A Novel Spectrum Sensing Algorithm in Cognitive Radio

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Abstract - Detecting the presence of primary users in a licensed spectrum is the very task upon which the entire operation of cognitive radio rests. The paper proposes a fast novel spectrum sensing algorithm for cognitive radios based on cyclic autocorrelation. The method is founded on the basic mathematical model of digitally modulated signals which can be ASK, PSK, QAM etc. When only the existence of primary users in noise is detected, special cyclic frequency $\alpha = 0$ can be choosed to sense, which will significantly reduce the computational cost in applying the cyclostationarity detection. In this way it is easily applicable because it is also a blind detection method. It outperforms the energy detector in the presence of noise power uncertainty. Derivation and analysis for the proposed algorithm is given. Computer simulations are presented to verify the method.

Keywords:- spectrum sensing, cyclostationary detection, cyclic autocorrelation, cognitive radio

1 Introduction

Cognitive radio (CR) has been proposed as a possible solution to improve spectrum utilization via opportunistic sharing. Cognitive radio users are considered lower priority or secondary users of spectrum allocation to a primary user. Their fundamental requirement is to avoid interference to potential primary users in their vicinity. That is, it is necessary to dynamically detect the existence of primary users' signals. Detecting the presence of primary users is currently one of the most challenging tasks in CR design and implementation.
There are several definitions of a vacant frequency band, but generally we can consider that a frequency band is unoccupied if the filtered radio signal within this band is only composed of noise. In the opposite case, this signal will consist of an unknown nonzero number of telecommunication signals in addition to the noise.
How to detect the existence of primary users in the given frequency bands? The solution to this problem was largely studied in the past and depends on the degrees of knowledge we have on the signal and the noise. Energy detection is a major and basic method. It needs the knowledge of accurate noise power. In practice, it is very difficult to obtain the accurate noise power. When noise power is unknown, the quality of detection is strongly degraded[1][2]. Matched filtering is the optimum method for detection of primary users. However, matched filtering requires the cognitive user/radio to demodulate the received signal hence it requires perfect knowledge of the primary users signal

features. Moreover, since the cognitive radio will need receivers for all signal types, it is practically difficult to implement. For the case of unknown noise power, the cyclostationarity property of communication signals is exploited. In contrast to noise which is a wide-sense stationary random signal with no correlation, the modulated signals are in general coupled with sine wave carriers, pulse trains, hopping sequences or cyclic prefixes which result in periodicity of the mean and autocorrelation of such signals. These features can be used to discriminate the noise from modulated signal. The detection based on cyclostationarity property chooses a cyclostationarity model[3][4] rather than a stationary one for the signal. This model is particularly attractive when the noise is of stationary type. Several works[5-8] are devoted to this kind of problem and propose various tests of cyclostationarity over a given set of cycle frequencies. Among these methods, cyclic spectrum or spectrum correlation density (SCD) function is the main estimator. To better depict cyclic spectrum, large estimation is needed. While the spectrum detection probability(P_d) and the probability of false alarm(P_{fa}) haven't been expressed in a closed analytical form.

In this paper, a sensing technique based on cyclic autocorrelation (CA) is proposed to detect the primary users in the given spectrum. The remainder of the paper is organized as follows. In section 2 the cyclic autocorrelation features are introduced and the detecting model of the primary users is presented. A fast spectrum sensing method is proposed in section 3 and probability distribution functions of the computed CA are given. In section 4, computer simulations are presented to verify the method. Finally we present our conclusion in section 5.

2 Cyclic Autocorrelation Features

2.1 The definition and features of cyclic autocorrelation

The cyclic autocorrelation (CA) of a complex-valued time series s(t) is defined by [9]

$$R_s(\alpha,\tau)=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} s(t+\tau/2)s^*(t-\tau/2)e^{-j2\pi\alpha t}dt \qquad (1)$$

which can be interpreted as the Fourier coefficient of any additive sine wave component with frequency α that might be contained in the delay product (a quadratic transformation) of $s(t)$. α is called cycle frequency. It is a discrete set of values and can be writen as $\{\alpha_n\}$, which includes zero values and nonzero values. In the degenerate case of $\alpha = 0$, the left member of (1) becomes the conventional autocorrelation.

2.2 Cyclic autocorrelation of digitally modulated signals

The basic mathematic model of digitally modulated signals can be described as [10]

$$s(t)=\sum_n a_n g(t-nT-\theta)e^{j2\pi f_c t},(n-1)T\le t<nT \qquad (2)$$

$$a_n = a(t)e^{j\phi(t)} \qquad (3)$$

where $a(t)$, $\phi(t)$ are narrow band modulating signals, $g(t)$ is the shaping signal. T is the symbol period and f_c is the carrier frequency. θ is the delay in a symbol period. Equation (2) can represent ASK, PSK, QAM signal and so on. a_n is kept constant in a symbol period. Complex stationary series $\{a_n\}$ satisfies the following equation

$$E\{a_n\} = 0, E\{a_n a_m^*\} = \sigma_a^2\delta_{m,n} \qquad (4)$$

where σ_a^2 is variance of $\{a_n\}$, $\delta_{m,n}$ is the discrete Dirac delta function.

When the shaping signal $g(t)$ is the square wave U (t)

$$U(t)=\begin{cases}1/T & -T/2\le t<T/2\\ 0 & otherwise\end{cases} \quad (5)$$

The CA of $s(t)$ can be

$$R_s(\alpha,\tau)=\sigma_a^2 e^{-j2\pi(f_c\tau-\alpha\theta)}\frac{1}{T}\frac{\sin(\pi\alpha(T-|\tau|))}{\pi\alpha},|\tau|<T \quad (6)$$

$$|R_s(\alpha,\tau)|=\sigma_a^2\frac{1}{T}\frac{\sin(\pi\alpha(T-|\tau|))}{\pi\alpha},|\tau|<T \quad (7)$$

3 Spectrum Sensing Based On Cyclic Autocorrelation

3.1 The estimation of cyclic autocorrelation

Define the numerical cyclic autocorrelation estimation of $s(t)$ as [9]

$$\hat{R}_x(\alpha,\tau)=\frac{1}{N}\sum_{n=1}^{N}x(n)x^*(n+\tau)e^{-j2\pi\alpha n} \quad (8)$$

where N is the number of observations, τ is time delay.

3.2 Hypothesis testing

Spectrum sensing can be modeled as a hypothesis test problem. There are two possible hypotheses H_0 and H_1

$$x(n)=\begin{cases}w(n) & H_0\\ s(n)+w(n) & H_1\end{cases} \quad (9)$$

hypothesis H_1 refers to the presence of a primary user and hypothesis H_0 refers to the presence of vacant frequency bands, where $x(n)$ is the received signal, $s(n)$ is the possible primary user signal passed through a wireless channel (including fading and multipath effect), and $w(n)$ is a White Gaussian Process with zero-mean.

In section Ⅱ we analyzed the CA of general modulation signal, now we analyze the CA of the White Gaussian Process. Because $w(n)$ is a stationary process, it doesn't have cyclostationarity property, its CA function is given as [5]

$$R_w^\alpha(\tau)=\begin{cases}\sigma_w^2\delta(\tau) & \alpha=0\\ 0 & \alpha\ne 0\end{cases} \quad (10)$$

where σ_w^2 is noise variance.

eq.(10) clearly displays two meanings. One is that $w(n)$ hasn't nonzero cycle frequency or $w(n)$ has only one cycle frequency $\alpha=0$. The second is $R_w^\alpha(\tau)$ has nonzero value only at $\alpha=0$ and $\tau=0$. If $\alpha\ne 0$ or $\tau\ne 0$, then $R_w^\alpha(\tau)=0$.

According to eq.(7), testing for the presence of primary user can change to test whether the estimated signal cyclic autocorrelation $\hat{R}_x(\alpha,\tau)$ is different from zero at $\alpha\ne 0$ or $\tau\ne 0$. There exists many cyclic frequencies, we can use their maximum value of CA as decision statistic.

$$\gamma=\max_\alpha\left|\hat{R}_s(\alpha,\tau)\right| \begin{array}{ll}\ge\lambda & H_1\\ <\lambda & H_0\end{array} \quad (11)$$

where *r* is decision statistic, λ is threshold.

There exists many cyclic frequencies, when we want to distinguish different signals such as ASK, PSK and QAM etc, we should know the specific cyclic frequencies. While if we just detect the existence of primary users in noise, we can chose cyclic frequency $\alpha=0$ to sense.

3.3 Fast spectrum sensing

According to eq.(7), we can find that $\hat{R}_s(\alpha,\tau)$ has maximum value at $\alpha=0$ and its value is

$$\hat{R}_{\max}(\alpha,\tau)=\sigma_a^2(1-\frac{|\tau|}{T}) \qquad |\tau|<T \qquad (12)$$

where $\hat{R}_{\max}(\alpha,\tau)$ gradually reduces with the growth of τ . According to eq. (10), we can see that the CA of $w(n)$ has nonzero value σ_w^2 only at $\alpha=0$ and $\tau=0$. If $0<|\tau|<T$, then $R_w^0(\tau)=0$, and

$$\hat{R}_x(0,\tau)=\hat{R}_s(0,\tau) \qquad \tau\neq 0 \qquad (13)$$

so we can use $\hat{R}_x(0,\tau)$ as feature detector to detect the presence of primary user. For special cyclic frequency $\alpha=0$, $\hat{R}_x(0,\tau)$ has maximum value, so has the best detecting performance. $\hat{R}_x(0,\tau)$ is one dimension function about τ , its search is simple. In practise, once given any nonzero τ_p , the computation complexity of $\hat{R}_x(0,\tau_p)$ is nearly as that of the energy detector. This method can be used to detect ASK, PSK, QAM signal and so on which can be represented by eq.(2). In this regard it is easily applicable because it is also a blind detection method.

3.4 Probability distribution function of the computed CA

Upon substituting $s(n)$ in eq.(8) with $w(n)$ which is a white Gaussian process with zero-mean and variance σ_w^2 . Then $\hat{R}_w(\alpha,\tau)$ are circularly symmetric i.i.d. complex Gaussian random varibles with zero-mean and variance σ_w^4/N. So

$$H_0:\hat{R}_w(\alpha,\tau)\rightarrow CN(0,\sigma_w^4/N) \qquad (14)$$

where $CN(\cdot,\cdot)$ represents the complex Normal distribution

Hypothesis H_1 corresponds to the presence of user signal and noise, i.e., $x(n)=s(n)+w(n)$.

It can be verified that

$$Var[\hat{R}_x(\alpha,\tau)]=\frac{2}{N}\sigma_w^2\sigma_s^2+\frac{1}{N}\sigma_w^4 \qquad (15)$$

4 Numerical Results

In this section the performance of the proposed cyclic autocorrelation based detector is discussed. As a signal of interest, a BPSK time series with baud-rate of $f_b=f_c/20$ is taken. f_c is the carrier frequency. Sampling frequency is f_s=5f_c.

The number of observations is *N=2000*. Fig.1 displays that the magnitudes of CA for signal in Additive Gaussian White Noise at cyclic frenquencies where τ is from *0.01T* to *0.1T*. The magnitudes of CA at τ=*0.1T* is illustrated in Fig.2. Fig.1 and Fig.2 clearly dispalys that the magnitudes of CA at some cyclic frenquencies (such as 0, 40) are not influenced by noise

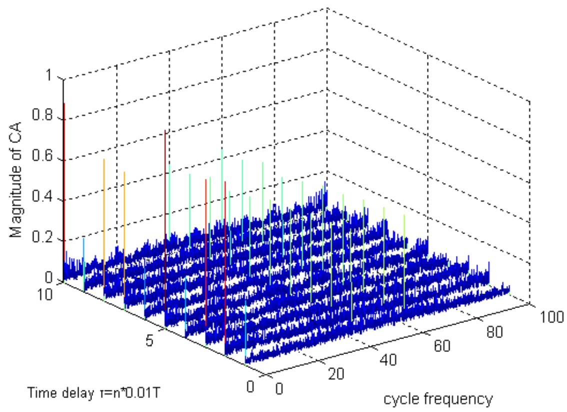

Fig.1 the magnitude of CA for BPSK signal in noise and SNR=0 dB

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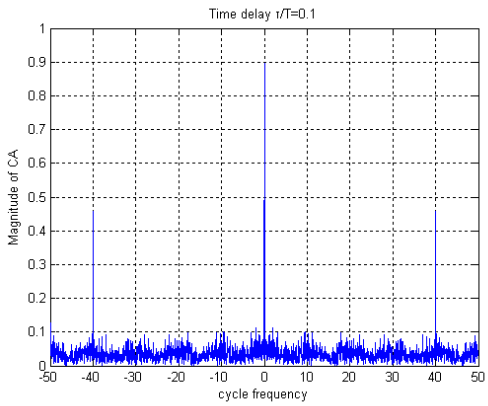

Fig.2 the CA at τ=0.1T for s(n)+w(n),SNR=0

In order to verify the performance of the proposed methed, theory results and computer simulations are made. We use constant false alarm rate (CFAR) method. First, we fix the thresholds based on probability of false alarm P_{fa}, then calculate and simulate the probability of detection P_d for various SNR cases. We set the target P_{fa}=0.1, choose τ =0.1T, 0.3T, 0.5T, 0.7T and N=2000. The threshold for energy detector (ED) is given in [11].

4.1 Without Noise Uncertainty

First the noise variance is exactly known, the detection results by these two methods are compared in Fig.3 and Fig.4 Fig.3 is a theory result. Fig.6 is a simulation result. From Fig.3 and Fig.4 we can find that the performance of CA is more better than ED when τ=0.1T. And it is equal to ED when τ=0.3T. When τ=0.5T, 0.7T, its detection performance is worse than ED.

4.2 Noise Uuncertainty Is Present.

However, in practice, noise uncertainty is always present. Due to noise uncertainty [11][12], the estimated (or assumed) noise power may be different from the real noise power. In practice, the noise uncertainty factor of a receiving device normally ranges from 1dB to 2dB. Environment/interference noise uncertainty can be much higher.

When the noise uncertainty is 1dB, the quality of energy detection is strongly degraded, while quality of the proposed method is much better than energy detection, which we can see clearly from Fig.5

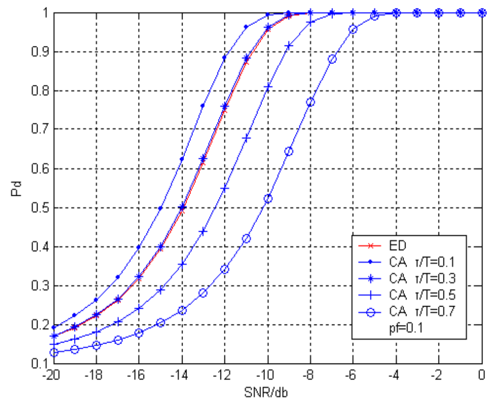

Fig.3 Pd versus SNR according to theory

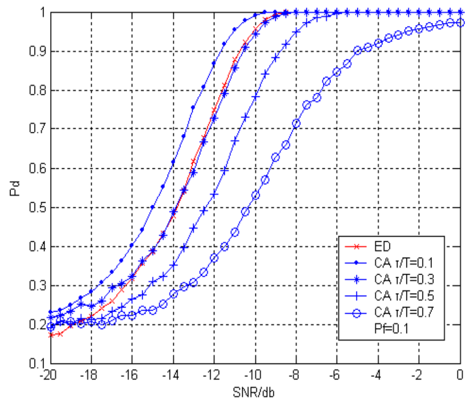

Fig.4 Pd versus SNR according to simulation

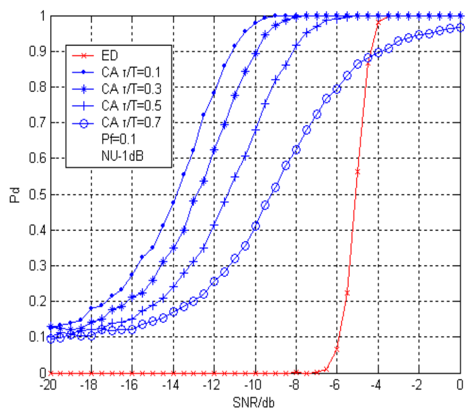

Fig.5 Pd versus SNR Noise uncertainty:1dB

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5 Conclusion

In this paper, a fast spectrum detecting algorithm based on cyclic autocorrelation (CA) of communication signals is proposed. Theoretical analysis and simulations have been carried out to evaluate the performance of the proposed methods. When only detect the existence of primary users in noise, special cyclic frequency $\alpha = 0$ is chosen to sense. In this way it is easily applicable because it is also a blind detection method. It is clearly shown that the proposed methods outperforms the energy detector in the presence of noise power uncertainty while the computation complexity of the algorithm is nearly as ED.

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