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SUBSECTION-AVERAGE CYCLOSTATIONARY FEATURE DETCTION IN COGNITIVE RADIO

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ABSTRACT

Spectrum sensing plays an important role in cognitive radios because the secondary users need to continuously monitor the spectrum for the presence of primary user. In this paper, we mainly investigated the cyclostationary feature spectrum detection in cognitive radios. Our analysis shows that cyclostationary feature detection requires partial information of the primary user and high computation cost although it is robust to interference in low SNR. We propose a novel strategy for spectrum sensing based on cyclostationary feature detection. Our new approach can effectively decrease the computational complexity and improve the performance of the inhibition of noise interference. At last, numerical results are provided in order to illustrate the advantages of our new technique.

Key Words —— Cognitive radio, Spectrum sensing, Cyclostationary feature detection, Cyclic spectrum, Cyclic autocorrelation.

1. INTRODUCTION

The proliferation of wireless services and devices for uses such as mobile communications, public safety, Wi-Fi, and TV broadcast serve over the past several years demonstrates the vast and growing demand of businesses, consumers, and government for spectrum-based communications. While land and energy constituted the most precious wealth creation resource during the agricultural and industrial eras respectively, radio spectrum has become the most valuable resource of the modern era. Spectrum access, efficiency, and reliability have become critical public policy issues. Notably, the unlicensed bands (e.g., ISM and UNII) play a key role in this wireless ecosystem given that many of the significant revolutions in radio spectrum usage has originated in these bands, and which resulted in a plethora of new applications including lastmile broadband wireless access, health care, wireless PANs/LANs/MANs, and cordless phones. This explosive success of unlicensed operations and the many advancements in technology that resulted from it, led regulatory bodies (e.g., the FCC through its Spectrum Policy Task Force (SPTF)) to analyze the way spectrum is currently used and, if appropriate, make recommendations on how to improve radio resource usage [4].

The term Cognitive Radio was first defined by Mitola [1], [2] in 1999. The new CR technologies are increasingly being used in spectrum based communication systems and are likely to become more and more prevalent over the next few years. These technologies hold tremendous promise in helping to facilitate more effective and efficient access to spectrum by opening opportunities for spectrum use in space, time, and frequency dimensions that until now have been unavailable. Also it include the ability of devices to determine their location, sense spectrum use by neighboring devices, change frequency, adjust output power, and even alter transmission parameters and characteristics. The ability of CR technologies to adapt a radio's use of spectrum to the real-time conditions of its operating environment offers regulators, licensees, and the public for more flexible, efficient, and comprehensive use of available spectrum while reducing the risk of harmful interference [3].

In cognitive radio, a spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user. In passively sensing the radio scene and thereby estimating the power spectra of incoming RF stimuli, we have a basis for classifying the spectra into three broadly defined types, as summarized here.

1) Black spaces, which are occupied by high-power "local" interferers some of the time.
2) Grey spaces, which are partially occupied by low-power interferers.
3) White spaces, which are free of RF interferers except for ambient noise, made up of natural and artificial forms of noise, namely:
   - broadband thermal noise produced by external physical phenomena such as solar radiation;
   - transient reflections from lightening, plasma (fluore-

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scent) lights, and aircraft;

- impulsive noise produced by ignitions, commutators, and microwave appliances;
- thermal noise due to internal spontaneous fluctuations of electrons at the front end of individual receivers.

White spaces (for sure) and grey spaces (to a lesser extent) are obvious candidates for use by unserviced operators. Of course, black spaces are to be avoided whenever and wherever the RF emitters residing in them are switched ON. However, when at a particular geographic location those emitters are switched OFF and the black spaces assume the new role of "spectrum holes," cognitive radio provides the opportunity for creating significant "white spaces" by invoking its dynamic-coordination capability for spectrum sharing [8].

Since cognitive radios are considered lower priority or secondary users of spectrum allocated to a primary user, a fundamental requirement is to avoid interference to potential primary users in their vicinity. On the other hand, primary user networks have no requirement to change their infrastructure for spectrum sharing with cognitive networks. Therefore, cognitive radios should be able to independently detect primary user presence through continuous spectrum sensing. Different classes of primary users would require different sensitivity and rate of sensing for the detection. For example, TV broadcast signals are much easer to detect than GPS signals, since the TV receivers' sensitivity is tens of dBs worse than GPS receiver [7].

The remainder of this paper is organized as follows. In Section II, the spectrum sensing techniques and the fundamentals of cyclostationarity are described. Section III presents a novel strategy that can decrease the computational complexity and improve the performance of the inhibition of noise interference. Section IV shows the numerical results from the new sensing scheme. Finally, conclusions are presented in Section V.

2. FUNDAMENTALS OF CYCLOSTATIONARITY

To be able to sense very weak signals, cognitive radios must have significantly better sensitivity than conventional radios. So to enhance the detection probability, many signal detection techniques can be used in spectrum sensing. In the following, we give an overview of some well-known spectrum sensing techniques [10], [11].

2.1. Matched Filter Detection

A matched filter is an optimal detection method as it maximizes the signal-to-noise ratio (SNR) of the received signal in the presence of additive Gaussian noise. A matched filter is obtained by correlating a known signal, or template, with an unknown signal to detect the presence of the template in the unknown signal. This is equivalent to convolving the unknown signal with a time-reversed version of the template. Matched filters are commonly used in radar transmission. In the cognitive radio scenario, however, the use of the matched filter can be severely limited since the information of the primary user signal is hardly available at the cognitive radios. If partial information of primary user signal such as pilots or preambles is known, the use of matched filter is still possible for coherent detection. For example, in order to detect the presence of a digital television (DTV) signal, we may detect its pilot tone by passing the DTV signal through a delay-multiply circuit. If the squared magnitude of the output signal is larger than a threshold, the presence of the DTV signal can be detected.

2.2. Energy Detection

The energy detection method is optimal for detecting any unknown zero-mean constellation signals. The implementation simplicity of the energy detector is perhaps its key advantage. In the energy detection approach, the radio frequency energy in the channel or the received signal strength indicator (RSSI) is measured to determine whether the channel is occupied or not. The received signals $x(t)$ sampled in a time window are first passed through an FFT device to get the spectrum $X(f)$. The peak of the spectrum is then located. After windowing the peak in the spectrum of $x(t)$, we get $Y(f)$. The signal energy is then collected in the frequency domain. Finally, the following binary decision is made,

$$\begin{cases} H_1, if \sum |Y(f)|^2 \geq \lambda \\ H_0, otherwise. \end{cases} \tag{1}$$

Although the energy detection approach can be implemented without any prior knowledge of the primary user signal, it still has some drawbacks. The first problem is that it can only detect the signal of the primary user if the detected energy is above a threshold. Another challenging issue is that the energy approach cannot distinguish between other secondary users sharing the same channel and the primary user. The threshold selection for energy detection is also problematic since it is highly susceptible to the changing background noise and interference level.

2.3. Cyclostationary Feature Detection

In this section, a brief review of the basic concepts and definitions associated with cyclostationary processes is presented. A more expansive survey of both theory and applications of cyclostationarity is given in [6].

A zero-mean process $x(t)$ is said to be cyclostationary (in the wide sense) if its autocorrelation is a periodic function of time,

$$R_x(t+\frac{\tau}{2}, t-\frac{\tau}{2}) = R_x(t+T_0+\frac{\tau}{2}, t+T_0-\frac{\tau}{2}), \tag{2}$$

for some period $T_0 \neq 0$ where

$$R_x(t+\frac{\tau}{2},t-\frac{\tau}{2}) = E\{x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})\}, \quad (3)$$

and $E\{\bullet\}$ denotes the mathematical expectation operation. Since R_x is periodic, it admits a Fourier series representation,

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

where the sum over α includes all integer multiples of the reciprocal of the fundamental period T_0. The Fourier coefficients $R_x^{\alpha}(\tau)$ are given by either

$$R_x^{\alpha}(\tau) = \frac{1}{T_0} = \int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} R_x(t+\frac{\tau}{2},t-\frac{\tau}{2})e^{-j2\pi\alpha t}dt, \quad (5)$$

or

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} R_x(t+\frac{\tau}{2},t-\frac{\tau}{2})e^{-j2\pi\alpha t}dt. \quad (6)$$

The function $R_x^{\alpha}(\tau)$, which-for each value of τ -is the strength of the sinusoid in t at frequency α in the autocorrelation $R_x(t+\tau/2,t-\tau/2)$, is referred to as the cyclic autocorrelation. If the process $x(t)$ is modeled as cycloergodic (which excludes all time-invariant random phases), as is assumed henceforth, then the cyclic autocorrelation can be obtained from the limiting time average

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-j2\pi\alpha t}dt. \quad (7)$$

for any sample path of the process $x(t)$. The cycloergodic model is a natural model for the applications of interest in this paper. Clearly, the cyclic autocorrelation (5), or (7), is not identically zero for all nonzero a if and only if the autocorrelation in (3), or the lag-product of the cycloergodic process $x(t)$ in (4), contains an additive periodic component, which will be the case if $x(t)$ is cyclostationary. The set $\{\alpha : R_x^{\alpha}(\tau) \neq 0\}$ is referred to as the set of cycle frequencies. By analogy with the terminology for the conventional autocorrelation (which is (7) with $\alpha = 0$), the Fourier transform of the cyclic autocorrelation,

$$S_x^{\alpha}(f) \triangleq \int_{-\infty}^{+\infty} R_x^{\alpha}(\tau)e^{-j2\pi f t}d\tau, \quad (8)$$

is called the cyclic spectrum. The cyclic spectrum can also be interpreted as a spectral correlation function (SCF) according to the following characterization [6]:

$$S_x^{\alpha}(f) = \lim_{T\to\infty}\lim_{\Delta t\to\infty}\frac{1}{T\Delta t}\int_{-\frac{\Delta t}{2}}^{\frac{\Delta t}{2}} X_T(t,f+\alpha/2)X_T^*(t,f-\alpha/2)dt, \quad (9)$$

where

$$X_T(t,v) \triangleq \int_{t-\frac{T}{2}}^{t+\frac{T}{2}} x(u)e^{-j2\pi uv}du. \quad (10)$$

is the complex envelope of the spectral component of $x(t)$ at frequency v with approximate bandwidth 1/T. Since the frequencies of the correlated spectral components are $f+\alpha/2$ and $f-\alpha/2$, the α cycle frequency α is also called the frequency separation [5]. We can detect the cyclic stationary signals from the stationary interference since the difference that the general stationary signals don't possess cyclic stationary characteristic.

The calculation of the cyclic spectrum autocorrelation function refers two variables: cyclic frequency α and spectrum frequency f. The spectrum frequency and the cyclic frequency must satisfy the following conditions for the reliable spectrum estimation [9]:

$$\frac{\Delta f}{\Delta\alpha} \gg 1 \text{ or } \Delta t\Delta f \gg 1. \quad (11)$$

Δf and $\Delta\alpha$ denote the resolution of the spectrum frequency and the cyclic frequency respectively. To obtain the reliable spectrum autocorrelation estimation, the method of smoothing the cyclic periodogram is employed because of the constraints of (11).

The discrete-frequency smoothing method is given by

$$\tilde{S}_{X\Delta t}^{\alpha}(t,f)_{\Delta f} = \frac{1}{M}\sum_{v=-(M-1)/2}^{(M-1)/2}\frac{1}{\Delta t}\tilde{X}_{\Delta t}(t,f+\frac{\alpha}{2}+vF_s)\tilde{X}_{\Delta t}^*(t,f-\frac{\alpha}{2}+vF_s) \quad (12)$$

where

$$\tilde{X}_{\Delta t}(t,f) \triangleq \sum_{k=0}^{N-1} a_{\Delta t}(kT_s)x(t-kT_s)e^{-j2\pi f(t-kT_s)} \quad (13)$$

which is the downconverted output of a sliding DFT, and where $a_{\Delta t}$ is the data-tapering window, $\Delta f = MF_s$ is the width of the spectral smoothing interval, $F_s = 1/NT_s$ is the frequency sampling increment, T_s is the time-sampling increment, and N is the number of time samples in the data segment of length Δt, which is Fourier transformed by the DFT, $N = \Delta t/T_s + 1$. Thus, the resolution product is $\Delta t\Delta f = M(N-1)/N \cong M \gg 1$. Also we can use the discrete-time averaging method to smooth the cyclic periodogram.

Based on the fundamentals of the cyclostationarity, given the input time series $x[n], n = 0,1,2,...,N$ and sampling interval T_s, the cyclostationary feature detection (CFD) is conducted through the following steps:

1) We first calculate N point FFT of the input time series $x[n], n = 0,1,2,...,N$ for the frequency spectrum $X_T[k]$,

$$X_T[k] = \sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi kn}{N}}, \quad (14)$$

2) The cyclic periodogram $S_{X_T}^{\alpha}[k]$ can be calculated via the periodogram average function, as

$$S_{X_T}^{\alpha}[k] = \frac{1}{N}X_T[k+\frac{\alpha}{2}]X_T^*[k-\frac{\alpha}{2}], \quad (15)$$

3) To satisfy the constraints of (11), the cyclic power spectrum estimation is smoothed by the discrete-frequency smoothing function

$$\tilde{S}_{X_T}^{\alpha}[k]_{\Delta f} = \frac{1}{M}\sum_{m=0}^{M-1} S_{X_T}^{\alpha}[kM+m]. \quad (16)$$

The CFD approach is more robust to random noise and interference from other modulated signals than the approaches of matched filter detection and energy detection, because the noise has only a peak of spectral correlateon function at the zero cyclic frequency and the different modulated signals have different unique cyclic frequencies.

3. SUBSECTION-AVERAGE CYCLOSTATIONARY FEATURE DETECTION

The cyclic spectrum correlation estimation algorithm has some disadvantages although it can obtain the cyclic power spectrum estimation effectively. The computational complexity of the CFD approach, which is mainly brought by FFT calculations and cyclic periodogram calculations, is about $O(N^2/4+N/2\log_2^N)$. The computational cost is high while N is large. Moreover, in the CFD method, the processing procedure that the statistical average is substituted by the time average induces large variances and impacts the quality of the estimation. Accordingly we propose a novel method to ameliorate the CFD algorithm.

Comparing with the CFD scheme, the SACFD strategy can be described as follows:

1) First we calculate P point FFT of the input time series for the frequency spectrum $X_T[k]$,

$$X_{T,l}[k]=\sum_{n=0}^{P-1}x[lP+n]e^{-j\frac{2\pi kn}{P}},l\in[0,L], \tag{17}$$

2) Then we get the cyclic periodogram $T_{X_T}^{\alpha}[k]$ via meaning the periodogram for each subsection,

$$S_{X_T,l}^{\alpha}[k]=\frac{1}{P}X_{T,l}[k+\frac{\alpha}{2}]X_{T,l}^{*}[k-\frac{\alpha}{2}],l\in[0,L], \tag{18}$$

3) The average of the L sections can be got by the following function,

$$S_{X_T}^{\alpha}[k]=\frac{1}{L}\sum_{l=0}^{L}S_{X_T,l}^{\alpha}[k], \tag{19}$$

4) Last we smooth the cyclic power spectrum estimation by the discrete-frequency smoothing function, as

$$\tilde{S}_{X_T}^{\alpha}[k]_{\Delta f}=\frac{1}{M}\sum_{m=0}^{M-1}S_{X_T}^{\alpha}[kM+m]. \tag{20}$$

In SACFD approach, we divide the input series into L P-length series and compute cyclic periodogram for each P-length series. The total cyclic periodogram can be calculated by meaning each subsection cyclic periodogram. The computational complexity of the SACFD approach is about $O(NP/4+N/2\log_2^N)$ that has linear relationship with the sample length. It can not only reduce the computational complexity but also facilitate the hardware implementation. As we know from the probability theory, given independent random variables $X_1,X_2,...,X_L$ with the same mean μ and variance σ^2, which the mean of these random variables is $X=(X_1+X_2+...+X_L)/L$, we can find that the mean of X is μ but the variance of X becomes σ^2/L. The step (3) in the SACFD strategy makes the total variance of the input random series decrease with the subsection number L increasing since we divide the input Gaussian white noise series which is a random series into L P-length independent random series. Then the SACFD algorithm improves the variance performance in statistical sense. Furthermore, it inhibits the noise interference more effectively than the conventional CFD approach.

4. NUMERICAL RESULTS AND DISCUSSION

In this section, we present some numerical results in order to get insight into the performance of SACFD method and further demonstrate the advantages of the new algorithm. Gaussian white noise series are used as the input random signals to illustrate the improvement effect generated by the SACFD method. For our experiments, α and M are assumed to be 100 and 40 respectively.

We first give the cyclic spectrum autocorrelation diagram of Gaussian white noise with conventional method in Fig. 1. Fig. 2 shows the cyclic spectrum autocorrelation diagram of Gaussian white noise with five times average using SACFD method. It can be seen from Fig. 1 and Fig. 2 that the interferences on the cyclic frequency $\alpha\neq 0$ are restrained effectively by the SACFD method. The average amplitude of the Gaussian white noise power spectrum reduces from 0.15 with the non-average method to 0.05 with SACFD method.

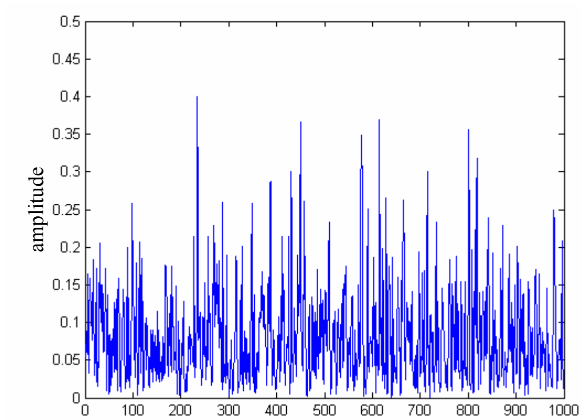

Fig. 1. Cyclic power spectrum of Gaussian white noise (without average)

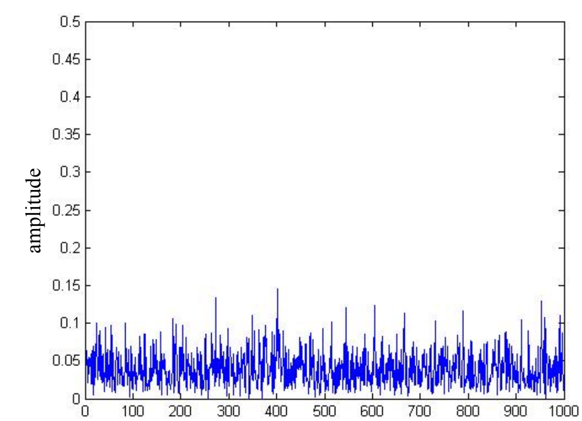

Fig. 2. Cyclic power spectrum of Gaussian white noise (with five times average)

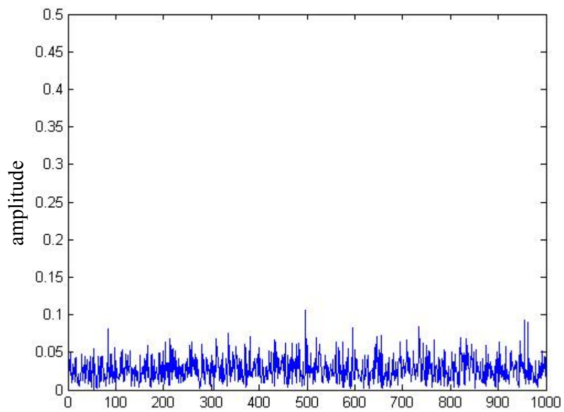

Fig. 3. Cyclic power spectrum of Gaussian white noise (with ten times average)

TABLE I
ADVANTAGES AND DISADVANTAGES OF SPECTRUM SENSING TECHNIQUES

Spectrum sensing approach	Advantages	Disadvantages
Energy detection	Does not need any prior information low computational cost	Cannot work in low SNR cannot distinguish users sharing the same channel
Matched filter	Optimal detection performance low computational cost	Requires a prior knowledge of the primary user
Cyclostationary feature detection	Robust in low SNR robust to interference	Requires partial information of the primary user high computation cost
Subsection-average cyclostationary feature detection	High quality of variance performance low computational cost	Requires partial information of the primary user

The inhibition effect of the noise interference will be better with the average times increasing. Ten times average are adopted in Fig. 3. Compared the Fig. 2 and Fig. 3 we can also observed that the average amplitude of the Gaussian white noise cyclic power spectra is reduced from 0.05 to 0.025 and the SNR on the cyclic frequency is enhancing with the average times increasing.

Finally, a summary about the advantages and disadvantages of spectrum sensing techniques is shown in Table I.

5. CONCLUSION

A subsection-average method based on the cyclostationary feature detection in cognitive radio systems is proposed in this paper. To decrease the computational complexity and improve the quality of variance performance of cyclostationary feature detection, subsection average means is exploited in cyclic spectrum autocorrelation estimation of cyclostationary feature detection approach. Simulation results show that the variance performance of the proposed method is improved considerably compared with conventional cyclostationary feature detection. That is to say, the subsection-average means can inhibit the noise interference more effectively in practical significance than conventional cyclostationary feature detection.

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