Realization and Performance Simulation of Spectrum Detection Based on Cyclostationarity Properties

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Abstract. With the wide application of radio technology, spectrum resources are becoming more and more important. Cognitive radio is a new subject that is used to make full use of spectrum resources. The paper studies the spectrum sensing in cognitive radio and focuses on non-cooperative detection method. Based on the energy detection and analysis of the principle of feature detection in periodic stationary process. Using MATLAB for simulation analysis, making comparison of performance between the two methods. The detection performance of the periodic stationary process feature method is 5–7 dB better than the energy detection performance. And the system overhead is about an order of magnitude higher than energy detection.

Keywords: Cognitive radio · Smooth cycle · Energy detection method · Periodic stationary process feature detection method

1 Introduction

With the widespread use of radio technology, modern society is increasingly dependent on radio spectrum resources, radio spectrum resources have become an important resource in today's society, and the scarcity of spectrum resources is becoming more and more obvious. In addition, the average utilization of spectrum resources is very low and extremely unbalanced [1]. Some unlicensed bands are overused, at the same time, the usage rate of some licensed frequency bands is at a low level. Since the current spectrum allocation policy is based on a fixed frequency, most of the spectrum is allocated to licensed band applications (e.g. TV broadcasts). The spectrum resources of unlicensed bands are much less. Most emerging radio applications operate on unlicensed bands, making spectrum occupancy overcrowded on unlicensed bands.

The US Federal Communications Commission have made a large number of studies which shown that some unlicensed bands, such as industrial, scientific, medical bands, and licensed bands around 2 GHz for land mobile communications are overcrowded while some licensed bands are often idle. This is clearly contradictory to the shortage of spectrum resources that are currently of widespread concern. It can be assumed that if the system can automatically sense the spectrum environment in which

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it is located, intelligently learn to adjust the transmission parameters such as modulation, coding, channel protocol and bandwidth in real time; or use the idle frequency band outside the original designated frequency band to realize the access of the spectrum in the multi-dimensional space. This will undoubtedly greatly improve spectrum utilization. So a revolutionary intelligent spectrum sharing technology, cognitive radio, has the original idea [2].

The core idea of cognitive radio is to realize dynamic spectrum allocation and spectrum sharing through spectrum sensing and intelligent learning ability of the system [3]. Cognition provides the ability to sense and reset spectrum so that the radio can operate dynamically according to the wireless environment, greatly improving spectrum utilization [4]. In this sense, cognitive radio meets the increasing demand for radio spectrum resources in today's society.

Spectrum sensing is the basic function of cognitive radio systems and is the prerequisite for spectrum management and spectrum sharing. The so-called "perception" means that in the time domain, frequency domain and airspace multidimensional space, the spectrum is allocated to the primary user (authorized user) and detect whether the primary user works in these frequency bands, thereby obtaining spectrum usage. If the band is not used by the primary user, it is under "spectral hole" state [5], and the cognitive user (unauthorized user) can use it temporarily. The purpose of spectrum sensing is to discover spectral holes without causing harmful interference to the primary user.

This paper studies the spectrum sensing in cognitive radio, focusing on non-cooperative detection methods, including energy detection and periodic stationary process feature detection. Firstly, the energy detection method and the signal detection method of the signal are introduced. Then the actual analysis method and simulation implementation of the cyclostationary process are carried out. The performance of the two detection methods was then compared and analyzed by MATLAB simulation.

The rest of this article is as follows: The first part briefly introduces the energy detection method and the periodic characteristic detection method of the signal; The second part introduces the actual analysis method and simulation implementation of the cyclostationary process; The third part compares and analyzes the two methods. Finally, the fourth part summarizes the full text.

2 Non-cooperative Detection

The source detection (i.e., non-cooperative detection) is based on cognitive radio to detect the weak signal emitted by the first user transmitter, which is low in complexity mature in technology and easy to implement. The source detection is further divided into energy detection and periodic stationary process feature detection [6].

2.1 Energy Detection

This method assumes that the power is different depending on whether or not the signal is present. Since this detection method is independent of the prior information of the input signal. Therefore there is no strict limit to the type of signal. The main idea of the energy detection method.

The energy detection method is a relatively simple signal detection method and belongs to signal incoherent detection. The detection method is to directly sample and model the time domain signal and then square it. In addition, it is also possible to convert the signal from the time domain to the frequency domain by using a Discrete Fourier Transform, and then modulo square the frequency domain signal. The main advantage of the energy detection method is that it does not require any prior knowledge of the detected signal [7].

In practical applications, the energy detection method is to accumulate energy in a certain frequency range. If the accumulated energy is greater than a preset threshold, the signal exists; If it is less than this threshold, the signal does not exist and only noise exists. The starting point of energy detection is that when there is additive noise on the channel, the energy of the signal plus noise is greater than the energy of the noise. The energy detection method is quite a blind detection algorithm. This method is applicable to any signal, but in addition to obtaining the approximate frequency band of the signal, this detection method cannot give other parameters of the signal more accurately, which brings trouble to the next processing. The input signal is averaged over a period of time and compared with a preset threshold to determine whether an input signal is present.

2.2 Periodic Characteristics Detection of Signals

In a communication system, the statistical characteristics of the signal are periodically changed due to modulation, sampling, encoding, and the like of the signal. Such a random signal is a cyclostationary signal and also becomes a periodic stationary signal. The periodic stationary process feature detection can be performed by extracting characteristic features of the modulated signal, such as carrier, modulation type, symbol rate, and the like. These characteristics are detected by analyzing the spectral correlation property function [8].

The main advantage of spectral correlation function detection is that it can distinguish noise energy from the modulating signal power. Compared with energy detection, the system robustness of periodic stationary process feature detection is better than energy detection, but the complexity is much larger than the energy detection method.

If the statistical mean of the signal has periodicity, its statistical mean can be expanded into a Fourier series.

$$m_X(t) = \sum_{m=-\infty}^{\infty} m_X^{\alpha} \exp(j2\pi\alpha t) \tag{1}$$

$$m_X^{\alpha} = \frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} m_X(t)\exp(j2\pi\alpha t)dt \tag{2}$$

Defined $\alpha = m/T_0$ as the cycle frequency, which m_X^α is the cycle average. The cyclic mean corresponds to the time average after the left shift of the signal spectrum by α.

Define a cyclic autocorrelation function $R_X^\alpha(\tau)$ when the signal $x(t)$ has loop ergodicity. The Wiener-Sinqin theorem shows that the result of the Fourier transform of the autocorrelation function $R_X^\alpha(\tau)$ is the spectral density function, which is denoted as $S_X^\alpha(f)$.

Analysis of the cyclic autocorrelation function, available

$$R_X^\alpha(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} u(t+\frac{\tau}{2})v^*(t-\frac{\tau}{2})dt = R_{UV}(\tau) \tag{3}$$

$$u(t) = x(t)\exp(-j\pi\alpha t) \tag{4}$$

$$v(t) = x(t)\exp(j\pi\alpha t) \tag{5}$$

Hypothesis $U(f)$ and $V(f)$ are the Fourier transform results of $u(t)$ and $v(t)$, respectively. $X(f)$ is the Fourier transform result of the original signal $x(t)$. According to the characteristic of the frequency shift of the Fourier Transform. $U(t) = X(f + \alpha/2)$ and $V(f) = X(f - \alpha/2)$. Therefore, $u(t)$ and $v(t)$ are equivalent to the signals obtained by shifting the original signal $x(t)$ to $\pm\alpha/2$ respectively. The spectral density function $S_X^\alpha(f)$ reflects the degree of correlation of the signal $x(t)$ at the frequency shift component $f \pm \alpha/2$, as can be seen from the above analysis. From the above analysis, $S_X^\alpha(f) = S_{UV}(f)$, the spectral density function $S_X^\alpha(f)$ is also called the spectral correlation density function.

When the signal is actually detected, since the length Δt of the received data cannot be extended indefinitely, the usual concern is how to obtain a valid estimate of the spectral density function from the finite-length data. The Fourier transform with a time length of T_0 is obtained for the signal.

$$X_{T_0}(t,f) = \int_{t-T_0/2}^{t+T_0/2} x(\xi)\exp(-j2\pi f\xi)d\xi \tag{6}$$

The estimated value of the cyclic spectral density function at this time is

$$\hat{S}_X^\alpha(f) = \lim_{T_0\to\infty\Delta t\to\infty} \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} S_{X_{T_0}}^\alpha(t,f)dt \tag{7}$$

$$S_{X_{T_0}}^\alpha(t,f) = \frac{1}{T_0} X_{T_0}(t,f+\frac{\alpha}{2}) X_{T_0}^*(t,f-\frac{\alpha}{2}) \tag{8}$$

$S_{X_{T_0}}^\alpha(t,f)$ is called a cycle diagram. The method of estimating the cyclic spectral density function is usually a time domain smoothing period diagram method and a frequency domain smoothing period diagram method.

Time domain smoothing period graph method: Let $T_0 = 1/\Delta f$, the cyclic spectral density function can be described as:

$$\hat{S}_X^\alpha(f) = \lim_{\Delta f \to 0 \Delta t \to 0} \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} \Delta f X_{\Delta f}(t, f + \frac{\alpha}{2}) X_{\Delta f}^*(t, f - \frac{\alpha}{2}) dt \tag{9}$$

$$X_{\Delta f}(t, v) = \int_{t-1/2\Delta f}^{t+1/2\Delta f} x(u)\exp(-j2\pi uv)du \tag{10}$$

Therefore $X_{\Delta f}(t, v)$ is the result of $x(t)$ short-time Fourier transform. Center frequency is v, the approximate bandwidth is Δf. When $\Delta f \to 0$, $\hat{S}_X^\alpha(f)$ represents the time-dependent limit between the two spectral components at frequencies $(f + \alpha/2)$ and $(f - \alpha/2)$.

Frequency domain smoothing period diagram method:

If $T_0 = \Delta t$, then

$$\hat{S}_X^\alpha(f) = \lim_{\Delta f \to \infty \Delta t \to \infty} \frac{1}{\Delta t} \int_{f-\Delta f/2}^{f+\Delta f/2} \frac{1}{\Delta t} X_{\Delta f}(t, v + \frac{\alpha}{2}) X_{\Delta f}^*(t, v - \frac{\alpha}{2}) dv \tag{11}$$

When Δt is large enough, the time domain smoothing period graph method is roughly the same as the frequency domain smoothing period graph method. In order to achieve high reliability, the cyclic frequency resolution must be much smaller than the traditional Fourier frequency resolution [9].

The use of periodic stationary process feature detection utilizes a spectral correlation function to distinguish between signal energy and noise energy from the power of the modulated signal. The noise is a generalized incoherent stationary signal, and the signal is periodic and spectrally coherent. The detection stability of the periodic stationary process feature detection is better than the energy detection, but the implementation complexity is higher than the energy detection. The energy detection only needs to calculate the result of the discrete Fourier transform, and the periodic stationary process feature detection also needs to calculate the mutual dryness of the discrete Fourier transform results.

3 Practical Analysis Method and Simulation Implementation of Cyclostationary Process

In the theoretical analysis, the mean value of the signal studied and the time value of the autocorrelation function are derived from it, so it is impossible to implement in practice because the length of the received data cannot be infinitely long. Therefor it is possible to estimate with a limited length sequence. There are N data in the actual sampled sample, which can be regarded as a real sequence of length, and the estimated value of the autocorrelation function is

$$\hat{R}(m) = \frac{1}{N} \sum_{n=0}^{N-|m|-1} x(n)x(n+|m|) \tag{12}$$

Assume that the actual signal is a band-limited signal, that is, when the signal is Fourier transformed and then expressed in the frequency domain, it is not 0 in the range of the lower limit frequency b and the upper limit frequency B, that is,

And then there is: $X(f) \neq 0(\mathrm{b} \leq |f| \leq B)$

$$S_X^\alpha \neq 0\left(\left||f| - \frac{|\alpha|}{2}\right| \leq b\right) \bigcup \left(\left||f| + \frac{|\alpha|}{2}\right| \geq B\right) \tag{13}$$

Then, the area which is not 0 in the plan view is a region of four diamonds (as shown in Fig. 1(a)).

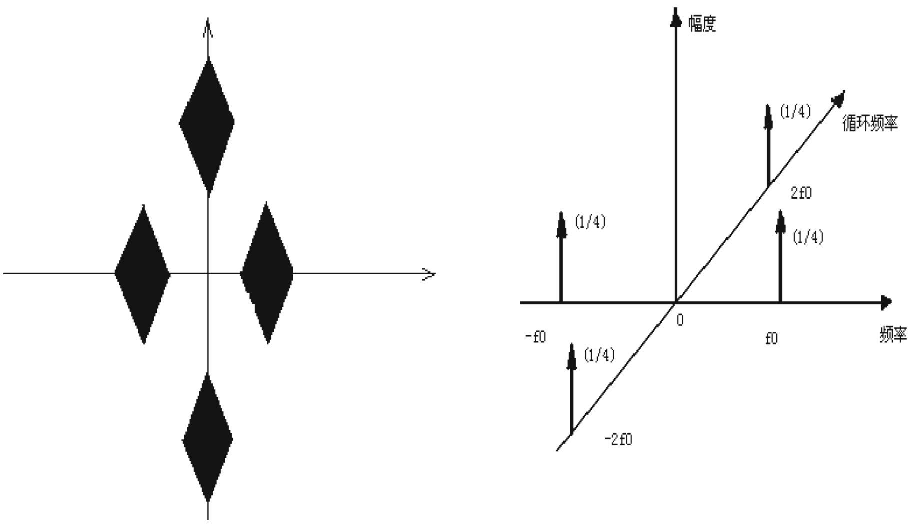
If the signal is in the form of a simple sine wave, i.e. $s(t) = \cos(2\pi f_0 t + \theta)$, then the cyclic autocorrelation function of the signal is found to be:

$$R_S^\alpha(\tau) = cos(2\pi f_0 \tau)/2 \ \alpha = 0 \bigcup \exp(\pm j2\theta)/4 \ \alpha = \pm 2f_0 \tag{14}$$

Finding the spectral correlation function of sine wave signal by Fourier transform

$$S_S^\alpha(f) = \frac{\delta(f - f_0)}{4} + \frac{\delta(f + f_0)}{4}(\alpha = 0) \bigcup \frac{\exp(j2\theta)\delta(f)}{4}(\alpha = \pm 2f_0) \tag{15}$$

On the three-dimensional graph of the spectral correlation function, four impulse functions can be seen, the impulse intensity is 1/4 unit, and the frequency points are at $(\pm f_0, 0)$ and $(0, \pm 2f_0)$. As shown in Fig. 1(b)



(a) Three-dimensional cross-section of the cyclic spectrum of a wideband signal.

(b) Three-dimensional map of the cyclic spectral density of a single frequency signal

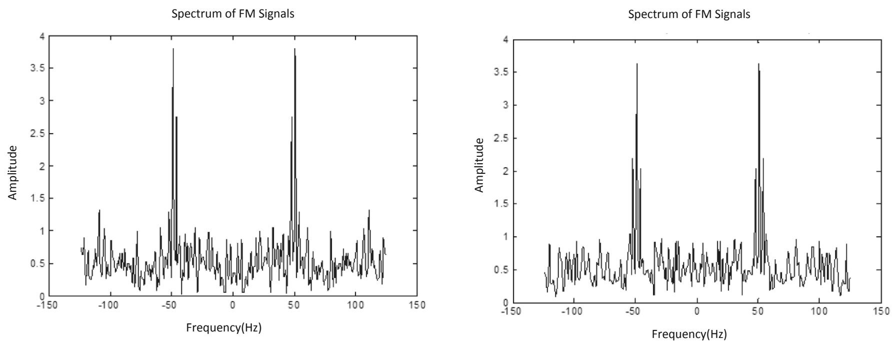
Fig. 1. Theoretical analysis of the three-dimensional map of the cyclic spectrum

4 Simulation Results and Analysis

In order to analyze and compare the performance of different spectrum detection methods, it is necessary to unify the external conditions, such as the time domain waveform of the signal, the sampling point, the number of accumulations, and the accumulated bandwidth. The above problem will be described before actually comparing the detection performance of different detection methods. After determining the detection performance of different detection methods, it involves how to select a reasonable detection method to achieve full utilization of system resources.

4.1 Relationship Between the Number of Sampling Points and the Noise Performance of the Detection Signal

For the same signal, the number of different sampling points will cause the noise characteristics of the actual analysis results to be very different. Since the power of the noise is calculated according to the accumulation in the entire frequency band, when the sampling time is constant and the number of sampling points is larger, the wider the frequency band to be referred to, the larger the noise power is (Fig. 2).



(a) Sampling point is 1024 Signal-to-noise ratio is -5dB

(b) Sampling point is 1024 Signal-to-noise ratio is 1dB

Fig. 2. Relationship between the number of sampling points and signal noise performance

Theoretical analysis shows that the power spectral density of Gaussian white noise is the same at each frequency. Therefore, the power of the Gaussian white noise in a certain frequency band is calculated to be proportional to the width of the frequency band. In the above actual signal analysis, it can be found that for the same signal, when the sampling point is increased from 256 points to 1024 points, the noise performance is significantly improved. The noise performance of 1024-point sampling at SNR −5 dB can be comparable to the noise performance of 256-point sampling analysis of the same signal at a signal-to-noise ratio of 1 dB. The theoretical value shows that $\log_{10} 4 = 6.02\ldots$, that is to say, for every 4 times increase in the number of sampling points, the energy of the signal is constant, and the energy of the noise is four times that of the original. That is, when the signal-to-noise ratio of the detection signal is increased by 6 dB, the resolution of the detection is substantially the same as the original. The actual analysis is close to the theoretical analysis value. The following analysis can approximate that when the number of sampling points is multiplied by 4, the experimental analysis value of the detection signal-to-noise ratio needs to be added by 6 dB, which is comparable with the original analysis result.

4.2 Performance Comparison Between Energy Detection Method and Periodic Stationary Process Feature Detection Method

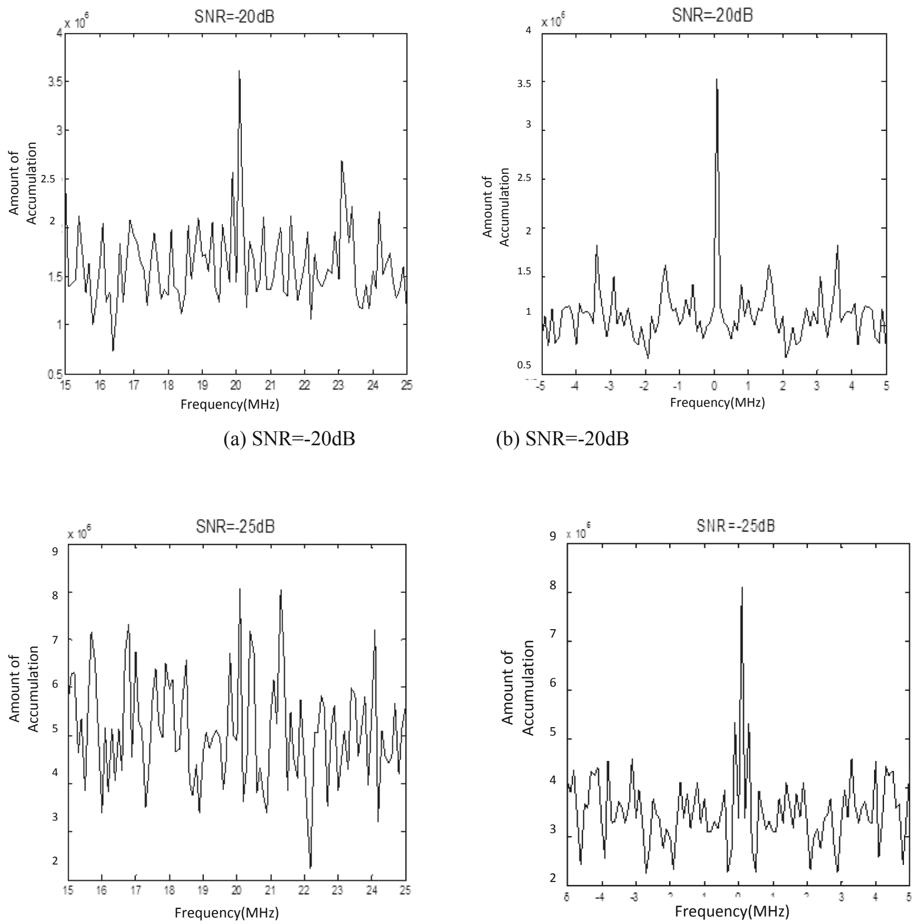
In the performance comparison, 15 independent test results were used for accumulation. At the sampling point, in order to accurately estimate the noise of the signal, the signal is analyzed by 1024 point sampling. If the actual number of sampling points is not 1024, the noise performance of the signal detection can be converted using the conclusions in the previous section.

The following is 15 times of independent sampling of the amplitude modulated signal. Using the principle of energy detection and periodic stationary process feature detection, the sequence after each sampling is calculated. Then, according to the frequency band to be detected, the sequence obtained by sampling and the transforming is intercepted, accumulated. The obtained result is represented by a spectrogram. Figure 3 (a), (b) is the noise performance of the energy detection method and the periodic stationary process feature detection method with a signal-to-noise ratio of −20 dB. Figures 3(c) and (d) are when the signal-to-noise ratio is −25 dB. The noise performance of the lower energy detection method and the periodic stationary characteristic detection method.

As can be sen from Fig. 3, when the amplitude modulation signal is detected by the energy detection method, if the signal-to-noise ratio continues to decrease, the presence or absence of the signal on the frequency band cannot be well resolved. In addition, when the signal-to-noise ratio is reduced, the spectrum of the signal is significantly distorted.

From the above results, it can be known that the energy detection method is a superior method when the signal to noise ratio is high. Since the energy detection only needs to do a discrete Fourier transform, the system overhead is small. However, when the signal-to-noise ratio is lowered, the resolution is significantly reduced. When the signal-to-noise ratio close to −15 dB, the amplitude modulated signal can only see the spectrum of the carrier signal, and the spectrum of the modulated signal can not be resolved. When the signal-to-noise ratio drops below −20 dB, it is completely unresolvable whether the spectrum to be detected is already occupied.

When using the periodic stationary process feature detection method, it can be seen that the noise fluctuation of the spectrum diagram is significantly smaller than that of the energy detection method when the signal-to-noise ratio is the same. In addition, the distortion of the signal frequency domain is more than the energy detection method at the same signal-to-noise ratio. In general, the noise performance of signal detection when using periodic stationary process feature detection is about 5–7 dB higher than that of energy detection.



(a) SNR=-20dB (b) SNR=-20dB

(c) SNR=-25dB (d) SNR=-25dB

Fig. 3. Noise performance of energy detection method and periodic stationary process feature detection method

However, the periodic stationary process feature detection method is much more computationally intensive. From the time of simulation calculation, the time taken by the system when using the energy detection method is about 2.5 s, and the time calculated by the periodic stationary process feature detection method is about 24 s, which is about one order of magnitude.

5 Summary

This paper first introduces the basic principles of energy detection and periodic stationary process feature detection in non-cooperative detection in spectrum sensing. Then the actual analysis and implementation method of the cyclostationary process are proposed. Finally, the performance of the two methods is analyzed by MATLAB simulation. It is concluded that the noise performance of signal detection when using periodic stationary process feature detection is about 5–7 dB higher than that of energy detection, and the detection time is about an order of magnitude. So energy detection is recommended when the signal-to-noise ratio is greater than −15 dB, and the periodic stationary process feature detection is used when the signal-to-noise ratio is lower than −15 dB.

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