Spectrum Sensing Based on Cyclostationarity

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Abstract

Real time spectrum sensing with certain accuracy plays a key role in cognitive radio. Cyclostationary feature is used for spectrum sensing in this paper. Usually, cyclostationary feature detection requires high computation complexity, in this paper we analyze the performance of some frequencies and cycle frequencies for detection according to the licensed users' signal features, which reduce the complexity significantly. The best detection point is determined through simulation analysis on different detection points, and then we propose combination detection method using multiple detection points to obtain better performance. Results validate the effectiveness of the proposed method.

1. Introduction

Today, by unprecedented growth of wireless applications, the problem of spectrum scarce is becoming apparent. Most of the spectrum has been allocated to specific users, while other spectrum bands that haven't been assigned are overcrowded because of overuse. However, most of the allocated spectrum is idled in some times and locations. The Federal Communication Commission (FCC) research report [1] reveals that, seventy percent of the allocated spectrum is underutilized. So we need a technique to deal with the problem of spectrum underutilization, which makes the birth of cognitive radio. Cognitive radio [2][3]can sense external radio environment and learn from past experiences. It can also access to unused spectrum band dynamically without affecting the licensed users, in such a way to improve the spectrum efficiency. Sensing external radio environment quickly and accurately plays a key role in cognitive radio. Energy detection [4], pilot detection [4], and cyclostationary feature detection [4] are three commonly used spectrum sensing methods. Energy detection is easy to implement, but its performance degrades greatly under low signal-to-noise ratio (SNR) or with noise uncertainty. Pilot detection can detect signals with low SNR, but it needs the licensed user's prior knowledge and perfect synchronization, which is hard to realize in reality. Cyclostationary feature detection can achieve high detection probability under low SNR, however, it usually needs high computation complexity. In [5], the author suggests to detect the cyclic features only in axis $f = 0$ and axis $\alpha = 0$, thus making the detection space from two dimensions to two one dimension and requiring less complexity.

Most of the papers [6][7] about spectrum sensing are based on given thresholds to analyze the detection performance, but in cognitive radio, we need to put the protection of licensed users in first and foremost, so we must ensure a predefined probability of detection ($\mathrm{P_D}$). In reality, based on a given location and channel, the licensed users' signal parameters are known and the SNR is changing slowly, so we assume that we can obtain the licensed users' signal type and SNR before making detection. In this paper, using of the licensed users' prior knowledge, we only make detections in some specific frequencies and cycle frequencies, and combine multiple detection points to improve the performance further. And then given the $\mathrm{P_D}$ required by licensed users, the probability of false alarm ($\mathrm{P_{FA}}$) under different SNRs is analyzed. Through the threshold adjustment, we reduce the $\mathrm{P_{FA}}$ to make better use of spectrum hole when the SNR is high and increase the $\mathrm{P_{FA}}$ to avoid interference to the licensed users when the SNR is low.

2. The principle of cyclostationarity

Modulated signals are in general coupled with cosine carrier, repeating spreading, over-sampling etc., resulting in built-in periodicity. When the signal's mean and auto-correlation exhibit periodicity, i.e., $m_x(t+T) = m_x(t)$, $R_x(t+T, u+T) = R_x(t,u)$, we call this signal a second-order cyclic statistics process[8]. The auto-correlation of signal $x(t)$ is defined as

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$$R_x(t,\tau) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=N}^{N} x(t+\tau/2+nT_0)x^*(t-\tau/2+nT_0) \quad (1)$$

Since $R_x(t,\tau)$ is periodic with period T_0, it can be expressed as a Fourier series representation

$$R_x(t,\tau) = \sum_{m=-\infty}^{+\infty} R_x^{m/T_0}(\tau) e^{j2\pi mt/T_0} \quad (2)$$

$$R_x^{\alpha}(\tau) = \frac{1}{T_0} \int_{-\infty}^{\infty} R_x(t,\tau) e^{-j2\pi\alpha t} dt \quad (3)$$

where α is the second-order cycle frequency equals to m/T_0, $R_x^{\alpha}(\tau)$ is referred to as the cyclic autocorrelation function. The spectrum α coherence function (SCF) can be obtained from (3) as

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau} d\tau = \frac{1}{T} X(f+\alpha/2) X^*(f-\alpha/2) \quad (4)$$

where $X(f)$ is the Fourier Transform of signal $x(t)$. From (4) we can find that $S_x^{\alpha}(f)$ is the correlation of the signal spectrum.

Different types of signals have different spectrum correlation features, in this paper we use BPSK signal with symbol period T_0 as an example for our research. From [9] we know that the SCF of BPSK signal have peaks at points $\alpha = \pm m/T_0, f = \pm f_c$ and $\alpha = \pm 2f_c \pm m/T_0, f = 0$ $(m = 0, \pm 1, \pm 2 \cdots)$. Fig. 1 demonstrates the SCF of a BPSK signal with symbol rate $R = 1/T_0 = 2\times 10^6$, carrier frequency $f_c = 4\times 10^6$ Hz. Fig. 2 depicts the contour figure of the SCF. The SCF of the Gaussian white noise is given in Fig. 3. These figures illustrate that the SCF of BPSK signal is different from the SCF of Gaussian white noise and cyclostationary features can be used for signal detection under low SNR environment.

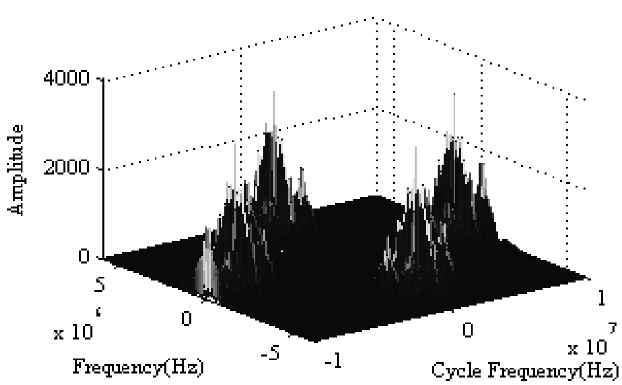

Figure 1. SCF of BPSK signal

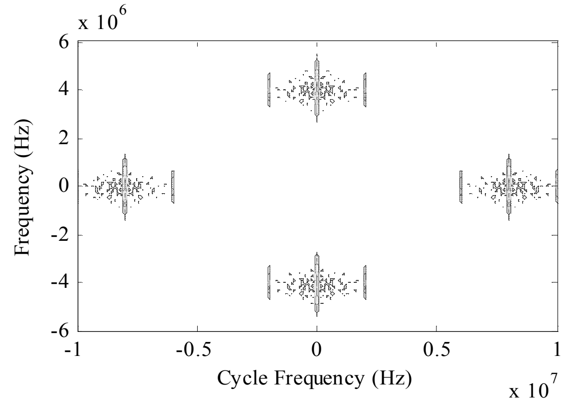

Figure 2. Contour figure of a BPSK signal

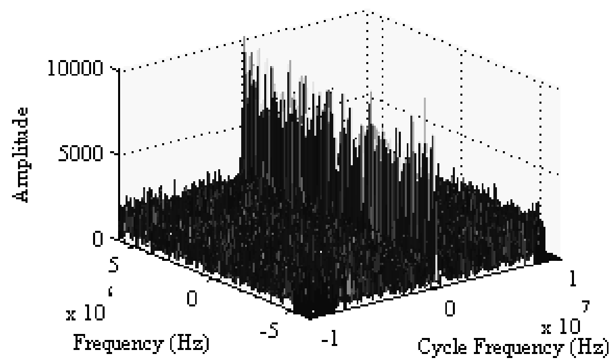

Figure 3. SCF of noise

3. Implementation

Usually, the cyclostationary detection requires high computation complexity and can't meet the real-time operation that required by spectrum sensing for cognitive radio. In order to reduce the complexity, in [5] the author suggests to make detection in axis $f = 0$ and axis $\alpha = 0$, and he also points out that when $f_c = f_s/4$, the detection point $f = 0$, $\alpha = 2f_c$ performs best, here f_s denotes the sample rate. However, from [9] we can find that the points $\alpha = \pm m/T_0, f = \pm f_c$ also have peaks, which can be demonstrated as in Fig. 4 that depicts the SCF of a BPSK signal at cycle frequency domain under $f = f_c$. Obviously, [5] ignores the detection of these points.

In this paper, we assume that the characteristics of licensed users' signals are known and detect these signals under specific points. We use time-domain averaging and frequency-domain smoothing to obtain SCF as follows [9]

1) Determine points of cycle frequency and carrier frequency that we need to analyze.
2) Get M groups of data with length of N, compute FFT for each group of data

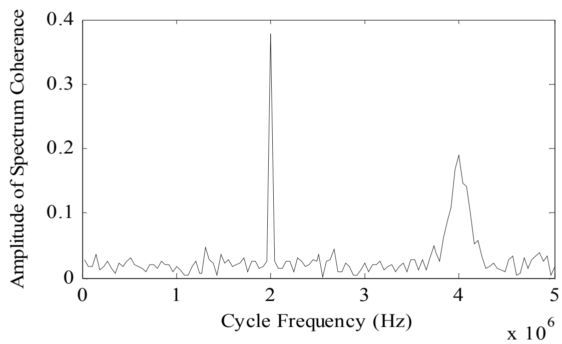

Figure 4. Cycle frequency domain profile of a BPSK signal

$$X_m(k) = \sum_{n=0}^{N-1} x_m(n) e^{-j2\pi nk/N} \tag{5}$$

where $X_m(k)$ is the FFT of m-th data group.

3) Compute power spectrum density(PSD)

$$S_m(k) = \frac{1}{N} X_m(k) X_m^*(k) \tag{6}$$

where $S_m(k)$ denotes the PSD of the signal from m-th group of data.

4) Compute SCF

$$S_m^{\alpha_i}(k) = \frac{1}{N} X_m(k+\alpha_i/2) X_m^*(k-\alpha_i/2) \tag{7}$$

where $S_m^{\alpha_i}(k)$ is the SCF of i-th detection point.

5) Frequency-domain smoothing

$$S_m^{\alpha_i}(k)_{\Delta f} = \frac{1}{P} \sum_{p=-(P-1)/2}^{(P-1)/2} S_m^{\alpha_i}(k+p) \tag{8}$$

where P is spectrum domain smoothing factor, $S_m^{\alpha_i}(k)_{\Delta f}$ is the SCF of i-th detection point from m-th group of data after spectrum domain smoothing.

6) Compute test statistics

$$I_m(\alpha_i) = \frac{S_m^{\alpha_i}(k)_{\Delta f}}{[S(k-\alpha_i/2)S(k+\alpha_i/2)]^{1/2}} \tag{9}$$

$$I(\alpha_i) = \frac{1}{M} \sum_{m=1}^{M} I_m(\alpha_i) \tag{10}$$

$$I(\alpha) = \sum_{i=1}^{D} w_i I(\alpha_i) \tag{11}$$

where $I_m(\alpha_i)$ is the test statistics at i-th detection point that we obtain from m-th group of data, $I(\alpha_i)$ is the test statistics at i-th detection point and $I(\alpha)$ is the overall test statistics. D is the number of point in decision, w_i is the weight at i-th detection point.

7) Detection decision

If $I(\alpha) < \lambda$ no signal

$I(a) > \lambda$ signal exist

where λ is the threshold determined by P_{FA}.

4. Simulation results

In this simulation, we choose BPSK signal with carrier frequency f_c=5 MHz, symbol rate R=2 Msps, and sample rate f_s =20 MHz. When $\alpha \neq 0$, the SCF of a BPSK will exhibit peaks at points $\alpha = \pm m/T_0, f = \pm f_c$ and $\alpha = \pm 2f_c \pm m/T_0$, $f = 0$ $(m = 0, \pm 1, \pm 2 \cdots)$, so we choose $\alpha = 2000000, f = f_c$, $\alpha = 8000000, f = 0$ and $\alpha = 10000000, f = 0$ for our simulation analysis. Fig. 5 is the detection performance of the BPSK signal at different detection points under $P_D = 0.99$, M=20, $P = 5$. It illustrates that the detection point $\alpha = 10000000, f = 0$ performs best, detection point $\alpha = 2000000, f = f_c$ takes the second place and the point $\alpha = 8000000, f = 0$ performs worst when only single point is used to detect. We use the best detection point $\alpha = 10000000, f = 0$ and the better detection point $\alpha = 2000000, f = f_c$ to detect at the same time to further improve the detection performance. Fig. 5 also shows that the performance of the combination detection method, the weight of the two detection points is chosen as 0.35 and 0.65 respectively. The performance is improved apparently. Of course, the combination detection method increases the computation complexity compare to single point detection, but from the section III we can find that the combination detection method only needs more correlation in step 4, so the complexity doesn't increase linearly as the detection point.

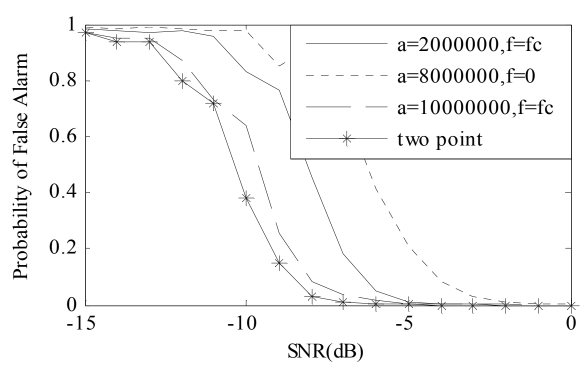

Figure 5. Performance under P_D =0.99

Fig. 6 is the detection performance of the BPSK signal on different detection points under $P_D = 0.95$, $M = 20$, $P = 5$. Comparing Fig. 5 with Fig. 6, we can find that when the required P_D decreases, the P_{FA} also decreases accordingly.

The performance using different number of data groups is studied as shown in Fig. 7, from which we can find that with the increasing of M the performance is also improved, but the computation complexity also increases linearly, so we need to make tradeoff between the complexity and the performance. Fig. 8 shows the receiver operating characteristic (ROC) of the performance under SNR=－12dB, it validates that the performance of this detection method is meaningful.

5. Conclusion

In this paper, spectrum sensing based on cyclostationarity in cognitive radio is considered. The second-order cyclic features built-in in modulated signals is used to detect the signals. Due to high complexity of cyclostationary feature detection, we choose to detect specific frequencies and cyclic frequencies based on the signal's feature to degrade complexity greatly. We compare the detection performance of different points to find the best detection points through simulation analysis and propose to combination detection method using multiple detection points to get better performance. Results validate the effectiveness of the proposed detection method.

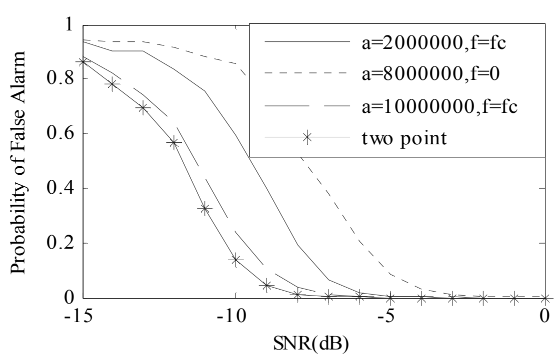

Figure 6. Performance under P_D =0.95

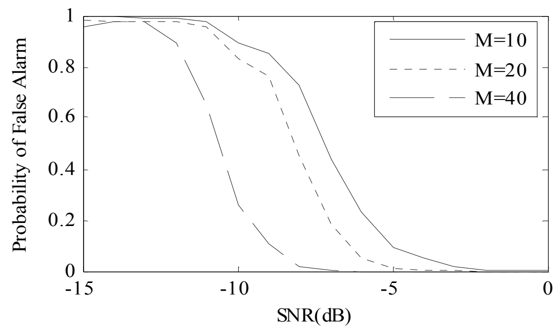

Figure 7. Performance with different groups

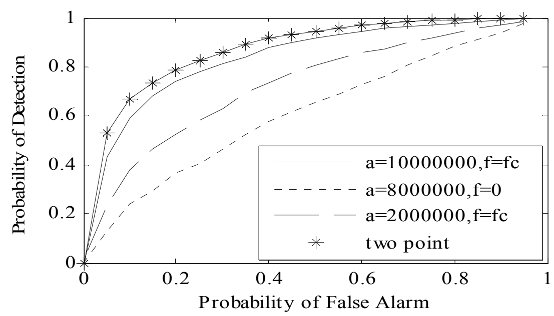

Figure 8. ROC of BPSK signal's detection

References

[1] Federal Communications Commission. Spectrum Policy Task Force Report. Washington: *ET Docket*, 2002:2-135.

[2] J Mitola, G.Q. Maguire, " Cognitive Radio:Making Software Rradios More Personal," *IEEE Personal Communications Magazine*, 6(4), pp.13-18, 1999.

[3] I .Akyildiz, Q Lee, M C.Vuran, "Next Generation/dynamic Spectrum Access/cognitive Radio Wireless Network: A Survey," *Computer Networks*, 50(13), pp.2127-2159, 2006.

[4] X Zhou, H Zhang, The Priciple and Application of Cognitive Radio. Beijing, *Beijing University of Posts and Telecommunications Press*, pp.16-25, 2007.

[5] Z Ye, J Grosspietsch,G Memik, "Spectrum Sensing Using Cyclostationary Spectrum Density for Cognitive Radios," *IEEE Workshop on Signal Processing Systems*, pp.1-6, 2007.

[6] K. Kim, I. Akbar, K.K. Bae, J.S. Um, "Cyclostationary Approaches to Signal Detection and Classificaton in CognitiveRadio," *IEEE International Symposium on DySPAN 2007*, pp.212-215, 2007.

[7] Y. Zhang, W.D. Yang, Y.M. Cai, "Cooperative Spectrum Sensing Technique," *WiCom2007*, pp.1167-1170, 2007.

[8] Z Huang, Y Zhou, W Jiang,The Process and Application of Cyclostationary Signals. *Beijing, Science Press*, pp.23-35, 2006.

[9] W Zhang, "Automatic Modulation Recognition of Digital Communication Signals," Doctor Thesis, *Graduate School of National University of Defense Technology*, 2006.