TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol.12, No.5, May 2014, pp. 3257 ~ 3265
DOI: http://dx.doi.org/10.11591/telkomnika.v12i5.4944

Adaptive Two-Stage Sensing in Cognitive and Dynamic Spectrum Access Networks

Yang Yu*, Yanli Ji, Weidong Wang, Yinghai Zhang
Beijing University of Posts and Telecommunications, Beijing, 100876, China
*Corresponding author, e-mail: yuyang1986@bupt.edu.cn

Abstract
In this paper, we first investigate and contrast the features of energy detection and cyclostationary feature detection for spectrum sensing. Combining the advantages of both, we propose an adaptive two-stage sensing scheme which first performs spectrum sensing using an energy detector in cognitive and dynamic spectrum access networks. Then this scheme decides whether or not to implement cyclostationary feature detection based on the sensing results of the first stage. On the premise of meeting a given constraint on the probability of false alarm, our proposed scheme aim to optimize the probability of detection. In order to obtain the optimal detection thresholds, the detection model is formulated as a nonlinear optimization problem. Furthermore, the performance of our scheme in sensing speed is also analyzed. The simulation results show that the proposed scheme improves the performance of spectrum sensing compared with the ones where only energy detection or cyclostationary feature detection is performed.

Keywords: *cognitive radio, dynamic spectrum access, two-stage sensing, energy detection, cyclostationary feature detection*

1. Introduction

Future wireless communication networks envisage the challenge that the available spectrum is becoming increasingly scarce. However, the conventional approach of static spectrum allocation leads to significant radio spectrum underutilization; e.g., at least 50% of broadcast television channels in the Washington area are unused, constituting known 'white spaces' in the spectrum [1].

Cognitive radio (CR) [2, 3] or dynamic spectrum access (DSA) technology is a promising approach for the more effective use of existing spectrum which can intelligently identify unused licensed bands and allow adaptive utilization of them as long as not causing unacceptable interference from unlicensed or secondary users (SUs) to licensed or primary users (PUs). In order to determine whether or not the licensed bands are unused, the SUs have to perform spectrum sensing. The need for fast and effective (reliable) spectrum sensing over a wide bandwidth is fundamentally important to DSA. Meanwhile, spectrum sensing is also a challenging task, because the received PU signal at SU receiver is possible to be very weak owing to path loss and fading [4], the perfect detection of PU's transmission is hard to implement in practice.

Various spectrum sensing schemes have been proposed. Many of them exploit two typical features, namely energy [5] and cyclostationary features [6]. Energy detection is one of the most popular techniques for spectrum sensing, where a SU makes a decision with respect to the presence of PUs according to the amount of its received energy [7]. This method is easy to implement, and does not need that the SU knows the information of the PU signal. However, it suffers from a relatively poor performance owing to the uncertainty of noise level in the low signal-to-noise ratio (SNR) regime. A significantly better performance can be achieved through cyclostationary feature detection exploiting the periodic structure of the PU signal, by carrying out cyclic spectral analysis [8]. Through this method, noise can be significantly suppressed, thus achieving more robustness than energy detection. In addition, this method detects only signals with the desired feature and therefore is able to distinguish certain types from others. However, the exact cyclostationary feature of the PU signal may not be known to the SU and needs a long observation to be obtained. Also, the downside of this method in general is its increased

Received October 15, 2013; Revised November 24, 2013; Accepted December 12, 2013

computational complexity and memory requirements, which makes this method difficult for practical use, especially in the environments of high real-time requirements.

In a practical CR system, one common requirement of sensing approaches is the fast and effective (reliable) detection of idle primary channels by SUs as characterized by the mean sensing time. The mean sensing time is the average time to successfully sense an available channel, which depends on the search algorithm. The importance of detector design is further enhanced by the impact of its operating characteristic which is represented by the probability of correct detection, P_d, and the probability of false alarm, P_f, respectively.

As mentioned above, cyclostationary feature detection has superiority in sensing effectiveness over energy detection, especially for low SNRs. On the other hand, energy detection is a much quicker and easier spectrum sensing method, while it has not too much degradation of sensing accuracy compared with cyclostationary feature detection for high SNRs [9], [10]. Thus, with the grain of nature, a tradeoff between sensing speed and sensing accuracy combining the advantages of these two detection methods will make the most sense.

In this paper, we first give a brief introduction to the mechanisms of energy detection and cyclostationary feature detection, and then propose an adaptive two-stage sensing approach based on energy detection and cyclostationary feature detection to achieve the tradeoff mentioned above. By now, a lot of papers have investigated two-stage sensing for CR systems. However, there has been few works on the combination of energy detection and cyclostationary detection, to the authors' knowledge. In the first stage of the proposed scheme energy detection is performed. Then, the proposed scheme decides whether or not to perform cyclostationary detection according to the sensing results of the first stage, i.e., if the energy is greater than a certain threshold, the given channel is sensed to be active, else, cyclostationary detection is performed. In the second stage, through comparing the decision metric with another certain threshold, the given channel is declare to be active or idle. Aiming at optimizing the probability of detection under the constraint on the probability of false alarm, we formulate the detection model as a nonlinear optimization problem and give the method to deduce the above two optimal thresholds. Moreover, we also analyze the performance of the proposed scheme in sensing speed by deducing the mean sensing time.

The remainder of this paper is organized as follows. In Section 2, we give a brief introduction to the proposed adaptive two-stage sensing scheme. In Section 3, the characteristics of energy detection and cyclostationary feature detection techniques are given, and the proposed scheme is described in more detail. The optimal thresholds for the proposed two-stage sensing scheme are also derived in this section. Moreover, we analyze the performance of the proposed scheme in sensing speed. Simulation results are presented in Section 4, and conclusions are drawn in Section 5.

2. The Proposed Algorithm

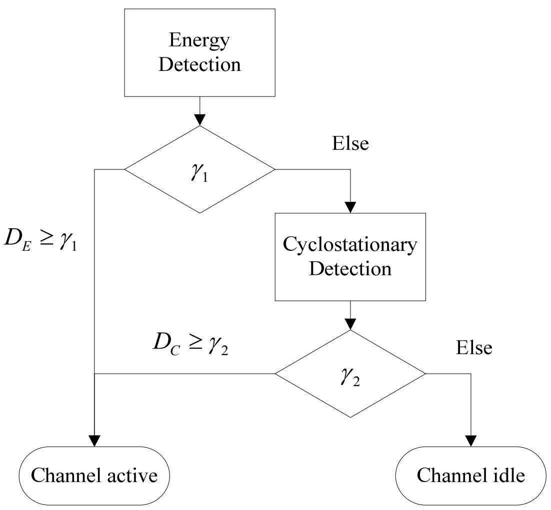

Figure 1. Adaptive Two-stage Spectrum Sensing

In this section, we will briefly introduce the adaptive two-stage spectrum sensing scheme. The flow chart of the proposed scheme is shown in Figure 1. For simplicity, we ignore the period of data communication and assume that the spectrum sensing is carried out without interruption. We further assume that there is only a single channel to be sensed.

In the first sensing stage, we use energy detection. If the decision metric D_E is greater than a certain threshold γ_1, we declare the channel is active and occupied by a PU. Else, the second stage is necessary and we reanalyze the received signal by cyclostationary feature detection. Similarly, we introduce another constituent detection metric D_C and compare it with another threshold γ_2. If D_C is greater than γ_2, we declare the channel is occupied, else it is declared to be idle.

3. Research Method

In this section, we first give the characteristics of energy detection and cyclostationary feature detection techniques and discuss them in the context of our adaptive two-stage spectrum sensing.

3.1. First Stage: Energy Detection

In the first stage, energy detection is performed. If SUs' prior knowledge is limited, the optimal detector is an energy detector, where the received signal over each frequency band is squared and integrated over the observation interval.

According to [11], spectrum sensing in CR networks can be formulated as a binary hypothesis-testing problem, where hypotheses H_0 and H_1 correspond to the cases of absence and presence of PUs, respectively. Assuming sensing at times $n \in \{1, 2, ..., N\}$, the received signal samples for the two hypotheses may be modeled as:

$$\begin{cases} \mathrm{H}_0 : y(n) = z(n), \\ \mathrm{H}_1 : y(n) = hs(n) + z(n), \end{cases} \tag{1}$$

Where $y(n)$, h, $s(n)$, and $z(n)$ denote the received signal samples, the channel gain, the PU signals, and zero-mean complex additive white Gaussian noise (AWGN) with variance σ_z^2, respectively. The channel gains are assumed to be constant for the duration of spectrum sensing. The PU signal is assumed to be an independent, identically distributed (i.i.d.) random process with zero mean and variance σ_s^2. The noise samples, the channel gains, and the PU signals are assumed to be mutually independent. We further assume that both the PU signals and the noise samples are temporally i.i.d..

The energy detector uses the following decision rule:

$$D_E = \sum_{n=1}^{N} y^2(n) \begin{cases} < \gamma_1 & \mathrm{H}_0 \\ \geq \gamma_1 & \mathrm{H}_1. \end{cases} \tag{2}$$

According to [12], we model the test statistic for large N as:

$$D_E \sim \begin{cases} \mathrm{N}\ (N\sigma_z^2, 2N\sigma_z^4) & \mathrm{H}_0 \\ \mathrm{N}\ (N(\sigma_z^2 + h^2\sigma_s^2), 2N(\sigma_z^2 + h^2\sigma_s^2)^2) & \mathrm{H}_1. \end{cases} \tag{3}$$

The probability of false alarm and the probability of detection for the given channel under the energy detection are given by:

$$P_f^E = P(D_E \geq \gamma_1 \mid \mathrm{H}_0) = Q\left(\frac{\gamma_1 - N\sigma_z^2}{\sqrt{2N\sigma_z^4}}\right), \tag{4}$$

$$P_d^E = P(D_E \geq \gamma_1 \mid \mathrm{H}_1) = Q\left(\frac{\gamma_1 - N(\sigma_z^2 + h^2\sigma_s^2)}{\sqrt{2N(\sigma_z^2 + h^2\sigma_s^2)^2}}\right), \tag{5}$$

Where $Q(\cdot)$ is the standard Gaussian complementary cumulative distribution function, i.e.:

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2}\, \mathrm{d}t .$$

3.2. Second Stage: Cyclostationary Feature Detection

In the second sensing stage, cyclostationary detection is performed. Cyclostationary processes are random processes for which the statistical properties such as the mean and autocorrelation change periodically as a function of time. This paper uses the second-order time domain cyclostationary detector presented in [13].

A random process $y(m)$, $m \in \{1, 2, ..., M\}$ is wide-sense second-order cyclostationary, if there exists a K>0 such that:

$$\mu_y(m) = \mu_y(m+K), \tag{6}$$

$$R_y(m,\tau) = R_y(m+K,\tau), \forall\, \tau, \tag{7}$$

Where K is the cyclic period, $\mu_y(m) = E[y(m)]$ is the mean value of the random process $y(m)$, and $R_y(m,\tau) = E[y(m)y^*(m+\tau)]$ is the autocorrelation function.

$R_y(m,\tau)$ has a Fourier-series representation due to its periodicity as follows [13]:

$$R_y(m,\tau) = \sum_{\alpha} R_y^{\alpha}(\tau) e^{j\alpha m}, \tag{8}$$

Where the Fourier coefficients can be expressed as:

$$R_y^{\alpha}(\tau) = \lim_{M \to \infty} \frac{1}{M} \sum_{m=0}^{M-1} R_y(m,\tau) e^{-j\alpha m},$$

With the cycle-frequency α.

In practice, we consider the following estimator of $R_y^{\alpha}(\tau)$ for a given K.

$$\hat{R}_y^{\alpha}(\tau) = \frac{1}{M} \sum_{m=0}^{M-1} y(m) y^*(m+\tau) e^{-j\alpha m} = R_y^{\alpha}(\tau) + \varepsilon_y^{\alpha}(\tau), \tag{9}$$

Where $\varepsilon_y^{\alpha}(\tau)$ denotes the estimation error which equals to zero if M approaches infinity. Due to this error, the estimator $\hat{R}_y^{\alpha}(\tau)$ hardly ever equals to zero in practice, which leads a difficult problem about determining whether or not the $R_y^{\alpha}(\tau)$ corresponding to a given value of $\hat{R}_y^{\alpha}(\tau)$ is zero. To solve this problem statistically, the decision-making approach in [13] is used.

We consider a vector of $\hat{R}_y^{\alpha}(\tau)$ rather than a single value to check for the presence of cycles in a set of lags τ at the same time. Let $\tau_1, ..., \tau_K$ be a fixed set of lags, α be a candidate cycle-frequency, and:

$$\hat{\mathbf{R}}_y = \left[\mathrm{Re}\left\{\hat{R}_y^{\alpha}(\tau_1)\right\}, ..., \mathrm{Re}\left\{\hat{R}_y^{\alpha}(\tau_K)\right\},\ \mathrm{Im}\left\{\hat{R}_y^{\alpha}(\tau_1)\right\}, ..., \mathrm{Im}\left\{\hat{R}_y^{\alpha}(\tau_K)\right\}\right], \tag{10}$$

Be a $1\times 2K$ row vector consisting of second-order cyclic-cumulant estimators from (9). If the asymptotic value of $\hat{\mathbf{R}}_y$ is given as:

$$\mathbf{R}_y = \left[\mathrm{Re}\left\{R_y^{\alpha}(\tau_1)\right\},...,\mathrm{Re}\left\{R_y^{\alpha}(\tau_K)\right\},\ \mathrm{Im}\left\{R_y^{\alpha}(\tau_1)\right\},...,\mathrm{Im}\left\{R_y^{\alpha}(\tau_K)\right\}\right], \tag{11}$$

Then using (9), we can write $\hat{\mathbf{R}}_y = \mathbf{R}_y + \boldsymbol{\varepsilon}_y$, where:

$$\boldsymbol{\varepsilon}_y = \left[\mathrm{Re}\left\{\varepsilon_y^{\alpha}(\tau_1)\right\},...,\mathrm{Re}\left\{\varepsilon_y^{\alpha}(\tau_K)\right\},\ \mathrm{Im}\left\{\varepsilon_y^{\alpha}(\tau_1)\right\},...,\mathrm{Im}\left\{\varepsilon_y^{\alpha}(\tau_K)\right\}\right], \tag{12}$$

Is the estimation error vector.

According to [3], the test statistic related to the detector in the second sensing stage can be expressed as follows:

$$D_C = M\hat{\mathbf{R}}_y\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_y^H , \tag{13}$$

Where $\hat{\Sigma}$ denotes the covariance matrix of $\hat{\mathbf{R}}_y$. In [13], the authors show that the test statistic follows a central chi-squared distribution under the hypothesis H_0, and it follows a Gaussian distribution under the hypothesis H_1. Therefore, assuming that M is large enough, the distribution of D_C can be expressed as:

$$D_C \sim \begin{cases} \mathrm{X}_{2K}^2 & \mathrm{H}_0 \\ \mathrm{N}\ (M\hat{\mathbf{R}}_y\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_y^H, 4M\hat{\mathbf{R}}_y\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_y^H)\ \mathrm{H}_1. \end{cases} \tag{14}$$

If $D_C \ge \gamma_2$ we can determine α is a cycle-frequency and the PU is present. Else, the PU is absent and the target channel can be used for the SU.

The probability of false alarm and detection can be given as:

$$P_f^C = P(D_C \ge \gamma_2 \mid \mathrm{H}_0) = \frac{\Gamma(\gamma_2/2, K)}{\Gamma(K)}, \tag{15}$$

$$P_d^C = P(D_C \ge \gamma_2 \mid \mathrm{H}_1) = Q\left(\frac{\gamma_2 - M\hat{\mathbf{R}}_y\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_y^H}{\sqrt{4M\hat{\mathbf{R}}_y\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_y^H}}\right), \tag{16}$$

Where $\Gamma(\cdot)$ is the gamma function and $\Gamma(a,x) = \int_x^{\infty} t^{a-1}e^{-t}\mathrm{d}t$ is the incomplete gamma function.

3.3. Performance Indexes of Our Proposed Scheme

In this section, we introduce the performance indexes of the proposed scheme: probability of detection and mean sensing time.

Based on (4), (5), (15) and (16), the overall probability of false alarm and detection for the adaptive two-stage sensing scheme can be formulated as:

$$P_f = P_f^E + (1 - P_f^E)P_f^C , \tag{17}$$

$$P_d = P_d^E + (1 - P_d^E)P_d^C . \tag{18}$$

In order to measure the agility of our adaptive two-stage sensing scheme, we need to compute its mean sensing time which can be expressed as follows:

$$\overline{T} = \overline{T}_E + \overline{T}_C , \quad (19)$$

Where $\overline{T}_E = N/2W$ is the mean sensing time for the first sensing stage (W is the channel bandwidth) and $\overline{T}_C$ is the second sensing stage mean sensing time, which can be derived as follows:

$$\overline{T}_C = P_{rep}\, M/2W , \quad (20)$$

Where P_{rep} is the probability that cyclostationary detection is performed and is given as:

$$P_{rep} = P(\mathrm{H}_0)(1-P_f^C) + P(\mathrm{H}_1)(1-P_d^C) . \quad (21)$$

Hence, the total mean sensing time and the sensing speed can be expressed as:

$$\overline{T} = \left(N + P_{rep}M\right)\big/2W , \quad (22)$$

$$\overline{v} = 1\big/\overline{T} . \quad (23)$$

3.4. Optimal Thresholds Derivation

In this section, our initial goal is to design the thresholds γ_1 and γ_2 for optimizing sensing accuracy and sensing speed under a given constraint on the probability of false alarm. Since there are two optimization goals, the corresponding nonlinear optimization problem can be formulated as:

$$\max_{(\gamma_1,\gamma_2)} w_1 P_d(\gamma_1,\gamma_2) + w_2\overline{v}, \;\; s.t. \;\; P_f \le \beta, \overline{v} \ge \overline{v}_0 \cdot , \quad (24)$$

Where w_1 and w_2 are the weights, $\overline{v}_0$ is the minimum sensing speed requirement. However, this problem is very complex to be solved. Additionally, the value of these two weights significantly impacts the performance of the detector and cannot be determined easily.

In general, sensing speed is mainly limited by cyclostationary detection which needs complex calculations and a long observation. To the contrary, the sensing accuracy is mainly limited by the first sensing stage. Thus, the probability of implementing the second sensing stage, P_{rep} determines the tradeoff between sensing speed and sensing accuracy. According to (21)-(23), since $P(\mathrm{H}_0)$ and $P(\mathrm{H}_1)$ cannot be known by the SU, we first focus on maximize the probability of detection, and then check whether the value of detection thresholds meets the requirement of sensing speed. If not, we fix the thresholds manually. Thus, problem (24) can be simplified as [14]

$$\max_{(\gamma_1,\gamma_2)} P_d(\gamma_1,\gamma_2) \;\; s.t. \;\; P_f \le \beta . \quad (25)$$

The inequality constraint in the problem (25) makes this problem hard to be solved. Fortunately, it can be reduced to an equality constraint because the optimal value of the probability of detection is attained by $P_f = \beta$. The reason why such a simplification can be applied is given as follows.

According to (5), (16) and (18), we can see that P_d is a differentiable and decreasing function of the thresholds γ_1 and γ_2. Hence, it is obvious that the derivative of P_d with respect to γ_1 or γ_2 is negative. Hence, we can obtain the maximum value of P_d if and only if γ_1 and γ_2 reach their minimum possible value. Also, the derivative of P_f with respect to γ_1 and γ_2 is also negative. We assume that (γ_1^*, γ_2^*) represents the optimal solution of (25) with the constraint $P_f \le \beta$. We keep the threshold γ_1^* to be constant and decrease γ_2^* until we reach $P_f = \beta$. In this case, a higher probability of detection is attained for $\gamma_2 < \gamma_2^*$. Thus it is quite obvious that (γ_1^*, γ_2^*) cannot be the optimal solution of problem (25). Therefore, the optimal P_d can be obtained when $P_f = \beta$.

Hence, the problem (25) can be rewritten as:

$$\max_{(\gamma_1,\gamma_2)} P_d(\gamma_1,\gamma_2) \;\; s.t. \;\; P_f = \beta . \tag{26}$$

For a given constraint β, we have the following relation between γ_1 and γ_2.

$$\gamma_1 = f(\gamma_2) = Q^{-1}\left(\frac{\beta - \dfrac{\Gamma(\gamma_2/2, K)}{\Gamma(K)}}{1 - \dfrac{\Gamma(\gamma_2/2, K)}{\Gamma(K)}} \right) \sqrt{2N\sigma_z^4} + N\sigma_z^2 . \tag{27}$$

Therefore, the problem (26) can be simplified as:

$$\max_{\gamma_2} P_d(f(\gamma_2), \gamma_2) . \tag{28}$$

This problem is unimodal in γ_2 and can be solved by unconstrained optimization algorithms, for example, the steepest descent algorithm. Due to the complex computation, we omit the solving process of γ_1 and γ_2.

After we obtain the value of γ_1 and γ_2, we can calculate the probabilities of false alarm and detection P_f^C and P_d^C in the second sensing stage. Thus, using (21), we can obtain the probability that cyclostationary detection is performed, P_{rep}. Then, the total mean sensing time $\bar{T}$ can be obtain through (22). However, this total mean sensing time may be longer than the maximum sensing time which we can tolerate. In this case, we should return to problem (24), and reconsider optimizing the sensing speed. As mentioned above, it is very complex to be solved. However, on the other hand, the physical meanings of the overall probability of detection P_d and the sensing speed $\bar{v}$ are different in problem (24), and the values of the weights w_1 and w_2 are subjective to a large extent. Thus, to solve problem (24) with inappropriate weights w_1 and w_2 is not very meaningful and needs huge and expensive effort. Therefore, in general, we apply problem (26). If the thresholds optimization are strictly subject to the overall probability of detection and the sensing speed constraints with appropriate weights w_1 and w_2, we turn to problem (24).

4. Results and Analysis.

In this section, we present simulation results to illustrate the performance of our scheme. These experimental results are used to compare the performance of the conventional one-stage (energy detection and cyclostationary detection) and proposed two-stage sensing schemes. In the simulation, we employ a channel bandwidth of 8MHz and a DVB OFDM signal as PU signal which consists of 18 OFDM symbols. Denoting the OFDM symbol length by T_s, we assume the considered PU signal exhibits cyclostationarity with $\alpha = 2\pi m / T_s$, $m \in N$ and $m \ne 0$. Further, we set $m = 1$. The simulation parameters are set in the following table.

Table 1. The Simulation Parameters

Parameter	Variable	Unit
bandwidth	8	MHz
Number of OFDM symbols	18	-
m	1	-
OFDM symbol length	100	us

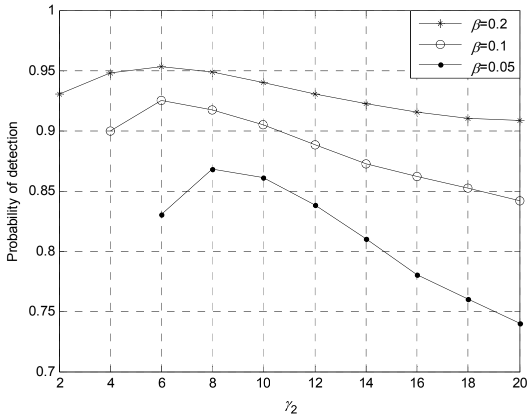

Figure 2. Probability of Detection of the Propose Scheme versus γ_2

Figure 2 presents the probability of detection of the adaptive two-stage sensing scheme with respect to γ_2 for different β at $SNR = -15\,\text{dB}$. From the figure, it can be seen that when $P_f = \beta$, the maximum probability of detection is attained.

Then, we assume that β=0.1, i.e. the same probability of false alarm constraint is imposed on all three sensing schemes.

Figure 3 presents the detection performance versus SNR for the adaptive two-stage sensing scheme, energy detection and cyclostationary detection. As we can see, for an SNR that is less than −10dB, the two-stage sensing scheme performs better than both energy detection and cyclostationary detection.

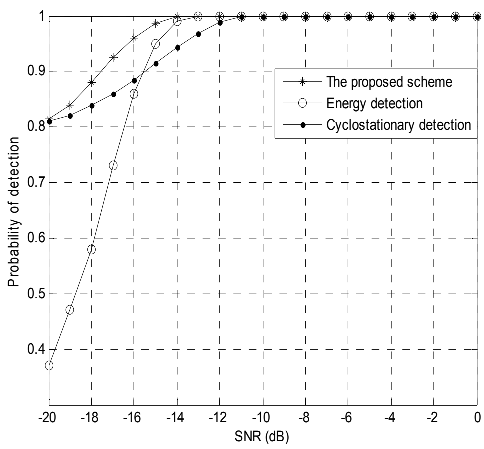

Figure 3. Probability of Detection versus SNR for Different Sensing Scheme

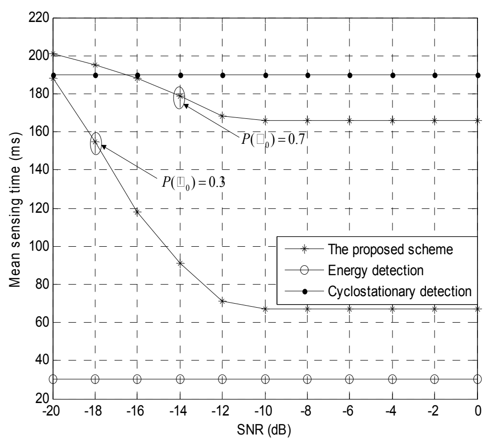

Figure 4. Mean Sensing Time versus SNR for Different Sensing Scheme

Next, we present the mean sensing time versus SNR for different sensing scheme to check the sensing speed for the proposed scheme compared with the other two detection schemes in Figure 4. As the figure shows, when $P(\mathrm{H}_0) = 0.3$, in the SNR range where the proposed scheme performs better than energy detection, (SNR less than −10dB), the proposed scheme performs better than cyclostationary detection in terms of mean sensing time and probability of detection. However, when $P(\mathrm{H}_0) = 0.7$, the proposed scheme does not always perform better than cyclostationary detection in terms of mean sensing time.

5. Conclusion

As the demand of spectrum resource increases in past few years and licensed bands are used inefficiently, improvement in the existing spectrum access policy is expected. DSA can resolve the spectrum shortage by allowing SUs to dynamically utilize spectrum holes across the licensed spectrum on non-interfering basis. In this paper, an adaptive two-stage sensing approach was presented. Under the considered system model, we analyzed the features of energy detection and cyclostationary feature detection and deduced the performance indexes of the proposed scheme. Most importantly, the optimal thresholds for the adaptive two-stage sensing scheme were designed in order to optimize the probability of detection and sensing speed under a given constraint on the probability of false alarm. Simulation results illustrated that at low SNR, where the energy detector is not reliable, the two-stage sensing scheme provides improved detection. Additionally, the mean sensing time is much lower than the cyclostaionarity detection scheme for most of the SNR range. However, the simplified version of the formulated original optimization problem (24) only focuses on optimizing sensing accuracy but does not optimizing sensing speed due to the high complexity of the original problem, which may result in that the total mean sensing time is longer than the maximum sensing time we can tolerate. In the further work, we will try to find an efficient solution to jointly optimize the probability of detection and sensing speed.

Acknowledgements

This work was financially supported by the Research Fund for the Doctoral Program of Higher Education of China (20120005110001).

References

[1] [Online]. Available: www.freepress.net/spectrum/whitespace/Seattle.pdf
[2] Goldsmith A, Jafar S, Maric I, Srinivasa S. *Breaking spectrum gridlock with cognitive radios: an information theoretic perspective.* Proc. IEEE. 2009; 97: 894-914.
[3] Haykin S. Cognitive radio: brain-empowered wireless communications. *IEEE J. Sel. Areas Commun.* 2005; 23: 201-220.
[4] Sahai A, Hoven N, Tandra R. *Some fundamental limits on cognitive radio*. Proc. 42nd Allerton Conf. Commun., Control, and Computing. Monticello. 2004.
[5] Sahai A, Tandra R, Mishra M, Hoven N. *Fundamental design tradeoffs in cognitive radio systems*. ACMoog TAPAS. Boston. 2006.
[6] Sutton P, Nolan K, Doyle L. Cyclostationary signatures in practical cognitive radio applications. *IEEE J. Select. Areas in Commun*. 2008; 26(1): 13-24.
[7] Digham D, Alouini M, Simon M. On the energy detection of unknown signals over fading channels. *IEEE Trans. Commun*. 2007; 55: 21-24.
[8] Gardner W. *Editor*. Cyclostationarity in Communications and Signal Processing. IEEE Press. 1994.
[9] Li H. *Cyclostationary feature based quickest spectrum sensing in cognitive radio systems*. Proc. IEEE 72nd VTC 2010-Fall. Ottawa. 2010: 1-5.
[10] Turunen V, Kosunen M, Vaarakangas M, Ryynanen J. *Correlation-based detection of OFDM signals in the angular domain*. *IEEE Trans. Veh. Technol.* 2012; 61: 951-958.
[11] Poor H. *Editor*. An Introduction to Signal Detection and Estimation (2nd edition). Springer. 1998.
[12] Cabric D, Tkachenko A, Brodersen R. *Spectrum sensing measurements of pilot, energy, and collaborative detection*. IEEE MILCOM 2006. Washington, DC. 2006: 1-7.
[13] Dandawate A, Giannakis G. Statistical tests for presence of cyclostationarity. *IEEE Trans. Signal Process*. 1994; 42(9): 2355-2369.
[14] Maleki S, Pandharipande A, Leus G. *Two-stage spectrum sensing for cognitive radios*. IEEE Acoustics Speech and Signal Processing (ICASSP). Dallas. 2010: 2946-2949.