A RECOGNITION ALGORITHM OF FREQUENCY HOPPING SIGNAL MODULATION IN MULTIPATH CHANNEL

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Aiming at the problem that a single characteristic parameter cannot meet the effectiveness and accuracy of frequency hopping signal modulation recognition under multipath interference, a modulation recognition algorithm, based on multiple characteristic parameter combinations and supporting vector machines, is proposed. The algorithm firstly divides the frequency hopping signal into single pulse signals according to frequency points, and then extracts various eigenvalues as input parameter for classifier, including wavelet energy spectrum Shannon characteristic entropy, cyclic spectrum cross-sectional correlation coefficient and higher-order cumulant.They are used as the input coefficient of the classifier, which are not severely affected by multipath interference and SNR changing. The simulation results show that the algorithm has strong recognition accuracy under low SNR and multipath interference.

Key Words : *frequency hopping, multipath interference, modulation recognition, characteristic, support vector mashine(SVM)*

1. INTRODUCTION

With the development of communication technology and increasing of interference methods, frequency hopping technology has been widely cited in modern communications due to its anti-interference and confidentiality characteristics. How to identify the parameters of the frequency hopping signal at the receiving end is the prerequisite for analyzing the enemy's signal and our signal. And although the frequency hopping technology has effectively improved the transmission quality of the wireless link and reduced the impact of interference, some types of interference such as multipath interference still affects the signal, so how to identify the modulation method of the frequency hopping signal under multipath interference is an important task.

At present, there are various methods for identifying the modulation mode of conventional fixed-frequency communication signals. Among them, the characteristic parameters that can still have a good recognition effect under the condition of low SNR are entropy characteristics[1)], cyclic spectrum cross-sectional correlation coefficient[2)], higher-order cumulants[3)] etc. Since frequency hopping, communication signals have the characteristics of pseudo-random hopping in frequency with time. There are few studies on the classification and identification of modulation modes of frequency hopping signals in China and at abroad. The literature[4)] proposes that the envelope square feature of the instantaneous signal is not sensitive to noise, and the envelope can be extracted by constructing a detection function related to the high-order cumulant to identify the frequency hopping fingerprint feature. But due to the short startup time of the transient feature , there will be a huge obstacle to capture and separate frequency hopping signals. The literature[5)] uses the fast Regions with CNN features(RCNN) with deep learning to identify and locate all the frequency hopping points in the spectrogram, uses AlexNet to obtain the number of frequency hopping signals, and gathers the frequency hopping signals through the time spectrum features extracted by the short-time

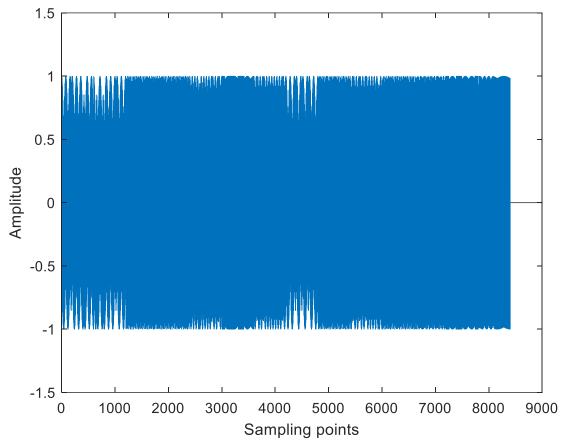

Fig.1 The time domain waveform

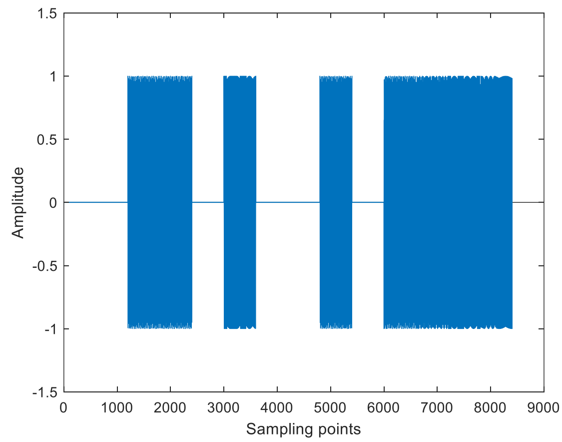

Fig.2 Time domain diagram after preprocessing

Fourier transform. But this method requires a relatively long training process and a huge amount of calculation, which is difficult to meet the actual battlefield environment. The literature[6)] proposes a method by using ambiguity function to measure the characteristics of frequency hopping. The theory of radar ambiguity function is applied to the recognition of frequency hopping radiation source, but the signal set that can be identified is less.

In this paper, for frequency hopping signals, the method of smoothing Pseudo-Wigner Wiley is used to transform the spectrogram to estimate the transition time of frequency hopping, and then extracts the single hopping signal from the frequency hopping signal. The effectiveness and adaptability of the current effective feature parameters under the condition of low SNR and multipath interference are compared. The Shannon feature entropy of wavelet energy spectrum, the correlation coefficient of two cyclic spectrum cross-sections, and the high-order cumulant are selected from them. The characteristic parameters are used as the input coefficients of the support vector machine classifier. The simulation results are compared with the recognition algorithm based on the fuzzy function, and the effectiveness of the method is verified when the recognition signal set is expanded and multipath interference is added.

The remainder of this paper is organized as follows. Section 2 introduces the frequency hopping signal model and the method of extracting the single hop signal. In Section 3, three types of effective feature quantities under low signal-to-noise are introduced, and a classification algorithm for frequency hopping signal modulation methods composed of four feature parameters is proposed, which is less affected by multipath interference. The simulation results are presented in Section 4 to prove the accuracy and effectiveness of the algorithm. The conclusion are finally presented in Section 5.

2. SIGNAL PREPROCESSING

(1) Frequency hopping signal model

The mathematical expression of the frequency hopping signal $s_n(t)$ can be described as:

$$s_n(t) = v_n(t)\sum_{k=0}^{K-1}\exp[j(f_{nk}t' + \varphi_{nk})]rect(\frac{t'}{T_n}) \qquad (1a)$$

$$t' = t-(k-1)T_n - \Delta t_{0n} \qquad (1b)$$

Where T_n is the hop period of the frequency hopping signal $s_n(t)$, K is the total hop count in the observation time Δt, f_{nk} is the carrier frequency of the k, the hop φ_{nk} is the initial phase, $v_n(t)$ is the baseband complex envelope of the frequency hopping signal $s_n(t)$, Δt_{0n} is the duration of the initial non-complete hop in Δt, t' is the instantaneous engraving, $rect$ is the unit rectangular window function. The frequency hopping transmitter mainly uses the pseudo-random sequence to control the carrier and then make the carrier frequency hop pseudo-randomly. The signal received by the receiver is after passing through the channel. After denoising processing, the frequency hopping time domain diagram shown in **Fig.1** can be obtained.

Due to the similarities between the frequency hopping signal and the radar signal, the single hop signal of the frequency hopping signal corresponds exactly to a pulse signal of the radar signal [5]. For this, we use the smooth Pseudo-Wigner method to find the frequency hopping of the frequency hopping signal. And so on, the time domain diagram of the frequency hopping signal can be preprocessed according to the entire section of the received frequency hopping signal, it is shown in **Fig 2**.

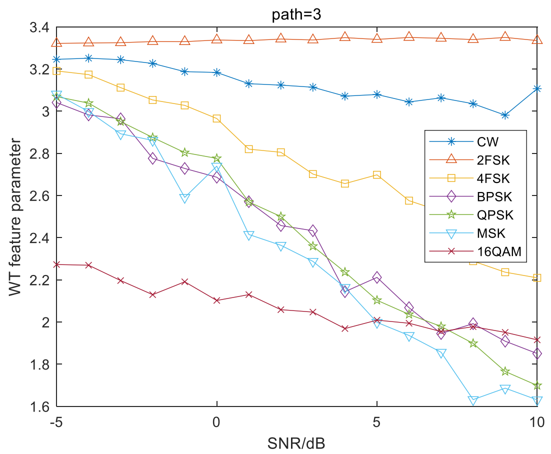

Fig.3 Shannon characteristic entropy of wavelet energy spectrum

3. ALGORITHM ESTABLISHMENT

At present, the feature parameters which can still have a good recognition effect in the case of low SNR is entropy features, cyclic spectrum cross sectional correlation coefficients, and high-order cumulants, etc. Given we need to reduce the impact of multipath interference on the characteristic parameters, it is necessary to simulate these characteristic parameters under different multipath conditions.

(1) Shannon characteristic entropy of wavelet energy spectrum

Information entropy is a quantitative evaluation index for the signal state uncertainty. The greater the information entropy, the greater the uncertainty of the signal. It has a strong ability to characterize the inherent complexity of the modulated signal. The definition of entropy is generally divided into two types, Shannon entropy and exponential entropy. The definition of Shannon entropy is:

$$H = H(p_1, p_2, \cdots p_n) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{2}$$

Then the wavelet transformation performed on the time series obtains wavelet coefficients $W_f(a,b)$ on n scales, the energy value at scale i is m_i. Then the probability distribution P_i can be obtained. And finally the wavelet energy spectrum Shannon entropy on the corresponding scale i can be calculated.

$$\mathrm{P}_i = \frac{m_i}{\sum_{i=1}^{n} m_i} \tag{3}$$

The wavelet entropy on n scales is calculated as $(m_1, m_2, \cdots, m_n)$. Finally, the wavelet energy spectrum Shannon characteristic entropy E of the signal can be obtained by formula (4):

$$E = \frac{m_1 + m_2 \cdots + m_n}{n} \tag{4}$$

Fig.3 shows the wavelet energy spectrum Shannon characteristic entropy of 7 kinds of signals (CW, 2FSK, 4FSK, BPSK, QPSK, MSK, 16QAM) when the number of multipath channels is 3. Under the SNR of $-5 \sim 10dB$, the Shannon characteristic entropy of the wavelet energy spectrum of CW and 2FSK signals is obviously deviated from other signals, and there is no intersection between them. It can be seen that as long as the appropriate decision threshold is set, the CW signal and 2FSK signal can be identified from the selected signal set through the wavelet energy spectrum Shannon feature entropy.

(2) Correlation coefficient of cyclic spectrum section

The cyclic spectral density function $S_x^\alpha(f)$ is obtained from the cyclic autocorrelation function $R_x^\alpha(\tau)$ through Fourier transform.

$$S_x^\alpha(f) = \int_{-\infty}^{+\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \tag{5}$$

Since the Fourier transform $S_x^\alpha(f)$ of the cyclic autocorrelation function $R_x^\alpha(\tau)$ can be obtained by taking the Fourier transform of the two signals in the expression of $R_x^\alpha(\tau)$ and then multiplying them, $S_x^\alpha(f)$ can be further expressed as:

$$S_x^\alpha(f) = \frac{1}{T} X_T(t, f+\alpha/2) X_T^*(t, f-\alpha/2) \tag{6}$$

Normalize the cyclic spectrum to get the spectral correlation coefficient ρ_x^α.

$$\rho_x^\alpha = \frac{S_x^\alpha(f)}{\sqrt{S_x^\alpha(f+\alpha/2)} * \sqrt{S_x^\alpha(f-\alpha/2)}} \tag{7}$$

Taking the cyclic spectrum of the received signal $y(t)$ to obtain $S_Y^\alpha(f)$, than $\max_f[S_Y^\alpha]$, $S_Y^\alpha(0)$, $S_Y^0(f)$ .And $\max_\alpha[S_Y^\alpha]$ can be obtained respectively. $\max_f[S_Y^\alpha]$ is the projection of the cyclic spectrum on the cyclic frequency α plane. $S_Y^\alpha(0)$ is the cross section of the cyclic spectrum at the frequency $f=0$. $S_Y^0(f)$ is the cross section of cyclic spectrum at cyclic frequency $\alpha=0$. $\max_\alpha[S_Y^\alpha]$ is the projection of the cyclic spectrum on the frequency f plane. Then, the characteristic parameters can be obtained

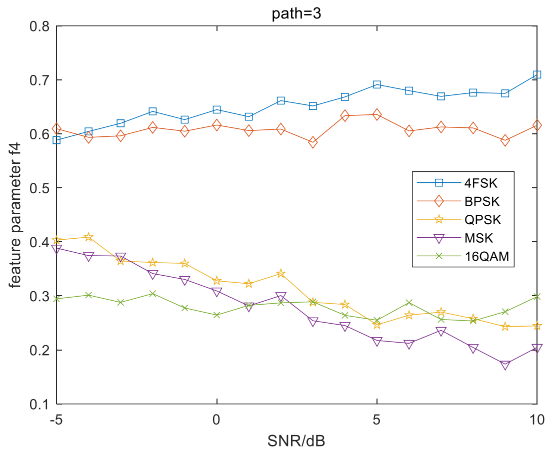

Fig.4 Cyclic spectrum cross section coefficient f_4

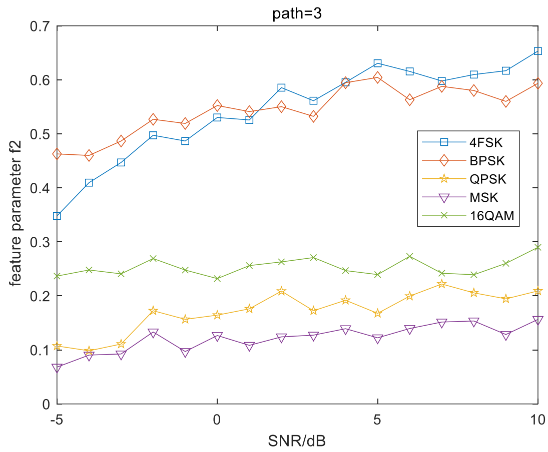

Fig.5 Cyclic spectrum cross section coefficient f_2

by the pairwise correlation operation of these four cyclic spectrum sections.

In the cyclic spectrum correlation coefficient feature, because there are so many pairwise correlation eigenvalues that can be extracted, it is necessary to perform a detailed analysis on the selected eigenvalues, such as the f_1 eigenvalue, which is the correlation value between $S_Y^0(f)$ and $S_Y^\alpha(0)$. It has very weak adaptability to the SNR, and changes greatly with the fluctuation of the SNR, so the selection of the threshold is very difficult.

For the correlation coefficient characteristic value f_5 of $S_Y^\alpha(0)$ and $\max_\alpha[S_Y^\alpha]$, the adaptability to the SNR is relatively good, and the QAM-type signal can be roughly separated from the rest of the signal set, but it is also affected by multipath interference. The fluctuation is more obvious, when the number of paths reaches 3, and the eigenvalues are mixed together when the SNR is large, which is not conducive to modulation recognition.

For the characteristic value f_4 of the correlation coefficient of $S_Y^\alpha(0)$ and $\max_f[S_Y^\alpha]$, the signal can be more accurately divided under the conditions of different SNR and different multipath numbers. As shown in **Fig.4**, 2FSK ,4FSK and BPSK can be separated from other signals.

As shown in **Fig.5**, the signals 16QAM and MSK show the particularity in the performance of the characteristic value f_2 , which is the correlation coefficient between $S_Y^0(f)$ and $\max_f[S_Y^\alpha]$ .And when the multipath channel reaches 3, the distribution is still stable. So 16QAM and MSK can be distinguished from other signals by setting the upper and lower thresholds.

(3) Higher order cumulants

After filtering by the Shannon characteristic entropy of wavelet energy spectrum and the correlation coefficient of cyclic spectrum section, the selected signal set is left with QPSK, BPSK, and 4FSK. Among them, BPSK and 4FSK can be obtained according to the cyclic spectrum cross section coefficient f_4, and an additional characteristic value is needed to distinguish these two signals. Because high-order cumulants is more adaptable to low SNR, we selecte it for analysis and research.

The basic theory of higher-order cumulants is to define the k -order cumulant of a stationary random process $x(t)$ with zero mean as formula (8):

$$C_{kx}(f_1, f_2, \cdots, f_{k-1}) = Cum(x(t), x(t+f_1), \cdots, x(t+f_{k-1})) \tag{8}$$

Where $Cum(\bullet)$ means to calculate the cumulative amount of $x(t)$.

The expression of the cumulant can be solved by the expression of the p -order mixed moment of the random process $x(t)$:

$$M_{pq} = E\left\{\left[x(t)^{p-q} x^*(t)^q\right]\right\} \tag{9}$$

Substituting the expression of the mixed moment into the high-order cumulant formula can deduce the cumulants of each order of $x(t)$ as follows:

$$C_{20} = Cum(x,x) = M_{20} \tag{10a}$$
$$C_{21} = Cum(x,x^*) = M_{21} \tag{10b}$$
$$C_{40} = Cum(x,x,x,x) = M_{40} - 3M_{20}{}^2 \tag{10c}$$
$$C_{42} = Cum(x,x,x^*,x^*) = M_{42} - |M_{20}|^2 - 2M_{21}{}^2 \tag{10d}$$

Although the high-order cumulant makes the characteristics of the signal stand out in a noisy environment, in many cases it is impossible to classify

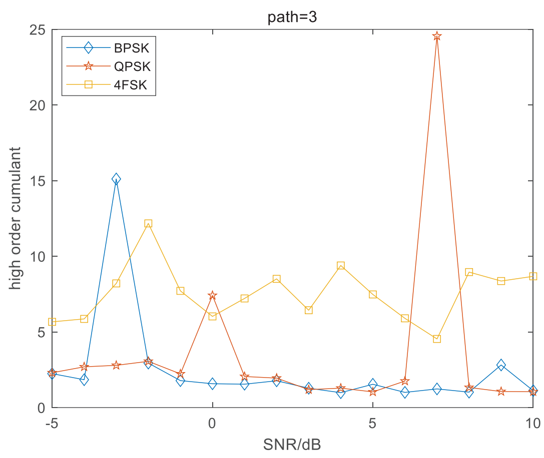

Fig.6 High-order cumulant eigenvalues

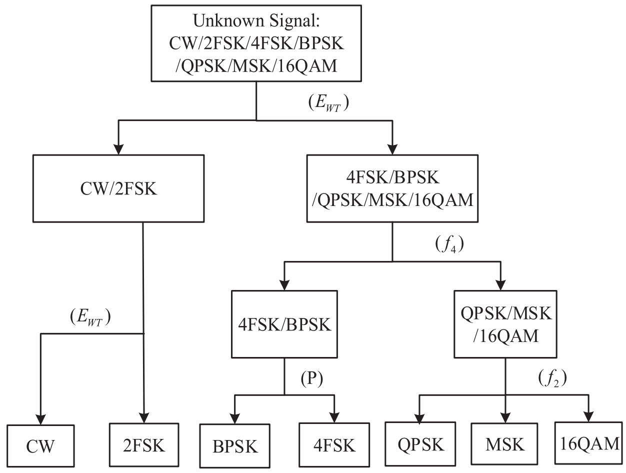

Fig.7 Flow chart of classification method

the modulated signal by relying on a single cumulant, because the cumulant value of each modulation method will be relatively close. So after calculating the high-order cumulant of each modulation method, we also need to take the absolute value and do the ratio processing for it, and the calculated value after this can be used as the gist for modulation identification. The eigenvalue selected in this paper is P .

$$P = \frac{|C_{40}|}{|C_{42}|} \tag{11}$$

For QPSK, BPSK, and 4FSK signal,the high-order cumulant is simulated under the number of multipath channels of 3 and different SNR, so **Fig.6** is obtained. It can be seen from the figure that the eigenvalues of BPSK and 4FSK are separated more obviously. Although the distribution of BPSK is relatively unstable and fluctuates greatly, it does not affect the recognition of the signal.

According to the simulation results of the three type eigenvalues of the above seven type signals under multipath channels and different SNR, this paper will construct a modulation pattern recognition algorithm based on a combination of multiple characteristic parameters. The classification flowchart is shown as **Fig.7**.

Since the above simulation results of each eigenvalue are obtained by averaging, the actual eigenvalue under each SNR fluctuates. However, the general distribution is maintained within a range. Therefore, in order to reduce the impact of small fluctuations in eigrnvalues and improve the accuracy of recognition, this paper adopts the SVM classification method based on the binary tree structure. SVM is a statistical learning theory proposed by V. Vapnik. Its basic idea is to perform a certain nonlinear transformation on the original feature space by defining an appropriate kernel function, map the original feature space to a high-dimensional space, and then find the optimal classification surface in this new space to make the sample correct separation and the largest classification interval.

4. EXPERIMENTAL SIMULATION AND ANALYSIS

This article uses the LIBSVM software package to perform simulation experiments on 7 common signals (CW, 2FSK, 4FSK, BPSK, QPSK, MSK, 16QAM). For each signal which is waiting to be classified, generate 100 samples to train the SVM in the SNR ranges from $-5 \sim 15\,dB$ with step $2\,dB$. And then in the hopping system simulation with simple 14-frequency hopping frequency, each frequency hopping frequency point generates 500 signals. The signal of each modulation mode randomly generates 1000 different carrier frequency samples. Test the recognition rate of the classifier in an environment where the number of multipath channels is 3 and the SNR which is set before. Training time takes 62.4 seconds, and the classification time for each signal is 14.2 seconds on average.

At the same time, this paper simulates the eigenvalues extraction method based on the radar ambiguity function theory in the literature[7]. After calculating the ambiguity function of the single-hop signal, this method uses the particle swarm algorithm to search the AFMR slices and extracts global features composed of feature quantities. Under the condition of SNR of $-5 \sim 35\,dB$, the five modulation signals of CW, BPSK, QPSK, 8PSK and 16QAM are recognized. The classification algorithm of this method uses the fuzzy cluster mean, referred to as the FCM ,

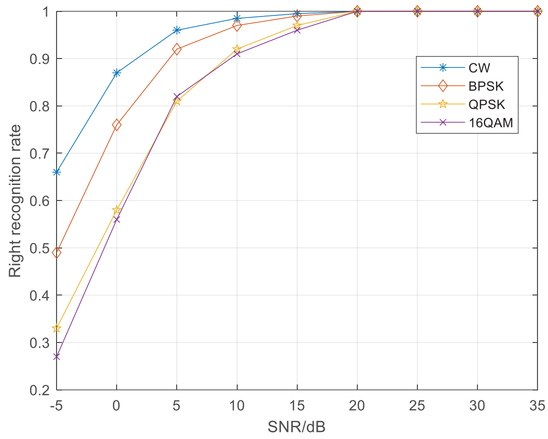

Fig.8 Fuzzy function recognition based on FCM algorithm

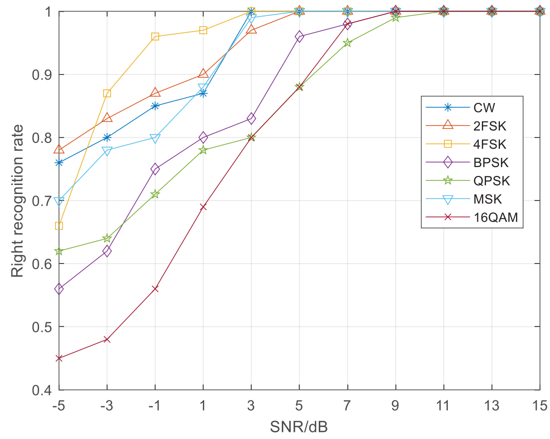

Fig.9 Recognition of multiple eigenvalues based on SVM

which is a fuzzy clustering algorithm based on the objective function.

The recognition rate of the fuzzy function recognition algorithm is shown in **Fig.8**, and the recognition rate of the SVM-based multiple eigenvalue recognition algorithm described in this paper is shown in **Fig.9**. The algorithm proposed in this paper adds three kinds of signals, 2FSK, 4FSK and MSK, based on the signal set studied in the literature[7], which has a wider application prospectly. And although this algorithm is in the case of low SNR and multipath interference, there is still a good recognition rate. In the case of -5 dB SNR, the recognition rate of CW, 2FSK and MSK signals can reach more than 70%. But the recognition algorithm based on fuzzy function under the condition of -5 dB SNR, the recognition rates of four signals are all lower than 70%. At 0 dB, the recognition rates of the CW, 2FSK, 4FSK and MSK signals in this paper have reached more than 85%, and the recognition rate of 4FSK signal has reached 95%. In addition, the algorithm in this paper can make the recognition rate of 7 kinds of signals reach more than 97% or even complete recognition at 10 dB. But only when the SNR at 20 dB, the recognition rate of the four signals of the fuzzy function algorithm tends to 100%. In summary, compared with the fuzzy function recognition algorithm, the algorithm in this paper not only expands the signal set, but also improves the recognition accuracy in the case of low SNR and multipath interference. So it has a wider application prospect.

4. CONCLUSION

This paper proposes a new modulation recognition method based on SVM and multi-feature extraction. It extracts the wavelet energy spectrum Shannon feature entropy, cyclic spectrum cross-sectional correlation coefficient and higher-order cumulant from the frequency hopping signal, and improves the recognition rate of the selected signal under low SNR and multipath interference by utilizing the SVM classification method based on the binary tree. It has a wide range of application prospects in engineering practice.

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