Deceptive Jamming Recognition Based on Wavelet Entropy And RBF Neural Network

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Abstract. The development of digital radio frequency memory has made the technology of deceptive jamming get a qualitative leap. The real-time and immersiveness are greatly improved, which makes it difficult to manually judge the type of deceptive jamming. Aiming at the problem of automatic identification of deceptive jamming, a method based on wavelet entropy for deceptive jamming is studied. Firstly, three mathematical models of deceptive jamming patterns are combed, then wavelet analysis is performed on the signal and wavelet entropy is extracted, and then sent to the radial basis function (RBF) neural network for automatic classification. The simulation results show that the proposed method has a high recognition rate for deceptive jamming patterns, which relatively less affected by the Jamming-to-Noise Ratio (JNR), and has a faster calculation velocity and better real-time performance.

1. Introduction

In modern warfare, due to the deep and practical application of Digital Radio Frequency Memory (DRFM)\(^\text{[1-3]}\), DRFM jammers can quickly intercept radar signals and generate high-fidelity deceptive jamming, making the electromagnetic environment of radar is getting worse and worse, and the traditional time domain and frequency domain methods are difficult to identify deceptive jamming, resulting in a sharp decline in the operational power of the radar. Therefore, the research on the identification method of deceptive jamming is the premise of adopting targeted anti-jamming means, which has important theoretical and military significance.

At present, some research results of deceptive jamming identification methods are as follows: Literature\(^\text{[4]}\) based on signal detection theory, using the combination of perspective detector and generalized likelihood ratio detection to complete the identification of deceptive jamming; literature\(^\text{[5]}\) based on the difference of amplitude ratio distribution between deceptive interference and real target echo in each receiving station, the multidimensional spatial threshold detection method is used to identify the deceptive jamming; literature\(^\text{[6]}\) uses the neural network to identify the two types of features of the frequency domain and the dual spectrum domain based on three deceptive jamming. All of the above documents have completed the expected tasks well, but the computational complexity is large, the recognition rate is low when the JNR is low, and the real-time performance of the recognition model is not high.

In view of the above problems, this paper first analyzes the mathematical models of three kinds of deceptive jamming signals. Secondly, the db3 wavelet is used to perform 4 layers of wavelet packet decomposition, and the wavelet entropy is extracted as the characteristic parameter. Finally, the wavelet entropy is sent to the RBF neural network for classification. The simulation results
show that the proposed method can effectively distinguish three kinds of deceptive jamming patterns, and the recognition rate is relatively high, which is relatively less affected by JNR.

2. Deceptive jamming signal mathematical model

Set the transmit signal during a single scan of the radar to \( x(t) = A_0 \cos(2\pi f_0 t + \phi) \) \(^{(1)}\)

In the formula: \( A_0 \) is the amplitude of the radar transmitted signal; \( f_0 \) is the intermediate frequency; \( \phi \) is the phase.

At present, deceptive jamming can be divided into velocity deceptive, distance deceptive and angle deceptive jamming. The jammer modulates and produces deceptive jamming on the basis of intercepting radar transmitted signals, so according to formula, the mathematical model of deceptive jamming can be unified as:

\[
J_d(t) = (1.3 - 1.5)A_0 \cos[2\pi(f_0 + \Delta f_j(t))(t - \Delta \tau_j(t)) + \Delta \phi_j(t) + \phi]
\]

\(^{(2)}\)

In the formula: \( \Delta f_j(t) \), \( \Delta \tau_j(t) \) and \( \Delta \phi_j(t) \) represent the modulation functions of velocity deceptive jamming, distance deceptive jamming and angle deceptive jamming, respectively, and their mathematical expressions are as follows:

\[
\Delta f_j(t) = k_1 t; \Delta \tau_j(t) = k_2 t^2; \Delta \phi_j(t) = k_3 t
\]

\(^{(3)}\)

In the formula: \( k_1, k_2, k_3 \) are constant. In the process of transmitting the jamming signal, if there is only one kind of deceptive jamming, the modulation function of the other two kinds of deceptive jamming is 0, that is, if the jammer produces angle deceptive jamming, then \( \Delta f_j(t) \) and \( \Delta \tau_j(t) \) are 0, \( \Delta \phi_j(t) \) is not 0.

3. Basic theory of wavelet entropy

A wavelet is a function that forms a wave over a distance. The multi-resolution analysis of the signal can be performed by changing the wavelet basis function obtained by changing the size and position of the mother wavelet and the scale function. Wavelet transform can locally analyze the signal in both time and frequency, and has high sensitivity to the characteristics of the signal details, which is beneficial to the extraction of local fine features of signal transients.

Let the signal \( x(n) \) undergo wavelet transform, the high-frequency component coefficient at time \( k \) at the \( j \)-th decomposition scale is \( cD_j(k) \), and the low-frequency component coefficient is \( cA_j(k) \), and the signal component obtained after single-branch reconstruction is performed. The frequency bands of the information contained in \( D_j(k) \) and \( A_j(k) \) are:

\[
D_j(k) : [2^{-(j+1)} f_s, 2^{-j} f_s], \quad A_j(k) : [0, 2^{-(j+1)}]
\]

\(^{(4)}\)

In the formula: \( f_s \) is the sampling frequency of the signal.

The original signal sequence \( x(n) \) is the sum of high and low frequency components, that is:

\[
x(n) = D_1(n) + A_1(n) = D_1(n) + D_2(n) + A_2(n)
\]

\(^{(5)}\)

So

\[
x(n) = \sum_{j=1}^{m} D_j(n) + A_m(n)
\]

\(^{(6)}\)

For the sake of unity, \( A_m(n) \) is represented here as \( D_{m+1}(n) \), so
Continuous wavelet transform is performed on $x(n)$, discrete scale $j (j=1,2,\cdots, m)$, and finally discretized wavelet coefficient $D_j$ is obtained, but at this time $D_j(k)$ is not a complete representation of the signal $x(n)$. The above definitions and calculations are the results of wavelet transform based on time domain and frequency domain analysis, and are also applicable to the discretization results of continuous wavelet transform [8].

Most of the energy of the signal wavelet transform is concentrated in very few expansion coefficients, since the wavelet transform is a two-dimensional transform. At the same time, the wavelet transform can finely describe the low and high frequency components of the signal and separate the subtle features of the signal. Wavelet entropy is a description of the complexity of energy distribution of signal wavelet coefficients. The larger the entropy of a signal, the greater the complexity.

In summary, the wavelet basis function has both high-frequency components and low-frequency components, and can effectively cover the time domain and the frequency domain. Therefore, the wavelet transform can locate the entropy characteristics of the signal in both the time domain and the frequency domain.

Let the scale $a$ and the time shift $b$ be the quantities that change the magnitude and positional relationship of the mother wavelet $\psi(t)$, respectively, and obtain the wavelet function $\psi_{a,b}(t)$, $C_\psi$ is a finite energy, then the method for obtaining the wavelet entropy feature is as follows:

(1) For the signal $f(t)$ to be analyzed, the continuous wavelet transform is expressed as:

$$Wf(a,b) = \int_{-\infty}^{\infty} f(t) \psi_a^*(\frac{t-b}{a}) dt$$

In the formula, the coefficient $\frac{1}{\sqrt{|a|}}$ is used to ensure the consistency of the signal energy.

(2) The corresponding wavelet inverse transform is:

$$f(t) = \frac{1}{C_\psi} \int_0^\infty \int_{-\infty}^{\infty} Wf(a,b) \psi(\frac{t-b}{a}) dadb$$

(3) Select the wavelet transform scale as $j$ and perform Fourier transform on the wavelet signal.

$$X(k) = \sum_{n=0}^{N} d_j(n)W_N^{kn}$$

In the formula, $d_j(n)$ is a high frequency detail component; $W_N^{kn} = \exp(-j \frac{2\pi}{N} kn)$.

(4) The calculation of the wavelet signal of each layer can obtain the power spectrum of the wavelet signal.

$$S(k) = \frac{1}{N}|X(k)|^2, k = 1, 2, \cdots, j+1$$

(5) Normalize the power spectrum.

$$p_k = \frac{S(k)}{\sum_{i=1}^{N}S(i)}$$

(6) The signal wavelet entropy is obtained.
In the formula, $N$ is the number of signals of the signal source; $p_i$ is the probability that the $i$-th signal may appear.

According to the above methods, the wavelet entropy of different signals can be extracted.

### 4. Simulation and analysis

According to formula (2) and formula (3), the simulation generates three kinds of jamming patterns: velocity deceptive jamming, distance deceptive jamming and angle deceptive jamming. The JNR variation range is -6~15dB. The length of the signal sequence is 192. When performing wavelet transform, the db3 wavelet is used to perform 4-layer wavelet packet decomposition. 300 Monte Carlo simulations were performed for each type of jamming to obtain 3 jamming patterns for a total of 4500 samples. 3,000 samples were randomly selected as training data to train the RBF neural network, and 1500 samples were used as test data to test the recognition rate. The wavelet entropy mean values of the three kinds of signals with the JNR are shown in Figure 1.

![Figure 1 Curve of the mean value of wavelet entropy with JNR](image)

Wavelet decomposition can obtain finer local features of the signal, which is an important means of distinguishing signals. Wavelet entropy is the energy distribution information after signal wavelet decomposition. The energy distribution after wavelet decomposition is different, which is also used as the theoretical basis for signal recognition. As can be seen from Figure 1, therefore, the wavelet energy spectrum entropy is suitable for deceiving inter-class classification of interfering signals.

The wavelet entropy mean value is taken as the characteristic parameter and sent to the RBF neural network for identification. The obtained recognition rate result is shown in Figure 2.
The simulation results show that when the JNR is higher than 2dB, the recognition rate can reach 60%; when the JNR is higher than 6dB, the recognition rate can reach 90%; when the JNR is higher than 9dB, the recognition rate can reach 98%, which proves that the method has a good recognition effect.

5. Conclusion
Based on wavelet theory and entropy theory, this paper proposes a deceptive jamming recognition algorithm based on wavelet entropy, and uses RBF neural network to identify three kinds of deception jamming. The simulation results show that the recognition rate of the algorithm is 98% when the JNR is higher than 9dB, which provides a good theoretical basis for the identification of deceptive jamming.

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