Frequency Hopping Signal Sorting Algorithm Based on Global Feature of Ambiguity Function

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Abstract. Aiming at the problem that the traditional feature parameters are difficult to meet the fastness and effectiveness of frequency-hopping signal sorting recognition, a feature extraction method based on ambiguity function theory is proposed. The algorithm applies the ambiguity function theory to the frequency hopping signal sorting and identification. Firstly, the ambiguity function of the single-hop signal is calculated, then the AFMR slice of the signal is extracted by the PSO algorithm, and the global features of the AFMR slice are extracted to form the feature vector. The results of FCM clustering experiments show that the extracted feature parameters have higher sorting accuracy and can adapt to the larger dynamic signal-to-noise ratio.

1. Introduction

Frequency hopping signal sorting and identification is an important part of frequency hopping reconnaissance processing. It can provide battlefield information for interference guidance, which is an important prerequisite for ensuring the operational effectiveness of communication interference equipment. It is of great significance to study the technique of frequency hopping signal sorting and identification.

The existing algorithms mainly use the spatial and temporal frequency domain characteristic parameters such as the azimuth information, power, and single-hop signal duration of the frequency hopping signal to realize the sorting and identification of the frequency hopping signal[1-4]. In [1], based on the array signal processing method, the DOA information of the frequency hopping signal is estimated, and the sorting and identification of the frequency hopping signal is realized. In [2], the DOA, carrier frequency, hopping time and power information of the frequency hopping signal are used to classify and identify the frequency hopping signal by using the improved K-means clustering algorithm. By presetting the clustering center and the number of categories, Improve the efficiency of the algorithm. However, with the increase of the number of frequency hopping stations in the same airspace configuration and the combination of the frequency hopping modes, it is difficult to achieve the requirements of the battlefield application only by the above conventional features.

In [5], based on the feature extraction of the AFMR (Ambiguity function main ridge), the radar signal sorting recognition is realized. The extracted AFMR slice features reflect the distribution of the signal ambiguity function energy very well. The noise ratio still has a high recognition accuracy. However, the calculation of the AFMR slice is large, which limits the practical applicability of the method. In [6], the particle swarm optimization algorithm is used to realize the accurate and fast
extraction of radar signal AFMR, which makes it possible to apply radar signal sorting based on ambiguity function in practical engineering.

The application of these new features and methods in frequency hopping signal sorting will be a good complement to traditional methods.

2. Ambiguity Function

The ambiguity function is used to study the resolution and measurement capabilities of the radar. It can examine the measurement accuracy, distance, velocity resolution, ambiguity and ability to suppress clutter of a signal waveform. It only depends on the signal waveform emitted by the radar, and can compare the structural information of the complete description signal. Features that facilitate signal identification can be extracted therefrom. For the narrowband radar signal \( s(t) \), its ambiguity function AF is defined as:

\[
\chi(\tau, f_d) = \left| \int_{-\infty}^{\infty} s(t-\tau) s^*(t) e^{j2\pi f_d t} dt \right|^2
\]

In the formula, \( s^*(t) \) is the conjugate of \( s(t) \), \( \tau \) is the time delay, and \( f_d \) is the frequency shift. It can be seen from equation (1) that AF is a joint two-dimensional function of the signals on the plane formed by the delay \( \tau \) and the frequency shift \( f_d \), indicating that the AF contains the time domain information and the frequency domain information, and the complete display signal can be compared. 

Waveform characteristics and structural information.

Ambiguity functions have the properties of volume invariance and uniqueness.

1. Volume invariance

\[
\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \chi(\tau, f_d) \, d\tau df_d = \| \chi(0,0) \|^2 = (2E)^2
\]

2. Uniqueness

If the ambiguity functions of signals \( x_1(t) \) and \( x_2(t) \) are \( \chi_1(\tau, f_d) \) and \( \chi_2(\tau, f_d) \), respectively, if \( \chi_1(\tau, f_d) = \chi_2(\tau, f_d) \), then \( x_1(t) \) and \( x_2(t) \) differ only by a constant \( c \) with a modulus of 1.

\[
\chi_1(t) = cx_2(t), |c| = 1
\]

It can be known from the uniqueness theorem that different signals have different ambiguity functions, and it is feasible to use the ambiguity function feature to sort and identify the signals.

Reference [5] pointed out that the ambiguity function can reflect the internal structural information of the signal more completely, and it can mine the difference characteristics between the signals. In the literature [8], the AFMR slice is taken as the research object, and the feature parameters with better sorting effect are extracted. In [6], the AFMR slice is preprocessed by derivative constrained smoothing, which further enhances the anti-noise performance of the AFMR slice. At present, AFMR slices have achieved certain results in radar signal sorting and recognition. In this paper, the ambiguity function theory is applied to the frequency hopping signal sorting and identification, and the frequency hopping signal needs to be preprocessed.

3. Signal Preprocessing

The frequency hopping signal has similarity with the radar signal, and the single hop signal of the frequency hopping signal corresponds exactly to the signal of one pulse of the radar signal. To calculate the ambiguity function of a single-hop signal, first estimate the transition time and extract the single-hop signal.

In this paper, the estimation accuracy of frequency hopping time is not high, and the estimation of hopping time can be realized by fast and simple method. In this paper, we use the method of [9] to estimate the hopping time, use PWVD to get the time-frequency matrix of the frequency hopping signal, and change the frequency axis of the time-frequency matrix to the amplitude axis to get a
sequence, and find the position with the fastest sequence change as the hop. Change the time, and then extract the single-hop signal and calculate its ambiguity function. Figure 1 shows the contour plots of the ambiguity functions commonly used in four types of signals in commonly used signals and frequency hopping communication systems in two radar systems.

4. Algorithm and Process Based on Ambiguity Function Feature Extraction

In order to obtain the main ridge plane of the ambiguity function, it is necessary to search within a certain angle. In [10], in the range of $|\alpha|<\pi/2$, the ambiguity function performs radial integration with the angle $\alpha$ to obtain the detection amount, and searches with an exhaustive search strategy. However, in order to achieve the required search accuracy, the number of searches must be sufficient and time consuming. This paper uses the PSO algorithm to improve the extraction efficiency of the section. The fitness function constructed in this paper is $RS(\alpha)$

$$RS(\alpha) = \int_{0}^{\infty} |\chi(\rho \cos \alpha, \rho \sin \alpha)|^2 d\rho$$

$$\hat{\alpha} = \arg \max_{\alpha} RS(\alpha)$$
The PSO algorithm is an evolutionary algorithm. It starts from the random solution and iteratively finds the optimal solution. It is simpler than the genetic algorithm and finds the global optimal through the current searched individual optimality. The particle swarm algorithm was first proposed by Eberhart R and Kennedy J in 1995. It is an optimization algorithm found in the behavior of bird foraging [11]. The advantage of the PSO algorithm is that it has a high probability of convergence to the global extremum, good global search ability, fast calculation speed, and does not depend on the problem domain. As long as it belongs to the optimization problem, it can be used, suitable for multi-objective, dynamic optimization environment, and constrained. Optimization, function optimization, biomedical, communication and many other fields have been widely used.

The particle swarm algorithm assumes a massless particle with only two properties, velocity \( v_i \) and displacement \( x_i \). Velocity indicates how fast the particle moves, and displacement indicates the direction and position of particle movement. There are a number of randomly distributed particles searching for the optimal solution in a \( D \)-dimensional space. The optimal solution found by a single particle is called \( p_{i \text{best}} \), and the optimal solution found by the entire particle group is \( p_{g \text{best}} \). Each particle will be based on The current individual optimal solution and the current global optimal solution of the particle swarm adjust their respective speeds and displacements, and stop when the number of searches or the accuracy of the objective function is sufficient.

\[
v_{id} = w \cdot v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{g \text{best}} - x_{id})
\]

\[
x_{id} = x_{id} + v_{id}
\]

Where \( w \) is the inertia weight, \( c_1 \) and \( c_2 \) are the acceleration constants, and \( r_1 \) and \( r_2 \) are uniform random numbers on \([0, 1]\).

The input of the AFMR slice extraction algorithm based on PSO algorithm is the number of particle swarms \( n=20 \), and each particle is set to obey the uniformly distributed displacement \( a_i \) and velocity \( v_i \) on \([-\pi/2, \pi/2]\), and the fitness function \( RS() \). And the inertia weight \( w=1 \), the acceleration constants \( c_1=2 \) and \( c_2=2 \), and the maximum number of cycles is set to 200; firstly, the extracted single-hop signal is down-converted to the intermediate frequency \( f_{IF}=1\text{MHZ} \), and the signal \( r_i(n) \). \( n=1,2,\ldots N \) is obtained and resampled. Ensure that each signal length is 1024; then \( \hat{a} \) and AFMR slice extraction is performed using PSO algorithm. Taking \( \hat{a} \) as a global feature and constructing the characteristic parameters \( \hat{P}_\alpha \) and \( \hat{P}_\rho \) to form three characteristic parameters of the global feature.

\[
\hat{P}_\alpha = \frac{\int_0^{\rho_{\text{max}}} \rho \left\{ \rho \cos \hat{\alpha}, \rho \sin \hat{\alpha} \right\}^T d\rho}{\int_0^{\rho_{\text{max}}} \left\{ \rho \cos \hat{\alpha}, \rho \sin \hat{\alpha} \right\}^T d\rho}
\]

\[
\hat{P}_\rho = \frac{\int_0^{\rho_{\text{max}}} (\rho - \hat{P}_\rho) \left\{ \rho \cos \hat{\alpha}, \rho \sin \hat{\alpha} \right\}^T d\rho}{\int_0^{\rho_{\text{max}}} \left\{ \rho \cos \hat{\alpha}, \rho \sin \hat{\alpha} \right\}^T d\rho}
\]

So far, three global characteristic parameters have been constructed, which form the angle between the main ridge plane and the time axis. It describes the direction of the AFMR, describes the center of gravity of the AFMR section, and describes the radius of inertia of the AFMR section relative to the center of gravity.

5. Experiment and Analysis

In order to verify the feasibility of the algorithm in this chapter, five typical frequency hopping signals CW, BPSK, QPSK, 8PSK and 16QAM were selected for experiments. The following experiments were designed in this section.
5.1. Experiment 1: Fixed Signal to Noise Ratio Experiment

The signal-to-noise ratio SNR is increased from -5dB to 35dB in 5dB steps. Under each SNR condition, each of the five types of frequency hopping signals produces 100 test samples. The PSO algorithm is used to search the AFMR slice and angle $\hat{\alpha}$ of the signal, and then calculate the global features $\hat{\rho}_a$ and $\hat{P}_a^2$. These features are used to construct the feature vector $V=[\hat{\alpha}, \hat{\rho}_a, \hat{P}_a^2]$, and the FCM clustering algorithm is used to cluster the test samples corresponding to each SNR. The clustering results are shown in Figure 2.

As can be seen from Figure 2, for a single-carrier CW signal, the clustering accuracy can reach 100% when the signal-to-noise ratio is greater than 10dB, and still have a good clustering effect under low SNR conditions; for BPSK signals the clustering accuracy can reach 100% when the signal-to-noise ratio is greater than 15dB, and the clustering effect is generally low under low SNR conditions. For QPSK, 8PSK and 16QAM signals, the clustering accuracy can reach 100% when the signal-to-noise ratio is greater than 20dB, and the clustering effect is poor under low SNR conditions. The above analysis shows that the characteristic parameters extracted in this paper can achieve better sorting effect under the condition of better signal to noise ratio.

5.2. Experiment 2: Dynamic Signal to Noise Ratio Experiment

In order to investigate the performance of the extracted features under dynamic SNR conditions, the signal-to-noise ratio SNR is increased from 0 dB to 35 dB in 5 dB steps. Under each SNR, each of the 5 types of signals randomly generates 50 test samples, which consists of 2000. The sample set of the sample is calculated in the same way as the experiment 1. Figure 3 shows the clustering map after the global feature are normalized.
### Table 1. FCM clustering results under dynamic SNR conditions

| signal type | CW   | BPSK | QPSK | 8PSK | 16QAM | Cluster accuracy |
|-------------|------|------|------|------|-------|------------------|
| CW          | 232  | 13   | \    | 5    | \     | 92.8%            |
| BPSK        | 17   | 220  | 2    | 8    | 3     | 88%              |
| QPSK        | \    | 5    | 203  | 19   | 23    | 81.2%            |
| 8PSK        | 3    | 10   | 19   | 201  | 17    | 80.4%            |
| 16QAM       | \    | 5    | 18   | 16   | 211   | 84.4%            |

Table 1 shows the FCM clustering results for this sample set. It can be seen from the table that the clustering accuracy of CW signal in the five types of signals is 92.8%, and the clustering accuracy of 8PSK signal is the lowest, only 80.4%. It is a satisfactory clustering accuracy under dynamic SNR conditions. The above FCM clustering experiments show the robustness of the extracted features for the change of signal-to-noise ratio. The features extracted in this paper can adapt to the large dynamic signal-to-noise ratio.

### 6. Conclusion

The diversity of the frequency hopping signal networking mode, the time-varying frequency of the frequency hopping signal carrier and the combination of the modulation modes bring great difficulties to the frequency hopping signal sorting and identification. Explore new ideas of frequency hopping signal separation and recognition, from different. It is of great significance to study the problem of scrambling signal scrambling processing in the information dimension. In this chapter, a feature extraction method based on radar ambiguity function theory is proposed. Firstly, signal preprocessing is used to extract single-hop signals and the ambiguity function is calculated. Then, the AFMR slice is searched by PSO algorithm, and the global features are extracted and composed of feature vectors. The results of FCM clustering experiments show that the extracted features can adapt to the large dynamic signal-to-noise ratio. The characteristic parameters based on the ambiguity function can be used as a supplement to the conventional parameters of frequency hopping signal sorting, which provides a basis for the subsequent sorting and identification of frequency hopping radio stations.

### 7. References

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