CYCLOSTATIONARY SPECTRUM DETECTION IN COGNITIVE RADIOS

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Abstract

With the rapid development of wireless communication, it becomes more important to address the spectrum scarcity problem. In the licensed spectrum band, users only utilize their designated resources partially, thus necessitating the need of cognitive radios (CR) which offers the promising feature of accessing the unused spectrum by dynamic spectrum management. In this paper, we are presenting the cyclostationary spectrum density detection method for estimation and spectral autocorrelation function technique to analyze the spectrum. This technique is robust in a sense that it can detect active or licensed user signals blindly. For efficient spectrum detection Kaiser window function was used. The effect of the observational data length on signal detection is also included. A simulational analysis suggests that cyclostationary spectrum detection is optimal for signal detection having low signal-to-noise(SNR) values. For 10% false alarm probability, 90% detection probability of BPSK signals with SNR of -8 dB or greater was achieved.

1 Introduction

With the development of a host of new and ever expanding wireless applications and services, spectrum scarcity is becoming an incomprehensible conundrum. Meanwhile, a Spectrum Policy Task Force reported vast temporal and geographic variations in the usage of allocated spectrum with utilization ranging from 15% to 85% [2][4], implying that licensed bands are significantly underutilized. This owes its cause to the fixed spectrum assignment policy regulated by the government. Cognitive Radios (CRs) have the potential to make optimal use of the available spectrum resources; because they are free from these license constraints [7]. The Federal Communications Commission's (FCC) has issued a notice of proposed rule making (NPRM – FCC 03-322 [3]) suggesting Cognitive Radio (CR) technology as a potential candidate for implementing negotiated or opportunistic spectrum sharing.

Spectrum sensing is currently one of the most challenging tasks in CR designing and implementation. CRs have the edge to adapt themselves to the external wireless spectrum environment by sensing spectrum pattern. Many approaches including matched filter, correlation detection, energy detection method, multi-resolution spectrum sensing, feature detection method, leak detection for local oscillator energy, collaborative detection, have been reported on spectrum sensing[2][6]. Matched filter technique is one of the optimal ways for signal detection in low SNR environments but it requires a priori knowledge of the primary user signal that includes the modulation type and order, pulse shape, and packet format. Furthermore a matched filter needs a dedicated receiver for every primary user class and cannot be exploited for blind spectrum sensing. On the other hand an energy detector can be used as a spectrum analyzer due to its simple and fast spectrum sensing method. A significant drawback is that an energy detector suffers from poor performance features in low SNR scenarios and the minimum SNR required for reliable energy detection is -3.3 dB when the noise power variation is 1 dB [2].

The wireless communication signals loaded with sinusoidal carriers, pulse trains, repeating codes, hopping sequences, cyclic prefixes, and signals are cyclostationary because their mean value and autocorrelation function exhibit periodicity [12]. This periodicity trend is used to perform various signal processing tasks that includes detection, recognition and estimation of the received signals. Though computationally complex, a cyclostationary feature detector is favourable for spectrum sensing in low SNR scenarios due to its robustness against the feature of uncertainty in noise power[1,2,8,9,10].

In this paper, a robust cyclostationary spectrum detection scheme is proposed and the effect of the observational data length on signal detection is presented. A simulational analysis suggests that cyclostationary spectrum detection is optimal for signal detection having low signal-to-noise (SNR) values. For 10% false alarm probability, 90% detection probability of BPSK signals with SNR of -8 dB or greater was achieved.

2 Cyclostationarity spectrum analysis

Signals of primary users can be regarded as a periodic signal or a cyclostationary signal, as their mean value and autocorrelation function exhibit periodicity. Assume a signal for a primary user is described as;

$$x(t) = s(t) + n(t) = \alpha e^{j(2\pi f_0 t + \theta)} + n(t) \qquad (1)$$

S (t) is the primary user's transmit signal and n (t) represents noise signal (AWGN) and f_0 is a carrier frequency. It has non-random components that can be exploited by CR to discriminate it from noise. These features include carrier frequency, symbol period, modulation type and chipping rate. The periodicity of the mean and autocorrelation functions can be expressed respectively as [8][10][11];

$$M_x(t) = E\left[x(t)\right] = \alpha e^{j(2\pi f_0 t+\theta)} = M_x(t+T_0) \quad (2)$$

$$\begin{aligned} R_x(t,\tau) &= E\left\{x(t+\tau/2)x^*(t-\tau/2)\right\} \\ &= R_x(t+T_0,\tau+T_0) \end{aligned} \quad (3)$$

where $T_0=1/f_0$. Eq.3 indicates that the autocorrelation function is periodic in time t for each time lag τ .Using the Fourier series, the autocorrelation function can be expanded as;

$$R_x(t+\tau/2, t-\tau/2) = \sum_{\alpha} R_x^{\alpha}(\tau)e^{j2\pi\alpha t} \quad (4)$$

where α is called cycle frequency, $\alpha = mf_0$, and m is an integer. The Fourier coefficient can be obtained by;

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} R_x(t,\tau)e^{-j2\pi\alpha t}dt \quad (5)$$

where T is the measurement interval. Equation (5) will be non-zero when evaluated at $\alpha = f_0$. For stationary processes like noise, Eq.5 will be zero-valued for $\alpha \neq 0$.

Taking the Fourier transform of the cyclic autocorrelation in equation (5), the spectral correlation function can be obtained as;

$$S_x^{\alpha}(\mathrm{f}) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau \quad (6)$$

The spectral correlation needs to be estimated from a finite set of samples as the number of observations is limited. Assume the time interval is T, i.e from t-T/2 to t+T/2, the time-variant finite-time complex spectrum is then defined by;

$$X_T(t,f) \stackrel{\Delta}{=} \int_{t-T/2}^{t+T/2} x(u)e^{-j2\pi fu}du \quad (7)$$

The cyclic periodogram can be expressed as;

$$S_{x_T}^{\alpha}(t,f) \stackrel{\Delta}{=} \frac{1}{T}X_T(t,f+\alpha/2)X_T^*(t,f-\alpha/2) \quad (8)$$

The cyclic periodogram reduces to the conventional periodogram for α = 0. The limit cyclic spectrum can be obtained from the cyclic periodogram by time-averaging, (using the notation $T = 1/\Delta f$) [10];

$$S_{x_{1/\Delta f}}^{\alpha}(u,f)_T \stackrel{\Delta}{=} \frac{1}{T}\int_{t-T/2}^{t+T/2} S_{x_{1/\Delta f}}^{\alpha}(u,f)du \quad (9)$$

or by frequency smoothing;

$$S_{x_T}^{\alpha}(t,f)_{\Delta f} \stackrel{\Delta}{=} \frac{1}{\Delta f}\int_{f-\Delta f/2}^{f+\Delta f/2} S_{x_T}^{\alpha}(t,v)dv \quad (10)$$

As in [10], cyclostationary spectrum density or the spectral correlation function is

$$S_x^{\alpha}(f) = \lim_{\Delta f\to 0}\lim_{T\to\infty} S_{x_T}^{\alpha}(t,f)_{\Delta f} \quad (11)$$

This is a two dimensional transform having two variables, the cyclic frequency α, and the spectral frequency f. Using the autocorrelation function and spectral correlation function for a signal, it can detect weak wireless signals buried in noise [2]. Implementation of the cyclostationary spectrum detection is performed digitally using fast Fourier transform (FFT) and spectral correlation. This method is computationally complex and tedious as it requires a long observation time for reliable signal analysis. In order to get good performance features, it is suggested to increase the observation length T and reduce the size of the smoothing window Δ f. Practically there exists a trade-off between optimal performance and efficiency.

For sampling frequency twice the carrier frequency, the cyclostationary spectrum feature of BPSK for SNR of -5dB is shown in Figure 1.

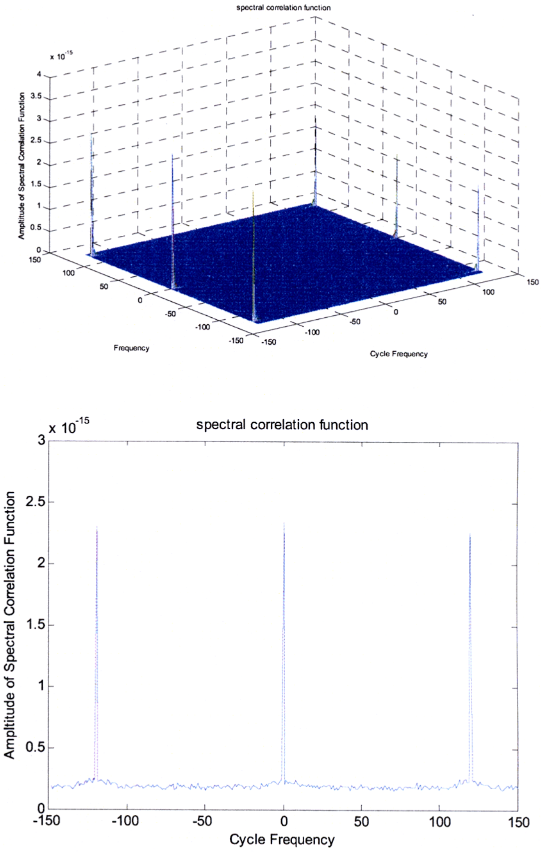


Fig. 1 Circular spectrum for BPSK SNR=-5dB

3 Spectrum sensing detection and analysis

A cyclostationary spectrum detection method can be implemented as illustrated in Figure 2. The performance features for the proposed cyclostationary spectrum detection scheme follows.

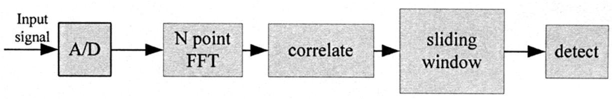


Fig. 2 Implementation of a cyclostationary feature detector

3.1 Sliding window

Sliding windows are of paramount significance in the analysis of dominant cyclic features and some frequently used widowing techniques are [5];

The rectangular window is defined by;

$$w(n)=\begin{cases}1 & 0\le n\le q\\ 0 & otherwise\end{cases} \tag{12}$$

Hamming window can be expressed as;

$$w(n)=\begin{cases}0.54-0.46\cos(\dfrac{2\pi n}{q}) & 0\le n\le q\\ 0 & otherwise\end{cases} \tag{13}$$

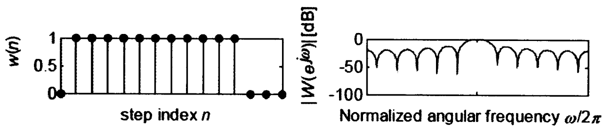
and the Blackman window function can be written as;

$$w(n)=\begin{cases}0.42-0.5\cos(\dfrac{2\pi n}{q})+0.08\cos(\dfrac{4\pi n}{q}) & 0\le n\le q\\ 0 & otherwise\end{cases} \tag{14}$$

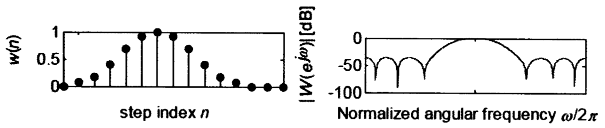
Finally the Kaiser window function has the following representation;

$$w(n)=\begin{cases}I_0\left(\beta\sqrt{1-\left[1-\dfrac{n}{q/2}\right]^2}\right) & 0\le n\le q\\ 0 & otherwise\end{cases} \tag{15}$$

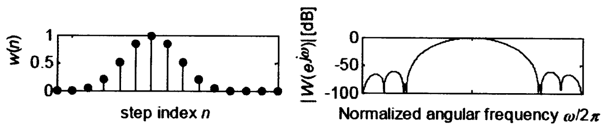
where $I_0\left(\beta\sqrt{1-\left[1-\dfrac{n}{q/2}\right]^2}\right)$ is the 0^{th} order modified Bessel function of the first kind, and β is a parameter for optimizing the threshold between the main lobe width and the side lobe amplitudes. Fig. 3 illustrates the n-domain shape and ω -domain spectra for these window functions.



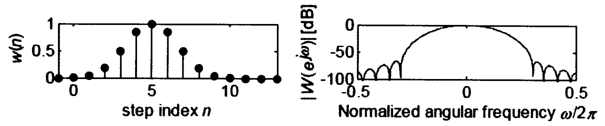
(a)



(b)



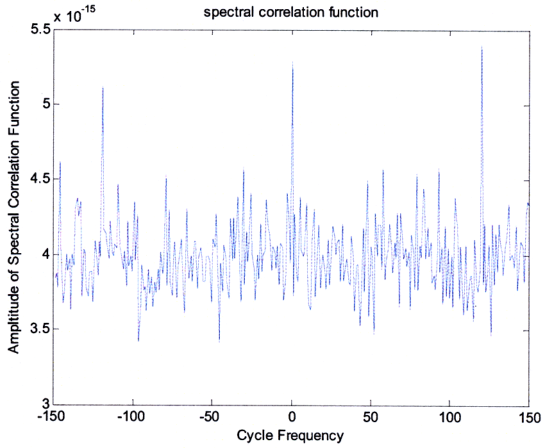
(c)



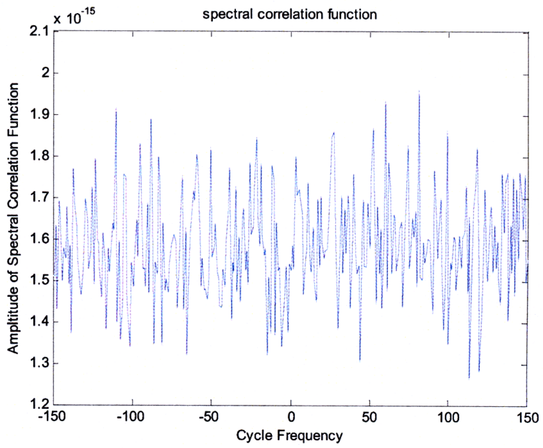
(d)

Fig. 3 n-domain shape and ω-domain spectra (a) Rectangular window, (b) Hamming window, (c) Blackman window, (d) Kaiser window (length q=10).

Cyclostationary spectrums are presented in Fig.4 using different window functions. This analysis suggests Kaiser window function to be used for the efficient detection of signal spectrum.



(a)



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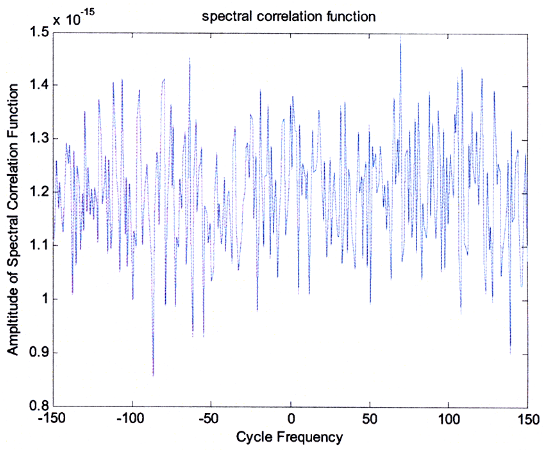

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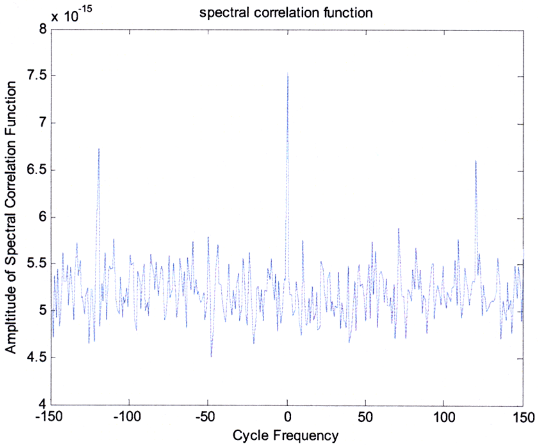
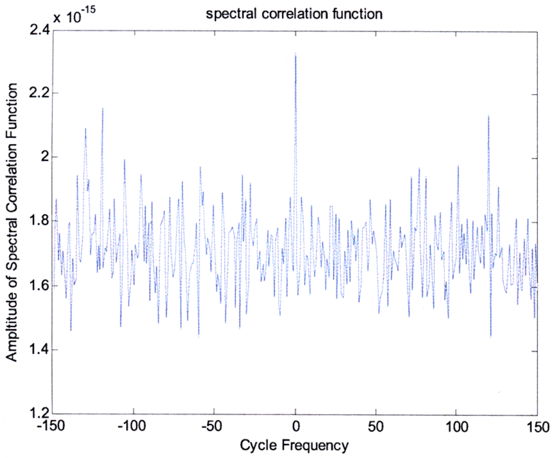


(d)

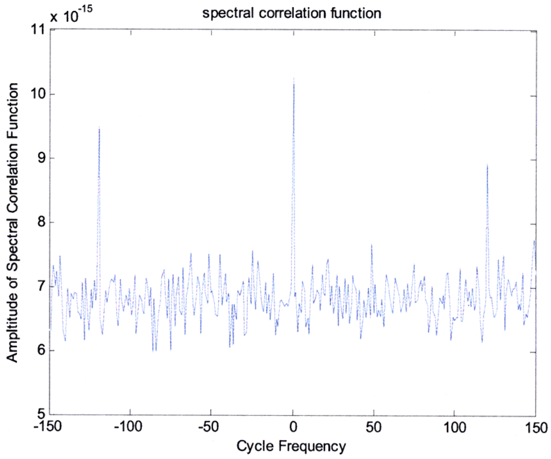
Fig. 4 Cyclostationary spectrum with different sliding windows (a) rectangular window, (b) Hamming window(c) Blackman window (d) Kaiser window (length q=10).

3.2 Length of observation data

Cyclostationary spectrums with different observation data lengths are presented in Fig.5. The longer the observation data, the easier it is to detect the signal of the primary user. But on the other hand this exercise is time consuming and makes the real time implementation more formidable.



(a)



(b)

Fig. 5 The effect of the length of observation data under SNR's = -15dB, Kaiser window (a) number of observation data =1200, (b) number of observation data =2400.

3.3 Threshold

Spectrum sensing is to determine the presence or absence of primary users so we need to distinguish between these two hypotheses;

$$H_0: x(t) = n(t)$$
$$H_1: x(t) = s(t) + n(t)$$

First we need to determine the threshold C_{TH} for signal detection and when no signal is present, i.e x(t) = n(t), C_{TH} can be using the relationship [8];

$$C_{TH} = \max[I(\alpha)] / \sqrt{(\sum_{\alpha=0}^{N} I^2(\alpha))/N} \tag{16}$$

where N is the length of observation data and I is given by;

$$I(\alpha) \overset{\Delta}{=} \max_{f} \left| C_x^{\alpha}(f) \right| \tag{17}$$

where $C_x^{\alpha}(f)$ defines the correlation coefficient and can be as expressed as;

$$C_x^{\alpha}(f) \overset{\Delta}{=} \frac{S_x^{\alpha}(f)}{[S(f+\alpha/2)S(f-\alpha/2)]^{1/2}} \tag{18}$$

Signal detection test can be performed as follows;

If $\quad C_I \leqslant C_{TH}$: Declare H_0
else $\quad C_I > C_{TH}$: Declare H_1

where C_{TH} is a random value due to the random noise n (t). It can be evaluated by plotting a histogram of C_{TH}.

Monte Carlo simulations were performed for signal detection. The result is shown in Fig.6. BPSK signals were detected with SNR changing from -20dB to 10dB. The carrier frequency was 60MHz with the sampling frequency of 120 MHz, and the sliding window was Kaiser window function.

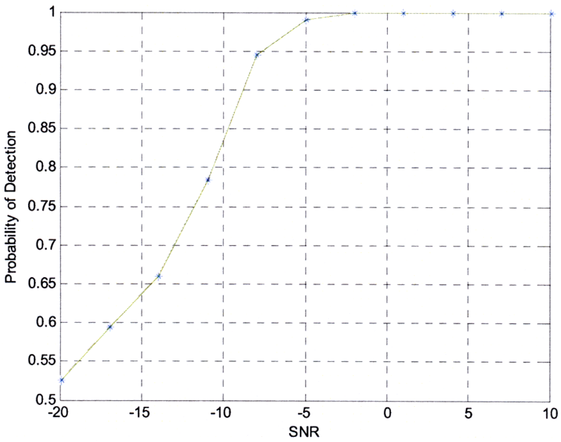


Fig6. BPSK Detection Probability of 10% False Alarm

4 Conclusions

In this paper, we have presented the cyclostationary spectrum density detection method for estimation and spectral autocorrelation function technique to analyze the spectrum. A simulational analysis suggests that cyclostationary spectrum detection is optimal for signal detection having low signal-to-noise (SNR) values. For 10% false alarm probability, 90% detection probability of BPSK signals with SNR of -8 dB or greater was achieved.

5 Acknowledgements

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