVM) model, and we utilized parameter optimization to address the overlearning issue. The process of classifying modulation signals involves the extraction of feature parameters through the application of support vector machine and radial basis function neural network (RBFNN) models, respectively. Real-world network communication involves the observation and collection of signals from various viewpoints or feature spaces. These views provide a variety of detailed insights into the signal, and feature extraction is carried out for each view to produce the associated feature vectors. An extensive description of the signal can be generated by extracting the features from several viewpoints. Various viewpoints' feature vectors are combined and synthesized. The robustness of signal recognition can be increased and the bias and inaccuracy that could be generated by a single view can be minimized by combining the data from several perspectives. The support vector machine performs better than the radial basis function neural network, according to experimental findings. When the signal-to-noise ratio (SNR) is high, network communication signals function effectively. However, the latter (RBFNN) performs significantly worse in low SNR settings whilst the former (SVM) retains good accuracy. Therefore, when it comes to computer network communication signals, the support vector machine model is thought to be more reliable.

Key words: Classroom interaction, Data analysis, Compound foreign language, Business English teaching, Communication technology, Data fusion

1. Introduction. This work provides an enhanced approach based on the dual-attention module to compensate for the limitations of the conventional communication recognition mechanism. When using the conventional communication recognition mechanism, in order to accomplish the desired mobilization communication goal, the mobilization recognition instruction must be prepared ahead of time and linked to the appropriate execution system [1]. By computing the similarity weights between the constituents of the input signals, self-attentive mechanisms can recognize the global interdependence of the input signals and produce the output of a weighted sum. This process increases the accuracy of signal detection and aids in locating significant characteristics in the time-series data. The primary purpose of the channel attention mechanism is to draw attention to the relative relevance of the various input signal channels [2]. The channel attention mechanism increases the robustness of signal identification by enhancing the important channels and ignoring or attenuating the unimportant ones by computing the importance weights of each channel. The self-attention mechanism and the channel-attention mechanism work together in the dual-attention module to improve recognition performance in a complimentary manner. The model's ability to capture signal features more thoroughly and improve identification performance is made possible by the combination of the self-attention mechanism, which concentrates on global features, and the channel-attention mechanism, which concentrates on local importance. The input signal in the particular implementation first travels through the feature extraction layer, after which it is processed by the channel attention mechanism and the self-attention mechanism, in that order. Lastly, the processed features are combined and sent into the classifier so that it may be recognized. This model architecture can substantially decrease mistakes and flaws while enhancing the ability to recognize signals in complex situations. In light of the aforementioned background circumstances, it is therefore required to combine the real communication recognition demands in order to create a more solid and systematic recognition approach [3].

*Computer Department,Zhengzhou Preschool Education College,Zhengzhou,Henan 450099, China.(sunpf2009@126.com).
†Computer Department,Zhengzhou Preschool Education College,Zhengzhou,Henan 450099, China.

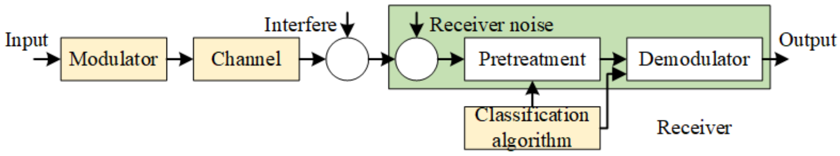

Fig. 1.1: Schematic Diagram of Modulation Identification.

Automatic identification methods for joint modulation via computer network communications are investigated and assessed in this work. It is necessary to process and modify the corresponding identification environment before developing the joint modulation automated identification technology for computer networks. Signal transmission and recognition are generally not too difficult while a computer network is operating, although this is only true in a single network setting [4]. The desired outcomes are frequently not obtained when there is a complicated environment or distinct recognition instructions. Capture identification is the primary mechanism used in traditional automatic identification systems. People are gradually becoming more aware of machine learning technology thanks to the invention of the automatic identification mode.

The two components of a modulation mode classifier's design are algorithm selection and signal preprocessing, as seen in Fig. 1.1. The first link is mainly for signal processing, including down conversion, noise suppression, parameter estimation and channel equalization. The next step is to select a proper classification algorithm, classify the signal after signal preprocessing, and then transmit the intercepted signal and the tag after signal classification to the demodulator to complete the demodulation of the intercepted signal.

Prior knowledge of the signal is typically difficult to come by in an electronic reconnaissance system. Starting from the spectrum, the third-party receiver will pick up the signal of interest and estimate its frequency hopping frequency, symbol rate, and other characteristics. To obtain the IF signal, the third-party receiver applies band-pass filtering and down conversion to the signal based on the characteristic parameters that were acquired in the preceding stage. Next, with a phase-locked loop, the carrier frequency and additional information of the IF signal are retrieved. After that, down conversion is used to retrieve the baseband signal. Then, in order to extract useful tactical information, modulation categorization and demodulation are done. The following study directions pertain to the modulation categorization of non-cooperative communication signals: (1) The different kinds of signal modulation patterns can be recognized using the classification method. Previous study has shown that the more modulation modes the algorithm can recognize, the better; however, this comes at the expense of a decrease in the system's overall recognition rate and an increase in its complexity. Consequently, creating a classification system with high identification performance and the ability to identify various modulation kinds will be a significant advancement.(2) A modulation classification method with a high identification rate in low SNR environments is created with the complicated ECM environment in mind. (3) The modulation classification algorithm's engineering realization. (4) The generalization and fitness of the algorithm. The two primary categories of modulation classification specific methods at the moment are maximum likelihood ratio detection method and statistical pattern identification method. The former establishes the threshold of the likelihood ratio result and thereafter ascertains the signal's modulation mode by calculating the likelihood function of the gathered signal. The latter is dependent on feature extraction.

Preprocessing is used to extract the feature parameters from the recorded signal. The retrieved parameters are then evaluated according to predefined decision criteria to get the pattern classification results. The classifier's tasks include summarizing the input feature vector into an appropriate category in line with a preset rule and completing the mapping of the feature space to the decision space, which yields the final recognition result. In the test phase, the classifier is fed the feature quantity of the test sample to determine the classification outcome; in the training phase, the classifier is trained using the feature quantity of the training sample until it fulfills the preset rules. Tree classifiers, neural network classifiers, support vector machines, and other classifiers based on machine learning algorithms are common classifiers. A hierarchical branch structure resembling a tree is used by the tree classifier. Each layer distinguishes the type of signals according to different parameters, and gradually completes the classification of multiple signals; Neural network

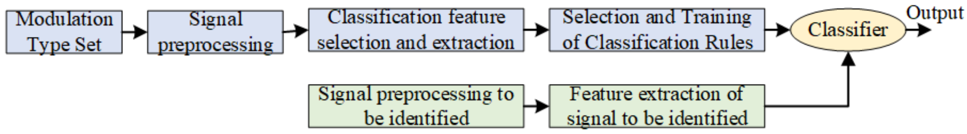

Fig. 2.1: Pattern recognition based on feature extraction.

classifier uses artificial neural network to train and test a variety of signals. Its disadvantage is that it is prone to local extremum, under learning and over learning problems. Support vector machine classifiers recognize and classify signals by constructing hyperplanes, and introduce kernel functions and relaxation variables to improve training error and generalization error. Therefore, it solves the problems of under fitting, over fitting and local extremum, and has good generalization. Nonetheless, the support vector machine classifier's performance will be impacted by its relaxation variables and kernel function, making the optimisation of these two parameters an unavoidable issue.

2. Related works.

2.1. Statistical pattern recognition. According to the concept of statistical models, modulation classification is essentially a pattern classification problem. The overall process is divided into two parts: (1) Training part. Given a set of alternative modulation types, select and extract the characteristic parameters of the training signal to form training samples for training the classifier until the classification output meets certain error requirements, or until an appropriate classifier decision threshold is generated; (2) In the performance test phase, feature parameters are extracted from test signals to form test samples for testing classifiers, and then the output prediction results are analyzed. Classifier, feature parameter extraction, and signal preprocessing are the main elements of the pattern recognition-based modulation classification strategy, as shown in Fig.2.1. A classifier is an important implementation tool that works in tandem with feature selection and extraction to produce a variety of pattern recognition methods. Feature selection and extraction are intermediate links that play a major role in determining the system's performance.

A double mapping from signal space to observation space and back to feature space is how feature extraction is understood. The purpose of the former mapping, which is a part of signal preprocessing, is to extract several signal characterisation parameters; The later mapping, which maps high-dimensional observation space to low-dimensional feature space and lowers computational cost, is the fundamental component of pattern recognition.

2.2. Characteristic parameters and classifier model of network communication signals. For the classification of modulated signals, the instantaneous envelope, phase and frequency included in the signal are the most straightforward characteristics. Among signals of different modulation types, the modulation information of MASK signal is included in the envelope, the modulation information of MPSK signal is included in the phase, and the modulation information of MFSK signal is included in the frequency [5]. Scholars are the pioneers of these researches, and have creatively put forward a lot of modulation signal recognition methods based on the instantaneous characteristic parameters of the signal: The instantaneous amplitude, frequency, phase, and other properties of the signal are extracted using the Hillbert transform. The simulation findings indicate that at 10 dB signal-to-noise ratio, the recognition rate for AM, FM, USB, LSB, VSB, and DSB signals is 91%; subsequently, these signals were classified using neural networks. According to the simulation results, at a signal-to-noise ratio of 10 dB, the recognition rate reached 98%. Signal modulation recognition also frequently makes use of the signal's spectrum, power spectrum, and other properties [6, 7]. Researchers recognise USB, LSB, FSK, and other signals ingeniously by using the spectrum information of signals. According to the simulation results, at 10 dB signal-to-noise ratio, the recognition rate surpasses 95% [8, 9]. By using the power spectrum characteristics of the signal, the scholars simulated the classification of MSK, FSK, FM, BPSK, QPSK, OQPSK and other signals without prior information, and the recognition rate of the simulation results reached more than 95% [10, 11]. By using spectral correlation features, scholars simulated and realized the classification of ASK, FSK, MSK, PSK and QPSK signals. In the simulation results, the recognition rate reached 97% at 0 dB SNR. The characteristics based on cyclic spectrum analysis are also commonly used in the recognition and classification of digital signals. Cyclic stationarity is very helpful to distinguish between digital communication signals and noise, because digital communication signals have cyclostationarity, while noise is generally non-stationary.

Its spectral correlation function has zero amplitude when the cyclic frequency is not zero, and a large value when the cyclic frequency is zero. Digital communication signals are just the opposite. When the cyclic frequency is zero, the amplitude of the spectral correlation function is zero. Otherwise, it has amplitude. When modulation identification is used to extract parameters, this characteristic greatly helps to lessen the effect of noise on the findings [12, 13]. Scholars simulated the classification of FSK, BPSK, QPSK, MSK and other signals by using cyclic spectrum correlation features. In the simulation results, the recognition rate reached 95% at 10 dB signal-to-noise ratio [14]. Scholars used cyclic spectrum analysis to classify BPSK, QPSK and OQPSK signals. In the simulation results, the recognition rate reached 95% at 8 dB signal-to-noise ratio. Higher order cumulants can characterize the distribution of constellation, and are generally used to distinguish MASK and MPSK signals. The parameters extracted by high-order statistics are robust to phase shift and frequency shift, and can also suppress colored Gaussian noise [15]. Scholars have proposed a digital signal classification method based on cumulants, which can effectively classify MPSK, MQAM and MPAM signals [16]. Scholars use the cumulant based extraction method to identify MPSK signals within a class. The simulation results show that the recognition rate exceeds 95% at 10 dB SNR [17]. Scholars classify MQAM and MPSK signals based on mixed cumulants. In the simulation results, the recognition rate reaches 100% at 10 dB SNR. Some scholars directly extract cyclic statistics from communication signals for modulation classification [18]. Based on cyclic cumulants, scholars have realized effective classification of 4PSK and 16QAM signals. In the simulation results, the recognition rate is close to 100% at 0 dB SNR. Scholars use cyclic cumulants to extract features and recognize SQAM signals with frequency offset. In the simulation results, the recognition rate is close to 90% at 8 dB SNR. Wavelet transform is comparatively appropriate for digital signal processing operations and has good local detail mining ability in both time domain and frequency domain, which may be used to better extract the delicate and instantaneous properties of signals. The scholars adopted Haar wavelet transform to capture the characteristics of instantaneous frequency and phase jump of the signal, and realized the classification of MPSK signal and MFSK signal.

The recognition rate is more than 90% at 10 dB signal-to-noise ratio. Scholars use wavelet packets to decompose IF communication signals, calculate the mean square deviation of the decomposition coefficient vector of the fine part and the approximation part of each layer, use these mean square deviations to form characteristic parameters, and simulate the classification of MASK, MFSK and MPSK signals. According to the simulation results, with a signal to noise ratio of 10 dB, the recognition rate exceeds 95%. Scholars adopted the classification algorithm of discrete wavelet transform combined with neural network, and simulated the recognition and classification of FSK, PSK and QAM signals. In the simulation results, the recognition rate at 5 dB signal-to-noise ratio reached 97%. The wavelet transform-based feature parameters provide good time-frequency domain fine features and operate well in low SNR environments. The constellation diagram is another widely used method for analyzing digital modulation signals. A trustworthy characteristic parameter for distinguishing between MPSK and MQAM signals is a constellation diagram. It usually takes some prior signal understanding for researchers to recreate constellation information. Clustering is the most effective method for reconstructing constellation information. Researchers classified 16QAM, QPSK, and 8PSK signals by reconstructing constellation diagrams from signal symbols that were first introduced with noise using the fuzzy C-means clustering technique.

The simulation results show that the recognition rate exceeds 90% at 5 dB SNR, and exceeds 90% at 0 dB SNR for 8PSK and V.29 signals. However, constellation based methods need to know some prior information or excellent estimation parameters in advance. Therefore, when using constellation based feature extraction methods, excellent preprocessing process and an effective constellation reconstruction method for fuzzy parameters must be adopted. In addition to the features described above, there are other feature extraction algorithms. Scholars used Lempel Ziv complexity method to classify seven kinds of signals. In the simulation results, the recognition rate is 95% at 5 dB signal-to-noise ratio; BPSK, QPSK, CW, BFSK and QFSK signals are classified by information dimension and box dimension analysis. The simulation results show that the recognition rate

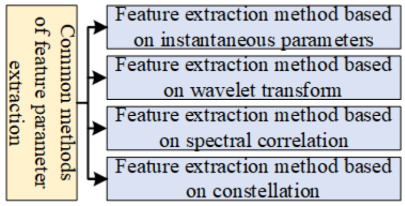

Fig. 3.1: Common Methods of Characteristic Parameters.

exceeds 98% at 5 dB SNR. Scholars used cloud mode parameter extraction method to classify V.29 and 8PSK signals. In the simulation results, the recognition rate reached 95% at 5 dB SNR.

Classifiers are very important; feature extraction and selection are even more important. After completing the mapping from the feature space to the decision space, the classifier's job is to summarize the input feature vector into a suitable category in accordance with a predetermined rule. In order to determine the classification outcome during the test phase, the feature quantity of the test sample is fed into the classifier. In the training phase, the classifier is trained using the feature quantity of the training sample until it meets the preset rules. Common classifiers include support vector machines, neural networks, trees, and other machine learning algorithm-based classifiers. The tree classifier uses a tree like hierarchical branch structure. Each layer distinguishes the type of signals according to different parameters, and gradually completes the classification of multiple signals; Neural network classifier uses artificial neural network to train and test a variety of signals. Its disadvantage is that it is prone to local extremum, under learning and over learning problems. Support vector machine classifiers recognize and classify signals by constructing hyperplanes, and introduce kernel functions and relaxation variables to improve training error and generalization error.

Therefore, it solves the problems of under fitting, over fitting and local extremum, and has good generalization. However, the kernel function and relaxation variables of support vector machine will affect the performance of the classifier, so the optimization of these two parameters is an inevitable problem for support vector machine classifier. Compared with the classification method based on maximum likelihood ratio, the classification method based on feature extraction has the following advantages: (1) The method is relatively simple, which is conducive to engineering implementation; (2) The complexity is small, and it is easy to classify online in real time; (3) The signal classification can be realized without too much prior knowledge. Its disadvantage is that this method will have a certain dependence on the number of training samples. Comprehensive analysis shows that the classification method based on feature extraction has a wider application prospect, especially in the field of electronic reconnaissance and electronic countermeasures. Therefore, the work carried out in this paper is based on pattern recognition methods.

3. Methodology.

3.1. Feature parameter extraction. The different feature extraction techniques for the modulation classification of network communication signals (Fig.3.1).

The first is a feature extraction technique based on immediate parameters. The easiest features to classify modulated signals based on are the signal's immediate envelope, phase, and frequency. The modulation information of the MASK signal is included in the envelope among signals with various modulation types. The MPSK signal's modulation information is contained in the phase, and the MFSK signal's modulation information is contained in the frequency. The second method of feature extraction is wavelet-based. Wavelet transform is very suitable for digital signal processing and may be used to better extract the subtle and instantaneous features of signals because of its strong local detail mining capabilities in both the time and frequency domains. The wavelet transform-based feature parameters provide good time-frequency domain fine features and can perform well in low SNR environments. A technique for extracting features that relies on spectral correlation is the third. Digital signals are frequently recognised and classified using features derived from cyclic spectrum analysis, and cyclostationarity is a valuable tool for differentiating digital communication signals from noise.

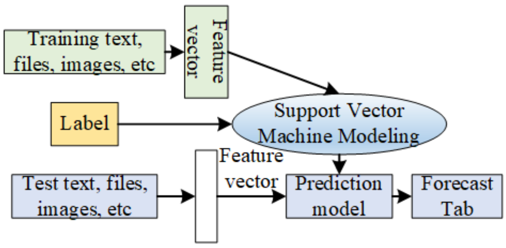

Fig. 3.2: Structural model of support vector machine.

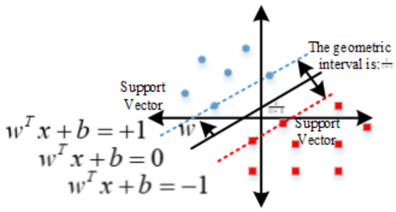

Fig. 3.3: Support Vector Machine Mathematical Model.

Because digital communication signals are cyclostationary, their spectral correlation function has zero amplitude when the cyclic frequency is not zero and a large value when the cyclic frequency is zero, while noise is usually non-stationary. Conversely, digital communication signals have amplitude when the cyclic frequency is non-zero and zero amplitude otherwise. This specific feature is very helpful in reducing the impact of noise on modulation recognition results. The fourth method extracts features using a constellation diagram. The constellation diagram is another widely used method for analyzing digital modulation signals. A trustworthy feature parameter for distinguishing between MPSK and MQAM signals is a constellation diagram. Usually, some prior information of signals is needed to reconstruct constellation information. Clustering is the most effective method to reconstruct constellation information. However, constellation based methods need to know some prior information or excellent estimation parameters in advance. Therefore, when using constellation based feature extraction methods, excellent preprocessing process and an effective constellation reconstruction method for fuzzy parameters must be adopted.

3.2. Classification of signals using support vector machines. Scholars proposed a unique concept in 1995: the Support Vector Machine (SVM). In order to achieve the best generalization ability, SVM uses limited sample information to search for the best compromise between the model's complexity and prediction ability, or, more specifically, between the model's ability to identify arbitrary samples and the accuracy of its training samples. The VC dimension theory and the structural risk minimization concept serve as the foundation for this strategy. Additionally, the SVM has shown good performance in addressing high-dimensional and nonlinear pattern problems due to the incorporation of the relaxation variable and kernel function. These benefits can be extended to other problems, such as function fitting. Its excellent generalisation ability makes it suitable for solving small sample problems (Fig.3.2).

In Fig.3.3, the central gap in the picture is supported by two classification planes, shown by dotted lines. The center hyperplane (black solid line) is the same distance from the two categorization planes. The two categorization planes will have a few "support" points. These "support" points are characterized as support vectors because they provide vivid support for the hyperplane; these support vectors make up a small portion of the sample.

In Fig.3.3, the mathematical definition of hyperplane is:

$$w^T x + b = 0 \tag{3.1}$$

The function interval is:

$$\gamma = y\left(w^T x + b\right) = yf(x) \tag{3.2}$$

The mathematical definition of geometric interval is:

$$\tilde{\gamma} = \frac{y\left(w^T x + b\right)}{||w||} = \frac{|f(x)|}{||w||} \tag{3.3}$$

where x is the eigenvector, y is the label value, and the function interval $y\left(w^T x + b\right) = yf(x)$ is $|f(x)|$ in essence, which is defined as the function interval for convenience; The geometric interval $\tilde{\gamma}$ is an intuitive distance from a point to a hyperplane, which has practical meaning.

3.3. Classification of signals using RBF neural networks. The bionics principle, which imitates brain neurons and learns from the outside environment to gather experience, is the basis of the artificial neural network concept. The experience is then stored in synapses that are connected to the neurons. The role of storing experience and the capacity to conduct computation are formed by artificial neural networks, which arrange basic processing units into a large-scale parallel distributed processing mechanism. Its large-scale parallel distributed architecture and capacity for learning generalization serve as examples of its potent computing capability. Properties and capacities of artificial neural networks include the following:

(1) Nonlinear: One crucial characteristic of artificial neurons, especially when modeling some nonlinear systems, is their ability to be classified as either linear or nonlinear.

(2) Input output mapping: Neural network is a popular algorithm with teacher learning or supervised learning. It uses labeled training samples to continuously update the synaptic weights of each artificial neural unit. By selecting a training sample from the training set each time and sending it to the network for training, the synaptic weight of the network is adjusted continuously according to the difference between the set statistical criteria and the actual response generated by the network operation, until the synaptic weight in the network system reaches a stable state that does not continue to change. Before the weight is stable, the network may receive the training samples that have been traversed throughout the period several times in a different order. Therefore, the neural network's foundation for realising the learning function from the training samples is the creation of input-output mapping.

(3) Adaptability: The artificial neural network will constantly change the synaptic weight value until it adapts to the external environment due to changes in the external environment. When the network is in a constantly changing external environment, the synaptic weight of the unit can change with the change of the environment. If neural network is used for pattern resolution, it can be developed into an adaptive pattern resolution method.

(4) Evidence response: The artificial neural network can select the pattern information in pattern resolution, and also provide the confidence information of the pattern. When there are patterns that cannot be judged, the confidence information obtained can be used to reject and screen out these patterns, thus improving the performance of the neural network (Fig.3.4). Neural unit is the basic unit of network operation and processing, which is composed of three basic links: synapse, adder and activation function:

$$u_k = \sum_{j=1}^{m} w_{ki} x_i \tag{3.4}$$

$$y_k = \Psi\left(u_k + b_k\right) \tag{3.5}$$

Fig.3.5 below depicts the neural network multilayer perceptron model.

3.4. Function of radial basis neural network architecture. Three layers must be designed in order to construct the Radial Basis Function (RBF) neural network depicted in Fig.3.6.

1. The input layer consists of m source nodes, where m is the input feature vector x's dimension.

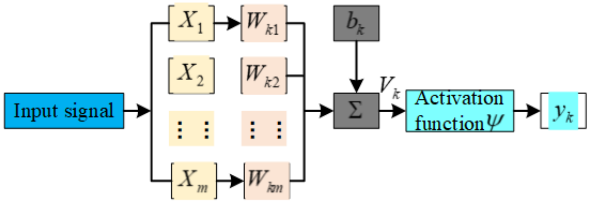

Fig. 3.4: Neuron model.

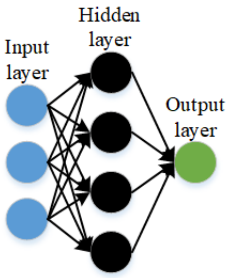

Fig. 3.5: Neural Network Model.

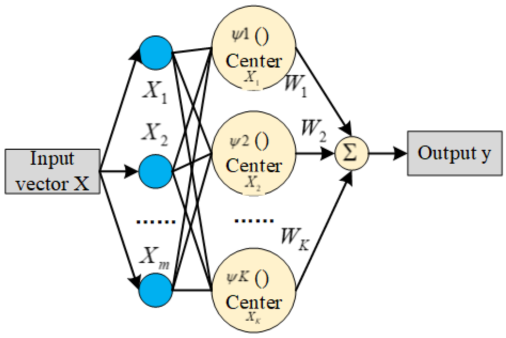

Fig. 3.6: RBF neural network model.

2. Hidden layer: Each of the K calculation units that make up this layer has the radial basis function:

$$\Psi_j(x) = \Psi\left(\|x - x_i\|\right), i = 1, 2, \ldots, K \tag{3.6}$$

The i source node x_i determines the radial basis function's centre. The radial basis function network's source node and hidden node are connected directly and without weight, in contrast to the multi-layer perceptron. The output layer is made up of just one adder unit. Since the Gaussian function is used as the radial basis function in this work, each hidden central layer calculation unit in Fig.3.6 is defined as:

$$\Psi_i(x) = \Psi\left(x - x_i\right) = \exp\left(-\frac{1}{2\sigma_i^2}\|x - x_i\|^2\right), i = 1, 2, \ldots, K \tag{3.7}$$

4. Experiments.

4.1. SVM network performance identification performance analysis. After manually adjusting the kernel parameter g and the penalty factor C, Fig.4.1 displays the simulation prediction performance; Fig.4.2

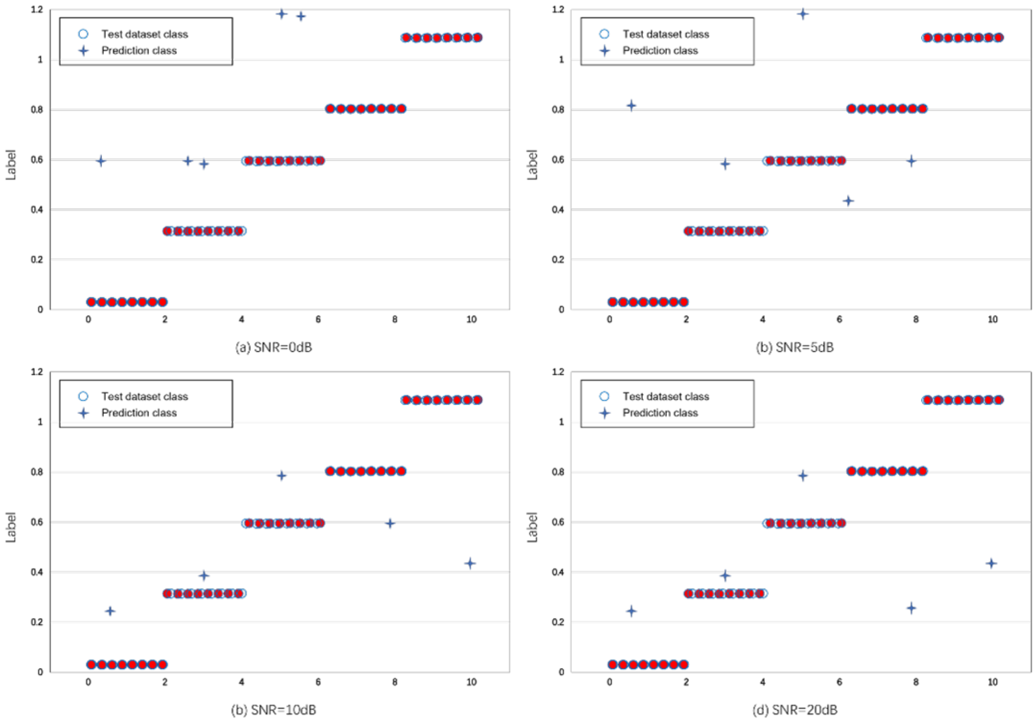

Fig. 4.1: SVM prediction accuracy when parameters are not optimized (SNR=0,5,10,20dB).

Table 4.1: Comparison between the results of manual parameter adjustment (bh) of c and g parameters and the results of genetic algorithm parameter optimization (GA algorithm).

SNR (dB)	0	5	10	15	20
C (bh)	40000	46583	46583	60000	50000
g (bh)	0.001	0.001	0.001	0.001	0.001
Accuracy (bh)	96.65%	97.76%	96.65%	96.65%	98.87%
C (ga)	76.6	93.2	78.1	22.3	22.1
g (ga)	0.054	0.0636	0.01	0.088	0.026
Accuracy (ga)	85.58%	90.00%	93.31%	91.13%	95.58%

shows the simulation prediction effect of C and g parameters after genetic algorithm optimization (when only the first four feature parameters are added).

The value of penalty factor C achieved by manual parameter adjustment is appalling when compared to the simulated performance before and after parameter optimization, and the identification rate essentially stays constant when the signal to noise ratio varies. In this case, the problem of hard spacing (overlearning) arises. The justification for this is that the minimum distance required to exist between every sample point and the categorization plane is known. The unfortunate outcome is that the model's capacity to generalize is reduced as a result of its ease of constraint by a small number of points. The parameters are healthier and the recognition rate is healthier with the trend of the signal to noise ratio after the genetic algorithm optimization, despite the fact that the recognition rate lowers. See Table4.1, Fig.4.3 and Fig.4.4.

When the aforementioned five characteristic parameters are applied, as the simulation results in Fig.4.4 demonstrate, the modulation recognition of nine signals 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, QAM, AM and FM is realized based on support vector machine simulation, and the simulation recognition accuracy rate

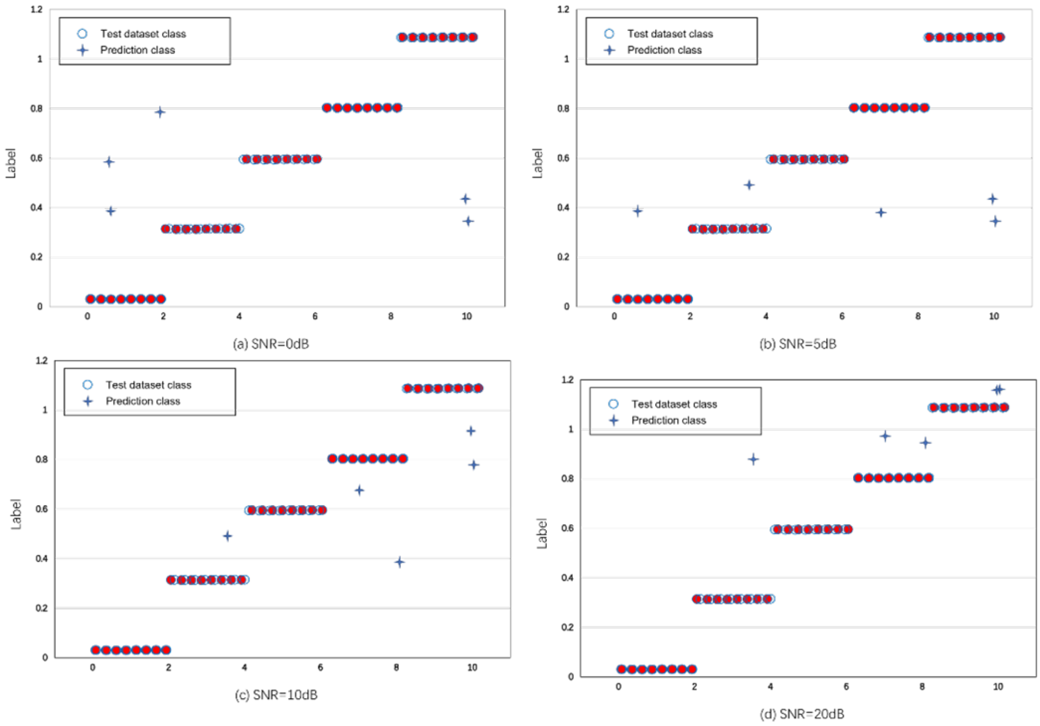

Fig. 4.2: SVM prediction accuracy after parameter ga optimization (snr=0,5,10,20dB).

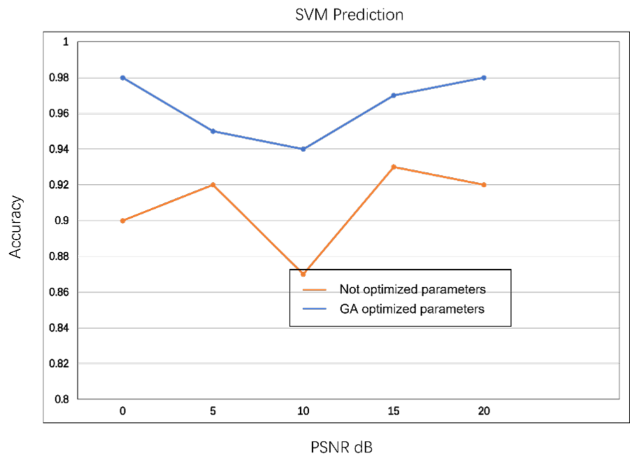

Fig. 4.3: Comparison of Prediction Results before and after Parameter Optimization.

exceeds 80% at - 10 dB signal-to-noise ratio; The simulation accuracy is close to 100% when the signal-to-noise ratio is equal to 0 dB. The simulation results validate the efficiency of the approach presented in this research. Simultaneously, it is discovered that the primary error arises during the identification of MFSK and 4PSK signals at low signal-to-noise ratios.

4.2. RBF network signal performance identification and analysis. According to the simulation results in Table4.2, Fig.4.5 and Fig.4.6, when the feature parameter group obtained in this paper is based on

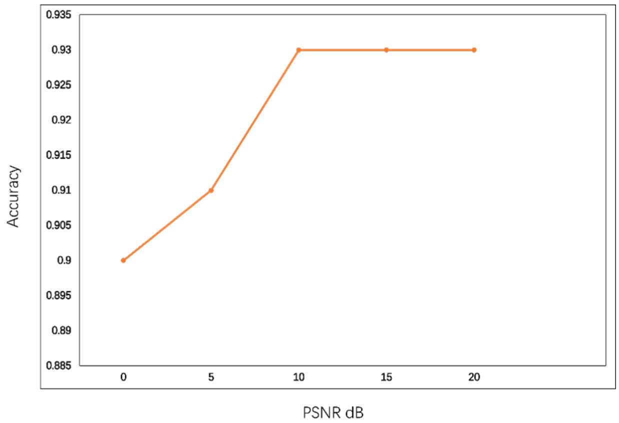

Fig. 4.4: Line Chart of SVM Prediction Results.

Table 4.2: Recognition rate and corresponding parameters of RBF neural network.

Signal-to-noise ratio	-10dB	-7dB	-5dB	-3dB	0dB	5dB	10dB	15dB	20dB
Basis function width	16	4	15	11	12	15	15	16	13
Number of hidden layer neurons	150	125	125	125	125	75	50	50	50
RBF	36.65%	54.42%	71.13%	75.54%	91.13%	100%	100%	100%	100%

Table 4.3: Comparison of Simulation Prediction Data Results of SVM Algorithm and RBF-NN Algorithm.

SNR/Accuracy	-10dB	-7dB	-5dB	-3dB	0dB	5dB	10dB	15dB	20dB
SVM	81.13%	87.76%	87.76%	94.46%	98.87%	100%	100%	100%	100%
RBF	36.65%	54.42%	71.13%	75.54%	91.13%	100%	100%	100%	100%

RBF neural network, it effectively realizes the recognition and classification of AM, FM, 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK and QAM signals, and the simulation accuracy reaches 100% at 5 dB SNR; However, the recognition performance is poor at low SNR, and the simulation accuracy is only 71.13% at - 5 dB SNR.

According to the simulation results in Table4.2, Fig.4.5 and Fig.4.6, when the feature parameter group obtained in this paper is based on RBF neural network, it effectively realizes the recognition and classification of AM, FM, 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK and QAM signals, and the simulation accuracy reaches 100% at 5 dB SNR; However, the recognition performance is poor at low SNR, and the simulation accuracy is only 71.13% at - 5 dB SNR.

4.3. Comprehensive comparative analysis of algorithms. In this paper, based on the MATLAB simulation platform, the support vector machine algorithm and the radial basis function neural network algorithm are used to classify the modulation signals according to the method of combining the obtained instantaneous parameters, cyclic spectrum analysis parameters and wavelet packet decomposition and reconstruction parameters. The simulation comparison between the two algorithms is as follows. See Table4.3 and Fig.4.7.

Based on the simulation results presented in Table4.3 and Fig.4.7, it is evident that the support vector machine outperforms the RBF neural network in this paper's modulation recognition problem, particularly when the signal to noise ratio is low and the machine still maintains a high accuracy rate. The support vector machine, for instance, can get an appreciable accuracy rate of more than 80% under the - 10 dB signal to noise ratio, whereas the radial basis function neural network rapidly degrades to only 36.65%, leading to significant performance deterioration. The simulation results of the two algorithms for this topic, in the author's opinion,

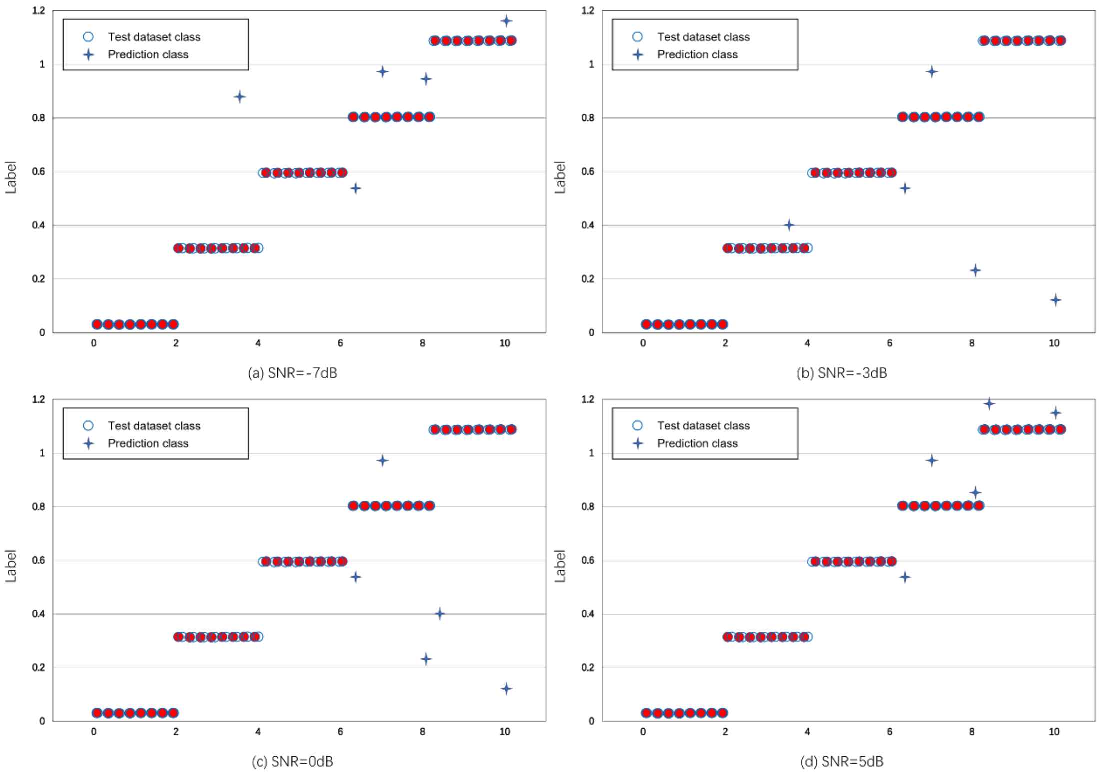

Fig. 4.5: RBF Neural Network Prediction Results.

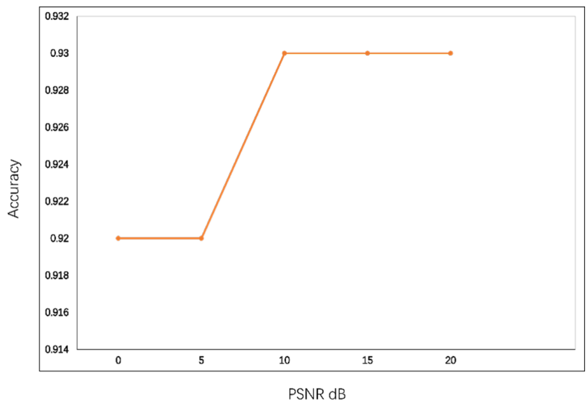

Fig. 4.6: RBF Neural Network Prediction Result Curve.

differ significantly. On the premise that the MATLAB program in this paper does not make mistakes, this difference can also be attributed to the difference in the principles of the two algorithms: RBF neural network is essentially an interpolation approximation idea, an extreme idea, which is too rigid and flexible, and its results are easily affected by the data model and the selected interpolation function; Support vector machine is essentially a compromise idea. The purpose of introducing relaxation variables and penalty factors is to fight for what should be fought for and give up what should be given up. Therefore, at high SNR, the classification

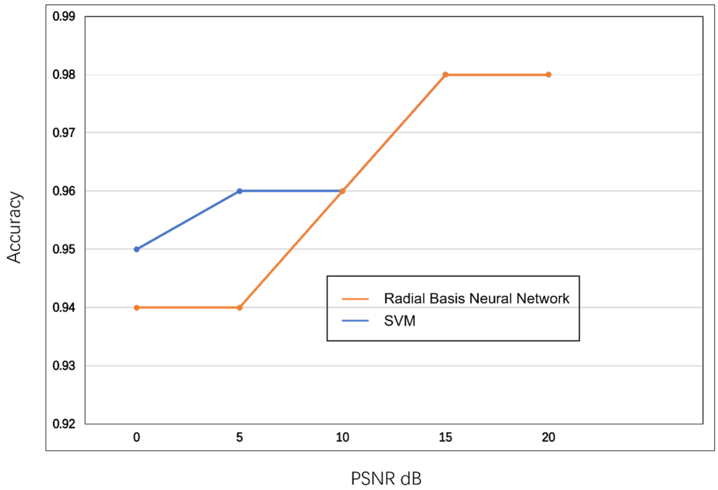

Fig. 4.7: Comparison of broken line trend predicted by SVM algorithm and RBF-NN algorithm.

features are good, and both have good performance; The classification characteristics deteriorate at low signal-to-noise ratios, and the radial basis function neural network is unable to give up a few outliers, making it little and small, while the support vector machine gives up by making the right trade-off in order to improve the overall situation.

5. Conclusion. Between signal detection and demodulation, a crucial technology in non-cooperative communication, is the process of modulation signal recognition. The relaxation variable and kernel function parameters in this research are provided based on the support vector machine's modulation recognition. After that, support vector machines are employed for signal classification, with the feature parameter group extracted in this study serving as the basis. In comparison to the same kind, the year-over-year recognition rate increases to 100% at a signal-to-noise ratio of 5 dB. Support vector machines perform better than radial basis function neural networks, especially when there is a low signal to noise ratio and the machine still maintains a high accuracy. Therefore, we verify that SVM in machine learning model can recognize network communication and has strong robustness.

Data Availability. The experimental data used to support the findings of this study are available from the corresponding author upon request.

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