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SNR-BASED ADAPTIVE SPECTRUM SENSING FOR COGNITIVE RADIO NETWORKS

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Abstract. *Cognitive radios are indispensable to shift paradigm from conventional exclusive spectrum assignment to dynamic spectrum access. They can boost up spectrum utilization significantly, by dynamically accessing unused primary spectrum while bringing no harm to primary users. The envisioned radio calls for fast and accurate spectrum sensing. Researchers are focusing on cooperative spectrum sensing to improve reliability but still there is room for improvement in local spectrum sensing. In cooperative spectrum sensing, it will be hard to cooperate with local network nodes in a short time as cognitive radio has to operate in heterogeneous wireless networks. Most of the renowned local spectrum sensing technique in the literature up to now is cyclostationary feature detection, although it is reliable but computationally complex. Other well-known local sensing techniques are energy detection and matched filter detection. This paper proposes an adaptive local spectrum sensing scheme, in which cognitive radio can adopt one-order cyclostationary or energy detector for spectrum sensing on the basis of estimated SNR, which is calculated in advance for available channels. Simulation results indicate that we can achieve reliable results equal to one-order cyclostationary detection with less mean detection time.*

Keywords: Cognitive radio networks, Spectrum sensing, Energy detection, Cyclostationary detection

1. **Introduction.** With the increase of customers in wireless network services, the demand for radio spectrum is also increasing significantly. The trend of new wireless devices and applications is expected to continue in coming years which will increase the demand for spectrum. The conventional fixed spectrum assignment policy is a big hurdle in the innovation of new technologies. In 2008, the Federal Communication Commission (FCC) allowed the unlicensed fixed and personal/portable devices in rural and urban area [1].

Cognitive Radio (CR) is a key technology that can help mitigate scarcity of spectrum. The most essential task of CR is to detect licensed user/Primary User (PU); if PU is absent, then spectrum is available for cognitive radio user/Secondary User (SU) and is called spectrum hole/white space. The process of detection of PU is achieved by sensing radio environment and is called spectrum sensing [2-4]. The prime concerns of spectrum sensing are about two things: first, the primary system should not be disturbed by SU communication and secondly, spectrum holes should be detected efficiently for required throughput and quality of service (QoS) [5].

Major local sensing techniques considered for cognitive radios are energy detection [6-8] and cyclostationary detection [9-12]. Energy detection is a simple technique that has short sensing time, but its performance is poor under low Signal to Noise Ratio (SNR) conditions. On the other hand, cyclostationary detection provides reliable spectrum sensing, but it is computationally complex and requires long sensing time. Cyclostationary detection is based on the autocorrelation function; on the other hand, one-order cyclostationary detection [13,14] is performed in time domain. In the one-order cyclostationary detection, the mean characteristic of the PU signal is exploited to improve efficiency of the channel sensing. Hence, real time operation and low computational complexity can be achieved by the one-order cyclostationary detection.

Metrics for detection performance are the probability of detection and false alarm. The probability that SU declares that PU is present when the spectrum is idle is called the probability of false alarm; on the other hand, the probability that SU declares that PU is present when the spectrum is occupied by PU is called the probability of detection. The probability of miss detection indicates the probability that SU declares that PU is absent when the spectrum is occupied. In view of the fact that spectral efficiency is reduced by false alarms and interference with PU is caused by miss detection, and generally it is vital for optimal detection performance that the maximum probability of detection is achieved subject to the minimum probability of false alarm [15]. In the draft of IEEE 802.22 standard [16], PUs should be detected within two seconds and the probability of false alarm and miss detection should be less than or equal to 0.1 [17].

Simultaneous transmission and sensing of licensed band is not possible. Therefore, for efficient utilization of spectrum holes, SU has to periodically sense the band every T_p seconds known as a sensing period. PU transmission may be obstructed because SU is unaware of its activity during the sensing period, i.e., until the next sensing moment. Therefore, PU's performance is highly dependent on the sensing period. Maximizing sensing period may increase throughput of SU but may make PU obstructed because PU is not often sensed. From a CR network perspective, SU desires to maximize the sensing period and minimize sensing time [18]. The SU has to properly schedule the sensing period to coexist with the licensed band. By reducing sensing time, the SU can achieve higher throughput and less interference with PUs without sacrificing sensing reliability.

For effective spectrum sensing, increasing reliability of PU detection and minimizing sensing time are two primary concerns in CR networks. In this paper, we propose the two-stage adaptive spectrum sensing scheme. In the first stage, SNR is estimated for the channel under observation in advance. The energy detection is simple but not robust in low SNRs while the one-order cyclostationary detection is reliable in low SNRs. Therefore, in the second stage, the SU performs either energy detection or one order cyclostationary detection based on the SNR estimated in the first stage. The proposed scheme can achieve the same reliability as one-order cyclostationary detection with low mean sensing time.

The rest of this paper is organized as follows. In Section 2, various two-stage spectrum sensing schemes are discussed briefly. Section 3 presents the proposed two-stage adaptive spectrum sensing scheme. Section 4 analyzes the scheme from the viewpoint of detection performance and mean detection time. In Section 5, we present simulation results and their detailed analysis and finally conclusions are drawn in Section 6.

2. **Related Work.** Spectrum sensing is the most crucial part in the successful implementation of cognitive radios. The main focus of current research in cognitive radio is divided in two main streams: the first one is to improve local sensing and the second one focuses on cooperative spectrum sensing for better data fusion results.

In cognitive radios during cooperative spectrum sensing, many SUs cooperate to achieve better data fusion results. In infrastructure-based networks, all the observations made by SUs are reported to a fusion center and a final decision about PU presence or absence is conducted at the fusion center [15].

In local spectrum sensing all the SUs made observations individually and final decision is made individually. In literature many improvements for local spectrum sensing are proposed but still there is a room for improvement.

Sensing a wide-band spectrum is significant in cognitive radio. Only a few researchers have worked on the wide-band spectrum sensing in cognitive radios. Two-stage spectrum sensing is considered as one of the techniques to deal with this issue.

As a two-stage wideband spectrum sensing technique, a scheme combining a coarse sensing and fine sensing was proposed by Y. Hur et al. [19]. In the first stage, the coarse sensing is performed over the entire frequency range with a wide bandwidth. A wavelet transform based Multi-Resolution Spectrum Sensing (MRSS) technique is presented as a coarse sensing. In the first stage, the occupied and candidate spectrum segments are identified. In the second stage, fine sensing is applied on candidate spectrum segments to detect unique features of modulated signals. Confirmation of an unoccupied segment is done by careful fine sensing.

In [20], authors proposed a two-stage Dynamic Spectrum Access (DSA) approach that consists of preliminary coarse resolution sensing (CRS) followed by fine resolution sensing (FRS). In CRS, the whole spectrum is divided into equal sized coarse sensing blocks (CSB) of equal bandwidth. One of CSBs is selected randomly and checked for at least one idle channel by applying energy detector of bandwidth equal to that of CSB. FRS is then applied on that CSB, using energy detector equal to the bandwidth of channel to determine idle channel.

Another two-stage sensing scheme was proposed in [21] by S. Maleki et al. Energy detector is used in coarse sensing and if required, cyclostationary detection is used in fine sensing. Only if a channel is declared as unoccupied in the coarse stage, the fine stage is used for the final decision. Otherwise, coarse sensing will give the final decision.

W. Yue et al. in [14] proposed a two-stage spectrum sensing scheme in which coarse detection is based on energy detection. Based on the power in each channel, it sorts the channels in ascending order. In the fine stage, a one-order cyclostationary technique is applied on the channel with the lowest power to detect weak signals.

In all the above-mentioned techniques, both stages perform spectrum sensing, hence, increase mean detection time. Only in [21], a final decision can be made at the first stage if all the channels are declared as occupied, otherwise, both stages run in a sequential manner, i.e., energy detection and then cyclostationary detection. Therefore, mean detection time is increased rather than that of cyclostationary detection. In our proposed scheme, only one of the detection techniques will run during the two stages, based on the estimated SNR. Under the worst case, mean detection time is equal to one-order cyclostationary detection. Although two stages are running in our scheme, SNR of the channel can be estimated in advance and the history of channel SNR can be maintained to further reduce the mean sensing time.

3. **Framework.** A binary hypothesis model for transmitter detection, i.e., the model of signals received by the SU, is defined as

$$r(t) = \begin{cases} n(t) & \text{in case of } \mathrm{H}_0, \\ hs(t) + n(t) & \text{in case of } \mathrm{H}_1 \end{cases} \tag{1}$$

where $r(t)$ is the signal received by CR, $s(t)$ is the transmitted signal of the primary user, $n(t)$ is additive white Gaussian noise (AWGN) and h is the amplitude gain of the channel. H_0 indicates only noise and H_1 indicates the presence of PU.

The proposed approach of spectrum sensing is shown in Figure 1. We assume that N is the number of channels to be sensed. The SU estimates the SNR of the channel in

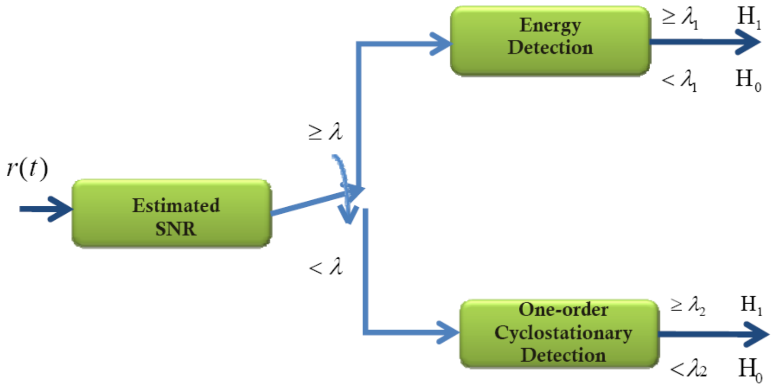

FIGURE 1. Adaptive spectrum sensing scheme

advance [22-24] and on the basis of that SNR the SU will select one of the spectrum sensing techniques between the energy detection and the one-order cyclostationary detection having thresholds λ_1 and λ_2, respectively. As it is already discussed in the introduction section, the energy detector performs very poor under low SNRs. We defined SNR threshold λ, below which the energy detector is unable to detect channels accurately, and we will perform the one-order cyclostationary detection to sense the channels.

Therefore,

$$\text{Detection Technique} = \begin{cases} \text{Energy detection}, & \text{if } SNR \geq \lambda, \\ \text{One-order cyclostationary detection}, & \text{if } SNR < \lambda. \end{cases}$$

3.1. **Energy detection.** Figure 2 depicts the block diagram of the energy detector. The elementary approach behind the energy detector is the estimation of the power of the received signal $r(t)$. To evaluate the power of the received signal, the output of the band pass filter of bandwidth W is squared and integrated over an interval T. Finally, the integrated value is compared with a threshold λ_1 to decide whether the PU is present or not [25].

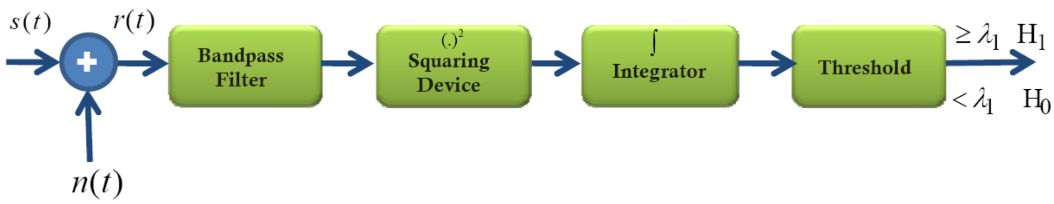

FIGURE 2. Block diagram of energy detection

The probability of detection P_d^E and probability of false alarm P_f^E of energy detector over AWGN channel are approximated in [25] as

$$P_d^E = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda_1}\right), \tag{2}$$

$$P_f^E = \frac{\Gamma\left(M_E, \dfrac{\lambda_1}{2}\right)}{\Gamma(M_E)} \tag{3}$$

where $\Gamma(.)$ and $\Gamma(.,.)$ are complete and incomplete gamma functions, respectively. $Q_m(.,.)$ is the generalized Marcum Q-function, γ is instantaneous SNR, M_E is time bandwidth product and λ_1 is decision threshold of energy detector.

3.2. **One-order cyclostationary detection.** Commonly, the primary modulated waveforms are coupled with patterns characterized as cyclostationary features like sine wave carriers, pulse trains, repeating spreading, hoping sequences or cyclic prefixes inducing periodicity [11]. CR can detect a random signal with a specific modulation type in the presence of random stochastic noise by exploiting the periodic statistics like mean and autocorrelation of the primary waveform. The cyclostationary detection is based on autocorrelation function, but in [13] the authors exploited the mean characteristics of the primary signals to improve the channel sensing in time domain and called it one-order cyclostationary detection.

Although the performance of cyclostationary detection is a bit better than that of one-order cyclostationary detection, this gain is due to hardware complexity and power consumed by additional multiplying algorithm [14]. For commercial implementation of CRs, it is necessary to minimize hardware complexity and power consumption. Therefore, we are using the one-order cyclostationary detection instead of the higher-order cyclostationary detection.

Figure 3 shows the block diagram of one-order cyclostationary detection. The basic approach behind the one-order cyclostationary detection is to determine statistical average of the signal $r(t)$. It is found that the mean of $r(t)$ is time varying and is the periodic function of time. Moreover, at each one-half of the periods, a peak value appears. The peak value is searched in the time domain and compared with the predetermined threshold λ_2. If periodicity is found (peak value $\geq \lambda_2$), it means that the band is used by PU and vice versa. If the period is known, periodicity can be extracted by synchronized averaging.

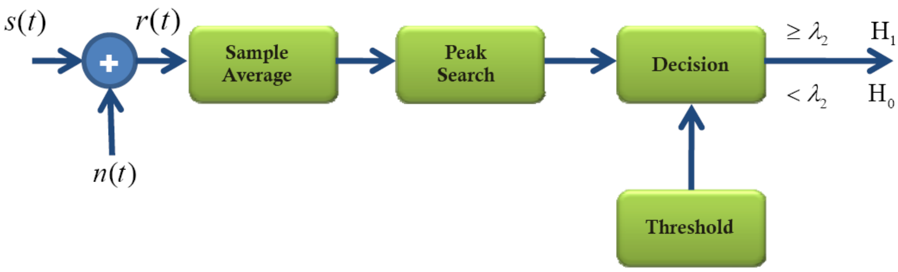

FIGURE 3. Block diagram of one-order cyclostationary detection [14]

The probability of detection P_d^C and probability of false alarm P_f^C of one-order cyclostationary detection over AWGN channel are approximated in [14] as

$$P_d^C = 1 - \left(1 - e^{-\frac{\lambda_2^2}{2\delta_A^2}}\right)^L, \tag{4}$$

$$P_f^C = 1 - \left[1 - Q_1\left(\frac{\sqrt{2\gamma}}{\delta}, \frac{\lambda_2}{\delta_A}\right)\right]^L \tag{5}$$

where δ^2 is the variance, $\delta_A^2 = \delta^2/(2M_C + 1)$ in which M_C is the number of samples for detection, L is the number of diversity branches, γ is instantaneous SNR, $Q_1(.,.)$ is the generalized Marcum Q-function and λ_2 is predetermined threshold.

4. **Problem Analysis and Formulation.** In this section, we will analyze the sensing performance of our proposed scheme with respect to detection performance. The overall probability of false alarm and probability of detection of two-stage spectrum sensing scheme are given in (6) and (7)

$$P_f = P_r P_f^E + (1 - P_r) P_f^C = P_r \left(P_f^E - P_f^C\right) + P_f^C \tag{6}$$

Table 1. Description of modeling variables

Symbols	Description
N	Number of channels to be sensed
$r(t)$	Received signal
λ	Threshold on SNR
λ_1	Threshold of energy detection
λ_2	Threshold of one-order cyclostationary detection
P_d^E	Probability of detection for energy detection
P_f^E	Probability of false alarm for energy detection
P_d^C	Probability of detection for one-order cyclostationary detection
P_f^C	Probability of false alarm for one-order cyclostationary detection
P_d	Overall probability of detection
P_f	Overall probability of false alarm
P_r	Probability of channels having SNR higher or equal to λ
$1-P_r$	Probability of channels having SNR lesser than λ
M_E	Number of samples in observation interval in energy detection
M_C	Number of samples in observation interval in one-order cyclostationary detection
$\overline{T_E}$	Mean detection time of energy detection
$\overline{T_C}$	Mean detection time of one-order cyclostationary detection
$\overline{T}$	Total mean detection time

$$P_d = P_r P_d^E + (1-P_r)P_d^C = P_r\left(P_d^E - P_d^C\right) + P_d^C \tag{7}$$

where P_r is the probability that a channel would be reported to energy detector as the second stage and therefore, the probability that a channel would be reported to one-order cyclostationary detector will be $1-P_r$. P_r is dependent on SNR of the channels to be sensed and overall P_f and P_d directly depend on P_r.

In order to evaluate agility of the proposed adaptive two-stage spectrum sensing scheme, its mean detection time is compared with the energy detection and the one-order cyclostationary detection, respectively. The mean detection time of proposed two-stage sensing is:

$$\overline{T} = \overline{T}_E + \overline{T}_C \tag{8}$$

where $\overline{T}_E$ and $\overline{T}_C$ are the sensing times of energy detection and one-order cyclostationary detection, respectively. $\overline{T}_E$ and $\overline{T}_C$ can be derived as follows:

$$\overline{T}_E = E[K_1]T_1 \tag{9}$$

where $E[K_1]$ represents the mean number of channels reported to energy detector and $T_1 = \dfrac{M_E}{2W}$ is the mean sensing time for each channel, in which M_E is the number of samples during the observation interval and W is the channel bandwidth. K_1 is a random variable which follows a binomial distribution, with parameters N and P_r, where N is the number of channels to be sensed and P_r is the probability that a channel would be reported to the energy detector. Hence, the mean detection time of the energy detection is

$$\overline{T}_E = NP_rT_1. \tag{10}$$

$\overline{T}_C$ can be derived as follows:

$$\overline{T}_C = E[K_2]T_2 \tag{11}$$

where $E[K_2]$ represents the mean number of channels reported to one-order cyclostationary detector and $T_2 = \dfrac{M_C}{2W}$ is the mean sensing time for each channel, in which M_C is the number of samples for detection and W is the channel bandwidth. K_2 is a random variable which follows a binomial distribution, with parameters N and $1 - P_r$, where N is the number of sensed channels and $1 - P_r$ is the probability that a channel would be reported to the cyclostationary detector. Hence, the mean detection time of cyclostationary detection is

$$\overline{T}_C = N(1 - P_r)T_2. \tag{12}$$

The total mean detection time is found by substituting (10) and (12) for $\overline{T}_E$ and $\overline{T}_C$ in (8):

$$\overline{T} = N[P_r T_1 + (1 - P_r)T_2]. \tag{13}$$

We can make the following two cases on the basis of P_r.

Case 1: When $0 \leq P_r < 0.5$, most of the channels are very noisy. SU will perform one-order cyclostationary detection for sensing the majority of the channels. The detection time will increase when more channels are being sensed by that detector because it consumes a longer detection time than the energy detector. In the worst case when $P_r \approx 0$, the probability of false alarm, the probability of detection and the total mean detection time can be evaluated by putting $P_r \approx 0$ in (6), (7) and (13):

$$P_f \approx P_f^C, \tag{14}$$

$$P_d \approx P_d^C, \tag{15}$$

$$\overline{T} \approx NT_2. \tag{16}$$

Case 2: When $0.5 \leq P_r \leq 1$, the majority of the channels have a very good SNR. Therefore, SU will perform energy detection for sensing most of the channels because the performance of the energy detector is excellent under good SNR. The mean detection time of energy detection is the least, and therefore it will be the best case for the detection time when majority of the channels are sensed by the energy detector. The best scenario is when $P_r \approx 1$ and the probability of false alarm, the probability of detection and the total mean detection time can be found by putting $P_r \approx 1$ in (6), (7) and (13):

$$P_f \approx P_f^E, \tag{17}$$

$$P_d \approx P_d^E, \tag{18}$$

$$\overline{T} \approx NT_1. \tag{19}$$

5. **Simulation Results.** In this section, we compare our proposed approach of spectrum sensing with the energy detection and the one-order cyclostationary detection. The sensing performance of each approach is quantified by the complementary receiver operating characteristic (ROC), i.e., P_f versus P_m, detection performance versus SNR and mean sensing time. Monte Carlo simulation is used for experimentation under the following system settings: there are 10 randomly distributed Gaussian channels with zero mean and variance 1 and one SU looking for spectrum holes in these channels.

Figure 4 shows the complementary ROCs of the proposed adaptive spectrum sensing scheme, energy detection and one-order cyclostationary detection. In this scenario, it is assumed that the average SNR is −10dB. The result shows that the proposed scheme performs better than the energy detector but equally to the one-order cyclostationary detector.

In this simulation, it is assumed that all the channels experience the same SNR and have the probability of false alarm 0.1. This assumption implies that they have the same

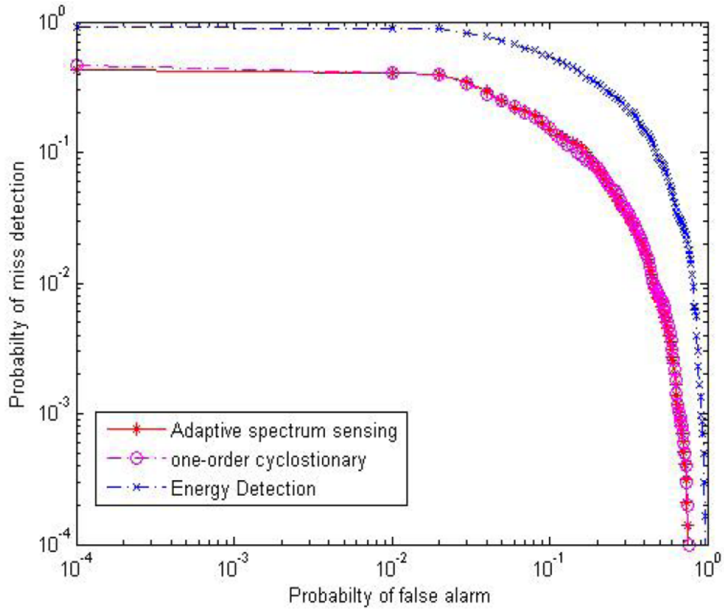

Figure 4. ROC curves of proposed adaptive spectrum sensing, one-order cyclostationary detection and energy detection

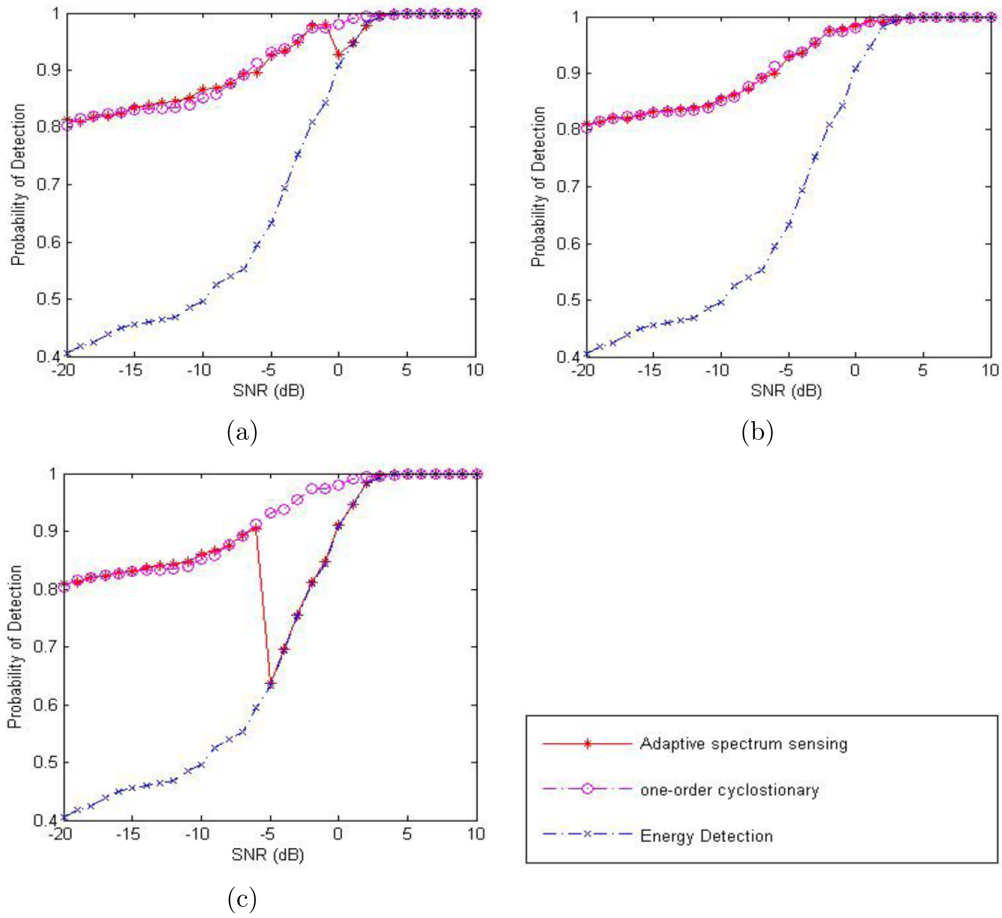

Figure 5. Detection performance versus SNR comparison of proposed adaptive spectrum sensing, one-order cyclostationary detector and energy detector for thresholds (a) $\lambda = 0$, (b) $\lambda = 5$, and (c) $\lambda = -5$

probability of detection in all individual sensing schemes. Figure 5 shows the detection performance versus SNR comparison of our proposed scheme, energy detection and one-order cyclostationary detection with $T_1 = 2$ms and $T_2 = 12$ms, respectively for three different values of $\lambda = 0, 5, -5$dB. Figure 5(a) shows that the probability of detection of the proposed scheme is approximately equal to that of the one-order cyclostationary when $\lambda = 0$dB except at some SNRs near 0dB. Figure 5(b) when $\lambda = 5$dB indicates that our proposed scheme's probability of detection is as high as the one-order cyclostationary detection. For SNR of 5dB or above, the energy detector performs equally well as the one-order cyclostationary detector. The performance of the proposed scheme is degraded when we set $\lambda = -5$dB because the energy detector is not robust at SNR values near the threshold. By using this fact, the proposed scheme performs the one-order cyclostationary detection for low SNRs and otherwise energy detection is used.

Figure 6 clearly shows the mean detection time of all the channels sensed at the same SNR having the same probability of false alarm. It is illustrated that if all the channels are in good SNR conditions then the mean sensing time is equal to the time taken by the energy detector and vice versa. The key advantage of the proposed adaptive spectrum sensing is that its reliable results equal to those of the one-order cyclostationary detection can be achieved in less mean sensing time.

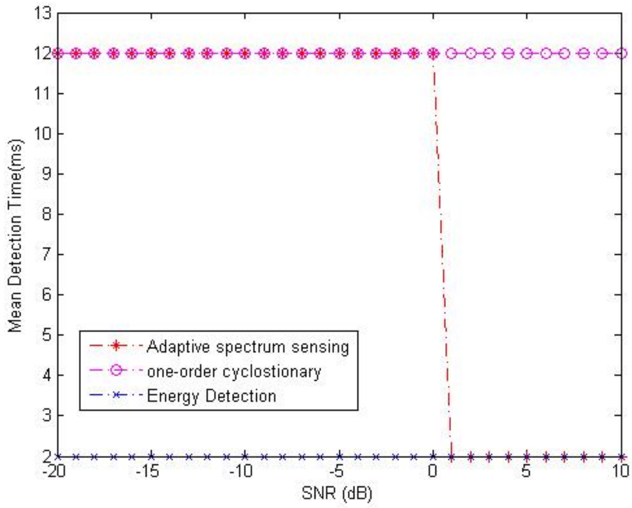

FIGURE 6. Mean detection time comparison of proposed adaptive spectrum sensing, one-order cyclostationary detector and energy detector

In order to evaluate more about the mean detection time, we present the mean detection time of one-order cyclostationary detection and proposed adaptive spectrum sensing with varying P_r in Figure 7. The mean detection time of one-order cyclostationary detection remains the same regardless of P_r. Whereas in the proposed scheme, in case 1, when $P_r \approx 0$, most of the channels are being sensed by the one-order cyclostationary detector, and thus the proposed scheme has its highest mean detection time which is equal to the sensing time of one-order cyclostationary detection. The probability of false alarm, the probability of detection and the total mean detection time for $P_r = 0$ are given in (14)-(16), respectively. In case 2, the majority of the channels are being sensed by the energy detector, thus mean detection time of proposed scheme decreases and becomes equal to the sensing time of energy detector when $P_r \approx 1$. The detection performance and the total mean detection time for $P_r \approx 1$ is given in (17)-(19).

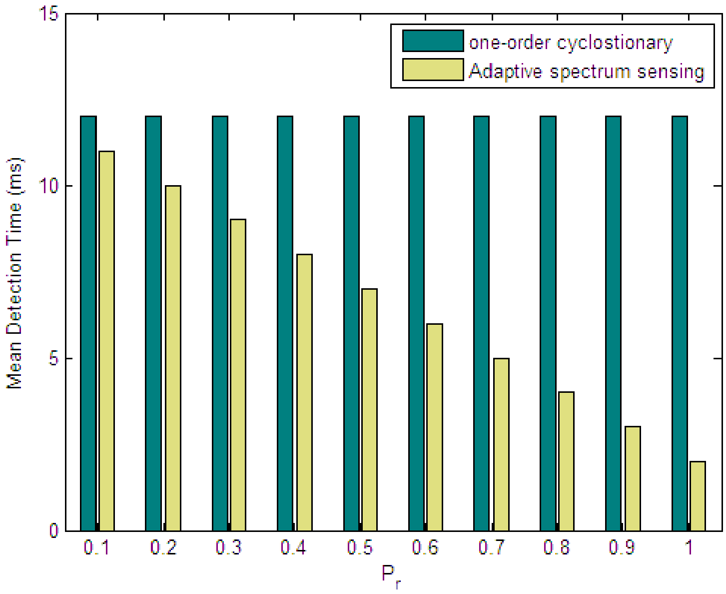

FIGURE 7. Mean detection time comparison for varying P_r

6. **Conclusions.** The adaptive spectrum sensing scheme was proposed in this paper to meet the accuracy and the minimum sensing time required in CR networks. The proposed scheme chooses either the energy detection or the one-order cyclostationary detection based on the estimated SNR. We observed that at low SNRs where energy detector is not reliable, the proposed scheme provides improved detection at the cost of mean detection time. At high SNRs, the proposed scheme provides fast detection using the energy detector. This paper showed from simulation result that the mean detection time of the proposed scheme is lower than that of the one-order cyclostationary detection. Even in the worst case, it may be equal to the one-order cyclostationary detection. In the best case, the total mean detection time is reduced dramatically to achieve the same accuracy. The results showed that the reliability of detection is also as high as that of the one-order cyclostationary detection with reduced total mean detection time. As future work, to further consider uncertainties, how to predict the channel state on the basis of the history will be studied.

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