A Signal Recognition Method Based on Evidence Theory

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Abstract. In modern complex communication environment, how to effectively identify signal modulation types has become a hot research topic. Based on information entropy and Dempster-Shafer evidence theory (D-S theory), a new signal modulation recognition algorithm is proposed. Through extracting the information entropy feature and normal test, a new acquisition method of basic probability assignment (BPA) is proposed, and then the D-S theory is used to identify the signals. Simulation results show that the proposed algorithm has a better recognition rate, which has great application value.

Keywords: Signal recognition · Rényi entropy singular entropy D-S theory

1 Introduction

The key technology of non-cooperative signal modulation recognition is feature extraction and classification Recognition. Typical feature extraction methods include instantaneous parameters' extraction [1], higher order cumulants [2], Cyclic spectrum method [3], fractal dimension method [4], etc. [5–7]. In recent years, the research on information theory on feature extraction becomes a hot topic. Information entropy represents the uncertainty of a system, which can be used to measure the uncertainty measure of the signal state distribution, so it provides a theoretical framework for signal characterization description [8]. D-S theory is an important method for reasoning about uncertainty, which can be used for the targets detection, classification and identification [9–11]. In this paper, we extracted the signals' entropy features including the Rényi entropy and singular entropy. In the process of simulation, the influence of symbol and noise are considered, signal symbol is generated randomly, and the Gauss noise is added to the signal. Simulation is carried out for different modulation types of signals, and verified the effectiveness of this method.

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2 Preliminaries

2.1 Dempster-Shafer Evidence Theory

The Demptster-Shafer evidence theory is firstly introduced by Dempster and later extended by Shafer, the rule of evidence combination is shown as follows:

Suppose m_1 and m_2 are two mass functions in the same frame of discernment θ; Dempster combines rules of two BPA m_1 and m_2 to yield a new BPA:

$$m(A) = \frac{\sum_{B \mathrm{I} C = A} m_1(B)m_2(C)}{1 - k} \tag{1}$$

$$k = \sum_{B \mathrm{I} C = \phi} m_1(B)m_2(C) \tag{2}$$

where k is often interpreted as a measure of conflict between the sources. The larger value of k is the more conflicting are the sources, and the less informative is their combination.

2.2 The Rényi Entropy Based on WVD

The Wigner-Ville distribution (WVD) [12] is an efficient time-frequency method for anlyzing the non-stationary signals. In order to eliminate or lessen the cross terms of WVD, the kernel function of WVD is presented and different kernels are used for the uniform Cohen distribution. The smooth Pseudo WVD (SPWVD) is one of these techniques, which is defined as follows:

$$SPWVD_{g,h}(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(u)h(\tau)x(t-u+\frac{\tau}{2})x^*(t-u-\frac{\tau}{2})e^{-j2\pi ft}dud\tau \tag{3}$$

where $h(\tau)$ is a rectangular windows and $g(u)$ is smoothing function. The time and frequency windows are adopted to smooth a signal in the two dimensions.

As is well known, Rényi entropy is a measure of complexity, which can be used to estimate the amount of information and complexity of signals, For the continuous form of the two-dimensional probability density distribution, Rényi entropy is defined as follows:

$$R^{\alpha}(P) = \frac{1}{1-\alpha}\log_2 \frac{\int\int f^{\alpha}(x,y)dxdy}{\int\int f(x,y)dxdy} \tag{4}$$

The time frequency distribution of signal is similar with two-dimensional probability density function $f(x,y)$. So time frequency distribution Rényi entropy can be defined as follows:

$$H_{\alpha,x} = \frac{1}{1-\alpha}\log_2 \iint \left(\frac{SPWVD_{g,h}(t,f)}{\iint SPWVD_{g,h}(t,f)dfdt} \right)^{\alpha} dtdf \tag{5}$$

2.3 The Rényi Entropy Based on CWT

Wavelet analysis is an effective and important method for non-stationary signals [13]. Different from the traditional Fourier analysis, wavelet packet analysis simultaneously decomposes the low and high frequency of different signals. And then, according to the analyzed type of the signal, wavelet packet analysis self-adaptively chooses the frequency band and confirms the signal resolution at different bands.

Suppose, wavelet transform scale selection is j, the signal is decomposed into low frequency part c_j and high frequency part $d_1, d_2, \ldots, d_j$, using Fourier Transform for each wavelet coefficients.

$$X(k) = \sum_{n=1}^{N} d_i(n) e^{-j\frac{2\pi}{N}kn} \tag{6}$$

The power spectrum $\{S_k, k = 1, 2, \ldots, j+1\}$ of each layer of wavelet coefficients can be calculated by the formula (7).

$$S(k) = \frac{1}{N}|X(k)|^2 \tag{7}$$

Therefore, according to formula above, the p_k can be calculated and the wavelet energy spectrum entropy is shown as follows:

$$H_{WESE} = -\sum_{k=1}^{N} p_k \log_2 p_k \tag{8}$$

2.4 Singular Spectrum Entropy

Singular spectrum entropy [14] is used to describe the signals in the perspective of singularity. Suppose, $X_t = \left\{x_t^1, x_t^1, \cdots, x_t^L\right\}$ represents the received signal sequence, it means that the receiver simultaneously collect signals from L different channels. For the signal in the each channel, the signal sampling is $\{x_i, i = 1, 2, L, N\}$, and the sampling number is N. The analysis window M is used to analyze the sampling sequence. Suppose the time delay parameter of analysis window is equal to 1. When the sampling sequence x_i can be divided into segments with the number of $N - M$, which is the matrix A with the dimension of $(N - M) \times M$.

$$A = \begin{bmatrix} x_1 & x_2 & \cdots & x_M \\ x_2 & x_3 & \cdots & x_{M+1} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N-M} & x_{N-M+1} & \cdots & x_N \end{bmatrix} \tag{9}$$

where, the track vector at time i of all the channels is shown as: $\{x^1_{t+1}, x^1_{t+1}, \cdots, x^1_{t+M}, x^1_{t+1}; x^2_{t+1}, \cdots, x^2_{t+M}; \cdots; x^L_{t+1}, \cdots, x^L_{t+M}\}$. Considering the singular decomposition of matrix A, and getting the singular spectrum value $\{\delta_i, 1 \leq i \leq N-M\}$. The δ_i reflects the proportion of corresponding pattern to the total pattern. Based on the information entropy theory, in time domain, the singular spectrum entropy of the signal is shown as follows:

$$H_{SSE} = -\sum_{k=1}^{N} p_k \log_2 p_k \quad P_k = \frac{\delta_i}{\sum\limits_{i=1}^{M} \delta_i} \tag{10}$$

where, P_i is the proportion of *ith* singular values to the whole singular spectrum value.

3 Experiments

During the simulation process, firstly, we need to train the features of the signal, the feature is $\mathbf{H} = [H_1, H_2, H_3]$, H_1, H_2, H_3 represent three entropy value matrices. Secondly, we extract the entropy features of test signal, we can get h_1, h_2, h_3. At last, we get BPA and make fusion calculation. The whole flow chart shows as Fig. 1.

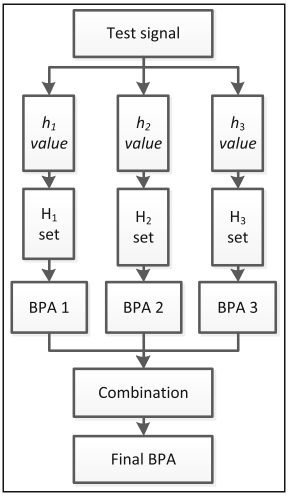

Fig. 1. The simulation flow chart of the system.

Step 1: Entropy features extraction
Information entropy describes the complexity of the signal in different domains, such as time frequency domain, wavelet domain. In this paper, we select the signal $x(t)$ length to 2048 points and the signal symbol is generated randomly to every simulation. The symbol rate f_d = 1000B, the carrier frequency f_c = 4 kHz, and the sample rate f_s = 1.6 MHz.

Actually, due to the presence of noise and the change of symbol, the entropy is unstable even in the same SNR and same sample points. The Fig. 2 are the probability distribution curve of entropy when SNR = 0 dB and SNR = 10 dB.

The entropy probability distribution curves show that the stability of the entropy. Through the entropy test, we can find that the entropy probability consistent with normal distribution. The curve is "fat", that means the entropy has poor stability, otherwise the entropy has better stability.

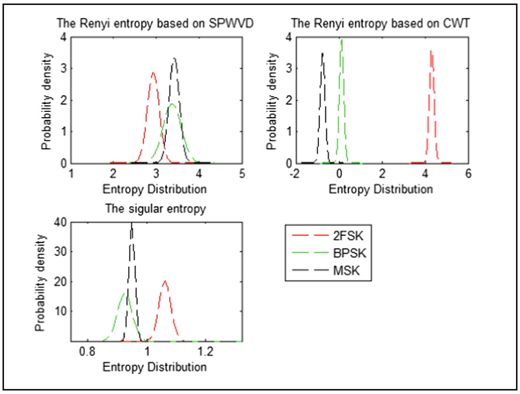

Fig. 2. The probability distribution curves of entropy (SNR = 10 dB).

Step 2: BPA acquisition
In order to realize the signal classification and recognition, we need to get the BPA function. The proposed method incorporates the test sample information with the attribution provided by the training samples to extract the BPA. Through the probability distribution of entropy, the entropy probability obey the normal distribution. Therefore, we define the rules to obtain BPA for test sample by using the relationship between the test data and the normal distribution model. The proposed method as follows:

(1) Calculating the mean μ_i and variance σ_i^2 of entropy value, $i = 1, 2, \ldots, K$, i presents the training signal types, K is the number of types of training signal, K = 3 and the label i respectively represent 2FSK, BPSK, MSK.
(2) Inputting a test signal, calculating three types entropy value $h = [h_1, h_2, h_3]$. The entropy value generation into the probability density function, and we can get the

probability value $p(i = 1, 2, \ldots n)$ through brought into the probability function of different signals $N \sim (\mu, \sigma^2)$, we can get:

$$p = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(h-\mu)^2}{2\sigma^2}\right) \tag{11}$$

$$m(p) = \{m(p_1), m(p_2), \cdots m(p_n)\} = \{p_1, p_2 \cdots p_K\} \tag{12}$$

Through the normalization of $m(p)$, we can get the BPA $m(A)$ function.

$$m(A) = \frac{p_i}{\sum_{i=1}^{n} p_i} \tag{13}$$

Step 3: Fusion calculation

The test signal with MSK signal as an example, calculating three types entropy value $h = [h_1, h_2, h_3]$, generating into the probability density function, we can get the probability value p. After the normalization, we get the BPA function $m_1(A), m_2(A), m_3(A)$, through the D-S theory fusion calculating, it get the final BPA function m.

Step 4: Simulation result

Based on the signal features, D-S classifier is used to classify the signal modulation, the recognition rates of three kinds of digital communication signals are shown in Fig. 3.

As it is shown in Fig. 3, based on three entropy features and D-S classifier, the three different signals can be recognized, and the 2FSK can reach high recognition rate even under low SNR. With the reducing of SNR, the recognition rate of BPSK, MSK decreased. For the modulation mode, the BPSK and MSK belong to digital phase modulation signal, the differences between these two kinds of signals are relatively small, with the effect of noise, the recognition rate of these two kinds of signals can be reduced sharply under low SNR.

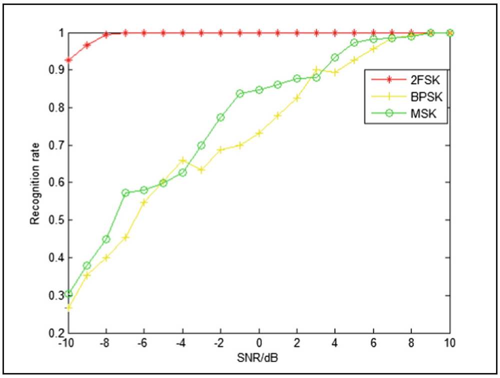

Fig. 3. The recognition rate of digital communication signals.

4 Conclusion

In this paper, a recognition algorithm of communication signal based on entropy features and D-S theory is proposed. Through extracting the entropy and normal test, a new BPA acquisition method is proposed, and D-S theory classifier is used to classify the signals. Simulation result shows, that the new recognition algorithm has a good performance, which can get 90% recognition rate when the SNR is greater than 5 dB.

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