J Inf Process Syst, Vol.15, No.3, pp.604~615, June 2019
https://doi.org/10.3745/JIPS.03.0122

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

# Adaptive Cooperative Spectrum Sensing Based on SNR Estimation in Cognitive Radio Networks

Shuiping Ni*, Huigang Chang**, and Yuping Xu**

**Abstract**

Single-user spectrum sensing is susceptible to multipath effects, shadow effects, hidden terminals and other unfavorable factors, leading to misjudgment of perceived results. In order to increase the detection accuracy and reduce spectrum sensing cost, we propose an adaptive cooperative sensing strategy based on an estimated signal-to-noise ratio (SNR). Which can adaptive select different sensing strategy during the local sensing phase. When the estimated SNR is higher than the selection threshold, adaptive double threshold energy detector (ED) is implemented, otherwise cyclostationary feature detector is performed. Due to the fact that only a better sensing strategy is implemented in a period, the detection accuracy is improved under the condition of low SNR with low complexity. The local sensing node transmits the perceived results through the control channel to the fusion center (FC), and uses voting rule to make the hard decision. Thus the transmission bandwidth is effectively saved. Simulation results show that the proposed scheme can effectively improve the system detection probability, shorten the average sensing time, and has better robustness without largely increasing the costs of sensing system.

**Keywords**

Adaptive Spectrum Sensing, Cognitive Radio, Detection Time, Fusion Center, SNR Estimation, Voting Rule

## 1. Introduction

Spectrum is a valuable natural resource for wireless communications. However, the static spectrum allocation policy only allows primary users (PUs) to access the licensed frequency band for data transmission, which makes low spectrum utilization. Wireless communication technology is developing very rapidly, which made spectrum resources more and more tense. Cognitive radio (CR) serving as an effective technology to improve spectrum utilization efficiency, the secondary user has opportunity to get access to the spectrum holes (SH) to realize the sharing of spectrum resources by sensing the surrounding wireless environment [1,2]. The detection probability (PD) of the SH must be improved to avoid affecting the normal communication of the PUs and to make full use of the spectrums. While the false alarm probability (PFA) must be reduced as much as possible to take full advantage of spectrum holes. Spectrum sensing is the core technology of CR, which required to detect the spectrum holes in a short time. In IEEE802.22 standards, the detection probability of cognitive users should be more than 90%, the PFA is


Manuscript received October 11, 2017; first revision January 2, 2018; accepted February 8, 2018
**Corresponding Author:** Huigang Chang (15836102411@163.com)
* School of Electronic Engineering, Beijing University of Posts and Telecommunications, Beijing, China (nishuiping@hpu.edu.cn)
** School of Computer Science and Technology, Henan Polytechnic University, Jiaozuo, China (15836102411@163.com, 807658792@qq.com)

less than 10%, the sensing time is not more than 2 seconds so as to ensure that the spectrum resources are fully utilized without affecting the normal communication of PUs [3].

Single user spectrum sensing often cannot achieve good performance, accordingly cooperative spectrum sensing is proposed which detects the licensed spectrum occupied or not through mutual cooperation by sensing node. It mainly includes local spectrum sensing and data fusion. That is, if we want to improve the cooperative detection performance, we should study from these two aspects: one is to improve the local detection probability and another is to use a better fusion rule. At present, the typical local spectrum sensing algorithms mainly includes energy detector (ED), cyclostationary feature detector and matched filter detector [4]. ED is widely used for coarse sensing because no prior information is needed and has low complexity. However, there are some disadvantages under low signal-to-noise ratio (SNR) conditions, such as poor robustness and inability to distinguish between primary signal and noise. Although the matched filter detector can maximize the SNR and achieve better detection performance. However, it is necessary to design a dedicated receiver which requires the Pus' prior information and it is difficult to implementing in the complex wireless environment. Cyclostationary feature detector has better anti-interference capacity and has a higher detection performance when SNR is low. However, it has higher computational complexity and much longer sensing time. Above all, in [5], the authors proposed a cooperative sensing method based on double threshold ED, which applied double threshold ED in the local nodes, and used the hard decision rule made the final judgement in the fusion center (FC). However, under low SNR, the detection performance is not ideal. In the document [6], authors proposed two-stage spectrum sensing method where first stage adopted the single threshold energy detection, If the detection result proved to be SH, the second stage involved in cyclostationary feature detection, then the final decision was made. Although in such way the detection probability of local sensor can be improved, but each sensing period need to go through sensing twice, therefore it increases the sensing time.

The different spectrum sensing strategies are selected in this paper by estimating the SNR. Which only one of the detection techniques operates in one cycle, thus making detection less redundant. The local results of CRs are transmitted to the FC by 1-bit information, and make the final decision through voting rule. When the decision statistic of the CRs for adaptive double threshold ED falls into the uncertain region where between the high and low threshold, the sensing information is not sent. Thus, it is not only preventing the interferences from the invalid users, but also saves the transmission bandwidth. When more than half of the participants in the FC determine the PU signal exists, then the fusion center determines the existence of PU signals, otherwise the PU signal does not exist [7].

The rest contents of this paper are arranged as follows. In Section 2, we introduce the system model of cooperative spectrum sensing. Section 3 describe the proposed scheme. Section 4 analyze the system performance. We provide simulation results to demonstrate the performance in Section 5. Finally, conclusions are drawn in Section 6.

# 2. Adaptive Cooperative Sensing System Model

## 2.1 System Model

The cooperative sensing system model is shown in Fig. 1, assuming that it includes 1 PU, a data FC, and N cognitive users which choose perform adaptive double threshold ED or cyclostationary feature detection according to the estimated SNR. First, each CR performs their own local spectrum sensing independently, then sends the sensing results to FC through control channel with the form of 1-bit information, if the PU signal is present, the result is 1, otherwise 0 is transmitted. Finally, the FC judges whether the PU is present or not according to local decision results, then the FC feedbacks the final decision results to CRs [8].

### 2.2 Cooperative Sensing Mathematical Model

Using the following hypothesis model to describe the signal detection problem of the $i^{\text{th}}$ CRs [9,10]:

$$y_i(n)=\begin{cases} w_i(n) & n=1,\ldots,\mathrm{M} \quad (H_0) \\ h_i s_i(n)+w_i(n) & \quad (H_1) \end{cases} \tag{1}$$

where $i$=1,2,... $N$, $N$ represents the number of cognitive users. $y_i(n)$ is the detected signal at the $i^{\text{th}}$ cognitive users and $s_i(n)$ represents the PU signal. Moreover, $w_i(n)$ is the AWGN with zero mean and variance of $\sigma_w^2$, which is recorded as $w_i(n)\sim \mathrm{N}(0, \sigma_w^2)$, $h_i$, M signify the sensing channel gain and the number of sample respectively. $H_0$ indicates that the authorized channel is idle, and $H_1$ indicates that the authorized channel is occupied.

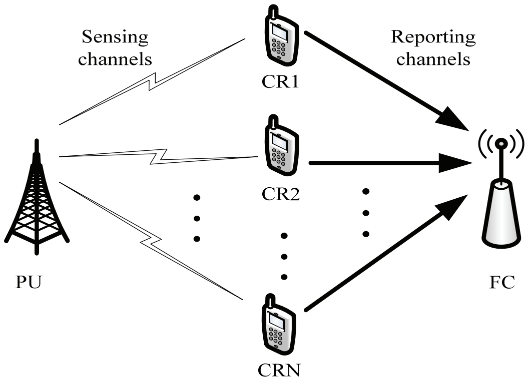


**Fig. 1.** System model.

## 3. Adaptive Spectrum Sensing Methods

### 3.1 SNR Estimation

SNR estimation is used to measure the signal-to-noise ratio in the channel, which is an important parameter that reflect the state of the channel. In this paper, each cognitive user according to the estimated SNR of the received signal selects one of the spectrum sensing methods from cyclostationary feature detection and adaptive double threshold ED. This is different from the methods of used single double-threshold energy sensing in the document [5] and the double sensing in one perceptual cycle in the document [6]. Under the low SNR, therefore, the cyclostationary feature detection method is used to make up for the disadvantage of poor detection performance by energy detection.

The $i^{th}$ cognitive user estimates the received signals' SNR and the mathematical formula to calculate estimated SNR value ( $E_{SNR}$ ) can be written as [11]:

$$E_{SNR} = \frac{P_s}{P_w} = \frac{\frac{1}{M}\sum_{n=1}^{M}|y_i(n)|^2}{\frac{1}{M}\sum_{n=1}^{M}|w_i(n)|^2} \tag{2}$$

where M represents the number of samples. Then converts the result obtained from (2) to the form of SNR $S_i$ in decibels (dB):

$$S_i = E_{SNR}\,|\,\mathrm{dB} = 10 \times \lg(E_{SNR}) \tag{3}$$

Replay (2) into (3) can be simplified as

$$S_i = E_{SNR}\,|\,\mathrm{dB} = 10 \times \lg\left[\frac{\sum_{n=1}^{M}|y_i(n)|^2}{\sum_{n=1}^{M}|w_i(n)|^2}\right] \tag{4}$$

The estimated SNR $S_i$ is compared with the selection threshold $\gamma$. If $S_i \geq \gamma$, performed the adaptive double threshold ED to obtain faster speeds and lower degree of computational complexity. Otherwise cyclostationary feature detection will be performed to increase detection accuracy when SNR is low [12]. According to experience, the value of $\gamma$ is equal to the SNR that can achieve higher detection probability when energy detection is used.

The architecture based on SNR estimation is shown in Fig. 2.

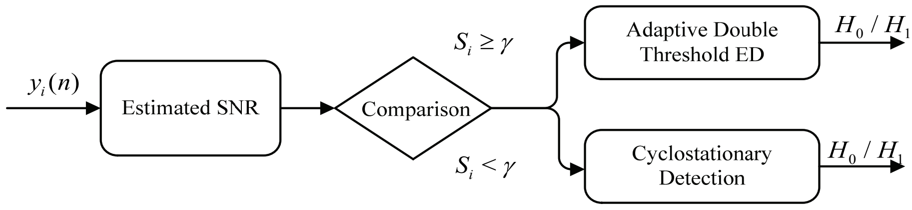


**Fig. 2.** Adaptive spectral sensing architecture.

## 3.2 Adaptive Double Threshold ED

Fig. 3 shows the block diagram of adaptive double threshold ED.

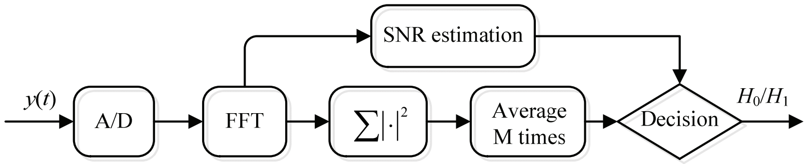


**Fig. 3.** Block diagram of adaptive double threshold ED.

The decision statistic of ED is X, then it compared with the two thresholds to determine if the PU signal is present. Thereby making the final decision.

$$\mathrm{X}=\frac{1}{\mathrm{M}}\sum_{n=1}^{\mathrm{M}}\left|y_i(n)\right|^2 \tag{5}$$

The detection probability is $P_d$ and the false alarm probability is $P_f$ for energy detection are calculated as follows [13]:

$$P_f=P\{\mathrm{X}>\lambda|H_0\}=Q\left(\frac{\lambda\text{-}\mathrm{M}\delta_w^2}{\sqrt{2\mathrm{M}\delta_w^4}}\right) \tag{6}$$

$$P_d=P\{\mathrm{X}>\lambda|H_1\}=Q\left(\frac{\lambda\text{-}\mathrm{M}\left(\delta_s^2+\delta_w^2\right)}{\sqrt{2\mathrm{M}\left(\delta_s^2+\delta_w^2\right)^2}}\right) \tag{7}$$

where $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty}e^{-t^2/2}dt$ denotes $Q$-function, $\delta_w^2$ and $\delta_s^2$ are representing the noise variance and signal variance, respectively. The target false alarm probability is $\overline{P_f}$. From formula (6) the threshold λ can be given by

$$\lambda=Q^{-1}\left(\overline{\mathrm{P}_f}\right)\times\sqrt{2\mathrm{M}\delta_w^4}+\mathrm{M}\delta_w^2 \tag{8}$$

where λ is a design of single threshold. Due to the influence of changes in the surrounding wireless environment, single-threshold energy detection may lead to misjudgment, which has greater limitations. Therefore, high and low thresholds are set based on the uncertainty of the noise and determined by the maximum and minimum noise variance. In the wireless network environment, defined the noise uncertainty is belonged to $[\delta_w^2/\rho,\rho\delta_w^2]$, where $\rho=E_{SNR}$ represents the quantified uncertainty parameters and $\rho\geq 1$, referring to the constant false alarm detection theory, the upper threshold $\lambda_\mathrm{H}$ and lower threshold $\lambda_\mathrm{L}$ can be given by

$$\begin{aligned}\lambda_\mathrm{H}&=Q^{-1}\left(\overline{\mathrm{P}_f}\right)\times\sqrt{2\mathrm{M}\rho\delta_w^4}+\mathrm{M}\rho\delta_w^2\\ \lambda_\mathrm{L}&=Q^{-1}\left(\overline{\mathrm{P}_f}\right)\times\sqrt{2\mathrm{M}\delta_w^4/\rho}+\mathrm{M}\delta_w^2/\rho\end{aligned} \tag{9}$$

The decision statistic is compared with $\lambda_\mathrm{H}$ and $\lambda_\mathrm{L}$, when $\mathrm{X}\leq\lambda_\mathrm{L}$, it means that the PU is not present, then the decision is $H_0$, and the binary information 0 is sent to the FC. If $\mathrm{X}\geq\lambda_\mathrm{H}$, it presents the PU exists, then judged as $H_1$, and the binary information 1 is sent to the FC. If $\lambda_\mathrm{L}<\mathrm{X}<\lambda_\mathrm{H}$, the fusion decision information is not sent.

## 3.3 Cyclostationary Feature Detection

### 3.3.1 Algorithm flow

The PU signal transmitted in the channel is modulated and encoded such that its mean and autocorrelation functions are periodically change with the cyclical stability characteristics. While noise due to its randomness does not include this feature. Therefore, by analyzing the cyclic correlation function of the detection signal, these characteristics can be detected, so that the signal and noise can be distinguished to realize the perception of the PU signal. The block diagram of cyclostationary feature detection is shown Fig. 4.

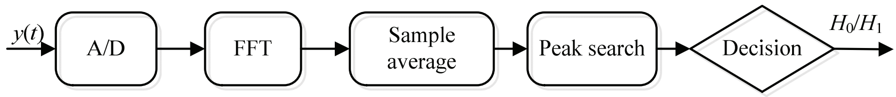


**Fig. 4.** Block diagram of cyclostationary feature detection.

First, the cyclic autocorrelation function (CAF) of the sampled signal can be formulated as [14]:

$$R_y^a(k) = \lim_{M\to\infty} \frac{1}{2M+1} \sum_{n=-M}^{M} \left[ y(n+k)e^{-j\pi a(n+k)} \right] * \left[ y(n)e^{-j\pi an} \right] \tag{10}$$

where $a$ is the introduced cyclic frequency (CF), and the spectral correlation function (SCF) can be obtained by the following formula through fast Fourier transform (FFT) [15].

$$S_y^a(f) = \sum_{k=-\infty}^{\infty} R_y^a(k) e^{-j2\pi fk} \tag{11}$$

where $S_y^a(f)$ is a two-dimensional function of frequency and cycle frequency, which can also called cyclostationary spectral density (CSD). Under certain conditions, the PU signal can be determined according to the value of CSD.

### 3.3.2 Cyclostationary decision rule

As the noise does not have the characteristics of cyclical stability, the energy of the noise is mainly concentrated on the zero cycle frequency, i.e., when the cyclic frequency $\alpha = 0$, the cyclic spectral density function has a larger value. However, when the cyclic frequency $\alpha \neq 0$, the value of the density function of the noise is very small or even close to zero, i.e., $S_y^a(f) \approx 0$, while the cyclic spectrum of PU signals will have a large peak. By searching for the peak value of the signal cycle spectrum when the cyclic frequency is non-zero determined whether the signal exists. After simplification, the decision rule can be determined as

$$S_y^a(f) = \begin{cases} S_s^a(f) & H_1 \\ 0 & H_0 \end{cases} \quad (\alpha \neq 0) \tag{12}$$

where $S_s^a(f)$ is the cyclic spectral density function of the authorized modulation signal, let $Y$ represent $S_y^a(f)$ and the decision threshold be $\lambda_c$. When $Y>\lambda_c$, the PU signal is present ($H_1$), and when $Y\leq\lambda_c$, the PU signal is absent ($H_0$), then sends hard decision information to the FC. The detection probability and false alarm probability of cyclostationary feature detection are expressed as

$$P_{di}^C = P(Y > \lambda_c \mid H_1), P_{fi}^C = P(Y > \lambda_c \mid H_0) \tag{13}$$

Cyclostationary feature detection can take full advantage of the cyclical stationary characteristics of the signal and is not susceptible to the uncertainty of noise. Therefore, it has a better robustness when the SNR is low. However, due to its high complexity and long running time, it is often used in the case of poor channel environment.

# 4. System Performance Analysis and Fusion Criteria

## 4.1 Performance Analysis

The cognitive user due to the different environment in the network, so the SNR estimation is uncertain. According to the different estimated SNR, there may be two detection methods which are adaptive double threshold ED and cyclization detection. The PD and the PFA of the local sensing node can be expressed as

$$\begin{aligned}\mathrm{P}_{di}&=\mathrm{P}(S_i \geq \gamma)P_{di}^{E}+\mathrm{P}(S_i<\gamma)P_{di}^{C}\\&=\mathrm{P}(S_i \geq \gamma)P(\mathrm{X}>\lambda_H \mid H_1)+\mathrm{P}(S_i<\gamma)P(Y>\lambda_c \mid H_1)\end{aligned} \tag{14}$$

$$\begin{aligned}\mathrm{P}_{fi}&=\mathrm{P}(S_i \geq \gamma)P_{fi}^{E}+\mathrm{P}(S_i<\gamma)P_{fi}^{C}\\&=\mathrm{P}(S_i \geq \gamma)P(\mathrm{X}>\lambda_H \mid H_0)+\mathrm{P}(S_i<\gamma)P(Y>\lambda_c \mid H_0)\end{aligned} \tag{15}$$

where $\mathrm{P}_{fi}^{E}$ and $\mathrm{P}_{di}^{E}$ are represent the PFA and PD of adaptive double threshold ED respectively, $\mathrm{P}(S_i \geq \gamma)$ and $\mathrm{P}(S_i<\gamma)$ are the probability of selecting the adaptive double threshold ED and the cyclostationary feature detection, respectively, $\mathrm{P}(S_i \geq \gamma)+\mathrm{P}(S_i<\gamma)=1$ . By adjusting the value of the selected threshold, the probability of selecting different detectors is changed to obtain a better balance between sensing time and sensing performance. The mean detection time of the system is

$$\mathrm{T}_i=\mathrm{P}(S_i \geq \gamma)\mathrm{T}_E+\mathrm{P}(S_i<\gamma)\mathrm{T}_C \tag{16}$$

where $\mathrm{T}_E$ and $\mathrm{T}_C$ are the time for adaptive double threshold ED and cyclostationary feature detection operation, respectively.

## 4.2 Fusion Rule

The FC adopts the voting rule to get the final decision according to the sensing results of the CRs. Assuming that $\eta$($\eta$≤N) users among the N sensing participators send 1-bit information ( $D_1, D_2\cdots\cdots, D_\eta$ ) to the FC. $D_\eta$ indicates whether the PU signals exists among the N CRs who are involved in cooperative sensing. The expression is as follows

$$D_i=\begin{cases}0 & H_0: \text{PU absent}\\1 & H_1: \text{PU present}\end{cases} \tag{17}$$

After fusion there is a total of $\sum_i^{\eta} D_i$ CRs which determine the existence of the PU signal. According to the paper [7], the voting rule is adopted in the fusion of information so as to minimize the total error probability. Let K=$\eta$/2, only more than half of the participants believe that the PU signal exists, the fusion center finally determines the PU signals exists and feedbacks the results to CRs, otherwise it is judged that the PU is absent. For $Q=\sum_i^{\eta} D_i$ , the final decision rule of the FC is given by the expression

$$\begin{cases} H_0 : Q < \mathrm{K} \\ H_1 : Q \geq \mathrm{K} \end{cases} \tag{18}$$

The total detection probability and PFA of the proposed scheme is given by [16]:

$$Q_d = \mathrm{P}\{\mathrm{H}_1 \mid H_1\} = \sum_{l=\mathrm{K}}^{\eta} \binom{\eta}{l} P_{di}^{l}(1-P_{di})^{\eta-l} \tag{19}$$

$$Q_f = \mathrm{P}\{\mathrm{H}_1 \mid H_0\} = \sum_{l=\mathrm{K}}^{\eta} \binom{\eta}{l} P_{fi}^{l}(1-P_{fi})^{\eta-l} \tag{20}$$

The total error probability ( $Q_e$ ) can be expressed as the sum of PFA and missed probability, which can be expressed by the following formula:

$$Q_e = Q_f + Q_m = Q_f + (1 - Q_d) \tag{21}$$

where $Q_m$ is the missing probability of cooperative spectrum sensing.

## 5. Simulations and Performance Analysis

In order to verify the effectiveness and feasibility of the proposed scheme, implemented simulations and compared with the double threshold energy detection [5] and the two step sensing method [6]. Applied Monte Carlo method for experimentation and the parameters of simulations are defined in Table 1.

**Table 1.** Simulation parameters

| Parameter | Value |
|---|---|
| Primary user | 01 |
| Secondary user | 11 |
| Number of samples | 1024 |
| SNR range (dB) | [-20, 5] |
| Selection threshold (dB) | -10 |

Assuming that the signal of the PU adopts BPSK modulation, and the number of CRs is N = 11, the sampling number M is equal to 1024 points, carrier frequency $f_c$ = 5 MHz, symbol rate $f_d$ = 2M bps, and the number of simulation count is equal to 3,000. In the simulation experiment, the SNR range is [-20, 5], set the adaptive cooperative sensing selection threshold γ=-10 dB. This is because as the SNR increases, the PD increases gradually. When the SNR is larger than -10 dB, the adaptive double threshold ED can achieve better detection effect.

The receiver operation characteristic (ROC) curves of the three detectors are depicted in Figs. 5 and 6 when $P_f$ is 0.05 and 0.005, respectively. From the figures we know that with the PFA increases, the PD increases under low SNR, the PD of double-threshold ED is the lowest which means that it is easy to cause misjudgment. With SNR changes, the PD of the proposed scheme is higher than the other two methods. Especially when SNR is -20 dB, the PD of the proposed scheme is about three times the double threshold

ED, and more than 20% higher than the two-step detector. This is because the proposed scheme can adopt the cyclostationary feature detection which has strong robustness under low SNR, and perform the adaptive double threshold ED when the SNR is higher, so it has a higher degree of PD. The proposed scheme can select a better sensing strategy which makes the system more robust and reduces the system costs, and this solution is ideal for cooperative spectrum sensing systems. Therefore, the proposed scheme can adapt to the complex and volatile wireless environment, improve the system detection performance, and comes to achieve intelligent detection.

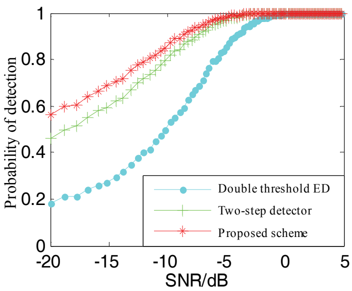


**Fig. 5.** ROC curve of PD vs. SNR at $P_f$=0.05.

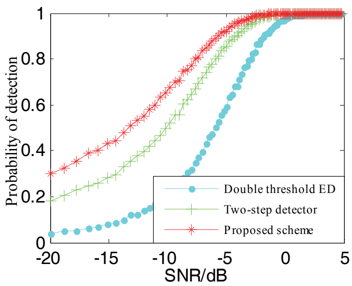


**Fig. 6.** ROC curve of PD vs. SNR at $P_f$=0.005.

Fig. 7 shows the relationship between the PFA and the PD of the three schemes when SNR is -18 dB. The figure shows that when the PFA is fixed, the PD of the proposed detection scheme is higher than the double threshold ED and the two-step spectrum detection. When $P_f$=0.1, the $P_d$ is approximately equal to 0.9, which is about two times the double threshold ED. Under the same PD, the proposed scheme has a smaller PFA compared with the other two methods, also exhibits good detection characteristics under low SNR conditions.

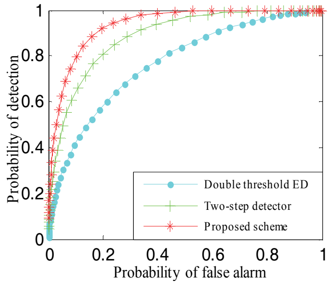


**Fig. 7.** ROC curve of PD vs. PFA at SNR=-18 dB.

Fig. 8 shows the total error probability of the proposed scheme ROC curves when the number of CRs is 3, 5, and 9, respectively and $P_f$=0.005. From the figure we can see, with the increase of SNR, the total error probability will gradually decrease or even reach to 0. It shows that the level of SNR has a big influence on the detection accuracy. And as the number of cooperating users increases, the total error rate of the proposed scheme decreases.

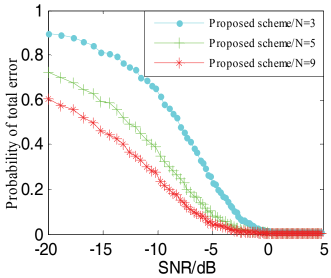


**Fig. 8.** ROC curve of probability of total error vs. SNR at N=3, 5, and 9, respectively.

Fig. 9 shows the mean detection time versus SNR when $P_f$ equal to 0.05. We know that there is an inverse relationship between mean detection time and SNR of the three detection measures, i.e., as SNR increases, the mean detection time decreases. The mean detection time of proposed scheme is shorter than two-step spectrum detection, which is consistent with the theoretical expectation. This is due to the two-step spectrum sensing in a detecting cycle involves two detectors which are energy detection and cyclostationary feature detection, so it takes a longer. However, the proposed scheme can adaptively adjust the sensing strategy according to the change of estimated SNR. When the average SNR is low, the mean sensing time is longer because the probability of performing cyclostationary detection is high. However, as the SNR increases, it tends to employ the adaptive double threshold ED, the mean detection time decreases, and even the detection speed is similar to that of double-threshold ED.

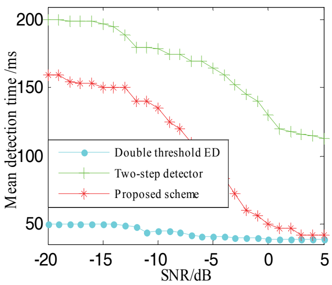


**Fig. 9.** ROC curve of mean detection time vs. SNR with M=1024.

## 6. Conclusion

The paper puts up with a novel cooperative spectrum sensing scheme where local CRs employ different sensing strategy according to the SNR estimation. When the SNR estimated by the cognitive user is higher than the threshold value, the adaptive double threshold ED is adopted, otherwise the cyclostationary detection is employed, thereby reducing system-aware complexity redundancy. The results of the local decision are transmitted to FC in the form of 1-bit. The FC adopts voting rule to make the final decision whether the PUs exists according to the number of cognitive users which involved in the data fusion. It can effectively reduce the interference of invalid cognitive users and save the transmission bandwidth. The simulation results show that the proposed scheme can improve the detection performance effectively and reduce the mean detection time.

## Acknowledgement

This paper is supported by National Natural Science Foundation of China (Grant No. 60872149 and 61503124), Henan Province Science and Technology Research Project (No. 172102210023).

## References

[1] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201-220, 2005.

[2] L. Ma and Q. Zhu, "Game-theoretic spectrum sharing for cognitive radio based on the expectation of primary users," *The Journal of China Universities of Posts and Telecommunications*, vol. 17, no. 3, pp. 6-12, 2010.

[3] K. Srisomboon, K. Thakulsukanant, A. Prayote, and W. Lee, "Adaptive two-stage spectrum sensing under noise uncertainty in cognitive radio networks," *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 14, no. 1, pp. 21-35, 2016.

[4] S. P. NI and H. G. Chang, "Double-threshold joint spectrum sensing based on energy and wavelet transform," *Journal of Beijing University of Posts and Telecommunications*, vol. 40, no. 4, pp. 46-50, 2017.

[5] A. Bhowmick, A. Chandra, S. D. Roy, and S. Kundu, "Double threshold-based cooperative spectrum sensing for a cognitive radio network with improved energy detectors," *IET Communications*, vol. 9, no. 18, pp. 2216-2226, 2015.

[6] H. Du, S. Fu, G. Shi, W. Li, L. Tian, and Y. Meng, "Performance evaluation for the two-stage cooperative spectrum sensing scheme in cognitive radio," *WSEAS Transactions on Signal Processing*, vol. 12, pp. 68-73, 2016.

[7] T. Sain and K. Sharma, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks using voting rule," *International Journal of Computer Applications*, vol. 127, no. 16, pp. 5-9, 2015.

[8] M. S. Khan and I. Koo, "The effect of multiple energy detector on evidence theory based cooperative spectrum sensing scheme for cognitive radio networks," *Journal of Information Processing Systems*, vol. 12, no. 2, pp. 295-309, 2016.

[9] H. Sakran and M. Shokair, "Hard and softened combination for cooperative spectrum sensing over imperfect channels in cognitive radio networks," *Telecommunication Systems*, vol. 52, no. 1, pp. 61-71, 2013.

[10] Y. Song, F. Zhang, Y. Shao, and H. Long, "Energy efficiency optimization of cognitive relay network based on cooperative spectrum sensing," *The Journal of China Universities of Posts and Telecommunications*, vol. 22, no. 3, pp. 26-34, 2015.

[11] A. Bagwari, J. Kanti, G. S. Tomar, and A. Samara, "A robust detector using snr with adaptive threshold scheme in cognitive radio networks," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 9, no. 5, pp. 173-186, 2016.

[12] W. Ejaz, N. U. Hasan, and H. S. Kim, "SNR-based adaptive spectrum sensing for cognitive radio networks," *International Journal of Innovative Computing, Information and Control*, vol. 8, no. 9, pp. 6095-6105, 2012.

[13] M. Lopez-Benitez and F. Casadevall, "Improved energy detection spectrum sensing for cognitive radio," *IET Communications*, vol. 6, no. 8, pp. 785-796, 2012.

[14] R. Kaur, P. Chawla, P. Sahni, and S. Kaur, "Analysis of energy detection and cyclostationary feature detection under fading channels in CRNs," in *Communication and Computing Systems*. London: Taylor & Francis, 2017, pp. 327-334.
[15] W. M. Jang, "Blind cyclostationary spectrum sensing in cognitive radios," *IEEE Communications Letters*, vol. 18, no. 3, pp. 393-396, 2014.
[16] N. R. Banavathu and M. Z. A. Khan, "Optimal number of cognitive users in k-out-of-m rule," *IEEE Wireless Communications Letters*, vol. 6, no. 5, pp. 606-609, 2017.

**Shuiping Ni** https://orcid.org/0000-0003-0524-367X

He received M.S. and Ph.D. degrees in School of Electronic Engineering from Beijing University of Posts and Telecommunications in 2004 and 2017, respectively. And He is currently an associate professor at the School of Computer Science and Technology, Henan Polytechnic University. His current research interests include wireless communication and embedded system.

**Huigang Chang** https://orcid.org/0000-0002-1067-1786

He is with the School of Computer Science and Technology from Henan Polytechnic University as a M.S. candidate since 2015. His current research interests include wireless communication and cognitive radio network.

**Yuping Xu** https://orcid.org/0000-0001-6481-9320

She is with the School of Computer Science and Technology from Henan Polytechnic University as a M.S. candidate since 2015. Her current research interest is intelligent measurement and control technology.