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Research Article

Xuemei Yang*

Feature extraction algorithm of anti-jamming cyclic frequency of electronic communication signal

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Abstract: Anti-jamming cyclic frequency feature extraction is an important link in identifying communication interference signals, which is of great significance for eliminating electronic communication interference factors and improving the security of electronic communication environment. However, when the traditional feature extraction technology faces a large number of data samples, the processing capacity is low, and it cannot solve the multi-classification problems. For this type of problem, a method of electronic communication signal anti-jamming cyclic frequency feature extraction based on particle swarm optimization-support vector machines (PSO-SVM) algorithm is proposed. First, the SVM signal feature extraction model is proposed, and then the particle swarm optimization (PSO) algorithm is used. Optimize the kernel function parameter settings of SVM to raise the classifying quality of the SVM model. Finally, the function of the PSO-SVM signal feature extraction model is tested. The results verify that the PSO-SVM model begins to converge after 60 iterations, and the loss value remains at about 0.2, which is 0.2 lower than that of the SVM technique. The exactitude of signal feature extraction is 90.4%, and the recognition effect of binary phase shift keying signal is the best. The complete rate of signal feature extraction is 85%. This shows that the PSO-SVM model enhances the sensitivity of the anti-jamming cyclic frequency feature, improves the accuracy of the anti-jamming cyclic frequency feature recognition, reduces the running process, reduces the time cost, and greatly increases the performance of the SVM method. The good model performance also improves the application value of the method in the field of electronic communication.

Keywords: SVM, PSO, electronic communication signal, anti-jamming cycle frequency

1 Introduction

In the process of electronic communication, due to natural or artificial reasons, some electromagnetic energy enters the radio reception channel, resulting in the error and absence of receiving signals, or even the communication is blocked, that is, the electronic communication interference [1]. Electronic communication interference reduces the quality of signal reception; seriously affects the development of aviation navigation communication, railway train command, and broadcast communication; and brings inconvenience to people's lives and travel, and it also poses a threat to the safety of people's lives and property [2]. Therefore, extracting the signal anti-interference cycle frequency characteristics and identifying the electronic communication interference signals are particularly important. Support vector machine (SVM) is one of the important technologies. The SVM algorithm is a binary classification method that uses the internal product kernel function to realize the transformation of sample feature dimension, so as to reduce the complexity and difficulty of

*** Corresponding author: Xuemei Yang,** School of Electrical and Electronic Information Engineering, Sichuan University Jinjiang College, Meishan 620860, China, e-mail: xuemeiy688@163.com

operation and improve the efficiency of sample classification [3,4]. Unlike other classification algorithms, the SVM algorithm uses a small amount of support vector to determine the classification effect, which reduces the classification error caused by redundant data and improves the robustness of the classification model [5]. However, the traditional SVM algorithm still has numerous practical limitations, such as difficulties in handling large numbers of data samples and the inability to solve multi-classification problems [6]. Therefore, in order to improve the cyclic frequency feature extraction effect of the electronic communication signal, the SVM signal feature extraction and recognition model optimized by the particle swarm algorithm (PSO) is proposed. By improving the model, we can process a large number of data samples and solve the problem of multiple classification, so as to provide a technical basis for improving the quality of the signal environment and realize the effective identification of electronic communication signals. The main contributions of this research are as follows: the research solves the problem of complex signal data that is difficult to deal with in the era of big data and provides an exploration idea for the field of big data processing. Section 2 briefly introduces the application of the SVM method in recent years and various studies in the field of electronic communication signals. Section 3 details the anti-interference cyclic frequency feature extraction method based on PSO-SVM and the feature extraction model constructed based on this method. In Section 4, the performance of the PSO-SVM algorithm proposed by the research is compared and the practical application effect of the proposed model is analyzed. In Section 5,the content of this study is analyzed and summarized.

2 Related work

SVM has been used in various fields of society as a binary linear classifier. Gu et al. [7] artificially optimized the detection effect of coconut water and proposed a brand discrimination method for coconut water by combining parallel factor analysis and SVM. Parallel factor analysis was used to process the data, and SVM was used to extract and classify the data features. The results demonstrate that the classification correctness of this method can reach 100%, which improves the application value of this method in the detection of coconut water. Wu et al. [8] expounded on the importance of tracking the pilot's attention and proposed to capture the pilot's pupil state using Haar wavelet transformation and SVM method to predict the pilot's concentration force. The experiment revealed that this method can enhance the sensitivity to spherical signal features and raise the accuracy of pupil location recognition, which proves the effectiveness of the proposed method. Liao and Chen [9] suggested a radar recognition method based on k-nearest neighbor integrated with SVM-BP to improve the accuracy and efficiency of radar recognition. Compared with the traditional classification ways, the experimental data indicate that this method greatly reduces the redundant samples, optimizes the performance of the classification model, and provides a technical basis for high-precision radar recognition. Wang and Xu [10] introduced the principle of SVM, analyzed the advantages and limitations of SVM in the application of network intrusion detection, and proposed the optimization method using the improved whale algorithm. The analysis implies that the detection rate of the research method is 99.89%. Compared with the traditional approach, the operation efficiency of the proposed method is significantly improved, and the detection performance is better. To increase the effect of sports training, Wang and Qu [11] designed an artificial intelligence sports effect prediction model based on SVM and improved the prediction performance of SVM by optimizing the kernel function. The experimental data emphasize that this method promotes prediction accuracy and reduces running time, which promotes the development of intelligent sports. Veluchamy and Karlmarx [12] aimed to study biometric recognition and developed a K-SVM classification model to achieve accurate recognition of knuckles and palm prints. The study implied that this way reduces the recognition error, and the recognition accuracy can reach 0.95, which greatly improves the classification performance of the model and lays a foundation for expanding the application scope of biometric recognition [12].

Electronic communication integrates information technology and electronic science and technology, which plays an active role in promoting people's level of life and driving social development. Sharma et al. [13] expounded on the necessity of cooperative communication technology and proposed a relay strategy based on time protocol to reduce the energy consumption of ethernet hosts relay by scaling system, so as to improve the efficiency of resource utilization and achieve green cooperation in wireless communication. Numerical simulation revealed that this way reduces energy consumption, which certificates the availability of this way. Mcrae et al. [14] introduced the application of radio communication in the field of search and rescue. Aiming at the limitations of communication equipment limited by terrain conditions, they developed a unmanned aerial vehicle relay system to complete the maintenance of radio communication during search and rescue. The simulation confirmed that the proposed method can realize successful communication recovery and enhance the stability of radio communication. Shehadeh et al. [15] artificially reduce the adverse effects of the environment on ultra high frequency and very high frequency bands to improve the quality of electronic communication signals and put forward three target algorithms, such as NSGA-II, to compare and analyze the advantages and disadvantages of several methods. The results verify that the NSGA-II method can reduce the loss of communication signals and improve the quality of radio communication signals. NSGA-II can be used as the optimal method for the layout of radio communication networks. Sezgin et al. [16] artificially expanded the application range of fiber radio and proposed a time-division duplex communication model to reduce the dependence of electronic communication effect on remote units by converting the received radio frequency into binary stream. The results attest that the error signal quality in this way is as low as −30 dB, which improves the shortcomings of optical fiber wireless communication. Dang and Peng [17] aimed to study virtual network technology. In order to improve the experience effect of the dashed line display, they designed a mobile virtual reality delivery model based on the F-RAN network to realize the storage and computing decisions of virtual reality video. The analysis indicates that this method increases the tolerance delay and promotes the spectrum efficiency, which proves the feasibility of the proposed method. Becvar et al. [18] summarized the outstanding advantages of radio frequency (RF) and visible light communication (VLC) in D2D communication. To evidence the mobility management level of D2D communication, they proposed a D2D communication customization algorithm to attest the throughput of electronic communication by judging the value of RF and VLC transformation. The study emphasizes that the said method is able to increase the throughput with fewer handovers.

According to the above research results, electronic communication technology has been extensively implemented in the field of human search and rescue and virtual networks, and plays a positive role in promoting social informatization and digitalization. The SVM algorithm is mostly used for data classification, which often needs to be combined with other optimization algorithms in practical applications to improve the application value of the SVM algorithm in various industries. In order to optimize the extraction effect of anti-interference cyclic frequency features of electronic communication signals, the PSO method is proposed to improve the sensitivity of SVM against interference signals and realize the effective recognition of electronic communication signals.

3 PSO-SVM-based electronic communication signal anti-jamming cyclic frequency feature extraction method

3.1 SVM signal feature extraction model

The SVM algorithm is a supervised learning algorithm. Its basic thought is to construct an optimal separation plane to correctly divide the data set. Specifically, it includes the use of the nonlinear mapping algorithm to realize the conversion of data from low-dimensional to high-dimensional, so as to solve the problem of sample non-linearity. When solving the problem of nonlinear characteristics of samples, it is necessary to find the best hyperplane to separate the sample data. The best hyperplane satisfies the following conditions: all samples are divided into two categories and distributed on both sides of the hyperplane, and the sample data on both sides to the distance of this plane is the maximum distance [19,20]. The core of the SVM is to determine the optimal hyperplane, which avoids the complex operation process, has the goodness of simple execution and low computational difficulty, and also helps to reduce the classification error caused by complex data, which has a positive effect on improving the classification accuracy [21]. Set the input signal as $f(n)$, where n represents the total number of input signals, then the original signal sample sequence is $\{f(x)\}$, where x

represents the sequence data. In the process of signal acquisition, factors such as equipment and environment generate noise and other interferences, which affect the detection and identification of electronic communication signals. Therefore, before the feature extraction of electronic communication signals, it is necessary to standardize the original signals to advance the level of communication signals. The calculation of the normalization process is shown in the following formula:

$$f(n)' = \frac{f(n) - \min\{f(x)\}}{\max\{f(x)\} - \min\{f(x)\}}, \tag{1}$$

where $\min\{f(x)\}$ and $\max\{f(x)\}$ denote the minimum and maximum values of the original signal sample sequence, respectively, and $f(n)'$ represent the standardized electronic communication signal, $f(n)' \in [0, 1]$. Assuming that the coordinates of the input signal are (a, b), then the sample set is $Z = \{(a_1, b_1), (a_2, b_2), \ldots, (a_j, b_j)\}$, where $b \in \{+1, -1\}$, j represents the number of input signal samples, and the dimension of the input sample geometry is y. The expression of the hyperplane is shown in the following formula:

$$\omega \cdot a_i + c = 0, \tag{2}$$

where ω represents the weight vector, which is used to represent the importance of the corresponding target in the problem; c represents the critical value, which is used to represent the highest or lowest value of the influence of the target; i represents the i th sample data in the sample set, $i = 1, 2, \ldots, j$. The solution of the optimal hyperplane needs to calculate the distance between various hyperplanes, and its operation is displayed in the following formula:

$$d = \frac{1}{2}||\omega||^2 + D\sum_{i=1}^{N} \alpha_i, \tag{3}$$

where d represents the distance between hyperplanes. When d is the maximum, $\frac{1}{2}||\omega||^2$ is the minimum, it indicates that the plane is the optimal hyperplane; D it represents the penalty factor, which plays the role of adjusting the number of outliers and the degree of outliers, and α represents the slack variable, which has the effect of reducing the difference in sample data size. The optimal classification plane is shown in Figure 1.

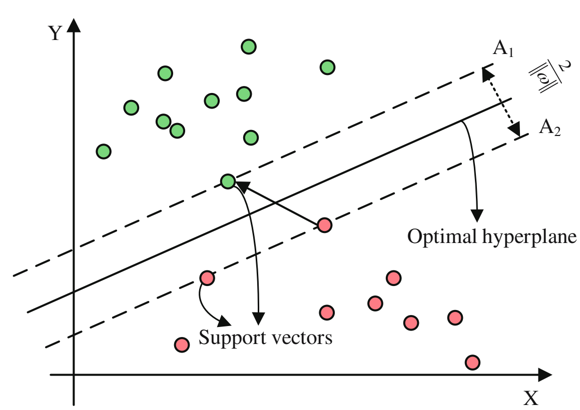

Figure 1: Optimal classification plane.

In Figure 1, different types of sample data are distributed on both sides of the optimal hyperplane, and the hyperplanes are parallel to each other; A_1 and A_2 are the two hyperplanes closest to their respective sample data, and the sample data located on the sum plane are A_1A_2 the support vector, which plays a decisive role in the classification hyperplane.

To solve the distance of the hyperplane, the Lagrangian function needs to be used, and its expression is shown in the following formula:

$$L(\omega, c, \beta, \varepsilon) = \frac{1}{2}||\omega||^2 + D\sum_{i=1}^{j}\varepsilon_i - \sum_{i=1}^{j}\alpha_i[b_i(\omega \cdot a_i + c) - 1 + \alpha_i] - \sum_{i=1}^{j}\varepsilon_i\alpha_i, \tag{4}$$

where β and ε represent the Lagrangian function multiplier, which is responsible for settling the constrained optimization matter. The supreme solution of the weight vector, critical value, and slack variable is obtained by calculation, and its operation is shown in the following formula:

$$\begin{cases} \dfrac{\partial L}{\partial \omega} = \omega - \sum_{i=1}^{N} b_i a_i \beta_i = 0 \\ \dfrac{\partial L}{\partial c} = -\sum_{i=1}^{N} b_i \beta_i = 0 \\ \dfrac{\partial L}{\partial \alpha} = D - \beta_i - \varepsilon_i = 0, \end{cases} \tag{5}$$

where the optimal solutions of ω, c, and α are obtained by partial derivative operation. To decrease the difficulty of the constrained optimization problem, it is necessary to use the duality of the Lagrangian function to transform the original problem into a dual problem, remove the original constraints, and complete the solution to the original optimization problem. The obtained optimal values of α, ω, and c are put into the Lagrange function. After the function changes, the performance of the dual form of the Lagrange function is as follows:

$$\min_{\beta} \frac{1}{2}\sum_{i=1}^{N}\sum_{s=1}^{N} b_i b_s \beta_i \beta_s (a_i \cdot a_s) - \sum_{i=1}^{N}\beta_i, \tag{6}$$

where s represents the number of sample sequences in the dual form. For the nonlinear inseparable electronic signal data, it is necessary to use the kernel function to realize the dimensional transformation of the data and complete the division of the hyperplane in the high-dimensional space. The expression of the kernel function refers to the following formula:

$$K(a_i, b_s) = (\phi(a_i)\cdot \phi(b_s)). \tag{7}$$

In equation (7), $\phi()$ a mapping function is represented. By solving the dual problem, the optimal function solution is obtained, and its calculation refers to the following equation:

$$h(x) = \mathrm{sgn}\left(\sum_{i=1}^{N}\beta_i^* b_i K(a_i \cdot a) + c^*\right), \tag{8}$$

where β_i^* and c^* are the optimal hyperplane parameters, respectively, which denote the supreme weight vector solution and the supreme critical value solution under the dual problem. The structure of the SVM signal feature extraction model is shown in Figure 2.

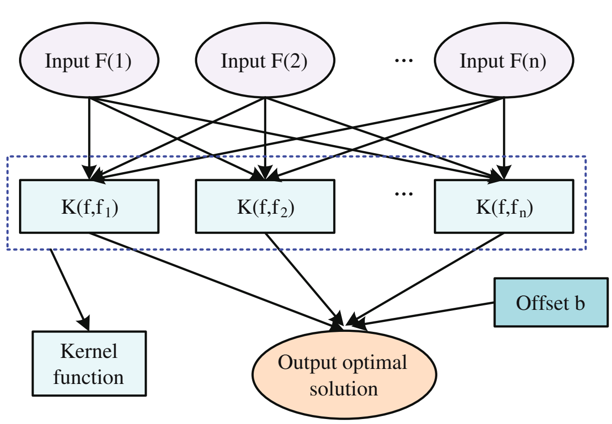

Figure 2: Signal feature extraction model based on support vector machine.

From Figure 2, it can be observed that the core of the SVM signal feature extraction model is the kernel function. The kernel function is used to complete the internal product operation in the low-dimensional enclosure, so as to obtain the optimal solution for spatial classification effectively solving the low-dimensional space linear inseparability problem. The problems of increased dimension and increased calculation amount brought about by mapping are beneficial to improve the accuracy of signal anti-jamming cyclic frequency feature extraction.

3.2 PSO-optimized SVM signal feature extraction model

The PSO algorithm is a smart algorithm derived from bird flock foraging. It uses information sharing between particles in space to adjust the optimal solution search strategy to achieve an efficient and reliable search for optimal solutions. Compared with other intelligent algorithms, PSO has the characteristics of randomness and parallelism, which can broaden the search scope of the optimum solution, speed up the convergence velocity, and improve the operation efficiency. At the same time, the advantages of ease of implementation support it as an optimization algorithm [22]. The kernel function is the key to the SVM signal feature extraction model. The selection of the kernel function parameters directly affects the effect of the frequency extraction of the signal anti-jamming cycle. The PSO method is applied to determine the optimal kernel function parameters for the SVM model and reduce the signal anti-jamming cycle. The difficulty and complexity of frequency feature extraction are reduced, the running process is simplified, and the classification performance of the SVM model is improved while improving the running speed of the model [23]. The electronic communication signal data are sent into the PSO-SVM model, and it is standardized to remove noise and improve the standardization and unity of the electronic communication signal data. The radial basis kernel function is selected as the processing tool for signal data features, and its expression is shown in the following formula:

$$K(x, x_i) = \exp\left\{-\frac{|x - x_i|^2}{\tau^2}\right\}, \tag{9}$$

where x and x_i represent the midpoint of the signal feature vector and the kernel function, respectively; $|x - x_i|^2$ represent the Euclidean distance between the two, and the vector τ is the scale factor representing the kernel width, reflecting the correlation between the support vectors. Set the penalty factor of the kernel function to D and the parameter of the radial basis kernel function to τ. At the same time, each sample data is regarded as a particle, the particle swarm size is set to E, and the search space dimension is set to Q. The initial position and initial velocity of each particle in the search space are shown below:

$$\begin{cases} m_z = (m_{z1}, m_{z2}, \ldots, m_{zq}) \\ v_z = (v_{z1}, v_{z2}, \ldots, v_{zq}), \end{cases} \tag{10}$$

where z represents the particle in the particle population z. To advance the accuracy of the optimal solution search, it is integral to set the fitness function to test the searched target solution, and its calculation is shown in the following formula:

$$\frac{1}{F} = d(D, \tau), \tag{11}$$

where $d(D, \tau)$ represents the distance between the kernel function parameter D and the parameter τ. The fitness ability is used to count the fitness value of each particle, and this is used as a basis to judge the pros and cons of the particle and adjust the search plan. During the search process, the place and speed of every particle are updated as shown in the following formula:

$$\begin{cases} m_{ij}(u + 1) = m_{ij}(u) + v_{ij}(u + 1) \\ v_{ij}(u + 1) = v_{ij}(u) + h_1 r_1[p_j(u) - m_{ij}(u)] + h_2 r_2[g_j(u) - m_{ij}(u)], \end{cases} \tag{12}$$

where u represents the number of iterations, j represents a random integer in the range of [1, q], h_1 and h_2 are the learning factors, representing the effect of the guiding behavior of the group on the particles, and the value range is usually (0, 2); r_1 and r_2 represent a casual number evenly distributed in the space [0, 1], p and g represent the best positions of the individual particle and the entire particle swarm in the current iteration, respectively. To improve the accuracy of the PSO, the inertia weight needs to be used δ to limit the flying velocity of the particle, and the position and velocity of the particle are calculated with reference to the following formula:

$$\begin{cases} m_{ij}(u+1) = m_{ij}(u) + v_{ij}(u+1) \\ v_{ij}(u+1) = \delta v_{ij}(u) + h_1 r_1[p_j(u) - m_{ij}(u)] + h_2 r_2[g_j(u) - m_{ij}(u)], \end{cases} \tag{13}$$

where $\delta \in [0, 1]$, the inertia weight δ plays the role of adjusting the particle search capacity. When the δ value is larger, the global search capacity of the particle is strengthened; when the δ value is smaller, the part search capacity of the particle is better. To solve δ the problem that the search cannot be performed when the value is 0, the inertia weight should be constrained, and its expression is shown in the following formula:

$$\delta_u = \delta_0 - u \times \frac{\delta_0 - \delta_1}{u_{\max}}, \tag{14}$$

where δ_u represents u the inertia weight at the first iteration, $u_{\max}$ expresses the total quantity of iterations set, δ_0 and δ_1 indicate the inertia weight at the beginning and end of the iteration. The influencing factors of particle position and velocity are shown in Figure 3.

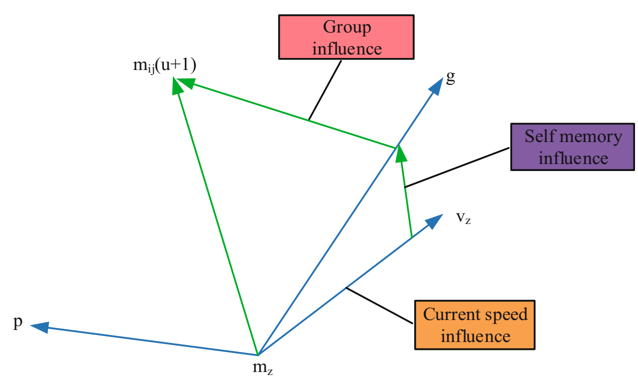

Figure 3: Influence factors of particle position and velocity.

Figure 3 shows the factors affecting the particle position and speed, which mainly include the present speed of the particle, the best place of the particle, and the best location of the particle group. The present speed of the particle reflects the adjustment effect of the inertia weight on the flying tempo of the particle; the embodiment of the historical best position adjusting its own flight plan reflects the cognitive part of the particle; the best tempo of the particle swarm reflects the cooperation ability between particles. It can be seen that the inertial part, the cognitive part, and the social part of the particle have an impact on the particle's flying speed, and by adjusting the particle's search ability, problems such as falling into local optimum and too slow search tempo are avoided.

In the process of searching for the best solution, the individual best value and the global perfect value are updated continuously iteratively until the set total amount of iterations is reached, and the optimal solution of the penalty factor D and parameters is output τ. On this basis, the kernel function of the SVM model is set and the classification optimal goal of the SVM model is adjusted, as follows:

$$h(x) = \operatorname{sgn}\left\{\sum_{i=1}^{s} \beta_i \exp\left\{-\frac{|x - x_i|^2}{\tau^2}\right\} - c\right\}, \tag{15}$$

where $s$indicates the amount of support vectors. The communication signal data are input into the PSO-SVM model, and through continuous training and testing, the learning ability of the PSO-SVM model for the characteristics of the communication signal is completed, and the extraction and classification of the characteristics of the electronic communication signal is completed. The model process of PSO-SVM signal feature extraction is shown in Figure 4.

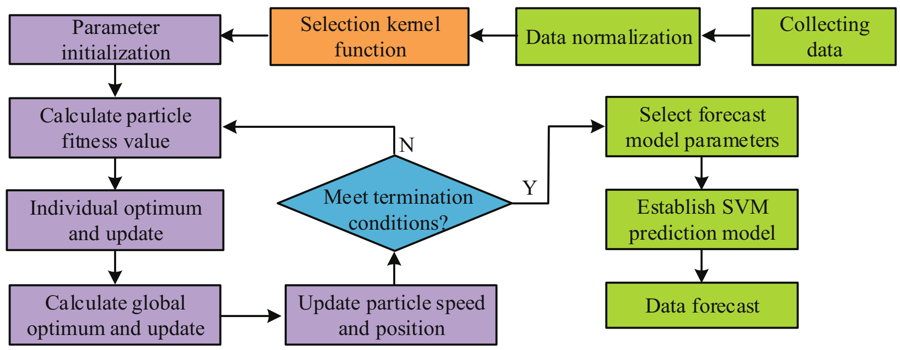

Figure 4: Structure of PSO-SVM signal feature extraction model.

Figure 4 shows that the PSO mainly performs the function of optimizing the kernel function. The global search advantage of PSO algorithm is utilized to determine the best parameters of the kernel function of the feature model of the SVM electronic communication signal, promote the improvement of the classification performance of the SVM model, and enhance the prediction ability of the SVM model for unknown communication signal data.

4 PSO-SVM electronic communication signal anti-jamming cycle frequency feature extraction model application

4.1 Performance analysis of the PSO-SVM algorithm

The Radio ML2016.04 C dataset and the Radio ML2016.10 A dataset are used for model training and testing and are represented by the A and B datasets, respectively, and 75% of the two datasets are randomly selected as the train set and 15% as the test suit and 10% as the validation set. The loss value, accuracy rate, and precision recall (PR) curve were used as model performance evaluation criteria, and three algorithm models, SVM algorithm, convolutional neural networks (CNN), and decision tree (DT) algorithm, were added as experimental comparisons. The experimental environment and data set-related information are shown in Table 1.

Table 1: Experimental environment and data set related information

		Parameter name	Parameter value
Experimental environment parameters	—	Operating system	Windows10 64 bit
		GPU	NVIDA Ge Force RTX 2070 SUPER
		CPU	Intel(R) Core(TM) i7-10700K CPU @ 3.80 GHz
		Memory capacity	32GB
Data set information	A data set	Number of samples	8,500
		Number of categories	5
		Communication signal category	BPSK, QPSK, CPFSK, GFSK, QAM64
	B Data set	Number of samples	7,789
		Number of categories	5
		Communication signal category	QAM16, 8PSK, 4PAM, WBFM, AM-DSB

The experimental environment are as follows (Table 1): operating system Windows10 64 bit, the graphics card NVIDA Ge Force RTX 2070 SUPER, the processor Intel(R) Core(TM) i7-10700K CPU @ 3.80 GHz, and the memory capacity 32 GB; the number of samples in the A dataset is 8,500, and the number of communication signal categories is 5, including Binary Phase Shift Keying (BPSK), Quadra-ture Phase Shift Keying (QPSK), CPFSK, GFSK, and QAM64; the amount of samples in the B data set is 7,789, and the number of communication signal categories is 5, including QAM16, 8PSK, 4PAM, WBFM, and AM-DSB. The comparison of loss values under different algorithm models is shown in Figure 5.

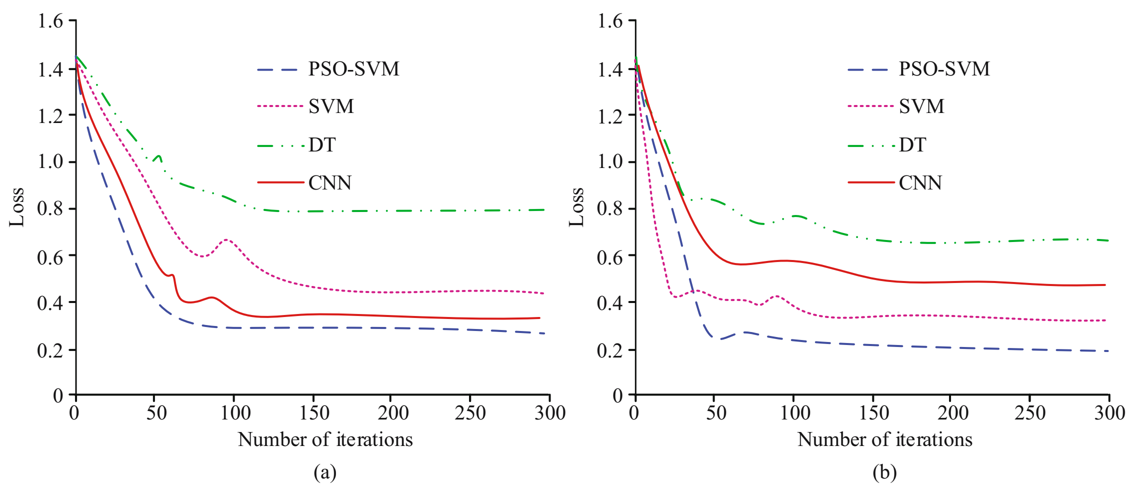

Figure 5: Comparison of loss values under different algorithm models. (a) Loss value of A data set and (b) loss value of B data set.

In Figure 5, in dataset A, the PSO-SVM model tends to be stable after 70 iterations, and the loss value remains at 0.3, and the CNN model reaches a stable level with a loss value of 0.35 after 100 iterations. The convergence speed of the DT model is faster and tends to be stable after 90 iterations, but its loss value is the highest, reaching 0.8. In the data set B, after 60 iterations of the PSO-SVM model, the loss value remains stable at the level of 0.2. Compared with the SVM model, the number of iterations and the loss value are reduced by 50 times and 0.2, respectively, best performance with test results. The PSO-SVM model reduces the loss of the model, expedites the convergence speed of the model, and elevates the operating efficiency of the classification model. The accuracy comparison of distinct algorithm models is displayed in Figure 6.

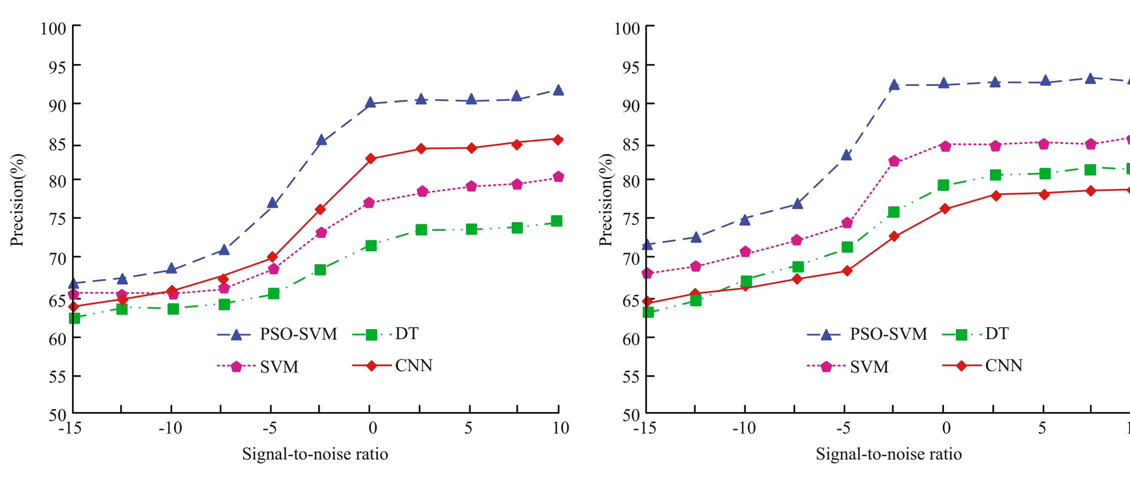

Figure 6: Comparison of accuracy under different algorithm models. (a) PR curve of A data set and (b) PR curve of B data set.

Figure 6 shows that the recognition accuracy of each algorithm model expands with the increase in the signal-to-noise ratio. When the signal-to-noise ratio is in the range of [−5, 0], the accuracy of each algorithm model improves the fastest. The correctness of the PSO-SVM model in dataset A remains in the range of [65,92], and the accuracy in dataset B remains in the range of [70,93]. The highest accuracy of the SVM model in datasets A and B is 80 and 84%, respectively. The DT model performs poorly in the two datasets, and its highest accuracy is 17 and 12% lower than that of the PSO-SVM model, respectively. Therefore, the PSO-SVM model can accurately extract the anti-interference cyclic frequency characteristics of communication signals, improve the recognition accuracy of communication signals, and reduce the adverse effect of signal-to-noise ratio on feature extraction. The comparison of PR curves under different algorithm models is shown in Figure 7.

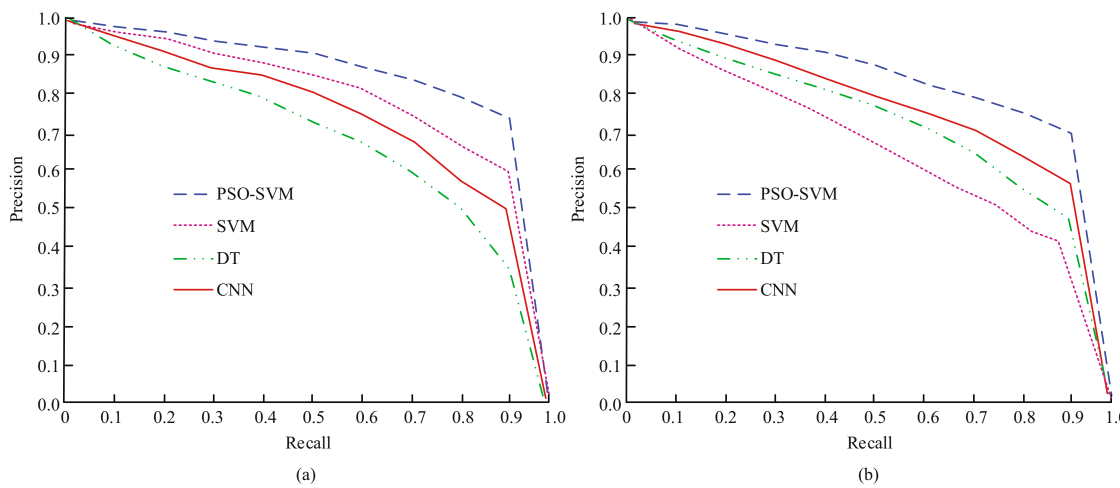

Figure 7: Comparison of PR curves under different algorithm models. (a) PR curve of A data set and (b) PR curve of B data set.

Figure 7 shows that the PSO-SVM model has the best training and testing results in the two datasets. In the training and testing of dataset A, under the same recall rate, the PSO-SVM technique and the SVM method, the maximum accuracy divergence between the DT model and the CNN model reached 0.18, 0.43, and 0.28, respectively; in the training and testing of dataset B, the maximum accuracy between the PSO-SVM model and the SVM model, the DT method and the CNN model reached 0.32, 0.25, and 0.2, respectively. The accuracy of the PSO-SVM model has always maintained the highest level under different recall rates. The PSO-SVM technique improves the probability of positive samples being correctly identified, enhances the accuracy and recall rate of the classification model, and optimizes the classification performance of the model.

4.2 Extraction result of electronic communication signal anti-jamming cyclic frequency feature

A radio station is selected as the model application object, and the electronic communication signals of the radio station are collected from October to November 2020, including four kinds of 250 electronic communication signals with cyclic frequency characteristics, which are quadrature phase shift keying QPSK, BPSK, minimum shift keying (MSK), and orthogonal quaternary phase shift keying (OQPSK) communication signal, the accuracy and integrity of feature extraction are used as evaluation indicators to judge the anti-interference cycle frequency extraction performance of the classification model for communication signals, and three algorithm models, SVM algorithm, CNN algorithm, and DT algorithm, are also added as the model application. The comparison of the accuracy of feature extraction of communication signals under different algorithm models is shown in Figure 8.

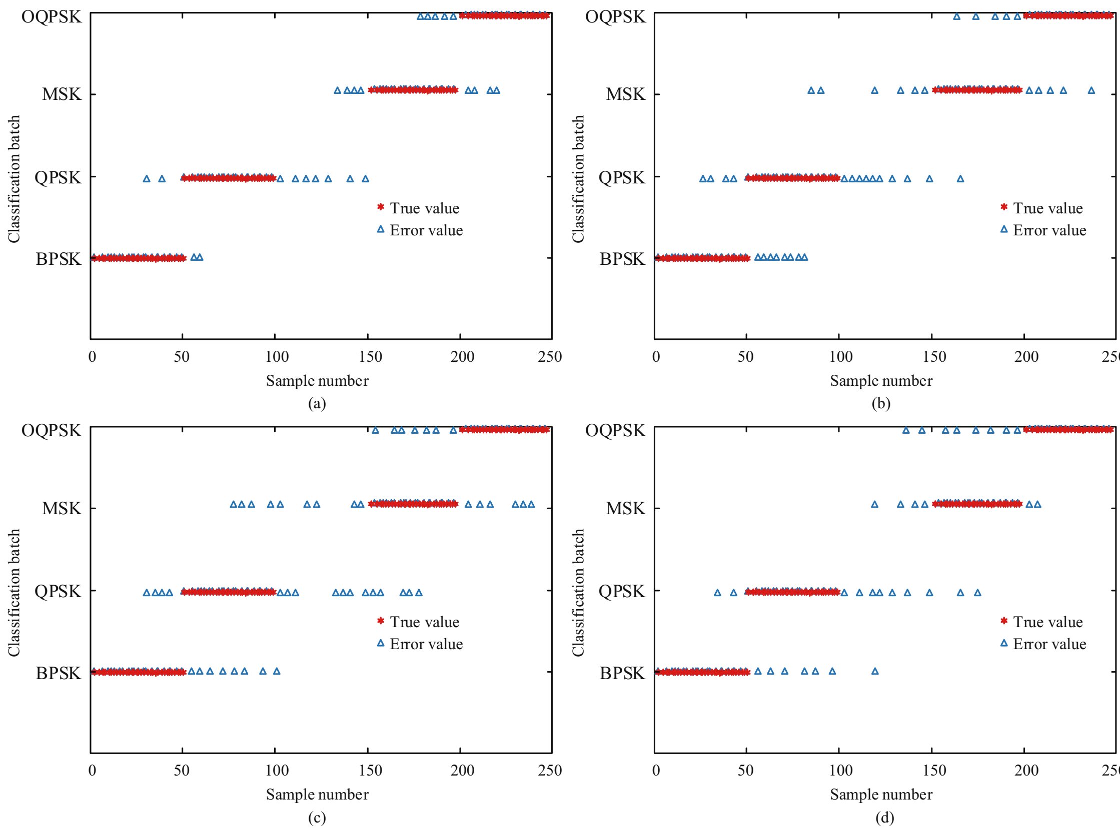

Figure 8: Comparison of feature extraction accuracy of communication signals under different algorithm models: (a) PSO-SVM model, (b) SVM model, (c) DT model, and (d) CNN model.

Figure 8 shows that compared with other algorithm models, the signal feature extraction correctness of the PSO-SVM technique is the highest. The extraction correctness of PSO-SVM technique for BPSK signal, QPSK signal, MSK signal, and OQPSK signal reached 96, 82, 84, and 90%, respectively, and the overall extraction accuracy reached 90.4%. The overall extraction accuracy of the SVM model is 84.8%, and the extraction accuracy of the four communication signals is 84, 72, 78, and 90%, respectively. The overall signal feature

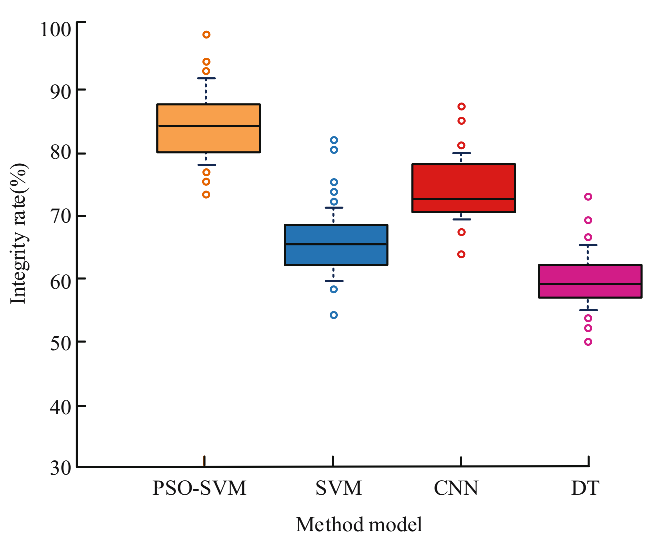

Figure 9: Integrity rate of communication signal feature extraction under different algorithm models.

extraction accuracy of the DT model and CNN model is 81.6 and 87.2%, respectively. The PSO-SVM technique greatly improves the accuracy of anti-jamming cycle frequency feature extraction and significantly improves the model's signal feature recognition effect. Figure 9 shows the complete rate of feature extraction of communication signals under different algorithm models.

Figure 9 shows that the signal feature extraction integrity rate of the PSO-SVM technique is about 85%, which is 20% higher than that of the SVM technique. The signal feature extraction efficiency of the CNN model is good, with the signal feature extraction integrity rate reaching 72%. The DT model has the lowest feature extraction integrity rate, about 60%, which is 25% lower than the PSO-SVM method. The PSO-SVM model improves the integrity of the feature extraction of communication signals, and its effect is far superior to other algorithm models. It has significant advantages in signal feature extraction, which is conducive to ensuring the comprehensiveness and availability of communication signal features and laying a good foundation for communication signal classification.

5 Conclusion

Identifying communication interference signals is the basis for the development of radio technology and is of great significance to maintaining social stability and unity. In order to make up for the limitation of the SVM method in the feature extraction of anti-jamming cyclic frequency of communication signal, a PSO-SVM electronic communication signal interference cyclic frequency feature extraction model is proposed, and its application effect is verified. During training and testing, the PSO-SVM model tends to be stable after 60 iterations, the loss value maintains a stable level of 0.2, and the accuracy rates in the two datasets remain in the interval [65,92] and [70,93], the accuracy rate is the highest among the four models. In the application of the model, the signal feature extraction correctness of the PSO-SVM model reaches 90.4%, and the extraction exactitude of BPSK signal, QPSK signal, MSK signal, and OQPSK signal reaches 96, 82, 84, and 90%, respectively. At the same time, the complete rate of signal feature extraction is about 85%, which is 20% higher than that of the SVM method. From this, the PSO-SVM model improves the shortcomings of the SVM technique, such as the inability to handle large sample sizes, and achieves high-accuracy electronic signal recognition in a relatively short period of duration, which is conducive to improving the ability to collect the characteristics of the interference cycle frequency of electronic communication signals and promote the development of electronic communication engineering. Although the research has achieved certain results, there is still the limitation that the sample size is not large enough. In future research, it is essential to enlarge the specimen size, build a more complete PSO-SVM signal feature extraction model, and further improve the research results.

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