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Active blanket jamming identification method based on rough set and decision tree

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***Abstract*—Aiming at the classification or identification problem of active blanket jamming, a jamming identification method is proposed, which combines the upper approximation set, lower approximation set, border set theory of rough set and decision tree. The method first extracts the time-domain features of the signals, and divides the training set according to the degree of noise impact of the sample to train the decision tree respectively; then, the noise detection of the jamming signals is carried out by using the rough set theory; finally, the identification of three typical jamming patterns is realized through the decision tree. The comparison of simulation experiments shows that compared with the traditional method, this method has higher recognition accuracy, good real-time performance and noise robustness.**

Keywords- jamming identification; rough set theory; noise detection; decision tree;

I. INTRODUCTION

Jamming identification is the premise of radar anti-jamming. With the rapid development of radar electromagnetic jamming technology, the electromagnetic environment faced by modern radar is getting worse and worse. Among them, the extensive use of active blanket jamming on the battlefield has restricted the radar's combat effectiveness to a certain extent. High-efficiency identification of active blanket jamming is a key problem that needs to be solved urgently in the current anti-jamming field.

At present, efforts have been made in the identification of active blanket jamming at home and abroad, and certain research results have been achieved. Reference [1] performs FRFT (fractional Fourier transform) on the signal and extracts the maximum and minimum order normalized variance in this domain, and distinguishes the jamming signals under the condition of manually determining the threshold. Its recognition speed is fast, however, the identification problem when the JNR (jamming-to-noise ratio) is low is not considered. Reference [2] establishes the correlation coefficient threshold through the features difference of the signal power spectrum to complete the identification of the blanket jamming, which has good real-time performance, but the identification accuracy is seriously reduced when the JNR is low. Reference [3] performs FFT (fast Fourier transform) on signals, and then extracts entropy features of the signals in the frequency domain for jamming identification. It still has a high recognition rate in the noise environment, but the feature extraction requires a certain amount of calculation. Real-time performance cannot be guaranteed. Reference [4] converts the echo signals from the time domain to the time-frequency domain, and designs a feedforward neural network to identify the jamming signals. Reference [5] extracts the information dimension and box dimension of the echo signal in the FRFT domain to realize the blanket of jamming identification. Both can achieve good results when the JNR is low, but feature extraction requires a large amount of computation, resulting in real-time deviations.

The above methods either fail to guarantee the recognition rate of the model for noisy samples under the condition of ensuring real-time performance, or sacrifice real-time performance in exchange for noise robustness, and fail to achieve a good trade-off between computational efficiency and robustness. Inspired by predecessors, this paper extracts signal features based on the time domain, avoiding the complex feature extraction process of domain transformation; and proposes a method of jamming identification based on rough set(RS) combined with decision tree. The method first uses rough set to determine whether the jamming signal is polluted by noise, and then send it into the corresponding decision tree for secondary classification according to the judgment result, and get a higher recognition rate.

II. ANALYSIS AND MODELING OF BLANKET JAMMING

A. Noise AM(Amplitude Modulation) Jamming

Noise AM jamming has the advantages of simple jamming generating circuit, easy frequency adjustment and good countermeasure effect. With the above advantages, this form of jamming has been widely used in a certain period of time.

The signal of noise AM jamming is expressed as [6]:

$$J(t)=[U_j+u_n(t)]\cos(w_j t+\phi) \tag{1}$$

The voltage U_j and the angular frequency w_j are constants; the modulation noise $u_n(t)$ is a generalized stationary random process distributed in the interval $[-U_j,\infty]$, with a mean value of 0 and a variance of σ_n^2; the initial phase ϕ is a random variable independent of the noise and uniformly distributed in the interval $[0,2\pi]$.

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B. Noise FM(Frequncy Modulation) Jamming

For broadband radar, noise FM jamming is the main jamming method. This kind of jamming has the following advantages: it can produce blocking jamming, the jamming frequency band is wide, and it has a good jamming effect on frequency agile radar, frequency diversity radar, or radar working at different frequency points.

The expression of noise FM jamming signal is as follows [7]:

$$J(t) = U_j \cos[w_j t + 2\pi K_{FM} \int_0^t u_n(t)dt + \phi] \quad (2)$$

Among them, $u_n(t)$ is the modulation noise of the generalized stationary random process with a mean value of 0, the initial phase ϕ obeys a uniform distribution and is independent of the modulation noise; K_{FM} is the frequency modulation slope; w_j is the center frequency of the jamming signal; U_j is the frequency modulation signal amplitude.

C. RF(Radio Frequency) Noise Jamming

The generation mechanism of RF noise jamming is based on the amplification of white noise by RF, which has the characteristics of high entropy and good shielding type. Since the noise power generated by the microwave device in the jammer is low, the power of the jamming signal is limited, and it is not suitable for the application scenario where a high-power jamming signal is required to cover the target echo.

The time domain expression of RF noise jamming is as follows [8]:

$$J_{RF}(t) = U_j(t)\cos(w_j t + \phi) \quad (3)$$

$U_j(t)$ is the envelope function, which obeys the Rayleigh distribution, w_j is the noise center frequency and is much larger than the signal bandwidth, and $\phi(t)$ is the phase function.

III. Time Domain Feature Extraction of Signals

A. Statistical Features

The kurtosis coefficient [9] is a statistic that describes how steep or flat the value distribution of a signal is. The kurtosis calculation method of a random variable is the ratio of the fourth order central moment to the fourth power of the standard deviation, which is defined as follows:

$$Kurtosis = \frac{E(X-\mu)^4}{\delta^4} \quad (4)$$

Among them, X is the sampled signal sequence, μ is the signal mean, and δ is the standard deviation.

The skewness coefficient [9] is also a statistic that describes the shape of the signal distribution, and it describes the symmetry of the signal value distribution. The calculation method of skewness is the third-order central moment divided by the cube of the standard deviation, and its definition is as follows:

$$Skewness = \frac{E(X-\mu)^3}{\delta^3} \quad (5)$$

The second-order central moment of the signal time domain can reflect the distribution characteristics of the signal time domain waveform relative to the centroid, which is defined as follows:

$$Variance = E(X-\mu)^2 \quad (6)$$

B. Time Domain Instantaneous Features[10]

In active blanket jamming, the noise modulates the jamming carrier in amplitude, phase and frequency. Among them, the noise FM jamming and the noise phase modulation jamming make the instantaneous phase of the jamming signal randomly distributed. The noise AM jamming makes the instantaneous amplitude of the jamming signal randomly distributed. Therefore, the above two types of jamming can be distinguished by comparing the changes in phase and amplitude.

Let the jamming signal be $x(t)$. take $x(t)$ as the real part, and use its Hilbert transform as the imaginary part to construct the analytical signal $s(t)$. The instantaneous amplitude and instantaneous frequency can be obtained by taking the modulo and derivation of $s(t)$. In the time domain, the instantaneous amplitude and instantaneous frequency are normalized and the variance is calculated, and finally two features of normalized instantaneous amplitude variance and normalized instantaneous frequency variance are obtained.

C. Entropy Features

Information entropy is used to solve the problem of information quantification. The originally vague and abstract concept of information is quantified because of information entropy, which intuitively expresses the amount of information in information, or uncertainty.

If the probability of the occurrence of signal x_i in an information source is $p(x_i)$, the information entropy can be defined as follows:

$$H = -\sum_{i=1}^{N} p(x_i)\ln p(x_i) \quad (7)$$

However, in practical applications, when the occurrence probability of information x_i tends to 0 infinitely, according to [11], the information entropy increment corresponding to information x_i tends to be infinite, resulting in non-convergence of information entropy.

The reason why the information entropy does not converge lies in the logarithmic part of its definition formula. Therefore, [11] proposes to replace the logarithmic part of the information entropy with the exponential to obtain the exponential entropy. Its definition is as follows:

$$S = \sum_{i=1}^{N} p(x_i)e^{1-p(x_i)} \quad (8)$$

IV. Jamming Identification Based on Rough Set and Decision Tree

A. Basic Theory of Rough Set

Rough set is a new mathematical tool for dealing with ambiguous and imprecise problems. It expands the traditional set theory and proposes three concepts of upper approximate set, lower approximate set and border set. Specifically, rough set theory believes that individuals who are confirmed to belong to a certain set can be classified into a lower approximate set, and individuals that may belong to a certain set can be classified into an upper approximate set. The difference between the upper approximate set and the lower approximate set is called the border set.

Let $X \subseteq U$ be any subset, R is an equivalence relation on U, and the approximate set is defined as [12]:

$$R_*(X) = \bigcup\{Y \in U / R : Y \subseteq X\} \tag{9}$$

The upper approximate set is:

$$R^*(X) = \bigcup\{Y \in U / R : Y \bigcap X \neq \varnothing\} \tag{10}$$

The border set is:

$$BN_R(X) = R^*(X) - R_*(X) \tag{11}$$

Among them, Y is the equivalence class on U divided by the equivalence relation R, and $\varnothing$ is the empty set. The lower approximation set is the union of all equivalence classes contained in X; the upper approximation set is the union of all equivalence classes that intersect with X; the border set $BN_R(X)$ can neither be classified on X through the equivalence relation R, nor cannot be classified on $\sim X$.

B. Rough Set Theory Noise Detection [12]

In pattern recognition, the ideal, noise-unaffected pattern i can be represented by a vector as:

$$X_i = [x_{i1}, ..., x_{ij}, ..., x_{ik}]^T \tag{12}$$

where x_{ij} is an attribute value of the pattern. When the attribute x_{ij} is discrete, that is, $x_{ij} \in \{a_{ij1}, ..., a_{ijl} ..., a_{ijk}\}$, the value set of x_{ij} is sorted in ascending order, and $d_{ijl} = a_{ijl+1} - a_{ijl}$ is defined to represent the difference between two adjacent attributes.

A pattern containing noise is defined as:

$$Y_i = [y_{i1}, ..., y_{ij}, ..., y_{ik}]^T = X_i + \Psi_i \tag{13}$$

where $y_{ij} = x_{ij} + \phi_{ij}$ and ϕ_{ij} can be positive or negative, representing the noise superimposed on the ideal signal.

When the signal is superimposed with noise, according to the rough set theory, the lower approximation set of attribute x_{ij} after being disturbed by noise is defined as the set of y_{ij} satisfying the following inequality.

$$\begin{aligned} & a_{ij1} - \lambda_{ij1} \leq y_{ij} \leq a_{ij1} + \lambda_{ij1}, \\ & a_{ijl} - \gamma_{ijl} \leq y_{ij} \leq a_{ijl} + \lambda_{ijl}, l \neq 1 \,\&\, l \neq k, \\ & a_{ijk} - \gamma_{ijk} \leq y_{ij} \leq a_{ijk} + \gamma_{ijk} \end{aligned} \tag{14}$$

where $\gamma_{ij} \leq \dfrac{d_{ijl-1}}{2}, \lambda_{ij} \leq \dfrac{d_{ijl}}{2}$, and other parts are border set.

When the attribute containing noise is in the lower approximation set, it is considered that the attribute is not disturbed by noise or is less affected by noise; when the attribute containing noise is in the border set, it is considered that the attribute is greatly affected by noise. Let $\beta_i = S_i / n$ denote the noise factor of the sample, and S_i denote the number of attributes in the border set in Y_i. The noise factor represents the ratio of the number of attributes in border set to the total number of attributes in the sample, and is proportional to the severity of the noise interference of the sample. Define δ as the threshold of the noise factor. When $\beta_i < \delta$, it is considered that the degree of influence of sample Y_i by noise is within the controllable range, when $\beta_i \geq \delta$, it is considered that sample Y_i is seriously disturbed by noise, and $S_\delta = \delta \times n$ is the critical value of the number of attributes in the sample that are seriously disturbed by noise.

C. Jamming identification based on decision tree

Decision tree is a common algorithm in machine learning. It has strong interpretability and can process samples of various data types. Under a reasonable design, the decision tree can obtain a good operation speed, and under the pruning operation unique to its tree structure, the operation speed can be further improved. The main disadvantage of decision tree is that it is easy to overfit in the face of noisy samples, even if it is pruned, which leads to a decrease in its generalization ability.

Therefore, this paper divides the training set of jamming signals into a subset that is greatly affected by noise and a subset that is less affected by noise according to the degree of the signal affected by noise. During training, the two subsets are trained separately. The subset less affected by noise is used for the training of the "positive tree", and the subset affected by the noise is used for the training of the "negative tree". The negative tree is implemented by random forest, which further strengthens the generalization ability. The samples of the positive tree are also used for the calculation of the lower approximate set and the border set under the attribute. Before the calculation, the K-means algorithm is used to eliminate the attribute values that are too close to reduce the calculation amount. When predicting, first use the rough set noise detection method mentioned above for pre-classification, and then send the samples into positive or negative tree for secondary classification according to the pre-classification results. This has 3 advantages: 1) For easy-to-identify non-noise samples, using a non-integrated positive tree can speed up the prediction. 2) Positive tree do not overfit due to noisy samples. 3) Using random forest training for noisy samples can enhance the generalization ability. Figure 1 shows the training process and identification process of the Jamming identification system described in this section, where the convolution integration is used to obtain the Hilbert transform of a signal.

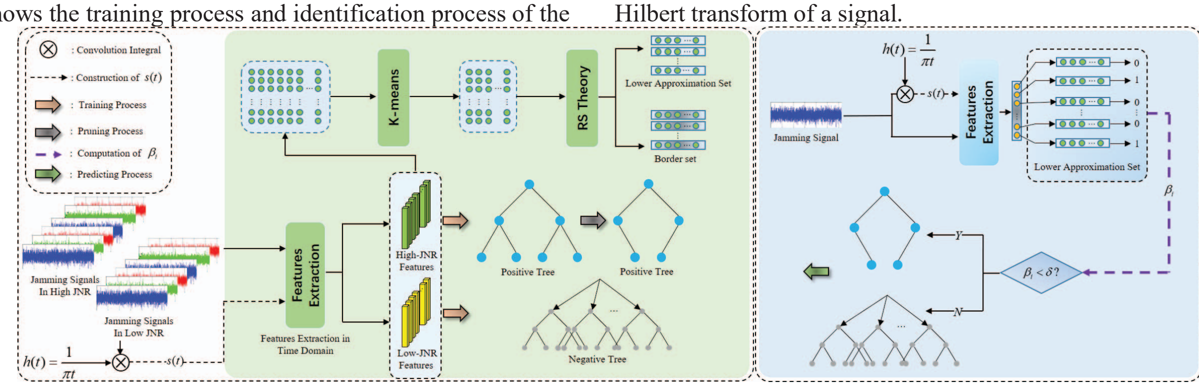

Figure 1. Jamming recognition system training process and recognition process

During training, the variation range of JNR is [-6,6] dB, and 450 Monte Carlo simulations are performed for each jamming pattern every 3dB, resulting in a total of 6750 signal samples. The 6750 samples are randomly divided into training set and test set, and the samples of each JNR and each jamming signal are randomly divided into training set and test set in a ratio of 2:1. Three jamming patterns are identified after training.

V. Analysis of Simulation Results

In order to evaluate the experimental results more comprehensively, this paper evaluates the algorithm proposed in this paper from three aspects: the recognition accuracy rate of the model, the influence of different JNRs on the recognition accuracy rate, and the real-time performance. The parameters of blanket jamming are set as shown in Table 1. The JNR threshold is 0 to divide the samples, and the noise factor threshold δ described above is set to 0.3.

TABLE I. Jamming Signal Simulation Parameter Table

Jamming Signals	Center Frequency	Modulation Noise	Modulation Coefficient	Time Width	Sample Frequency
Noise AM	20MHz	White Noise	0.5	60us	80MHz
Noise FM	20MHz	White Noise	100	60us	80MHz
RF Noise	20MHz			60us	80MHz

A. Recognition Accuracy

The correct rate of model recognition is an important indicator to evaluate the experimental results. This paper uses the confusion matrix to show the correct rate of recognition. Table 2 shows the types corresponding to each label in the confusion matrix.

TABLE II. Labels for Each Type

Types	Labels
Non-Noise	Pos
Noise	Neg
Noise AM Jamming	1
Noise FM Jamming	2
RF Noise Jamming	3

Figure 2 shows the confusion matrices obtained by the noise detection and jamming identification methods described in this paper under the training set and test set, where the jamming identification is performed under the samples with JNR greater than 0. It can be found that the noise detection and jamming identification in this paper have achieved high accuracy. The overall noise detection accuracy can reach more than 99.5%, which provides a strong foundation for subsequent identification; the overall recognition accuracy of non-noise samples can reach more than 98%. Analysis of the confusion matrix shows that the classification errors mainly include the following two categories: 1) non-noise samples or samples less affected by noise are wrongly classified as noise samples, so that the samples are sent to the wrong decision tree for identification; 2) The influence of JNR. When the JNR is low, the feature difference between noise FM jamming and noise AM jamming based on time domain extraction is small.

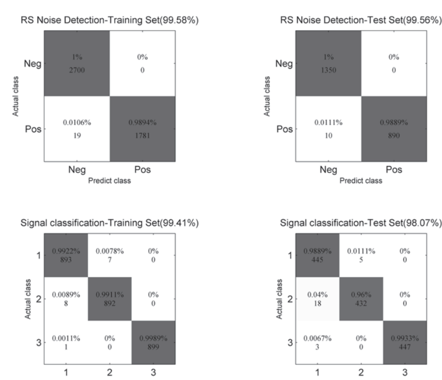

Figure 2. Confusion Matrix of Experiment Result.

B. JNR Test

In order to verify the advantages of the proposed method in dealing with noisy samples, the proposed method is compared with the methods of [2], [3] and [13] under the same simulation parameters. For all patterns under active blanket jamming, 20 Monte Carlo simulations were performed under different JNRs, and the recognition results of each method are shown in Figure 3.

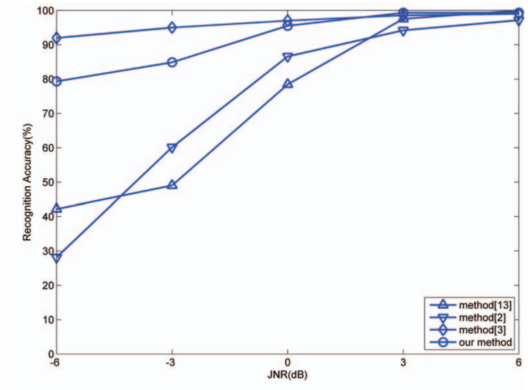

Figure 3. Comparison of recognition rates of each method

When the JNR is greater than 0, each method has a higher recognition rate, among which our method and method [3] perform better. When the JNR is less than 0, the recognition rate of each method shows a downward trend, but the downward trend of the recognition rate of the methods [2] and [13] is significantly larger than that of the other two, indicating that our method and the method [3] are robust to noise. It also shows that the features extracted by the method [3] based on the frequency domain are not easily affected by noise.

C. Real-time testing

50 Monte Carlo simulation experiments were carried out respectively. The time-consuming of feature extraction and prediction of our method and method [2] and method [14] are shown in Table 3. The real-time feature extraction of this paper is significantly better than the other two, which is mainly due to the feature extraction based on the time domain in this paper, and the time-consuming prediction of this paper is also less. In summary, this paper is better in real-time computing.

TABLE III. TIME-CONSUMING COMPARISON

Time	Features Extraction	Classification	Total
Our Method	0.5825s	0.103156s	0.6857s
Method[2]	1.774s	0.131s	1.905s
Method[14]	7.159s	13.227s	20.386s

VI. CONCLUSION

Aiming at the problems of high computational time and overfitting of noise samples in general jamming identification methods, this paper uses simple time-domain features and decision tree with fast prediction rate for jamming identification, and cleverly applies rough set to noise detection. The recognition of 3 jamming patterns is realized. Compared with the existing methods, our method has better performance in both real-time computation and recognition accuracy in noisy environments.

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