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Modulation Recognition based on Wavelet Transform and Fractal Theory

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Abstract

With the rapid development of communication technology, digital signal processing and other technologies, wireless communication environment is becoming more and more complex. Communication signals with different frequencies and modulated modes are usually scattered over a wide frequency band. In this paper, an improved algorithm based on wavelet transform and fractal theory is proposed. To improve the traditional fractal theory, wavelet transform is applied to the modulation signal, and then four fractal dimensions (Fractal box dimension, Petrosian fractal dimension, Katz fractal dimension and Sevcik fractal dimension) are used to extract the features. Through the simulation of the six modulation signals generated by Matlab, it can be seen that the recognition rate of the proposed method reaches 90% at the SNR of 2dB. Moreover, by comparing the method of this paper with the short-time Fourier transform and the fractional Fourier transform, we can find that the recognition rate of this method is 3% ~ 10% higher than the two comparison methods. It can be seen that the proposed method can effectively identify different signals in the case of low SNR.

Keywords: modulation recognition; wavelet analysis; fractal theory; feature extraction

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1. Introduction

With the rapid development of information and communication, in order to make full use of channels and meet the actual needs, multiple digital modulation modes will be adopted simultaneously in the same communication system. Therefore, the automatic recognition technology of digital modulation signal has very important research significance. The main task of this technology is to identify the modulation mode to realize the intelligent reception and processing of modulation signal. Especially in the field of non-cooperative communication [1-2] and fault diagnosis [3-4], signal recognition has an important application. Because fractal theory [5] and wavelet transform [6] have a certain degree of noise suppression, these two methods are widely used in digital modulation recognition.

Reference [7] proposed a recognition method based on cumulant and spectral characteristics for square-type MPSK, MQAM and MSK of satellite communication signal modulation, and analysed the impact of ascending cosine filter on the recognition results. Reference [8] proposed the classification method of MASK, MPSK, MFSK and 16-QAM based on fourth-order and sixth-order cumulants, using support vector machine as classifier. However, the algorithm fails to distinguish binary amplitude modulation (2ASK) signals with identical characteristic parameters from binary phase modulation (2PSK) signals, so its application is limited. Reference [9] proposed a recognition method based on fourth-order cumulants for MPSK and MQAM in multi-path fading channels. Reference [10] proposed a new classification method based on high cumulative volume to complete the recognition of MPSK and MQAM in Gaussian channel and fading channel. Reference [11] proposed to extract feature parameters based on high-order cumulants, and applied ant colony algorithm in the design of classifier. Reference [12] proposed the recognition of 2ASK, 2FSK, 2PSK, 4PSK, 4PSK, 4quaternary amplitude modulation (4ASK) and 4FSK based on the instantaneous characteristic parameters after wavelet de-noising. Reference [13] proposed the classification method of MPSK and MQAM signals by using the characteristic parameters of signal wavelet packet transform, such as variance, fourth order moment and zero-crossing rate. In the above

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methods based on high-order cumulant, wavelet transform and combining other characteristic parameters, MASK, MPSK, MFSK and MQAM cannot be fully recognized, or feature parameters extracted are too many and the algorithm is relatively complex.

In the traditional modulation recognition algorithm [14-16] based on fractal dimension, the fast Fourier transform is usually used to extract the spectral characteristics of the modulated signal [17]. In this paper, wavelet transform is combined with four fractal dimensions to extract the characteristics of modulated signals, and a hybrid recognition algorithm is implemented, which is verified by simulation with software. Firstly, the scene of a real receiver is simulated to generate various modulated signals with low signal noise. Then, characteristic parameters are extracted from the signals after wavelet transformation. KNN classifier is used to classify 2ASK, 4ASK, 2FSK, 4FSK, 8FSK and BPS. In this paper, short-time Fourier and fractional Fourier transform are selected as the comparison methods. Under the condition that SNR is -5~15dB, the recognition rate of this method and the two comparison methods is compared. This algorithm makes full use of the advantages of wavelet transform and fractal dimension with good anti-noise performance, expands the range of modulation modes that can be recognized, improves the recognition rate, reduces the number of characteristic parameters and reduces the complexity of the algorithm. Theoretical analysis and simulation results show that this algorithm can identify the 6 digital modulation modes effectively and has good recognition effect. The proposed method can provide a good theoretical basis in other application field [18].

2. Method Theory

2.1. Wavelet Transform Theory

Compared with Fourier transform, the wavelet transform is more suitable for detecting the transient change phenomenon of signals. It makes multi-scale detailed analysis and processing by scaling and shifting and other operations. In any $L^2(R)$ space, the continuous wavelet transform (CWT) of function can be expressed as

$$CWT(a,b) = \int s(t)\Psi^*_{(a,b)}(t)\mathrm{d}t = \frac{1}{\sqrt{a}}\int s(t)\Psi^*(\frac{t-b}{a})\mathrm{d}t \tag{1}$$

Where a is scale factor, b is the translation factor, * is the complex conjugate, and $\Psi^*_{(a,b)}(t)$ is the wavelet basis function obtained by the mother function $\Psi(t)$ through time scale transformation and translation, as shown in Equation (2)

$$\Psi^*_{(a,b)}(t) = a^{-1/2}\Psi(\frac{t-b}{a}) \tag{2}$$

The mother wavelet function $\Psi(t)$ satisfies the allowable conditions:

$$W_g = \int_{-\infty}^{+\infty} \frac{\mathrm{F}(\Psi(t))}{|w|}\mathrm{d}w < \infty \tag{3}$$

Where $\mathrm{F}(\Psi(t))$ is the Fourier transform of $\Psi(t)$. CWT has the following characteristics:

- Linearity: the wavelet transform of multi-component data can be expressed as the sum of its component wavelet transforms
- Translation invariance
- Telescopic covariance
- Self-similarity: for different transformation scales a and b, the continuous wavelet transform is self-similar
- Redundancy: when restoring the original data, the reconstructed fraction of continuous wavelet transform is more than one, and the kernel function of wavelet transform has multiple choices

In practical application, the choice of wavelet AA is very important. Wavelet function has two characteristics. First, its definition domain is finite. In the time domain has tight support set or similar tight support set, wavelet generating function in the time frequency domain local characteristics are better. Second, the wavelet function has positive and negative alternating characteristics, and its dc component is 0. Haar wavelet is the earliest and simplest orthogonal wavelet function, and its parent wavelet is defined as follows:

$$\Psi(t)=\begin{cases}1, & -0.5<t<0\\ -1, & 0<t<0.5\\ 0, & \text{others}\end{cases} \tag{4}$$

2.2. Fractal Box Dimension

Fractal dimension is a tool for characterizing the complexity of objects. There are many calculation methods. Among them, the box dimension algorithm is simple, and the calculation is small, which can well characterize the complexity of the signal. (X,d) is a metric space, M is a non-empty compact set family of X, let A be a non-empty compact set in X, for each positive ε, the number of minimum boxes covering A can be expressed by $N(A,\varepsilon)$, the box side length is ε, then:

$$N(A,\varepsilon)=\left\{M:A\subset\sum_{i=1}^{M}N(x_i,\varepsilon)\right\} \tag{5}$$

Where $x_1,x_2,\cdots,x_M$ are the differences between X. Then, the box dimension is defined as:

$$D_b=\lim_{\varepsilon\to 0}\frac{InN(A,\varepsilon)}{In(1/\varepsilon)} \tag{6}$$

Fractal box dimension has no absolute meaning, only relative value. Therefore, in engineering applications, the same processing method should be used for several signals to calculate the box dimensions of different signals, so as to have comparative value.

2.3. Petrosian Fractal Dimension

Let the waveform signal be composed of a series of points $\{y_1,y_2,\cdots,y_N\}$. First, binarization is carried out. Let the binarization matrix be z_i. Petrosian fractal dimensions are defined as follows:

$$D=\frac{\log_{10}N}{\log_{10}N+\log_{10}\left(\frac{N}{N+0.4N_\Delta}\right)} \tag{7}$$

Where N_Δ is the total number of adjacent symbol changes of sequence z_i:

$$N_\Delta=\sum_{i=1}^{N-2}\left|\frac{z_{i+1}-z_i}{2}\right| \tag{8}$$

Petrosian fractal dimension is a relatively simple definition of fractal dimension. Compared with other fractal dimensions, Petrosian fractal dimension is relatively easy to calculate.

2.4. Katz Fractal Dimension

Let the waveform signal consist of a series of points (x_i,y_i), and the signal length is N. Katz's fractal dimension can be obtained from the following equation:

$$D=\frac{\log(N)}{\log(N)+\log(\frac{d}{L})} \tag{9}$$

Where L is defined as the length of the signal waveform. L is:

$$L=\sum_{i=0}^{N-2}\sqrt{\left(y_{i+1}-y_i\right)^2+\left(x_{i+1}-x_i\right)^2} \tag{10}$$

D is defined as the maximum distance from the initial point $\left(x_1, y_1\right)$ to other points; d is:

$$d=\max\left(\sqrt{\left(x_i-x_1\right)^2-\left(y_i-y_1\right)^2}\right) \tag{11}$$

2.5. Sevcik Fractal Dimension

Similarly, let the waveform signal consist of a series of points $\left(x_i, y_i\right)$, and the signal length is N. Firstly, the signal is normalized, then:

$$x_i^*=\frac{x_i-x_{\min}}{x_{\max}-x_{\min}},\ y_i^*=\frac{y_i-y_{\min}}{y_{\max}-y_{\min}} \tag{12}$$

Therefore, Sevcik fractal dimension D can be obtained as follows:

$$D=1+\frac{\ln(L)+\ln(2)}{\ln\left[2\times\left(N-1\right)\right]} \tag{13}$$

Where L is the length of the waveform. L can be obtained from the following equation:

$$L=\sum_{i=0}^{N-2}\sqrt{\left(y_{i+1}^*-y_i^*\right)^2+\left(x_{i+1}^*-x_i^*\right)^2} \tag{14}$$

In summary, four commonly used one-dimensional fractal dimension algorithms are defined, which extract features from the waveform of the signal.

3. The Simulation Analysis

3.1. Data Set Generation

In this paper, the Matlab 2015a software platform is used to conduct simulation experiments on MASK (M = 2.4), MFSK (M = 2, 4, 8) and BPSK signals. The setting of signal related parameters is shown in Table 1. The baseband signal is a random code, and six kinds of different signals are added with the same distribution of white noise signal, and the simulation experiment is carried out in the range of SNR of -5 ~ 15dB.

Table 1. Setting of signal related parameters

The parameter name	The parameter value
Carrier frequency	4MHz
Sampling frequency	16MHz
MFSK signal initial frequency	1MHz
Frequency offset	1MHz
Signal length	2048
Digital signal symbol rate	1000Sps

The data set of the six signals contains a total of 2400 signal samples, 400 samples per signal. Among them, the training set contains six kinds of signals, each of which contains 200 samples. The test machine also contains six kinds of signals, each of which contains 200 samples.

3.2. Simulation Process and Results Display

The overall flow of the experiment is shown in Figure 1.

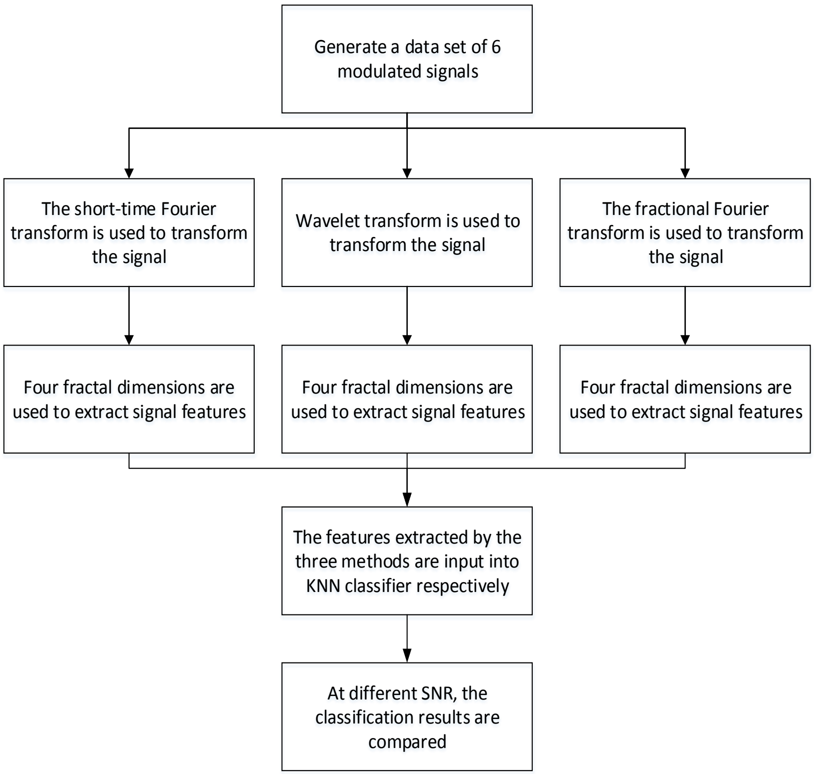
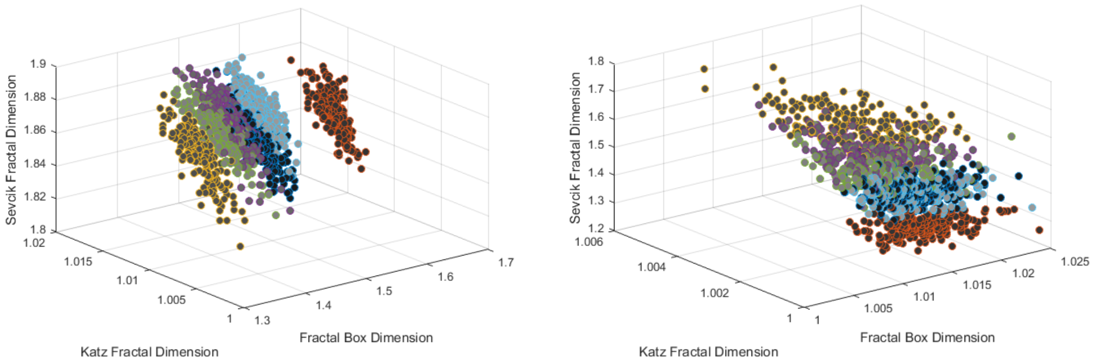


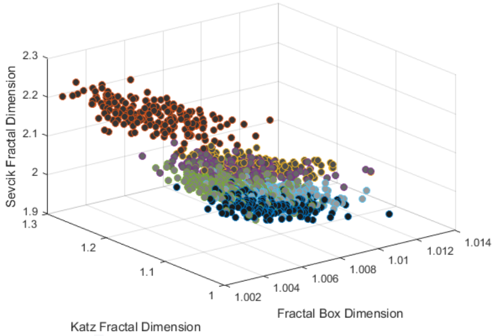
Figure 1. Simulation process

In this simulation experiment, short-time Fourier transform (STFT) and fractional Fourier transform (FRT) were selected as the comparison methods. In addition to the differences in the transformation methods, other parameters were set in the same way as the method proposed. In the process of signal recognition, the result of recognition is often closely related to the distribution of features. The more dispersed the feature distribution of different signals is, the higher the degree of discrimination they have. Based on the consideration of the intuitiveness of feature extraction effect, this paper presents the feature distribution map after feature extraction, and presents the feature extraction effect of different methods in an intuitive form.

In the case of the SNR of 0dB, we can see that the characteristics of wavelet transform have the lowest degree of aliasing. The result of separating different signals has been achieved, but the characteristic distribution of different signals is still relatively compact. The other two methods are also intertwined and do not separate different types of signals.

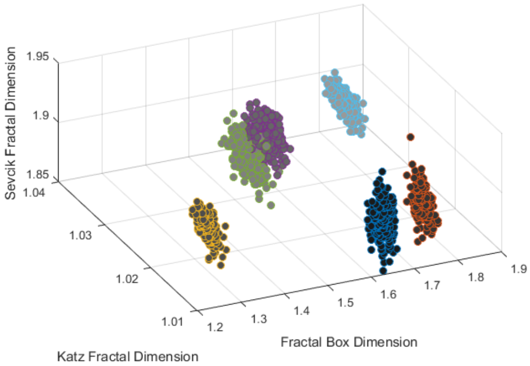


(a) Feature distribution of wavelet transform (b) Feature distribution of short-time Fourier transform

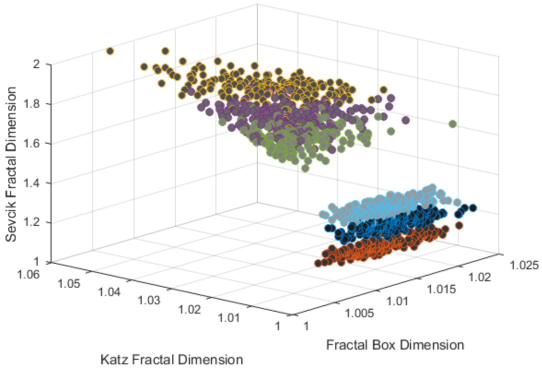


(c) Feature distribution of fractional Fourier transform

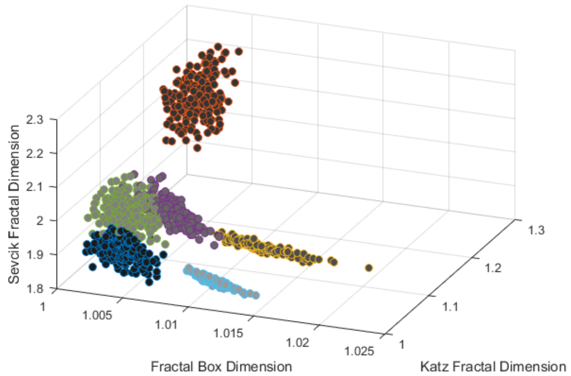
Figure 2. Feature distribution diagram of the three methods (SNR = 0dB)



(a) Feature distribution of wavelet transform



(b) Feature distribution of short-time Fourier transform



(c) Feature distribution of fractional Fourier transform

Figure 3. Characteristic distribution of the three methods (SNR = 15dB)

As can be seen from Figure 3, in the case of an SNR of 15dB, the characteristics of the wavelet transform can already complete the task of classification, and the degree of separation of different signals is also high. The classification can also be done by the features of the FRT, but there is some room for improvement in the degree of separation. After the characteristics of the STFT, it is barely possible to classify different signals, but the effect is not ideal.

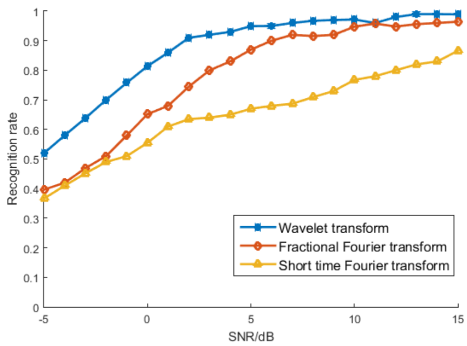


Figure 4. Recognition rate of the three methods

After feature extraction, the next step is to classify different signals and calculate the quality of the classification results.

The Figure 4 shows the change rate of the recognition rate of the three methods when the SNRs are -5~15dB. It can be seen that the recognition rate of the method based on wavelet transform and fractal dimension is the best in both low SNRs and high SNRs. At the SNR of 2dB, the recognition rate reaches 90%. The FRT and the STFT are relatively slow as the SNR is improved. The STFT has a recognition rate of just 90% at the SNR of 15dB. It can be seen that the proposed method is ideal for the recognition of six kinds of modulation and recognition signals including Gaussian white noise.

4. Conclusions

In the paper, a modulation recognition method based on wavelet transform and fractal theory is introduced. At about 2dB SNR environment, the recognition rate can reach 90%. This paper not only makes statistics on the recognition rate of different SNR, but also presents the features extracted by three methods intuitively in the form of a 3d feature distribution map. From the two forms of comparison mentioned above, the same conclusion can be drawn. The method proposed in this paper has better results, which is suitable for the study in the relative field.

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