Frequency hopping radio individual identification based on energy spectrum blended subtle characteristics

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Abstract. For the problem of low recognition rate and large computational complexity of frequency hopping radio stations, a blended subtle characteristic extraction method based on energy spectrum is proposed. Considering that the time-frequency energy distribution is widely used in individual feature extraction, the time-frequency energy spectrum of the frequency hopping signal is obtained by the sparse reconstruction method firstly. Then the fractal theory is used to extract the feature vector set including time-frequency energy spectrum Rayleigh entropy, multi-fractal dimension and difference box dimension with multi-scale block extraction. Finally, the support vector machine classifier is used to train, classify and identify the feature set to realize the individual identification of the frequency hopping station. The recognition performance of the proposed method and the other two methods are compared and verified through the frequency hopping signals of four stations. The experimental results show that compared with the other two methods, the proposed method has higher recognition rate under low SNR and a small number of training samples.

1. Introduction

Frequency hopping communication network station sorting is the primary prerequisite for intercepting enemy communications and generating the best interference signal. The existing frequency hopping signal network station sorting mainly uses the parameters of the duration, orientation information, power and signal time correlation of the frequency-hopping signal to realize the network station sorting identification of the frequency-hopping signal. Literature [1] achieves network station sorting by calculating the direction information of the frequency-hopping signal. In [2], the classification of frequency hopping signals is achieved by clustering and sorting parameters such as power, time and azimuth of frequency hopping signals. Taking into account the frequency-hopping signal of its own radiation has different subtle characteristics from other hopping radio signals [3], the subtle features unique to different frequency hopping radio signals, namely the "fingerprint" feature, can be used to realize the sorting and identification of the frequency-hopping signal. In [4], the frequency hopping station sorting is realized by using the different subtle characteristics of the transmitting power amplifier in the transient response process. However, the transient signal has a short duration and is susceptible to noise interference, which is difficult to identify [5-6]. In [7], the individual identification of mobile phone radiation sources is realized by extracting the multi-dimensional characteristics of the time-frequency energy spectrum of the radiation source signals. The literature [8] composes the feature set by extracting the first and second moments and the energy spectrum entropy of the fixed-scale time-frequency energy spectrum. However it does not consider that the time-frequency energy spectrum of the frequency-hopping signal has different energy distribution under different block conditions. So, the correct
classification rate is not high. The existing research on the fine-grained feature recognition algorithms of frequency hopping radios is mostly carried out under the conditions of large samples and high SNR ratio, which cannot effectively overcome the adverse effects of sample size and SNR on classification and recognition rate. Aiming at the above problems, this paper proposes a subtle feature recognition method based on multi-scale time-frequency energy spectrum fractal and Rayleigh entropy. The experimental results show that the recognition accuracy of this method is higher than that of the literature [7-8] under the condition of less training samples.

2. Algorithm flow
Firstly, the time-frequency energy spectrum surface of the frequency-hopping signal is obtained by the approximate $l_0$ norm (AL0) algorithm, and then the feature set of time-frequency Rayleigh entropy, multi-fractal dimension and differential box dimension is calculated under different segmentation scales. Finally, the support vector machine classifier is used for classification and recognition.

2.1. Principle of time-frequency energy spectrum algorithm based on sparse reconstruction
The AL0 sparse reconstruction algorithm is widely used because of the characteristics of high resolution, small amount of calculation and less sample points [9]. The main principle of the AL0 algorithm is to approximate the $l_0$ norm by a smooth Gaussian function. Then it uses the steepest descent method to solve the approximate $l_0$ norm. Finally, the sparse signal reconstruction is realized.

The time-frequency energy spectrum of two synchronous networking frequency hopping stations obtained by sparse reconstruction of the AL0 algorithm is shown in figure 1:

![Time-frequency energy diagram of two frequency hopping stations.](image1)

It can be seen from figure 1 that the two frequency hopping stations with the same model and working mode carry their own subtle characteristic information due to different radiation sources. The individual identification of the frequency hopping radio can be realized by extracting the characteristic laws such as the energy variation and the frequency distribution of the time-frequency energy spectrum surface of each station signal.

2.2. Fractal Feature Extraction
The fractal dimension can not only measure the complexity of the shape of the object, but also has the invariance characteristics of multi-scale and multi-resolution changes. In this paper, the differential box dimension and multifractal dimension of the time-frequency energy spectrum surface are extracted under different block scale conditions.

2.2.1. Differential box dimension
Using the method in [10] to calculate differential box dimension, the sparsely reconstructed time-frequency axis of the time-frequency energy spectrum of is regarded as a flat, and the energy spectrum value is regarded as the gray value of the image. Differential box dimension can be expressed as:
\[ FD = \lim_{r \to 0} \frac{\log(N_M)}{\log\left(\frac{1}{r}\right)} \]  

2.2.2. Multifractal

Single fractals do not fully measure their complexity and nonlinear characteristics when describing most objective fractal objects. To a certain extent, they cannot fully reflect their full characteristics. Multifractal can study its overall characteristics from a local perspective, and improve the fineness of the geometric features and local scale behavior of objects. In order to describe the local characteristics of time-frequency energy spectrum more effectively, this paper extracts the multi-fractal dimension of the time-frequency energy spectrum of the frequency-hopping signal as the second-dimensional feature.

As can be seen from the literature [11], multifractal can be expressed as:

\[ MD(q) = \frac{1}{q-1} \lim_{r \to 0} \frac{\log \sum_{\mu,\nu} \left( \frac{n_M(\mu,\nu)}{N_M} \right)^q}{\log r}, \quad q \neq 1 \]  

2.3. Time-frequency energy spectrum Rayleigh entropy feature extraction

Entropy can be defined as an amount that measures the disordered state of disorder, uncertainty, and so on. It can be seen from figure 1 that the time-frequency energy distribution of the two frequency hopping radio signals has a certain difference. The difference of this distribution can be measured by the statistical time-frequency energy spectrum Rayleigh entropy. Intuitive differences are transformed into numerical differences. Therefore, in order to ensure the full separability of the feature set, this paper extracts the time-frequency energy spectrum Rayleigh entropy as the third dimension feature.

After sparse reconstruction of the frequency hopping signal, the time-frequency energy spectrum has time-frequency edge characteristics and energy retention characteristics, as shown in equations (3) and (4):

\[ \int P(t, f) df = |s(t)|^2, \quad \int P(t, f) dt = |s(f)|^2 \]  
\[ \iint P(t, f) dt df = \int |s(t)|^2 dt = \|s(t)\|_2^2 \]  

\( s(f) \) is the Fourier transform of \( s(t) \). The time-frequency energy spectrum Rayleigh entropy of the frequency hopping signal can be defined by \( P(t, f) \), as in the formula:

\[ R^\alpha = \frac{1}{1-\alpha} \log_2 \iint P^\alpha(t, f) dt df \]  

The stable condition of the equation (5) is \( \iint P^\alpha(t, f) dt df > 0 \). For the convenience of calculation, the discrete expression of the Rayleigh entropy of the time-frequency energy spectrum:

\[ R^\alpha = \frac{1}{1-\alpha} \log_2 \sum_{k} \sum_{\psi} \left( \frac{X[k,\psi]}{\sum_{k'} \sum_{\psi'} X[k',\psi']} \right)^\alpha \]  

\( X \) is a time-frequency matrix, \( 1 \leq k \leq K, 1 \leq k' \leq K, \alpha_0 \leq \psi' \leq \omega_{p-1}, \omega_0 \leq \psi \leq \omega_{p-1} \).

Finally, the above three features are composed into feature set \( V = [FD, MD(q), R^\alpha] \), and then the support vector machine classifier is used for classification and recognition.
3. Experimental results and analysis

3.1. Multi-scale feature extraction and analysis
The data of this experiment were collected in four frequency hopping stations of the same model. The working frequency of the radio was 150MHz, the frequency hopping bandwidth was 6.4MHz, the sampling rate was 600MHz, and the sampling duration was 5 seconds. When the time-frequency energy spectrum after sparse reconstruction is divided, if the scale $L$ value is too large, the boundary information of the energy spectrum cannot be fully utilized. The extracted features cannot completely reflect the essential information of the signal. If the scale $L$ value is too small, the calculated amount of calculation will increase. Therefore, in the simulation experiment of this paper, the block size $L$ selects five values of 4, 8, 12, 16, and 20.

From equation (2), the $q$ affects the stability of the $MD(q)$ value. After repeated experiments, the $MD(q)$ of the frequency hopping signals of the four stations tend to be stable at $q = 13$. In order to ensure the stability of the extracted features $q = 13$ is selected.

3.2. Time-frequency energy spectrum Rayleigh entropy feature extraction and analysis
The time-frequency energy spectrum Rayleigh entropy can well reflect the time-frequency energy spectrum law and complexity of each frequency hopping signal. It can be seen from equation (6) that the value of the order $\alpha$ has a great influence on the extraction of the Rayleigh entropy feature. When $\alpha = 3$, the time-frequency energy spectrum Rayleigh entropy value of each station signal has the largest difference and has strong distinguishability. At the same time, it is verified in the literature [12] that the stability of Rayleigh entropy is best when the order $\alpha = 3$. Therefore, the order of the Rayleigh entropy feature of the time-frequency energy spectrum is chosen as three.

3.3. Comparison and analysis of recognition results
The collected four radio frequency hopping signal data are intercepted separately. First, 200 pieces of data are intercepted from the head of the sampled data as training samples. The number of sampling points for each training sample data is 1024, and 200 points separate each segment. Then, in the same way, 200 pieces of data are taken from the end of the sampled data as test samples. Under the condition of different training samples, the method in this paper and literature [7], [8] extract the three characteristics of time-frequency energy spectrum Rayleigh entropy, difference box dimension and multi-fractal dimension. The support vector machine classifier identifies the classification, and then the recognition performance of the three methods is compared and analyzed. The average recognition accuracy rate of the 5 times for each of the three methods is shown in figure 2.

![Figure 2. The correct rate of recognition varies with the number of training samples.](image-url)

It can be seen from figure 2 that the recognition accuracy rate of the literature [7] method gradually increases as the number of training samples increases. When the number of training samples increased to 200, the recognition accuracy rate of the literature [7] reached a maximum of 68.6%. However, the recognition accuracy of the method and the literature [8] method is not affected by the change of the number of training samples, and it is always maintained at 85.6% and 60.4%. The main reason is that...
the three features extracted by the method can quantitatively describe the energy variation of time-frequency energy spectrum, the complexity and regularity of time-frequency energy spectrum. They can avoid the misjudgment caused by the similarity of single features. In order to make the visualization effect of the classification result better, the classification effect of the three-dimensional feature obtained by the proposed method in this paper is shown in figure 3.

Figure 3. Classification effect chart.

It can be seen from figure 3 that the classification features of the proposed method are only partially overlapped and have obvious clustering effects, which are consistent with the recognition results of figure 4.

4. Conclusion
In this paper, a blended subtle characteristic extraction method based on energy spectrum is proposed. Firstly, the frequency hopping signal is sparsely reconstructed to obtain the time spectrum. Then the time-frequency energy spectrum of the frequency hopping signals of different stations is segmented under different scale conditions. The three characteristics of differential box dimension, multifractal dimension and time-frequency energy spectrum Rayleigh entropy are extracted respectively, which avoids the misjudgment problem caused by the similarity of single features and improves the characterizing ability of feature set. The classification and recognition experiments show that the number of training samples less affects the recognition performance of the proposed method, and it can have higher recognition accuracy under the condition of less training samples.

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