ISBN 978-952-5726-00-8 (Print), 978-952-5726-01-5 (CD-ROM)
Proceedings of the 2009 International Symposium on Web Information Systems and Applications (WISA'09)
Nanchang, P. R. China, May 22-24, 2009, pp. 327-330

A Two-Stage Spectrum Sensing Technique in Cognitive Radio Systems Based on Combining Energy Detection and One-Order Cyclostationary Feature Detection

Wenjing Yue[1], and Baoyu Zheng[1, 2]
[1] Department of Electronic Engineering, Shanghai Jiaotong University, Shanghai, China
Email: yuewenjing@sjtu.edu.cn
[2] Institute of Signal Processing and Transmission, Nanjing University of Posts and Telecommunications, Nanjing, China
Email: zby@njupt.edu.cn

***Abstract*—In cognitive radio systems, the main requirement of cognitive radio architectures is the ability to detect the presence of the primary user with fast speed and precise accuracy. To achieve that, we suggest a possible two-stage spectrum sensing approach. More specifically, a fast spectrum sensing algorithm based on the energy detection is introduced focusing on the coarse detection. A complementary fine spectrum sensing algorithm adopts one-order cyclostationary properties of primary user's signals in time domain. This feature detection technique in time domain realizes simple and low computational complexity compared to spectral feature detection methods. Also, it drastically reduces hardware burdens and power consumption as opposed to two-order feature detection. The sensing performance of the proposed method is studied and the analytical performance results are given. The results indicate that better performance can be achieved in proposed two-stage sensing detection compared to the conventional energy detector.**

***Index Terms*—cognitive radio, spectrum sensing, energy detector, cyclostationary feature detector**

I. Introduction

Nowadays, with the rapid growth of wireless communication, it becomes more and more congested for our limited spectrum at frequencies. In connection with an evaluation of future communications-related demands, the spectrum is expected to become even more tremendously in the coming years. However, the current spectrum scarcity is largely due to the inefficient static spectrum allocations than the physical shortage of the spectrum. This point of view is supported by recent studies of the FCC [1].

To deal with the conflicts between spectrum congestion and spectrum under-utilization, cognitive radio has been recently considered as an efficient approach to improve the spectrum utilization via opportunistic spectrum sharing [2]. However, cognitive radios are considered lower priority to a PU. This fundamental requirement is to avoid interference to potential PUs in their vicinity. To implement without interference to the primary signal, the cognitive radio needs to sense the availability of the spectrum before accessing the channel. Currently, the spectrum sensing techniques mainly focus on primary transmitter detection and they usually can be classified as matched filter, cyclostationary feature detection and energy detection.

The matched filter is viewed as optimal since it maximizes received signal-to-noise ratio (SNR) in communication systems [3]. However, a significant drawback of a matched filter is that it needs the prior knowledge of the primary user's signal such as the modulation type and order, pulse shaping and packet format. Cyclostationary feature detection [4] can detect the signals with very low SNR but still requires some prior knowledge of the PU. Another shortcoming is that its computational complexity is a bottleneck for its implementation. As all the frequencies should be searched in order to generate the spectral correlation function, the calculation complexity is huge. Energy detectors [5] are the most common way of spectrum sensing because of their low computational complexity. However, it is well-known that such a method lacks the capability to differentiate different signal types.

To meet the time and sensitivity requirements, a CR system with two-stage spectrum sensing is proposed which consists of coarse and fine detection in IEEE 802.22 WRAN systems [6]. Firstly, the coarse detection based on energy detection is performed by searching the whole detected bandwidth. Then fine/feature sensing is performed for the selected channel for identifying the type of incoming signal. However, to the best of our knowledge, recent research on cyclostationary features sensing mainly focus on two-order cyclostationary, i.e. auto-correlation function. We propose for the first time that fine sensing is performed by one-order cyclo-stationary feature sensing. Unlike previous two-order cyclostationary feature sensing schemes, since this feature detection technique is performed in time domain, low-power consumption and fast spectrum-detection can be achieved.

In this paper, we propose the two-stage spectrum sensing as followings: Firstly, the coarse detection based on energy detection is performed by searching the whole detected bandwidth. It selects the unoccupied candidate

AP-PROC-CS-09CN001

channels by sorting the channels in the ascending order based on the power of each channel, and it is rational due to the fact that the channel with low power has high probability to be an unoccupied channel. Then the channel with lowest power is examined by one-order feature sensing to detect weak signals at the fine stage.

The rest of this paper is organized as follows. A two-stage detection model is briefly described in Section II. Conditional probability of detection and probability of a false alarm are evaluated in Section III over additive white Gaussian noise (AWGN) and Rician fading channels respectively. Performance evaluation and comparisons are given in Section IV, and finally, our conclusions are offered in Section V.

II. A Two-Stage Spectrum Sensing Architecture

The detection problem for spectrum sensing at secondary user (SU) can be formulated as a binary hypothesis. Therefore, the goal of spectrum sensing is to decide between the following two hypotheses,

$$\begin{cases} H_0: & x(t) = n(t) \qquad 0 < t \le T \\ H_1: & x(t) = h\,s(t) + n(t) \qquad 0 < t \le T \end{cases} \tag{1}$$

where T denotes the observation time. $x(t)$ is the received signal by SU, $s(t)$ is the transmitted signal of the PU and h is the amplitude gain of the channel. $n(t)$ is the AWGN whose value n at any arbitrary time t is a Gaussian random variable with zero mean and variance δ^2.

A. Energy Detection Technique

The recent work on detection of the PU has generally adopted the energy detector for low computational complexity. The output of energy detector, Y, follows the distribution

$$Y \sim \begin{cases} \chi^2_{2TW} & H_0 \\ \chi^2_{2TW}(2\gamma) & H_1 \end{cases} \tag{2}$$

where χ^2_{2TW} and $\chi^2_{2TW}(2\gamma)$ represent central and conditionally non-central chi-square distribution respectively, each with $2TW$ degrees of freedom and 2γ is a non-centrality parameter for the latter distribution. γ is a instantaneous SNR and for simplicity we assume that time-bandwidth product, TW , is an integer number which we denote by m.

An approximate expression for the conditional detection probability P_d and the false alarm probability P_f over AWGN can be given by, respectively [7],

$$P_d = Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) \tag{3}$$

$$P_f = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \tag{4}$$

where $\Gamma(.)$ and $\Gamma(.,.)$ are complete and incomplete gamma function respectively. $Q_m(.,.)$ is the generalized Marcum Q-function and λ stands for decision threshold.

We suggest possible energy detection architecture like following. The coarse detection based on energy detection is performed by searching the whole detected bandwidth. It selects the candidate channels by sorting the channels in the ascending order based on the power of each channel, and it is rational due to the fact that the channel with low power has high probability to be an unoccupied channel. Then the channel with lowest power is examined by a fine sensing. This fine sensing is detailed in the following part.

This coarse sensing algorithm has an improvement that it can easily select the unoccupied candidate channels without setting threshold. This is accomplished by sorting the channels in the ascending order based on the power of each channel. Since it is commonly recognized that the threshold of energy detector is susceptible to the noise uncertainty, the coarse sensing scheme can alleviate this problem.

B. One-order Cyclostationary Feature Technique

According to the cyclostationary signal processing theory, most modulated signals are characterized as cyclostationarity since their mean and autocorrelation exhibit periodicity [3, 8]. Common analysis of cyclostationarity signal is based on autocorrelation function, however, we exploit the mean characteristics of the primary signals to improve the efficiency of the channel sensing in time domain.

Consider a deterministic complex sine signal $s(t)$, and it may be expressed as

$$s(t) = a e^{j(2\pi f_0 t + \theta)} \tag{5}$$

In the transmission of $s(t)$ through an AWGN channel, $x(t) = s(t) + n(t)$. Let us determine statistical averages for this process $x(t)$, the mean function of $x(t)$ can be written as

$$M_x(t) = E\{x(t)\} = s(t) \tag{6}$$

We observe that the mean is time-varying. Moreover, it is periodic function of time with period T_0 $(= 1/f_0)$. If we know the period T_0, there is a method called synchronized averaging which can extract this periodicity. In such method, the process $x(t)$ is periodic sampled at the sampling instants $..., t - kT_0$, $..., t - T_0$, t, $t + T_0$, $...$, $t + kT_0, ...$ for any time instant t and for any positive integer value of k.

$$M_x(t)_T \triangleq \frac{1}{2N+1} \sum_{k=-N}^{N} x(t + kT_0) \tag{7}$$

where, as before, $T \triangleq (2N+1)T_0$ denotes observation time. When T goes to infinite, this relation becomes [8]

$$M_x(t) = \lim_{T\to\infty} M_x(t)_T = \lim_{N\to\infty} \frac{1}{2N+1}\sum_{k=-N}^{N} x(t+kT_0) \quad (8)$$

We note that $M_x(t)$ is also periodic with period T_0. In other words, $M_x(t) = M_x(t+kT_0)$ for $k = 0, \pm 1, \pm 2, \ldots$. Such characteristic is called one-order cyclostationary.

As an example, we consider noise $n(t)$. In this case, no periodicity will be found.

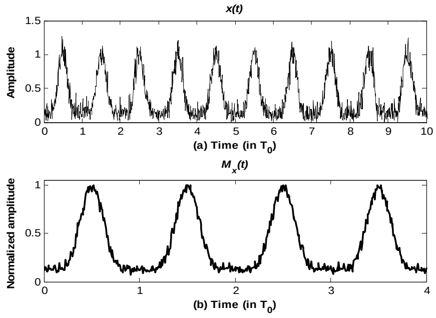

Figure 1. Amplitude of (a) BPSK signal in AWGN $x(t)$ and (b) $M_x(t)_T$.

In order to show the conceptual functionalities of the proposed technique, numerical results are given for a BPSK signal in AWGN, as shown in Fig. 1 (a). The normalized amplitude of $M_x(t)_T$ is plotted in Fig.1 (b) as a function of the time. It shows that $M_x(t)_T$ is also periodic with period T_0 in time domain. Meanwhile, $n(t)$ are the Gaussian random variables with zero mean and can be ignored after the periodic sampling. Moreover, there is a peak value for each one-half of the periodicity location. Search for the peak value in time domain and compare it with the predetermined threshold. If no periodicity is found, it means that there is no signal in the detected band. Otherwise, the band is used by PU.

The proposed one-order cyclostationary feature detection method is described as shown in Fig. 2.

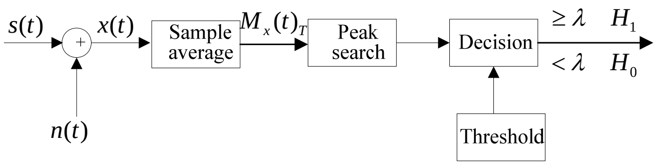

Figure 2. Block diagram of the proposed fine sensing technique.

III. Spectrum Sensing Performance Analysis

In this section, we will analyze the sensing performance of one-order cyclostationary feature detection over AWGN and Rician channels, respectively.

$$\begin{aligned} P_{M_x(t)_T}(t:H_0) &= N\left(0, \frac{\delta^2}{2N+1}\right) \\ P_{M_x(t)_T}(t:H_1) &= N\left(\mu, \frac{\delta^2}{2N+1}\right) \end{aligned} \quad (9)$$

According to the Central Limit Theorem, when the number of terms added in (7) is sufficiently large, the pdf of $M_x(t)_T$ for both hypotheses can be approximated by Gaussian distributions, which are given by (9).

Thus, under hypothesis H_0 and H_1 , the envelope of $M_x(t)_T$, r , are respectively Rayleigh and Rician distributed [9]

$$p(r:H_0) = \frac{r}{\delta_A^2} e^{-\frac{r^2}{2\delta_A^2}} \qquad r \ge 0 \quad (10)$$

$$p(r:H_1) = \frac{r}{\delta_A^2}\exp\left[-\frac{\left(r^2+A^2\right)}{2\delta_A^2}\right] I_0\left(\frac{Ar}{\delta_A^2}\right), A \ge 0, r \ge 0 \quad (11)$$

where $\delta_A^2 = \delta^2 / (2N+1)$. $I_0(.)$ is the zeroth-order modified Bessel function and A^2 stands for a non-centrality parameter.

For a particular threshold λ , the cumulative density function (CDF) of the envelope of $M_x(t)_T$ under different hypotheses over AWGN channel are respectively given by

$$F(\lambda:H_0) = \Pr(r \le \lambda) = 1 - \exp\left(-\frac{\lambda^2}{2\delta_A^2}\right) \quad (12)$$

$$F(\lambda:H_1) = \Pr(r \le \lambda) = 1 - Q_1\left(\frac{\sqrt{2\gamma}}{\delta}, \frac{\lambda}{\delta_A}\right) \quad (13)$$

In order to detect whether the PU is present or not, we need to search for the peak value of $M_x(t)_T$ within a period. Therefore, in the following, we look into the one-order cyclostationary feature detection performance when maximum-selection diversity (MSD) scheme is employed.

Define the test statistic M_{MSD} as

$$M_{MSD} = \max\left(M_x^{(1)}, M_x^{(2)}, \ldots, M_x^{(L)}\right) \quad (14)$$

where L is the number of diversity branches. For simplicity, we assume that $\left\{M_x^{(i)}\right\}_{i=1}^{L}$ are i.i.d.

Under H_0, and given $\left\{M_x^{(i)}\right\}_{i=1}^{L}$ variates, the false alarm probability for variable M_{MSD} , $P_{f,MSD}$, can be evaluated as

$$P_{f,MSD} = 1 - \left(1 - e^{-\frac{\lambda^2}{2\delta_A^2}}\right)^L \quad (15)$$

Similarly, and conditioning on γ , the detection probability $P_{d,MSD}$ over AWGN can be obtained as

$$P_{d,MSD} = 1 - \left[1 - Q_1\left(\frac{\sqrt{2\gamma}}{\delta}, \frac{\lambda}{\delta_A}\right)\right]^L \quad (16)$$

Since the signal strength follows a Rician distribution in such scenario, the pdf of SNR, $f_{Ric}(\gamma)$, will be [10]

$$f_{Ric}(\gamma)=\frac{K+1}{\bar{\gamma}}\exp\left(-K-\frac{(K+1)\gamma}{\bar{\gamma}}\right)I_0\left(2\sqrt{\frac{K(K+1)\gamma}{\bar{\gamma}}}\right) \tag{17}$$

where $K = A^2/(2\delta_A^2)$, which is the Rician factor. For K=0, this expression reduces to the Rayleigh expression.

The average $P_{d,MSD}$ in the case of a Rician channel, $\bar{P}_{d,MSD}$, is then obtained by averaging (16) over (17).

$$\begin{aligned}\bar{P}_{d,MSD} &= 1-\left[\int_0^\infty\left(1-Q_1\left(\frac{\sqrt{2\gamma}}{\delta},\frac{\lambda}{\delta_A}\right)\right)f_{Ric}(\gamma)\,d\gamma\right]^L \\ &= 1-\left(1-Q_1\left(\frac{\sqrt{2K\bar{\gamma}}}{\delta\sqrt{K+1+\bar{\gamma}}},\frac{\lambda\sqrt{K+1}}{\delta_A\sqrt{K+1+\bar{\gamma}}}\right)\right)^L\end{aligned} \tag{18}$$

It is note that, $\bar{P}_{d,MSD}$ is the special case for u=1[11, Eq.(45)] when setting L=1 in (18). Meanwhile, $\sqrt{\lambda}$ is replaced by λ.

IV. Numerical Results

In this section, numerical results are presented to evaluate the performance for proposed scheme. We assume that average SNR, $\bar{\gamma}$, time-bandwidth product, m, and Rician factor, K, are respectively 10 dB, 5 and 10 dB.

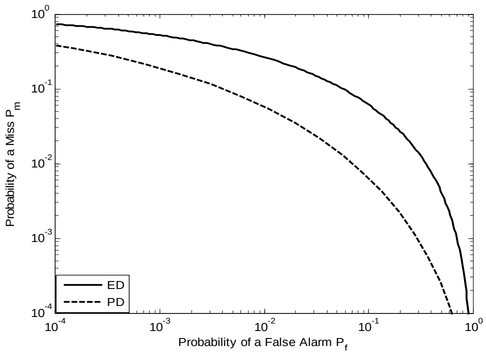

Figure 3. Performance comparison between proposed two-stage detection (PD) and energy detector (ED).

In order to carry out a comparison between the proposed two-stage detection (PD) and energy detection (ED), simulations are carried out in AWGN environment for the case $\delta^2 = 1$ and L=1, as shown in Fig. 3. The results indicate that better performance can be achieved in proposed two-stage sensing detection compared to the conventional energy detector.

The probability of a miss P_m for L=1, 3 and 5 are plotted in Fig. 4 as a function of P_f using one-order feature detector with unit noise variance. It can be seen that, for a given P_f, with the increase of L, P_d becomes larger. This means that a diversity gain of L is achieved. As trade off of performance and complexity, we can set L= 3. A plot for pure AWGN case is also provided for comparison for the case L=3. Simulation shows that performance is degraded due to Rician fading.

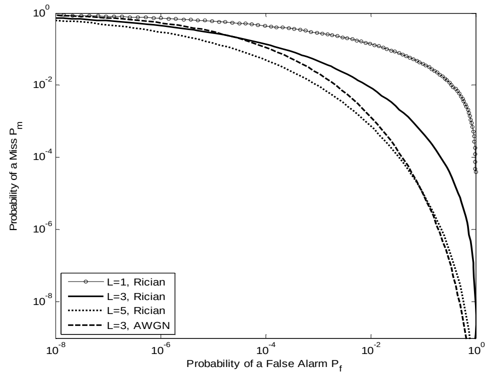

Figure 4. Complementary receiver operating characteristic for L=1,3 and 5.

V. Conclusions

A two-stage spectrum sensing technique is proposed to meet the requirements to speed and accuracy in cognitive radio systems. Numerical results are presented to show that the proposed approach can guarantee a reliable sensing while enhancing the spectrum utilization greatly.

Acknowledgment

This work was supported in part by the Major Development Program of Jiangsu Educational Committee (No. 06KJA51001) and Key Science Foundation of Jiangsu Province (No. BK2007729).

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